Regional Studies, Regional Science

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/rsrs20

Measuring daily tourism mobility spillover at the intra-metropolis level with mobile positioning data

Nicola Camatti, Giulia Carallo, Roberto Casarin & Xiang Feng

To cite this article: Nicola Camatti, Giulia Carallo, Roberto Casarin & Xiang Feng (2024) Measuring daily tourism mobility spillover at the intra-metropolis level with mobile positioning data, Regional Studies, Regional Science, 11:1, 701-723, DOI: 10.1080/21681376.2024.2412015

To link to this article: https://doi.org/10.1080/21681376.2024.2412015

Published online: 23 Oct 2024.

REGIONAL STUDIES, REGIONAL SCIENCE
2024, VOL. 11, NO. 1, 701–723
https://doi.org/10.1080/21681376.2024.2412015

Measuring daily tourism mobility spillover at the intra-metropolis level with mobile positioning data

Nicola Camatti [a], Giulia Carallo [a], Roberto Casarin [a] and Xiang Feng [b]

ABSTRACT

Although tourism mobility spillover continues to be a key indicator for tourism management, more innovative research must be conducted at the micro level and high sampling frequency. Against the backdrop of an increasing number of global cities, in this paper, we evaluate the daily tourism mobility spillover inside a worldwide city of China: Shanghai. Based on the Granger causal network model and an original mobile positioning dataset, we analyse the causal relationship between local tourism flows and the spillover effects of tourism mobility within Shanghai. By categorising tourists into 'local tourists from Shanghai' and 'tourists from out of Shanghai', we reveal a significant causal relationship between Shanghai districts and flows generated by 'tourists from out of Shanghai'. The analysis of the causal network structure also reveals key districts and points of interest that significantly contribute to congestion in tourism mobility and Shanghai's dynamics. This econometric approach offers policymakers a valuable tool to monitor mobility drivers and optimise flows within the city.

ARTICLE HISTORY

Received 28 March 2024; Accepted 5 September 2024

KEYWORDS

Spillover effects; tourism; intra-metropolis mobility; Granger causal network; mobile positioning; Shanghai

JEL

R11; R58; Z30; L83; C01; C32; C45; C11; C55

1. INTRODUCTION

Visitor flow and individual visitors' mobility have been examined from numerous angles and at multiple scales, mainly to consider inter-destination flows (Chung et al., 2020; Ferreira & Hunter, 2017; Hyde & Laesser, 2009; Park et al., 2023) but more recently, to focus on intra-destination flows and tourism micro-mobility (Huang et al., 2020; Kim et al., 2022; Stienmetz & Fesenmaier, 2019). This shift reflects a growing recognition of the need for detailed information on visitor movements within a destination (Vu et al., 2015) and an understanding of how tourists interact with various sites, which is crucial for the sustainable and competitive management of attractions (Zhou et al., 2019).

CONTACT Xiang Feng rachel@shnu.edu.cn
[a] Department of Economics, Ca' Foscari University of Venice, Venice, Italy
[b] Urban Science and Regional Planning Department, School of Environmental and Geographical Sciences, Shanghai Normal University, Shanghai, People's Republic of China

Supplemental data for this article can be accessed online at https://doi.org/10.1080/21681376.2024.2412015

Extending the analysis of what tourists do and how they behave while visiting a location to the micro-scale – a single district or attraction – can enable planners to organise local tourist offerings better and ensure high-quality tourism experiences while safeguarding local resources (Zhao et al., 2018). Likewise, the study of intra-destination tourist mobility is fundamental to specific fields, such as tourism product development (Park et al., 2021), transportation management (Chen et al., 2021) and resolution of overcrowding problems (Vu et al., 2015), as well as the analysis of consumer preferences and the value generated by flows (Park et al., 2020).

The COVID-19 pandemic has also influenced tourist behaviour, with a preference for travelling closer to home rather than long distances (Xu, Choi, et al., 2022). This behaviour shift will likely increase the supply or improve the quality of tourism offerings near tourists' residences, significantly altering the tourism product structure of entire cities in the post-pandemic era (Jeon & Yang, 2021). Therefore, studying tourist flows at the intra-destination level, rather than only between destinations, during the epidemic period has significant implications for understanding urban tourism development in the post-epidemic era (Zenker & Kock, 2020).

In this context, it is essential to equip tourist destinations with tools to gain a deeper understanding of the dynamics influencing the formation of intra-destination tourist flows (Caldeira & Kastenholz, 2020). Particularly, it is important to examine the relationships between specific attractions of a destination and other unique aspects of a city's tourism offerings in shaping these flows (Zhou & Chen, 2023).

In this study we apply Granger networks to investigate the co-movements of the intra-destination tourist flows. To the best of our knowledge, Granger networks have been used in various fields such as neuroscience (see, e.g., Ding et al., 2006; Seth et al., 2015), finance (see, e.g., Ahelegbey et al., 2016a, 2016b, 2022, 2024; Casarin et al., 2020; Corsi et al., 2018) and knowledge economy growth (Heidinger et al., 2024), to extract latent causal relationships among observable variables. Recently, they have been effectively utilised to enhance road traffic forecasts (see, e.g., Hasan & Kim, 2016; Kong et al., 2015; Lu et al., 2016), particularly in smart city studies (Fay et al., 2013). However, their application in tourism research remains relatively limited. Lyócsa et al. (2019) focused primarily on transnational flows, other studies have applied Granger causality to explore various facets of tourism without incorporating network analysis. Notably, Fonseca and Sánchez-Rivero (2020) examined the Granger causality between tourism and income, and Bilen et al. (2017) analysed the impact of tourism on economic growth using panel Granger causality analysis. This highlights a gap in the use of Granger networks to analyse the broader and more interconnected dynamics within the tourism sector, including at the local destination level.

Additionally, we propose integrating data from other sources into our network approach and studying the impact of air quality on tourism. This topic has garnered increasing interest, especially in highly congested destinations. The importance of air quality in tourism planning is well-documented (Rodrigues et al., 2021), with some empirical studies available (Eusébio et al., 2021; Wang et al., 2018). In this study, we apply our Granger network approach to introduce a model that investigates how Shanghai's air quality affects the co-movements of tourism flows and their spatial and temporal persistence.

Shanghai, as one of China's major economic and population centres, has experienced significant urban expansion and redevelopment in its downtown area. It has emerged as mainland China's leading global city, with growing connectivity in global business networks (Derudder & Taylor, 2020), an influx of domestic and international tourists (Li, 2020) and the presence of multinational company headquarters (Cai & Sit, 2005). The city's strategic location as a major gateway to the vast urban hinterland of the Yangtze River Delta, coupled with its status as China's largest seaport, has led to rapid growth in the tourism industry and infrastructure development (Feng, 2011).

In China, with the changes in municipalities' roles from a complementary one that supported state projects to a more proactive one that prepares the local development strategy (Zhang, 2002), the urban administrative districts which are one hierarchical level lower than municipalities have gradually gained a whole array of administrative powers, including planning, public works maintenance, approval of local foreign trade, commercial administration and, more importantly, the organisation of urban development (Wu & Li, 2005). This means that the urban administrative districts have relatively independent power in governing tourism products, tourism investment, tourist services, etc., bringing intensive competition among local districts, even if they belong to the same urban matrix. Due to the annual evaluation pressure given by the upper-level administrative body (i.e., the Shanghai municipality), local districts often place greater emphasis on their competitiveness of tourism development (e.g., tourist numbers), while largely ignoring the complementarity and correlation between each district, especially neglecting the movement of visitors from one area of interest to another is one of the primary ways that a place creates value (Stienmetz & Fesenmaier, 2019). Therefore, studying the spillover effects of tourist flow and revealing the spatial intra-destination relationships (not competition) across municipality districts (Kim et al., 2022) not only has certain academic value but also has significant practical application value. More importantly, from 2020 to the beginning of 2022, with its 'precise dynamic controlling model', Shanghai was one of the few metropolises in China that was least affected by the citywide 'COVID-19' lockdown policy (Meng et al., 2023).

Therefore, with its real-time tourism mobile data, the case of Shanghai can, to some extent, better reflect how Chinese tourism, especially Chinese domestic tourism, was practised during the epidemic period compared to other major cities in China. Against this background, the major objective of this paper is to demonstrate the potential of using mobile data through the novel application of the Granger causal network to carefully specify the still understudied topic of spatial spillover effects in intra-destination tourism mobility (Bo et al., 2017; Kim et al., 2022). Granger network analysis has become the method of choice to determine whether and how time series exert causal influences on each other (Fay et al., 2013). In this paper, we apply this method to study the dependence of mobility flows between urban sub-areas and specific points in the Shanghai metropolis through the concept of spillover effects, measuring how the number of visits to a certain area in a given period affects the number of visits to other areas in subsequent periods. We try to identify the urban administrative districts and attractions that cause the most daily tourist movement in Shanghai metropolis, which has in turn practical implications for managing well-known issues in a metropolitan area: traffic management (Ning et al., 2019; Yu et al., 2016), safety (Wang et al., 2019; Zhang et al., 2016) and overcrowding (Bao et al., 2017).

2. BACKGROUND

2.1. Spatial and political spillovers of tourist flows

Different specifications of spillover effects caused by tourist flows have been used in the literature. In the literature, spillover effects are usually related to the variability in tourist flows (see, e.g., Hoti et al., 2007; Shareef & McAleer, 2008), whereas a few studies consider spillover effects among flow levels (Lyócsa et al., 2019). Also, spillover effects have been used to study flows at the macro level and low sampling frequency, e.g., monthly flows among countries (see, e.g., Hoti et al., 2007; Lyócsa et al., 2019; Shareef & McAleer, 2008), or at a very small scale and high frequency, e.g., intra-day traffic on road segments (e.g., see Cai et al., 2016; Zheng et al., 2019; Zhou et al., 2022).

In micro-scale tourism movements, spillover effects are the indirect, inadvertent effects that tourist demand for certain sub-regions or attractions can have on demand in other areas and the attributes therein (Yang & Wong, 2012; Bo et al., 2017). Depending on whether these effects are positive or negative, the dependencies between places and tourist attractions are characterised as spatial complementarity or spatial competitiveness, respectively (Patuelli et al., 2016; Zhou et al., 2019). As an example, flow management (Li et al., 2021), destination marketing (Yang & Zhang, 2019), effects on pollution (Deng et al., 2017) and the identification of areas best for regional tourism cooperation (Zhu et al., 2022) are all immediately affected by the presence of these effects. The previous 'overtourism' studies further clarify that via analysing and predicting the overtourism or excessive numbers of tourists at a specific location in a definite period, the local municipality or districts could avoid, to the largest extent, some negative impacts being brought by tourism to the whole community such as opposition from residents, unwanted physical alterations, deterioration of natural and cultural resources or general congestion (Dodds & Butler, 2019). Especially after the 'revenge' rapid return of the tourism industry, which was severely damaged by the outbreak of COVID-19, urban tourism will have a large possibility of the potential occurrence of overcrowding in tourism destinations once the lockdown finished (Lim, 2021). In this sense, creating methods to assess these spillover effects at the micro-scale level is critical to successful destination management, especially if these methods can integrate scarce visitor prediction research at the level of specific attractions (Bo et al., 2017; Volchek et al., 2019).

In this paper, we introduce a spillover measure based on the predictability of flow dynamics across multiple locations. Our measure accounts for the significance of the relationships between flows without considering their sign. This approach highlights the relevance of specific locations in generating various effects (complementarity and competitiveness) on other locations. Since our notion of spillover is grounded in flow dynamics, it effectively distinguishes between receiving and diffusing locations. The flows of receivers can be predicted based on past flows of other locations. The flows of spreaders have an impact on future flows of different locations. This spillover concept is particularly useful for managing tourist flows and organising services for tourists. In situations of overtourism, it helps identify the locations that drive flow dynamics and those most affected by them.

2.2. Use of mobile data in the field of tourist flows

Only recently have we witnessed the development of concrete solutions that support the detection and analysis of intra-destination tourist movements and corresponding spillover effects. This is due to the broad use of information and communication technologies to manage tourism destinations and the strengthening of the smart destination paradigm (Raun et al., 2020; Shafiee et al., 2019; Volchek et al., 2019). A review of different approaches to tracking intra-destination movements is given in Hardy et al. (2017). In this paper we use mobile positioning data since they provide many advantages. Their use stands out as a fruitful solution capable of providing more practical operational benefits in terms of sensing tourism mobility on a micro-scale, as opposed to solutions based on location-sensing technologies (Park et al., 2020) such as GPS and other micro-sensors (Gray & Wikle, 2021; Liu et al., 2022) or solutions based on geocoded web traces that exploit social webs, such as Fink or TripAdvisor (Confente et al., 2024; Mirzaalian & Halpenny, 2021; Zhang et al., 2019). This benefit is due to mobile positioning data's distinct characteristics and attributes, which correspond to those of big data (Park & Zhong, 2022; Wang et al., 2020) and to the methods used to collect mobile data, which are more accurate, timely and, to some extent, more cost-effective and easier to manage than other smart solutions for detecting tourist flows (Baldin et al., 2024; Raun et al., 2016). In terms of quantitative analyses, the same characteristics and properties that distinguish mobile big data, such as high frequency, massive sampling sizes and the extension of coverage periods (Zhao et al., 2018, Tang et al., 2022), also enable spatiotemporal and behavioural analyses of tourism mobility on a larger micro-scale (Qian et al., 2021), paving the way for the expansion of econometric applications previously implemented primarily on a macro-scale (Balli et al., 2015; Majewska, 2015; Pompili et al., 2019). As a result, the use of mobile positioning data is proving its potential to broaden research possibilities regarding tourism micro-mobility by covering insights that more closely match those that local planners and tourism businesses describe as underpinning their day-to-day work (Li et al., 2020; Wu et al., 2020).

To demonstrate this potential, our analysis uses high-frequency mobile positioning sampling data on tourism mobility for each administrative district in Shanghai and 35 major tourist interest points.

3. METHODOLOGY

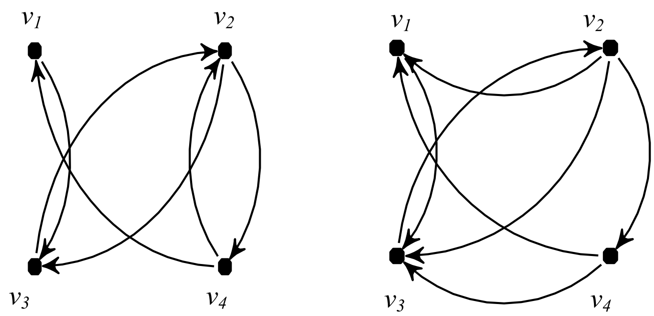
In this section, we introduce the econometric tools to analyse the spillover effects between tourist flows. First, we introduce the notion of a network (graph) as a set of relationships (graph edges) between the districts or points of interest (graph nodes). Networks and graph representations are very useful for measuring, through connectivity measures, the effect of each district on the flows of all the other districts. Different notions of graph connectivity can also be used to measure a flow's direct and indirect effects on the others. Second, we define the relationship between districts as co-movements among the number of visits in different districts or points of interest (POIs). Since they are not observable, we extract them through a vector autoregressive model and a Granger causal test between pairs of time series of visits. The model accounts for the dynamic features of the flow, such as persistence and linear dependence at different dates, and the Granger causality is useful to study how much the flow in one district at a certain date is affected by flows in other districts at previous dates or affects the flows of other districts at future dates. Finally, a statistical graph model for networks is introduced, which allows for investigating the determinants of the network effects and their features, such as formation and persistence over time of the co-movement effects.

3.1. A Network Approach

A network can be defined as a set of vertices (or nodes) and arcs (or edges) between vertices. In our mobility networks, a node represents a statistical area of interest (e.g., points, districts, regions, countries), and an edge has the interpretation of spillover effect between two areas (or points) of interest. A graph $G = (V, E)$ provides a representation of a network as a set of vertices (or nodes) $V = \{1, \ldots, n\}$ and a set of edges (or arc) $E \subset V \times V$. The number of vertices in V returns the order of a graph (see Bollob´as, 1998). An edge between two nodes represents a statistical relationship between two series of visits for distinct areas and is defined as the (ordered) pair of nodes $\{u, v\}$ with $u, v \in V$. If there is no direction in the statistical relationships between series, then the edges are not directed, the nodes in the pairs $\{u, v\}$ are unordered, and the graph G is undirected. If there is a direction, each edge is directed, the nodes in the pairs $\{u, v\}$ are ordered, and the graph G is directed. In this paper directed graphs will be considered.

A directed graph $G = (V, E)$ of order n can be associated with a n-dimensional adjacency matrix A. *If* $\{u, v\} \in E$, with $u \neq v$, then the (u, v)-th element of A, $a_{u,v}$ is equal to 1, otherwise it is equal to 0. Undirected graphs have symmetric adjacency matrices, that is, $a_{u,v} = a_{v,u}$, whereas directed graphs have asymmetric adjacency matrices. Figure 1 includes two examples of directed graphs and their adjacency matrices.

The connectivity level in a directed graph can be measured by counting the number of edges directed from other nodes to a given node i (in-degree), from a node i to other nodes (out-



$$\begin{pmatrix} 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 1 \\ 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{pmatrix} \qquad \begin{pmatrix} 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 1 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 \end{pmatrix}$$

Figure 1. Typologies of graphs.
Note: Directed graphs $G = (V, E)$ (top) with vertex set $V = \{v_1, v_2, v_3, v_4\}$, edge sets $E = \{e_1, e_2, e_3, e_4, e_5, e_6\}$, with $e_1 = \{v_1, v_4\}$, $e_2 = \{v_2, v_3\}$, $e_3 = \{v_2, v_4\}$, $e_4 = \{v_3, v_2\}$, $e_5 = \{v_3, v_1\}$, $e_6 = \{v_4, v_2\}$ (top left), $E = \{e_1, e_2, e_3, e_4, e_5, e_6, e_7\}$, with $e_1 = \{v_1, v_4\}$, $e_2 = \{v_2, v_3\}$, $e_3 = \{v_2, v_4\}$, $e_4 = \{v_2, v_1\}$, $e_5 = \{v_3, v_4\}$, $e_6 = \{v_3, v_1\}$, $e_7 = \{v_4, v_2\}$ (top right) and their adjacency matrices (bottom). Edges (arcs) are clockwise directed (i.e., following the edge clockwise indicates the direction of the spillover effect).

degree), and the total number of incident edges (total degree) that are:

$$d_u^{out} = \sum_{v=1}^{n} a_{vu}, \quad d_u^{in} = \sum_{v=1}^{n} a_{uv}, \quad d_u^{tot} = d_u^{out} + d_u^{in}$$

These connectivity measures, also known as in-degree, out-degree and total degree centrality, assess the importance of a node in the connectivity structure. Nodes with large in-degree are called receivers since they absorb spillover effects from the others, whereas nodes with large out-degree generate spillover effects and are called spreaders.

The in- and out-degree measures direct connectivity; nevertheless, some nodes can be central because they are connected to other central nodes, a fact that can be captured by indirect connectivity measures. In this paper, we consider two popular measures, the Clustering Coefficient and the Eigenvector Centrality, which are based on the undirected graph $G^* = (V, E^*)$ obtained from the original directed graph $G = (V, E)$ by removing the edge direction, that is by defining a new adjacency matrix A^* with the (u, v)-th, $a^*_{u,v}$ equal to 1 if either $a_{u,v}$ or $a_{v,u}$ is in E, or to 0 otherwise.

The Clustering Coefficient of a node i denoted by CC_i is a local indirect connectivity measure which counts the number of fully connected triplets of nodes that are in a neighbourhood of the node i and compares it with the potential number of connected triplets,

$$CC_i = \frac{2|\{u', v'\} \in E^*; u' \neq v', u' \in N_i(G^*), v' \in N_i(G^*)|}{k_i(k_i - 1)}$$

where $N_i(G^*) = \{u \in V; \ e_{u,i} \in \ E^*\}$ is the set of neighbouring nodes of i and k_i denotes its cardinality.

The Eigenvector Centrality of a node i denoted by EC_i is a global indirect connectivity measure which accounts for both direct connections of i and indirect connections (paths) of i

with all the nodes of the graph G^*, in formulae it is given by the quantity x_i which satisfies:

$$\lambda x_i = \sum_{v \in N_i(G^*)} a^*_{v,i}\, x_v$$

where $(x_1, \ldots, x_n)$ is a score vector and λ a constant which corresponds to the eigenvector and eigenvalue of the adjacency matrix A^*.

3.2. Granger Causal Network Extraction

Granger causality is used to extract the co-movements between visits at different districts and POIs. Assume the number of visits y_{it} in the area i at time t is available with $i = 1, \ldots, n$ and $t = 1, \ldots, T$. In the pairwise-Granger approach, a vector autoregressive model (VAR) of the order p is estimated on the two series of visits y_{it} and y_{jt} at different locations:

$$\begin{cases} y_{it} = \varphi_{10} + \sum_{l=1}^{p} \varphi_{11,l}\, y_{it-l} + \sum_{l=1}^{p} \varphi_{12,l}\, y_{jt-l} + \sum_{l=1}^{r} \gamma_{1l}\, x_{lt} + \varepsilon_{it} \\ y_{jt} = \varphi_{20} + \sum_{l=1}^{p} \varphi_{21,l}\, y_{it-l} + \sum_{l=1}^{p} \varphi_{22,l}\, y_{jt-l} + \sum_{l=1}^{r} \gamma_{2l}\, x_{lt} + \varepsilon_{jt} \end{cases}$$

where $(\varepsilon_{it}, \varepsilon_{jt})'$, $i \neq j$, $t = 1, \ldots, T$ are i.i.d. from a bivariate normal distribution $N_2(0, \Sigma)$ with null mean and variance-covariance matrix Σ and x_{lt} $l = 1, \ldots, r$ is a set of exogenous variables that can be incorporated to account for possible spurious effects. In our analysis $r = 1$ and x_{1t} is a dummy variable, which takes value one at holiday dates and zero otherwise. It is included to capture spurious sudden co-movements related to holidays. Regarding the VAR order in our application a Bayes information criterion (BIC) is used to select the best model, which is a VAR of the order $p = 1$.

To detect the temporal changes in the co-movements, the VAR is estimated on a rolling window basis with a window size of τ observations. Regarding the estimation method, the standard generalised least squares (GLS) is applied, which accounts for the covariance, Σ, between error terms. In addition, a weighted GLS (WGLS) is used to give more importance to the most recent observations. The optimal weights w_t of Pesaran et al. (2013) are used, that is $w_t = v_t/(v_1 + \ldots + v_{-}\tau)$ where $v_t = -\log(1 - t/\tau)/(\tau - 1)$, $t = 1, \ldots, \tau - 1$ and $v_\tau = \log(\tau)/(\tau - 1)$.

For each window, the estimated VAR of order 1 is used to extract the graph's adjacency matrix A by testing for a causal relationship between the visits of the two areas considered. The notion of Granger causality is used and the (i, j)-th element of the adjacency matrix A is defined as follows:

- $a_{j,i} = 1$ and $a_{i,j} = 0$ if $\varphi_{12,1} \neq 0$ and $\varphi_{21,1} = 0$ (y_{jt} Granger causes y_{it}).
- $a_{j,i} = 0$ and $a_{i,j} = 1$ if $\varphi_{21,1} \neq 0$ and $\varphi_{12,1} = 0$ (y_{it} Granger causes y_{jt}).
- $a_{j,i} = 1$ and $a_{i,j} = 1$ if $\varphi_{12,1} \neq 0$ and $\varphi_{21,1} \neq 0$ (co-causal effects between y_{it} and y_{jt}).

The three hypotheses above are tested with an F-based Wald test, and a significance level of 5% is used (see Lütkepohl (2007) for further details). The methodology mitigates potential heteroskedasticity due to the moving window properties.

3.3 . Network model

To study the impact of node-specific network statistics and covariates on network connectivity, we implemented the exponential random graph model (ERGM). ERGMs were introduced by Besag (1975) to overcome the limitations of statistically independent dyad models. Then, ERGMs can capture links between nodes with a triangular configuration, edge attributes and predictive networks. They were extended to directed graphs by Frank (1991) and temporal ERGMs (TERGMs) by Robins and Pattison (2001) and further developed by Hanneke et al. (2010).

Exponential random graph models (ERGMs) are models based on the exponential family theory that specify the probability distribution of a set of networks. The main advantage of ERGMs is the possibility of defining a network including covariates that are both exogenously given or represent specific graph features, such as homophily or triad effects.

A standard formulation of the TERGM model is

$$\Pr(A_t = a | A_{t-K}, \ldots, A_{t-1}) = \frac{\exp(\boldsymbol{\theta}' g(a, A_{t-K}, \ldots, A_{t-1}))}{c(\boldsymbol{\theta}, A_{t-K}, \ldots, A_{t-1})},$$

where A_s is the random variable for the adjacency matrix of the network at time s, with $s = t - K, \ldots, t - 1$, a is a realisation of A_t, $g(a, A_{t-K}, \ldots, A_{t-1})$ is the vector of statistics for the network a, $\boldsymbol{\theta}$ is the coefficient vector and $c(\boldsymbol{\theta}, A_{t-K}, \ldots, A_{t-1})$ is a normalising constant. Hence, the probability attached to the network a depends on the network only through the vector $g(a, A_{t-K}, \ldots, A_{t-1})$ and maximum likelihood estimation might be carried out. See also Krivitsky and Handcock (2014) for further details.

To overcome the computational difficulty of TERGM parameter estimation, we applied Bayesian inference combined with Markov chain Monte Carlo (MCMC) methods to sample from the posterior distribution of the parameters. In our application, we used the *tergm* package from *statnet, developed by Krivitsky et al.* (2003–2024), which uses the conditional maximum likelihood estimator as the initial value for the MCMC algorithm.

4. EMPIRICAL APPLICATION

4.1. Data description

The dataset used in this study was provided by Shanghai Unicom, the second largest mobile phone provider in Shanghai, and includes real-time tourists' positions in Shanghai metropolis from 1 December 2020 to 17 January 2022. This dataset encompasses users from diverse telephone companies, offering a sample that accurately reflects the market shares of these operators. Notably, the Shanghai municipal government relies on this dataset for precise tourism flow predictions, establishing it as a significant, accurate and inclusive data repository. This dataset serves as an asset for conducting comprehensive analyses and gaining insights into the broader tourism landscape of Shanghai.

The number of tourists is computed daily for district and attraction. We designate a 'tourist' as a mobile user who has recorded an overnight stay in the days before or after the visit, not attributable to other categories of mobile users. Consequently, our analysis concentrated exclusively on mobile users whose device activity indicated an overnight stay in a specific district (target area) of Shanghai either the night prior or the subsequent day of their visit. Other mobile user categories were excluded from consideration. China Unicom assisted in this process by providing pre-filtered mobile user data, ensuring that individuals not meeting our defined criteria were excluded. This filtering process eliminated hikers (those visiting a target area without an overnight stay), residents (mobile users detected frequently in a target area at night throughout the year), as well as workers, students and commuters (mobile users not residing in a target area but detected regularly in the weeks leading up to the examination period, without staying overnight). Additionally, our inclusion criteria required a minimum stay of six hours within a district or a minimum visit duration to an attraction, ranging from 10 to 25 minutes, depending on the type of attraction. According to the intra-destination flow concept used in this study, a tourist is counted only once per district or POI daily. However, a tourist may visit multiple POIs or districts daily.

Table 1. Statistics of district tourist mobility in Shanghai from 1 December 2020–17 January 2022.

District name	District label	Average number of tourists (in thousands)	Average number of 'local tourists from Shanghai' (in thousands)	Average number of 'tourists from out of Shanghai' (in thousands)
Huangpu	Huan	231.80	136.68	95.11
Xuhui	Xuhu	155.70	96.30	59.40
Changning	Chan	91.98	54.77	37.20
Jing'an	Jing	196.21	127.74	68.46
Putuo	Putu	124.16	84.97	39.19
Hongkou	Hong	109.84	76.90	32.93
Yangpu	Yang	118.30	78.28	40.01
Minhang	Minh	203.30	121.80	81.50
Baoshan	Baos	138.28	89.74	48.54
Jiading	Jiad	138.48	78.88	59.59
Pudong	Pudo	342.86	218.71	124.14
Jinshan	Jins	62.55	40.31	22.23
Songjiang	Song	164.07	95.37	68.70
Qingpu	Qing	112.43	64.12	48.31
Fengxian	Feng	84.54	55.57	28.97
Chongming	Chon	49.81	39.45	10.36
Shanghai	Shan	2159.75	1364.33	795.41

Based on SIM card activation records, we classify tourists into 'Shanghai local tourists' and 'tourists from outside Shanghai'. An initial processing of the dataset was conducted to calculate the number of daily visits to all 16 administrative districts (see Table 1) and several major tourist attractions (see Table A.1 in the Appendix in the online supplemental data) within the Shanghai metropolis.

The final dataset includes 409 daily observations for 16 districts and 35 attractions. The Phillips and Perron and augmented Dickey-Fuller tests for all series resulted in the rejection of the null hypothesis of unit root at the 5% level.

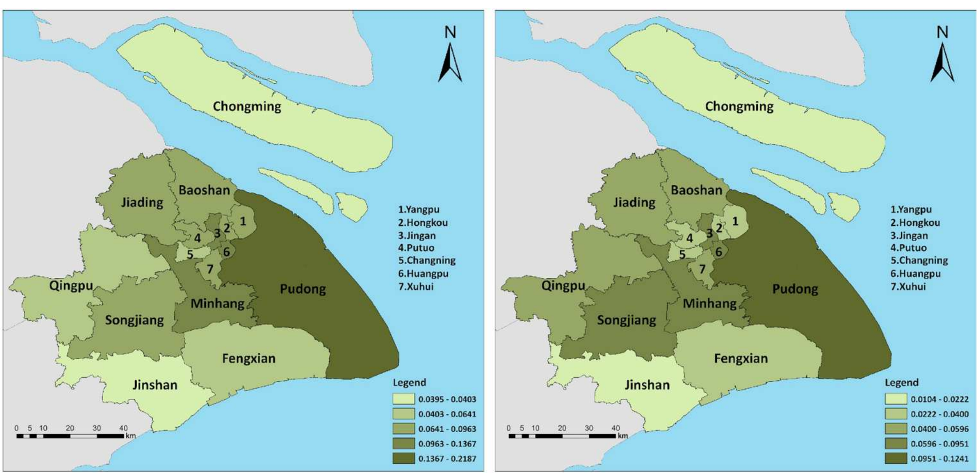


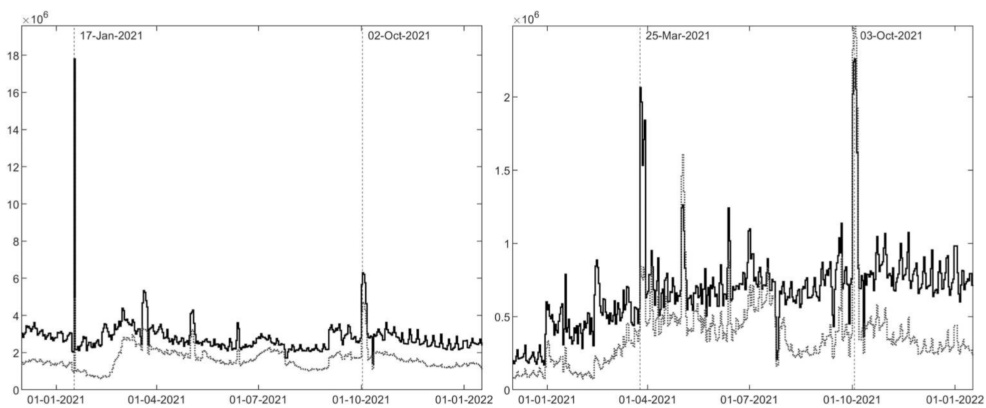
Figure 2. Mobility created by 'local tourists from Shanghai' (left) and mobility created by 'tourists from out of Shanghai' (right).

Figure 2 shows the study area and the average daily number of visits per district (different colours) and origin (different panels). From the left plot in Figure 2, it identifies that the most concentrated mobility created by 'local tourists from Shanghai' is in the very centre of Shanghai (i.e., the Pudong District, Huangpu District and Jing'an District) where most of the municipal government organisations, busy shopping streets, and lively cultural and performance centres are located. In comparison, Chongming District and Jinshan District, the two far-remote suburbs of Shanghai, have relatively the lowest mobility created by 'local tourists from Shanghai'. The right plot of Figure 2, showing the mobility created by 'tourists from out of Shanghai' illustrates a similar situation. Pudong and Huangpu districts have the highest mobility concentration, while Chongming and Jinshan districts have the lowest levels. An interesting phenomenon here is that a suburb of Shanghai, Songjiang District, also has concentrated mobility created by 'tourists from out of Shanghai'. The Sheshan National Tourism Resort could play a key role in generating such larger mobility.

The left plot in Figure 3 shows the number of visits of 'local tourists from Shanghai' (solid line) and of 'tourists from out of Shanghai' (dashed line). The vertical dashed lines show the dates of two major peaks in the visits. The right plot in Figure 3 shows the total number of visits to the 35 major attractions of Shanghai Metropolis. The two plots both demonstrate that local tourists in Shanghai generated more overall mobility than tourists from out of Shanghai. Meanwhile, no matter visits to local districts or to major attractions, the mobility created by 'tourists from Shanghai' and 'tourists from out of Shanghai' share similar peak dates which are highly related to Chinese statutory holidays such as the traditional Chinese Spring Festival holiday, May holiday and National Celebration holiday.

4.2. Spillover effects

We extract two dynamic Granger networks, one for the district and the other for the attraction. This tool allows for extracting relationships among districts and POIs due to unobservable intra-destination flows or to other factors affecting the flows jointly. This section presents the main results obtained by a rolling window GLS estimation with a window size of 60 daily observations. Further results are given in the online supplemental data, Appendices



(a) Millions of visits to the Districts of Shanghai (b) Millions of visits to the Points of Interest of Shanghai

Figure 3. Millions of visits to the Districts (a) and Points of Interest (b) of Shanghai metropolis by 'local tourists from Shanghai' (solid line) and 'tourists from out of Shanghai' (dashed line).
Note: period from 1 December 2020 to 17 January 2022. Vertical dashed lines: the two major peaks in the tourist flows. Figure on the right 'Millions of visits to the Districts of Shanghai'; figure on the left 'Millions of visits to the Points of Interest of Shanghai'.

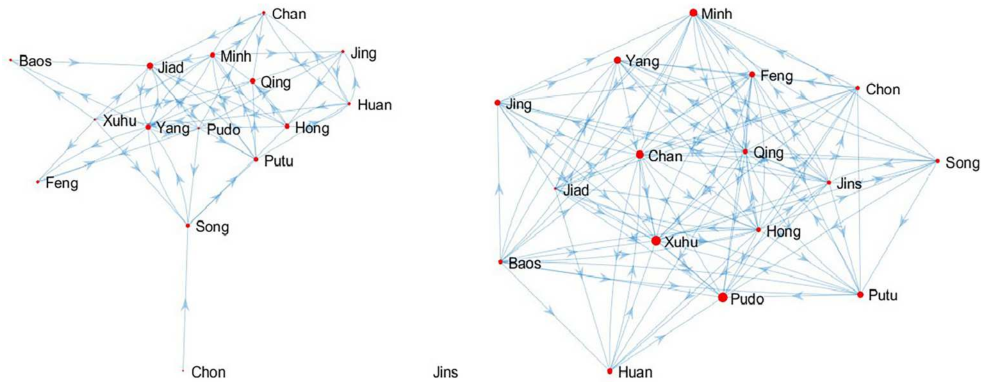


Figure 4. Estimated networks (directed graphs) for mobility generated by 'local tourists from Shanghai'.
Note: period 23 January –25 March (left) and 31 July –29 September 2021 (right). The size of the nodes is proportional to the node In-degree.

A3–A10. Some robustness checks with WGLS estimation and WGLS with holiday dummy are reported in Appendices A9–A10.

The figures in Appendix A2 provide a graphical example of the in-degree and out-degree measures, and Figure 4 further illustrates the relationship between districts at given dates.

The plots in Figure 4 show two mobility networks within Shanghai extracted for 23 January –25 March (left) and 31 July –29 September (right) 2021. In each graph, the size of the nodes is proportional to the magnitude of the node spillover effect measured by the node in-degree. From a visual inspection, the graph in the right column exhibits a larger number of edges than the one in the left, reflecting a higher level of spillover effects. Following our results, the level of spillover effect (i.e., the number of connections among districts) can change substantially over time (compare the two columns in the figure). Similar results are also given in Appendix A3 and A4 in the online supplemental data. Another stylised fact emerging from the analysis is that the districts have different roles in generating mobility spillover effects. For instance, in Figure A3 on the 17th of January, Xuhui is the district most affected by the overall mobility together with Baoshan (large in-degree, middle-right plot). In contrast, in Figure A4 Changning and Baoshan are the districts driving the visits to the other districts (large out-degree, middle-right plot).

In the following, we disentangle the spillover effects of mobility from 'local tourists from Shanghai' and 'tourists from out of Shanghai'. The figures in Appendix, materials from A5 to A8, provide some examples of Granger networks for the different types of visits. The results confirm that the centrality of the nodes changes over time and visit types. We measure the spillover effects with the average in-degree.

Figure 5 shows the spillover in the district (left) and attraction (right) networks for the mobility generated by 'local tourists from Shanghai' (solid black) and 'tourists from out of Shanghai' (solid blue) and Table A9 in the Appendix in the online supplemental data reports the network statistics for the whole sample. There are substantial spillover effects and some asymmetries in the effects. Regarding the visits to Shanghai districts (left plot), the spillover effects generated by the mobility of 'local tourists from Shanghai' among local administrative districts (black dashed) are usually larger than other spillover effects, with a larger impact on the flows generated by 'tourists from out of Shanghai'.

From January to March 2021, mobility generated by 'local tourists from Shanghai' is the leading variable for predicting the number of visits to Shanghai. The changes in the spillover

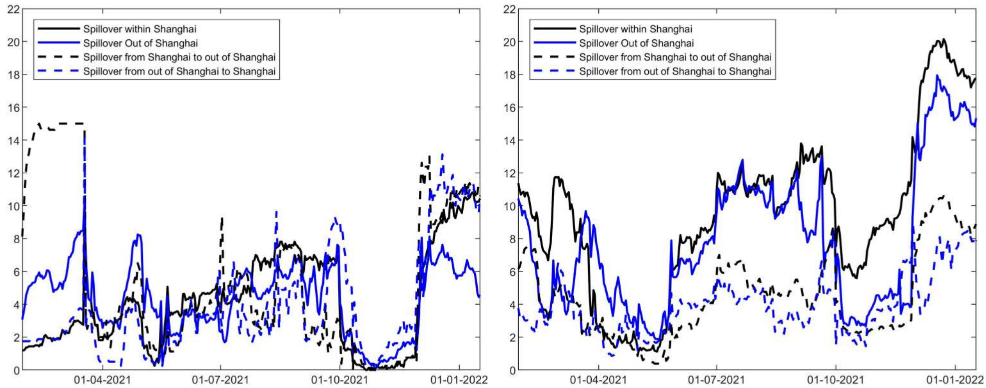


Figure 5. Average in-degree of the spillover network for the Shanghai Districts (left) and Points of Interest (right).
Note: The degree is estimated on a rolling window of 60 daily observations from 29 January 2021 to 17 January 2022.

effects start after the Spring Festival holiday in mid-January and continue during mid-February 2021 with the Chinese New Year and the week after.

We notice that this spillover effect, extracted from mobile data, is associated with a period of large changes in traffic congestion detected by Xu, Li, et al. (2022) from GPS data. Our research provides a complementary tool for analysing mobility, which can be useful for mobility management of the city in combination with other data sources.

During the year 2021, mobility generated by 'local tourists from Shanghai' has scarce predictive power on the flows generated by 'tourists from out of Shanghai' (black dashed) except in the period from October to December when tourist flow dynamics become more complex and incoming tourist flows co-evolve with the mobility generated by 'local tourists from Shanghai' (blue and black dashed). Starting in October 2021, traffic congestion increased rapidly due to events attracting many visitors, such as exhibitions and expos. In this period of the year, more accurate monitoring of all types of flows is needed to achieve better prediction and management of the visits.

We performed several robustness checks using WGLS and WGLS with holiday dummies. By comparing panels (a) to (c) in Figure A11 of the Appendix in the online supplemental data, we confirmed the presence of trends, persistence and asymmetries in the spillover effects. The WGLS model with holiday dummies provided the best fit, particularly improving the estimation of spillover effects at the start of the sample period and during October to December 2021. In the new estimates, the drop in spillover effects at the beginning of October is temporary, with clearer evidence of the significant spillovers originating from outside of Shanghai (represented by the blue dashed line). There are some changes in the district rankings based on the average centrality measures; however, the districts that ranked highly are confirmed (see Tables A9 and A10 compared to Tables A13 and A15).

From Figures 6 and 7 where the Shanghai districts represent the nodes of the network, and the number of visits generated by 'local tourists from Shanghai' or by 'tourists from out of Shanghai' is the observable variable used to extract the causal network, one can see the average in- and out-degree centrality of the districts over the period from 29 January 2021 to 17 January 2022 (see also Table A9 in the online supplemental data).

The most central districts are centrally located Changning and far-suburb Qingpu for the mobility generated by 'local tourists from Shanghai' (column S) and both centrally located

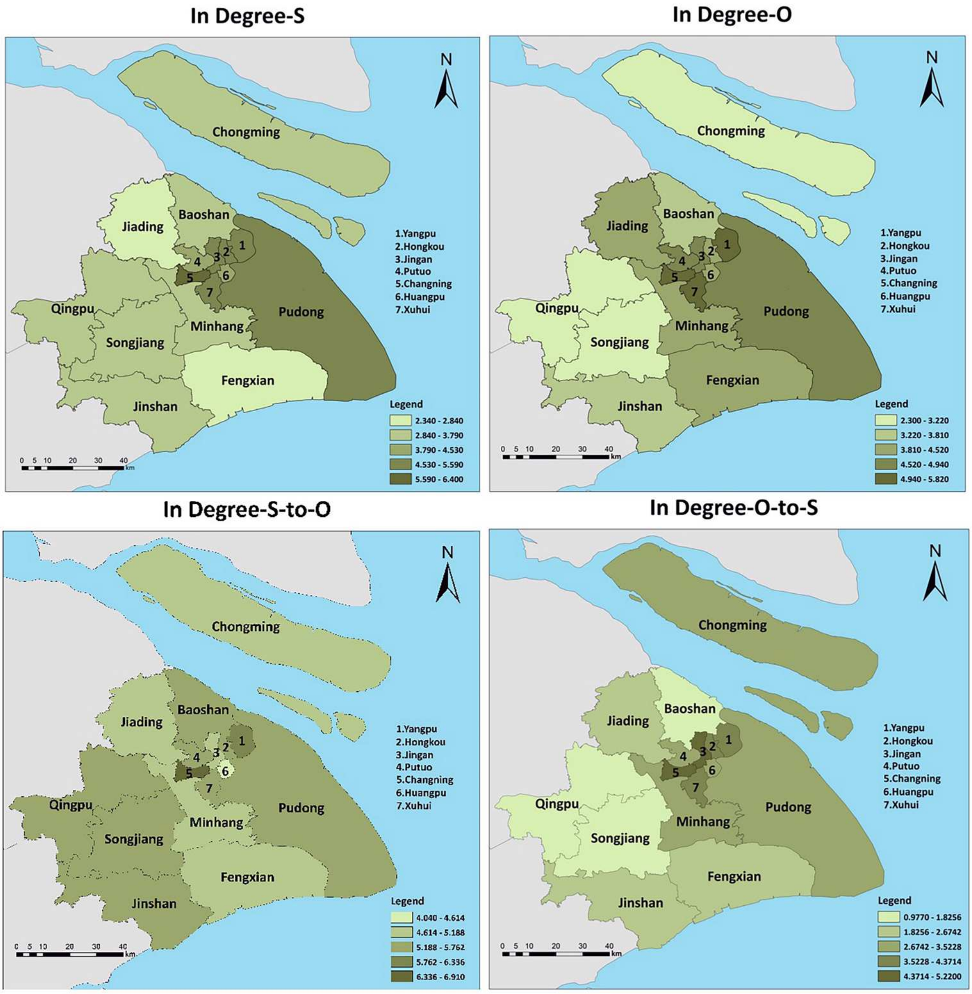


Figure 6. Maps of the district spillover effects measured as the average in-degree centrality of the latent connectivity network.
Note: Spillover effects generated by 'local tourists from Shanghai (S)', by 'tourists from out of Shanghai (O)', spillover effects generated by flows of 'local tourists from Shanghai (S)' to flows of 'tourists from out of Shanghai' (S-to-O), spillover effects generated by flows of 'tourists from out of Shanghai (O)' to flows of 'local tourists from Shanghai (S)' (O-to-S).

Xuhui and Huangpu for the mobility generated by 'tourists from out of Shanghai' (column O). The most central district with mobility of 'tourists from out of Shanghai' generating spillover effects on mobility of 'local tourists from Shanghai' (O-to-S columns) are centrally located Changning and far suburb Songjiang. The most central district with mobility of 'local tourists from Shanghai' generating spillover on the mobility of 'tourists from out of Shanghai' (S-to-O columns) are both centrally located Changning and Jing'an.

Regarding the most affected district by mobility (in-degree centrality columns in Table A9 in the online supplemental data), the overall performance of Shanghai shows a certain pattern. Changning, located in the city centre, has become the district most affected by mobility, whether it is the mobility generated by 'local tourists from Shanghai' (column S), the mobility

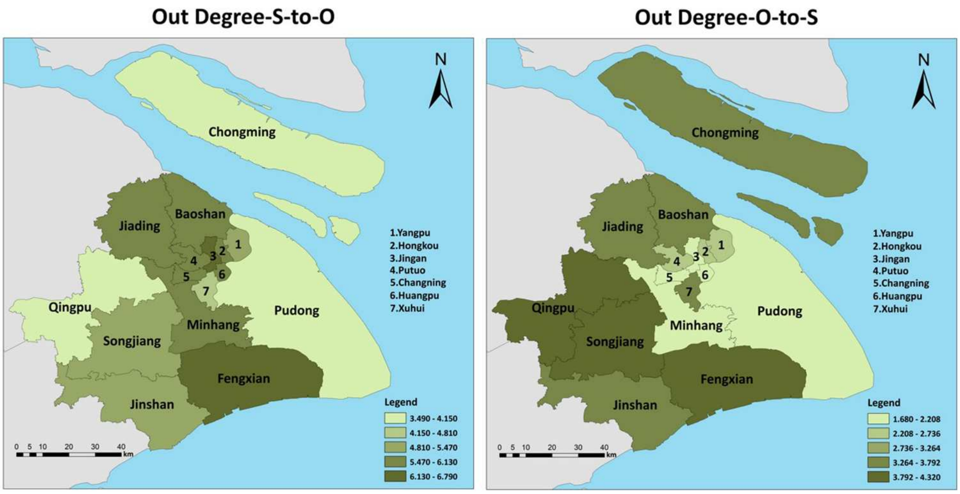


Figure 7. Maps of the district spillover effects measured as the average out-degree of the latent connectivity network.

Note: Spillover effects generated by 'local tourists from Shanghai (S)', by 'tourists from out of Shanghai (O)', spillover effects generated by flows of 'local tourists from Shanghai (S)' to flows of 'tourists from out of Shanghai' (S-to-O), spillover effects generated by flows of 'tourists from out of Shanghai (O)' to flows of 'local tourists from Shanghai (S)' (O-to-S).

of 'local tourists from Shanghai' generating spillover on the mobility of 'tourists from out of Shanghai' (S-to-O columns) or the mobility of 'tourists from out of Shanghai' generating spillover effects on mobility of 'local tourists from Shanghai' (O-to-S columns). This is an interesting finding because Changning only has one major attraction, the Shanghai Zoo, but it also accommodates the transportation hub of Shanghai Hongqiao Airport. This indicates that the presence of transportation hubs could have a large impact on the mobility of 'most affected district' instead of being largely affected by the mobility of other districts.

This 'in-degree' situation may also be related to a specific phenomenon that tourists tend to travel within the city during the pandemic. In addition, from the perspective of the mobility generated by 'tourists from out of Shanghai' (column O), Xuhui is the most important district, which may be related to its artistic and cultural destination identity and accommodating the most popular and concentrated city walk itineraries.

Concerning the mobility largely affecting mobility to other districts (out-degree centrality columns of Table A9 in the online supplemental data), the overall performance of Shanghai has not formed a certain pattern: different districts become representatives of different out-degrees. However, our study further reveals that these representative districts still share some common attributes. They can be divided into two categories. The first category is the most centrally located districts, which own a remarkable number of traditional tourist attractions, such as Huangpu (the mobility generated by 'tourists from out of Shanghai') and Jing'an (the mobility of 'local tourists from Shanghai' generating spillover on the mobility of 'tourists from out of Shanghai'). The second type is suburban areas that can provide outdoor natural environments, such as Qingpu (the mobility generated by 'local tourists from Shanghai') and Songjiang (the mobility of 'tourists from out of Shanghai' generating spillover effects on mobility of 'local tourists from Shanghai').

In addition to the attraction of nature landscapes, these suburban areas also play a certain role in distinguishing themselves in this column by having large theme parks (such as the Sheshan National Tourism Resort in Songjiang) and large exhibition spaces (such as the National

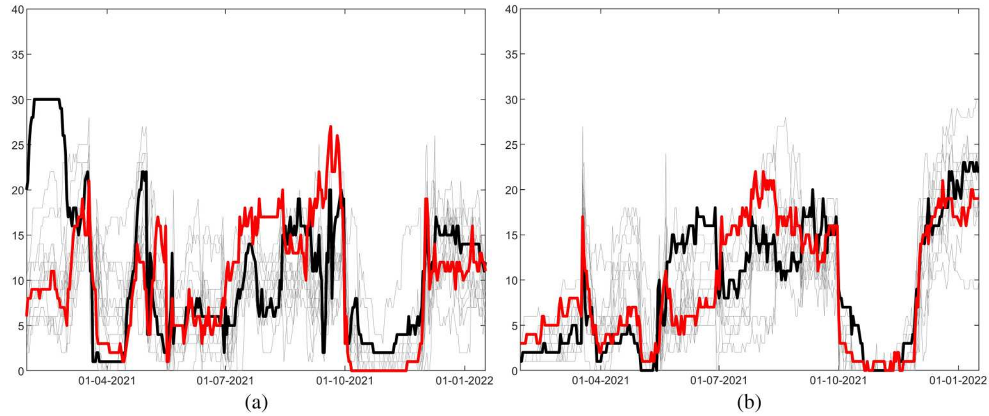


Figure 8. Spillover effect (total degree) of the mobility generated by 'tourists from out of Shanghai' (a) and by 'local tourists from Shanghai' (b) to each district.
Note: Spillover effect estimated on a rolling window of 60 daily observations from 29 January 2021 to 17 January 2022. The black and red lines represent Huangpu and Yangpu in the left plot and Changning and Qingpu in the right plot. The grey lines indicate the other districts.

Convention and Exhibition Center in Qingpu). These important tourist flows and economic agglomerations might explain the increase of the tourist flows in other districts of Shanghai to some degree, as those leisure and business tourists could spend more days visiting other parts of Shanghai, either for business intentions or just for leisure and sightseeing.

The indirect centrality measures can be used to identify districts most relevant for all direct and indirect spillover effects and to concentrate the monitoring effort on a few districts. Comparing the results in Table A10 and the robustness check in Table A15, at the intersection between the most central districts following the clustering coefficients (CC) and the ones following the Eigenvector centrality (EC), we find Huangpu, Xuhui, Hongkou and Qingpu. These districts are also among the most central following the degree measure.

The analysis of the POIs (right plot in Figure 5) shows that mobility generated by 'local tourists from Shanghai' is the main driver during the year (black solid) except in February–March (2021) when visits generated by 'tourists from out of Shanghai' play a major role in generating spillover effects. A comparison with the results for districts indicates that the flows to the POI generated by 'local tourists from Shanghai' and by 'tourists from out of Shanghai' can be monitored and predicted separately. In addition, there are cross-flow effects in the flows to districts: mobility generated by 'local tourists from Shanghai' affects mobility generated by 'tourists from out of Shanghai', and mobility generated by 'tourists from out of Shanghai' affects mobility generated by 'local tourists from Shanghai'. The rolling window analysis confirms the results for the whole sample analysis. For example, the left plot in Figure 8 shows the central role of Changning and Qingpu in the overall mobility generated by 'local tourists from Shanghai'. The right plot in Figure 8 shows the major role of Huangpu and Yangpu in the overall mobility generated by 'tourists from out of Shanghai'.

4.3. Spillover determinants

We consider different specifications of the TERGM model, each describing a specific type of tie dynamic through different terms. In each specification, we included the network density (*edges*), the network triangles (geometric weighted triangle term, *gwesp*), and some node covariates related to the air quality in the districts of Shanghai.

The *Form* term of the specification tracks the formation of ties between time steps, and the term *Persist* tracks the tie's persistence over time. The term *Change* captures the status change over time of the total number of dyads, and the term *Cross* captures the change over time of the average network structure. These terms are combined to obtain the following specifications:

1. Cross and Change with edges, gwesp and air quality covariates.
2. Form and Persist with edges, gwesp and air quality covariates.

As covariates, we considered the values of the different pollutants used to evaluate the air quality index (see Wang et al., 2018) publicly available from the Shanghai Environment Monitoring Center through the China National Urban air quality platform. We included two

Table 2. TERGM estimates for the mobility network generated by 'local tourists from Shanghai' with density (edges), triangles (gwesp) and air quality covariates ($PM_{2.5}$, PM_{10}, O_3, NO_2, SO_2, CO).

	Estimate	Std. error	z value	Pr(Z>|z|)
Cross and Change model				
θ_{0Cr} (*edges*)	0.009313	0.050111	0.186	0.852564
$\boldsymbol{\theta_{1Cr}}$ (*gwesp*)	**−0.19441**	**0.017266**	**−11.26**	**<0.0001*****
θ_{2Cr} ($PM_{2.5}$)	0.000574	0.000222	2.589	0.009615**
$\boldsymbol{\theta_{3Cr}}$ ($\boldsymbol{PM_{10}}$)	**−0.00259**	**0.000557**	**−4.646**	**<0.0001*****
$\boldsymbol{\theta_{4Cr}}$ ($\boldsymbol{O_3}$)	**−0.00132**	**0.000343**	**3.848**	**0.000119*****
θ_{5Cr} (NO_2)	0.001828	0.001197	1.527	0.126669
θ_{6Cr} (SO_2)	0.017217	0.009075	1.897	0.057785
$\boldsymbol{\theta_{7Cr}}$ ($\boldsymbol{CO}$)	**0.023304**	**0.004077**	**5.716**	**<0.0001*****
$\boldsymbol{\theta_{0Ch}}$ (*edges*)	**−2.86481**	**0.034391**	**−83.302**	**<0.0001*****
$\boldsymbol{\theta_{1Ch}}$ (*gwesp*)	**1.015916**	**0.0211**	**48.147**	**<0.0001*****
θ_{2Ch} ($PM_{2.5}$)	−0.00028	0.000156	−1.794	0.072859
$\boldsymbol{\theta_{3Ch}}$ ($\boldsymbol{PM_{10}}$)	**−0.00257**	**0.000455**	**−5.648**	**<0.0001*****
θ_{4Ch} (O_3)	0.000694	0.000232	2.996	0.002737**
θ_{5Ch} (NO_2)	7.48E-05	0.000892	0.084	0.93317
θ_{6Ch} (SO_2)	0.012511	0.007027	1.78	0.075018
$\boldsymbol{\theta_{7Ch}}$ ($\boldsymbol{CO}$)	**0.010804**	**0.003099**	**3.487**	**0.000489*****
Form and Persist model				
$\boldsymbol{\theta_{0Cr}}$ (*edges*)	**−2.44E+00**	**7.00E-02**	**−34.945**	**<0.0001*****
$\boldsymbol{\theta_{1Cr}}$ (*gwesp*)	**−1.38E-01**	**1.97E-02**	**−6.995**	**<0.0001*****
θ_{2Cr} ($PM_{2.5}$)	−1.06E-04	3.29E-04	−0.321	0.74846
$\boldsymbol{\theta_{3Cr}}$ ($\boldsymbol{PM_{10}}$)	**−7.78E-03**	**8.44E-04**	**−9.216**	**<0.0001*****
θ_{4Cr} (O_3)	1.50E-06	5.40E-04	0.003	0.99778
θ_{5Cr} (NO_2)	7.88E-04	1.81E-03	0.436	0.66267
$\boldsymbol{\theta_{6Cr}}$ ($\boldsymbol{SO_2}$)	**3.60E-02**	**1.28E-02**	**2.806**	**0.00502****
$\boldsymbol{\theta_{7Cr}}$ ($\boldsymbol{CO}$)	**4.98E-02**	**6.10E-03**	**8.163**	**<0.0001*****
$\boldsymbol{\theta_{0Ch}}$ (*edges*)	**2.30E+00**	**7.37E-02**	**31.257**	**<0.0001*****
$\boldsymbol{\theta_{1Ch}}$ (*gwesp*)	**−1.75E-01**	**2.17E-02**	**−8.083**	**<0.0001*****
$\boldsymbol{\theta_{2Ch}}$ ($\boldsymbol{PM_{2.5}}$)	**1.47E-03**	**3.48E-04**	**4.233**	**<0.0001*****
θ_{3Ch} (PM_{10})	2.33E-03	8.72E-04	2.676	0.00746**
$\boldsymbol{\theta_{4Ch}}$ ($\boldsymbol{O_3}$)	**−3.22E-03**	**5.01E-04**	**−6.426**	**<0.0001*****
θ_{5Ch} (NO_2)	2.82E-03	1.88E-03	1.5	0.13351
θ_{6Ch} (SO_2)	−4.37E-03	1.39E-02	−0.315	0.75312
$\boldsymbol{\theta_{7Ch}}$ ($\boldsymbol{CO}$)	**−2.44E+00**	**7.00E-02**	**−34.945**	**<0.0001*****

Note: In column Pr($Z > |z|$), *p*-values: *< 0.05, **< 0.01 and ***< 0.001. All other values are not significant.

measures of atmospheric particulate matter, $PM_{2.5}$ and PM_{10}, a measure for ground-level ozone or the 'bad' ozone, O_3, the value of nitrogen dioxide, NO_2, the value of sulphur dioxide, SO_2, and the value of carbon monoxide, CO. $PM_{2.5}$ includes emissions from gasoline and oil combustion. PM_{10} dust from wildfires and construction sites, industrial sources and others. O_3 is emitted from cars, refineries, chemical plants and solvents. NO_2 is a gaseous pollutant forming from the burning of fossil fuels, cars and other vehicles and industrial processes. SO_2 is also a gas from combustion of fossil fuels and industrial facilities. Lastly, CO is a gas released from combustion and the source of emissions are vehicles.

Table 2 presents the results for the spillover effects within Shanghai, and Tables A16–A18 in the Appendix provide further results. The MCMC chains have a good mixing, and the Geweke diagnostics, with an average p-value across model specifications of about 20%, indicate that the MCMC achieved convergence. Note that the coefficients are on a log-odds scale, and negative and positive signs can be interpreted as increasing or decreasing the probability at the dyad level.

For almost all specifications, the network density and the triangle coefficients are significant in the formation of ties and their persistence, as well as in the rate of turnover in dyad status and the cross-sectional network statistics over the whole network.

Overall, there is strong evidence of a relationship between air quality variables, network topology and network dynamics. Including the pollution indicators reducing, on average across model specifications, the Akaike information criterion (AIC) and BIC by 0.67% and 0.45%, respectively. In almost all specifications and terms, CO, together with one of the most impacting factors on life expectancy in China, PM_{10} are significant at the 0.1% level (boldfaced rows in Table 2 and Tables A16–A18), whereas NO_2 is not significant at any level (Table 2 and Tables A16–A18). In the spillover effects for visits from Shanghai and from out of Shanghai $PM_{2.5}$ is not statistically significant in the majority of the models for the formation of the ties (Form in Table 2 and Table A16) and the changes over time of the average network structure (Cross term in Table 2 and Table A16). Nevertheless, $PM_{2.5}$ is significant in the spillover between visits from Shanghai and out of Shanghai (Tables A17 and A18), which can be related to road traffic conditions in the connections between Shanghai and neighbouring regions. Ozone, O_3, which is responsible for breathing problems, is significant at the 0.1% level in some specifications and terms for all spillover effects within Shanghai and from out of Shanghai.

5. CONCLUSION

Analysing tourist flows is crucial for defining policies promoting sustainable urban tourism. To this end, integrating diverse data sources helps to gain valuable insights to plan targeted and timely interventions in tourism, mobility and resource management.

This paper aims to demonstrate how mobile data, analysed through the innovative application of Granger causal network analysis, can enhance our understanding and specification of spatial spillover effects in tourist mobility within a destination. Network models are used to integrate variables from additional data sources, such as environmental data, and to study the development and interaction of tourist flows over time, thus providing insights that traditional methods may not reveal.

We offer an introduction to graph theory as a backdrop for analysing spillover effects in tourist visits. Since the spillover effects are not observable, a Granger network analysis enabled us to extract intra-destination tourism networks, utilising daily data on mobility flows in the Shanghai metropolis. Our analysis identified significant co-movements between the visits to a particular area or attraction in Shanghai during a specific period and subsequent visits to other places in the city. The spillover dynamics exhibit asymmetry in two ways: between flows generated by domestic Shanghai tourists and those from outside Shanghai, and in variations in flows to different districts and hotspots. The evidence of the districts' different roles in the network, asymmetric effects and time variations calls for separate and continuous monitoring throughout the year. A network model is employed to demonstrate how to integrate variables from other data sources to analyse the determinants of the tourism network, thus providing valuable insights tailored to the specific destination type under examination. The application of air quality data reveals a significant relationship between air pollution and the topology and dynamics of the tourism networks.

Our proposed network approach offers an effective tool for managing tourism dynamics within a destination and across various local spatial units, fostering the development of more sustainable tourism. The research highlights the intrinsic connections between tourism activities in different districts of Shanghai. These districts compete to attract tourists while sharing interconnected tourist flows, revealing the potential for cooperation among them.

These findings advocate for a shift from pure competition to a 'cooperation and competition' model, providing valuable insights to encourage and guide each district to collaborate while maintaining its competitive edge. As our research demonstrated, the nature of these interconnections is influenced by each district's unique characteristics and tourism attractions, as well as other environmental factors.

To leverage these insights, strategies should focus on creating coordinated tourism networks at the inter-district level and promoting collaboration in areas such as air quality management. This approach lays a strong foundation for planning and scaling up-targeted interventions related to Shanghai's tourism, including organising and managing tourist facilities and services based on anticipated visitor flows, addressing overcrowding issues and developing targeted marketing strategies that optimise local resources while enhancing the visitor experience.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author, upon reasonable request.

DISCLOSURE STATEMENT

No potential conflict of interest was reported by the author(s).

ORCID

Nicola Camatti http://orcid.org/0000-0002-1899-2728
Giulia Carallo http://orcid.org/0000-0001-5550-3404
Roberto Casarin http://orcid.org/0000-0003-1746-9190
Feng Xiang http://orcid.org/0000-0002-1926-7923

REFERENCES

Ahelegbey, D. F., Billio, M., & Casarin, R. (2016a). Bayesian graphical models for structural vector autoregressive processes. *Journal of Applied Econometrics*, *31*(2), 357–386. https://doi.org/10.1002/jae.2443

Ahelegbey, D. F., Billio, M., & Casarin, R. (2016b). Sparse graphical multivariate autoregression: A Bayesian approach. *Annals of Economics and Statistics*, *123/124*, 1–30. https://doi.org/10.15609/annaeconstat2009.123-124.0333

Ahelegbey, D. F., Billio, M., & Casarin, R. (2024). Modeling turning points in the global equity market. *Econometrics and Statistics*, *30*, 60–75. https://doi.org/10.1016/j.ecosta.2021.10.004

Ahelegbey, D. F., Fianu, E. S., & Grossi, L. (2022). Modeling risk contagion in the Italian zonal electricity market. *European Journal of Operational Research*, *298*(2), 656–679. https://doi.org/10.1016/j.ejor.2021.06.052

Baldin, A., Bertocchi, D., & Camatti, N. (2024). Crowding-in and (temporary) crowding-out in venice. The effect of cultural events on residents. *Tourism Economics*, 13548166241233773. https://doi.org/10.1177/13548166241233773

Balli, F., Curry, J., & Balli, H. O. (2015). Inter-regional spillover effects in New Zealand international tourism demand. *Tourism Geographies*, *17*(2), 262–278. https://doi.org/10.1080/14616688.2014.1003394

Bao, Y., Fan, G., Zou, D., Wang, T., & Xue, D. (2017). Patient experience with outpatient encounters at public hospitals in Shanghai: Examining different aspects of physician services and implications of overcrowding. *PLoS One*, *12*(2), e0171684. https://doi.org/10.1371/journal.pone.0171684

Besag, J. (1975). Statistical analysis of non-lattice data. *Journal of the Royal Statistical Society Series D: The Statistician*, *24*(3), 179–195. https://doi.org/10.2307/2987782

Bilen, M., Yilanci, V., & Eryüzlü, H. (2017). Tourism development and economic growth: A panel granger causality analysis in the frequency domain. *Current Issues in Tourism*, *20*(1), 27–32. https://doi.org/10.1080/13683500.2015.1073231

Bo, Z., Bi, Y., Hengyun, L., & Hailin, Q. (2017). The spillover effect of attractions: Evidence from eastern China. *Tourism Economics*, *23*(4), 731–743. https://doi.org/10.5367/te.2016.0541

Bollob´as, B. (1998). *Modern graph theory*. Springer.

Cai, J., & Sit, V. F. (2005). Measuring world city formation—the case of Shanghai. *Globalization and Urban Development*, 239–250. Springer. https://doi.org/10.1007/3-540-28351-X_16

Cai, P., Wang, Y., Lu, G., Chen, P., Ding, C., & Sun, J. (2016). A spatiotemporal correlative k-nearest neighbor model for short-term traffic multistep forecasting. *Transportation Research Part C: Emerging Technologies*, *62*, 21–34. https://doi.org/10.1016/j.trc.2015.11.002

Caldeira, A. M., & Kastenholz, E. (2020). Spatiotemporal tourist behaviour in urban destinations: A framework of analysis. *Tourism Geographies*, *22*(1), 22–50. https://doi.org/10.1080/14616688.2019.1611909

Casarin, R., Iacopini, M., Molina, G., Ter Horst, E., Espinasa, R., Sucre, C., & Rigobon, R. (2020). Multilayer network analysis of oil linkages. *The Econometrics Journal*, *23*(2), 269–296. https://doi.org/10.1093/ectj/utaa003

Chen, J., Becken, S., & Stantic, B. (2021). Harnessing social media to understand tourist mobility: The role of information technology and big data. *Tourism Review*, *77*(4), 1219–1233. https://doi.org/10.1108/tr-02-2021-0090

Chung, M. G., Herzberger, A., Frank, K. A., & Liu, J. (2020). International tourism dynamics in a globalized world: A social network analysis approach. *Journal of Travel Research*, *59*(3), 387–403. https://doi.org/10.1177/0047287519844834

Confente, I., Mazzoli, V., Camatti, N., & Bertocchi, D. (2024). Integrating tourists' walk and talk: A methodological approach for tracking and analysing tourists' real behaviours for more sustainable destinations. *Journal of Sustainable Tourism*, 1–21. https://doi.org/10.1080/09669582.2024.2322120

Corsi, F., Lillo, F., Pirino, D., & Trapin, L. (2018). Measuring the propagation of financial distress with granger-causality tail risk networks. *Journal of Financial Stability*, *38*, 18–36. https://doi.org/10.1016/j.jfs.2018.06.003

Deng, T., Li, X., & Ma, M. (2017). Evaluating impact of air pollution on China's inbound tourism industry: A spatial econometric approach. *Asia Pacific Journal of Tourism Research*, *22*(7), 771–780. https://doi.org/10.1080/10941665.2017.1331923

Derudder, B., & Taylor, P. J. (2020). Three globalizations shaping the twenty-first century: Understanding the new world geography through its cities. *Annals of the American Association of Geographers*, *110*(6), 1831–1854. https://doi.org/10.1080/24694452.2020.1727308

Ding, M., Chen, Y., & Bressler, S. L. (2006). Granger causality: Basic theory and application to neuroscience. *Handbook of Time Series Analysis: Recent Theoretical Developments and Applications*, 437–460. https://doi.org/10.1002/9783527609970.ch17

Dodds, R., & Butler, R. (2019). The phenomena of overtourism: A review. *International Journal of Tourism Cities*, *5*(4), 519–528. https://doi.org/10.1108/IJTC-06-2019-0090

Eusébio, C., Carneiro, M. J., Madaleno, M., Robaina, M., Rodrigues, V., Russo, M., Relvas, H., Gama, C., Lopes, M., Seixas, V., Borrego, C., & Monteiro, A. (2021). The impact of air quality on tourism: A systematic literature review. *Journal of Tourism Futures*, *7*(1), 111–130. https://doi.org/10.1108/JTF-06-2019-0049

Fay, D., Thakur, G. S., Hui, P., & Helmy, A. (2013). Knowledge discovery and causality in urban city traffic: A study using planet scale vehicular imagery data. In *Proceedings of the sixth ACM SIGSPATIAL international workshop on computational transportation science* (pp. 67–72). Association for Computing Machinery. https://doi.org/10.1145/2533828.2533836

Feng, X. (2011). *Regional tourism cooperation: Factors influencing the performance of regional tourism cooperation in China*. Shaker Publishing.

Ferreira, S. L., & Hunter, C. A. (2017). Wine tourism development in South Africa: A geographical analysis. *Tourism Geographies*, *19*(5), 676–698. https://doi.org/10.1080/14616688.2017.1298152

Fonseca, N., & Sánchez-Rivero, M. (2020). Publication bias and genuine effects: The case of granger causality between tourism and income. *Current Issues in Tourism*, *23*(9), 1084–1108. https://doi.org/10.1080/13683500.2019.1585419

Frank, O. (1991). Statistical analysis of change in networks. *Statistica Neerlandica*, *45*(3), 283–293. https://doi.org/10.1111/j.1467-9574.1991.tb01310.x

Gray, E. S., & Wikle, J. S. (2021). Using webcam video feed to measure and evaluate national park recreation patterns. *Journal of Park and Recreation Administration*, *39*, 1. https://doi.org/10.18666/jpra-2020-10496

Hanneke, S., Fu, W., & Xing, E. P. (2010). Discrete temporal models of social networks. *Electronic Journal of Statistics*, *4*(none), 585–605. https://doi.org/10.1214/09-EJS548

Hardy, A., Hyslop, S., Booth, K., Robards, B., Aryal, J., Gretzel, U., & Eccleston, R. (2017). Tracking tourists' travel with smartphone-based GPS technology: A methodological discussion. *Information Technology & Tourism*, *17*(3), 255–274. https://doi.org/10.1007/s40558-017-0086-3

Hasan, M. M., & Kim, J. (2016). Analysing functional connectivity and causal dependence in road traffic networks with granger causality. In *Australasian transport research forum 2016 proceedings* (pp. 19). Melbourne: Australasian Transport Research Forum Incorporated.

Heidinger, M., Fuchs, M., & Thierstein, A. (2024). The contribution of knowledge-intensive firms to employment growth: A granger causality approach for German regions. *Regional Studies, Regional Science*, *11*(1), 103–121. https://doi.org/10.1080/21681376.2024.2312186

Hoti, S., McAleer, M., & Shareef, R. (2007). Modelling international tourism and country risk spillovers for Cyprus and Malta. *Tourism Management*, *28*(6), 1472–1484. https://doi.org/10.1016/j.tourman.2007.02.014

Huang, X., Han, Y., Gong, X., & Liu, X. (2020). Does the belt and road initiative stimulate China's inbound tourist market? An empirical study using the gravity model with a DID method. *Tourism Economics*, *26*(2), 299–323. https://doi.org/10.1177/1354816619867577

Hyde, K. F., & Laesser, C. (2009). A structural theory of the vacation. *Tourism Management*, *30*(2), 240–248. https://doi.org/10.1016/j.tourman.2008.06.006

Jeon, C. Y., & Yang, H. W. (2021). The structural changes of a local tourism network: Comparison of before and after COVID-19. *Current Issues in Tourism*, *24*(23), 3324–3338. https://doi.org/10.1080/13683500.2021.1874890

Kim, Y. R., Liu, A., Stienmetz, J., & Chen, Y. (2022). Visitor flow spillover effects on attraction demand: A spatial econometric model with multisource data. *Tourism Management*, *88*, 104432. https://doi.org/10.1016/j.tourman.2021.104432

Kong, W., Lin, W., Babiloni, F., Hu, S., & Borghini, G. (2015). Investigating driver fatigue versus alertness using the granger causality network. *Sensors*, *15*(8), 19181–19198. https://doi.org/10.3390/s150819181

Krivitsky, P. N., & Handcock, M. S. (2014). A separable model for dynamic networks. *Journal of the Royal Statistical Society Series B: Statistical Methodology*, *76*(1), 29–46. https://doi.org/10.1111/rssb.12014

Krivitsky, P. N., Handcock, M. S., Hunter, D. R., Butts, C. T., Bojanowski, M., Klumb, C., Goodreau, S. M., & Morris, M. (2003–2024). *statnet: Software tools for the Statistical Modeling of Network Data*. Statnet Development Team. http://statnet.org

Li, J. (2020). Culture and tourism-led peri-urban transformation in China–the case of Shanghai. *Cities*, *99*, 102628. https://doi.org/10.1016/j.cities.2020.102628

Li, H., Hu, M., & Li, G. (2020). Forecasting tourism demand with multisource big data. *Annals of Tourism Research*, *83*, 102912. https://doi.org/10.1016/j.annals.2020.102912

Li, S., Yang, Y., Zhong, Z., & Tang, X. (2021). Agent-based modeling of spatial spillover effects in visitor flows. *Journal of Travel Research*, *60*(3), 546–563. https://doi.org/10.1177/0047287520930105

Lim, W. M. (2021). Toward an agency and reactance theory of crowding: Insights from COVID-19 and the tourism industry. *Journal of Consumer Behaviour*, *20*(6), 1690–1694. https://doi.org/10.1002/cb.1948

Liu, W., Wang, B., Yang, Y., Mou, N., Zheng, Y., Zhang, L., & Yang, T. (2022). Cluster analysis of microscopic spatio-temporal patterns of tourists' movement behaviors in mountainous scenic areas using open GPS-trajectory data. *Tourism Management*, *93*, 104614. https://doi.org/10.1016/j.tourman.2022.104614

Lu, Z., Zhou, C., Wu, J., Jiang, H., & Cui, S. (2016). Integrating granger causality and vector auto-regression for traffic prediction of large-scale WLANs. *KSII Transactions on Internet and Information Systems (TIIS)*, *10*(1), 136–151. https://doi.org/10.3837/tiis.2016.01.008

Lütkepohl, H. (2007). *New introduction to multiple time series analysis*. Springer-Verlag. https://doi.org/10.1007/978-3-540-27752-1

Lyócsa, Š, Vašaničová, P., & Litavcová, E. (2019). Interconnectedness of international tourism demand in Europe: A cross-quantilogram network approach. *Physica A: Statistical Mechanics and its Applications*, *526*, 120919. https://doi.org/10.1016/j.physa.2019.04.155

Majewska, J. (2015). Inter-regional agglomeration effects in tourism in Poland. *Tourism Geographies*, *17*(3), 408–436. https://doi.org/10.1080/14616688.2014.997279

Meng, Y., Wang, X., Dong, P., Yang, Y., Wang, K., Yan, X., Hu, G., Mao, A., & Qiu, W. (2023). Comparative analysis of prevention and control measures toward COVID-19 epidemic between Shanghai and Beijing. *Frontiers in Public Health*, *11*, 1121846. https://doi.org/10.3389/fpubh.2023.1121846

Mirzaalian, F., & Halpenny, E. (2021). Exploring destination loyalty: Application of social media analytics in a nature-based tourism setting. *Journal of Destination Marketing & Management*, *20*, 100598. https://doi.org/10.1016/j.jdmm.2021.100598

Ning, Z., Huang, J., & Wang, X. (2019). Vehicular fog computing: Enabling real-time traffic management for smart cities. *IEEE Wireless Communications*, *26*(1), 87–93. https://doi.org/10.1109/MWC.2019.1700441

Park, C., Kim, Y. R., & Yeon, J. (2023). Stronger together: International tourists "spillover" into close countries. *Tourism Economics*, *29*(5), 1204–1224. https://doi.org/10.1177/13548166221098320

Park, S., Xu, Y., Jiang, L., Chen, Z., & Huang, S. (2020). Spatial structures of tourism destinations: A trajectory data mining approach leveraging mobile big data. *Annals of Tourism Research*, *84*, 102973. https://doi.org/10.1016/j.annals.2020.102973

Park, S., Yuan, Y., & Choe, Y. (2021). Application of graph theory to mining the similarity of travel trajectories. *Tourism Management*, *87*, 104391. https://doi.org/10.1016/j.tourman.2021.104391

Park, S., & Zhong, R. R. (2022). Pattern recognition of travel mobility in a city destination: Application of network motif analytics. *Journal of Travel Research*, *61*(5), 1201–1216. https://doi.org/10.1177/00472875211024739

Patuelli, R., Mussoni, M., & Candela, G. (2016). The effects of world heritage sites on domestic tourism: A spatial interaction model for Italy. In R. Patuelli & G. Arbia (Eds.), *Spatial econometric interaction modelling* (pp. 281–315). Cham. https://doi.org/10.1007/978-3-319-30196-9_13

Pesaran, M. H., Pick, A., & Pranovich, M. (2013). Optimal forecasts in the presence of structural breaks. *Journal of Econometrics*, *177*(2), 134–152. https://doi.org/10.1016/j.jeconom.2013.04.002

Pompili, T., Pisati, M., & Lorenzini, E. (2019). Determinants of international tourist choices in Italian provinces: A joint demand–supply approach with spatial effects. *Papers in Regional Science*, *98*(6), 2251–2274. https://doi.org/10.1111/pirs.12467

Qian, C., Li, W., Duan, Z., Yang, D., & Ran, B. (2021). Using mobile phone data to determine spatial correlations between tourism facilities. *Journal of Transport Geography*, *92*, 103018. https://doi.org/10.1016/j.jtrangeo.2021.103018

Raun, J., Ahas, R., & Tiru, M. (2016). Measuring tourism destinations using mobile tracking data. *Tourism Management*, *57*, 202–212. https://doi.org/10.1016/j.tourman.2016.06.006

Raun, J., Shoval, N., & Tiru, M. (2020). Gateways for intra-national tourism flows: Measured using two types of tracking technologies. *International Journal of Tourism Cities*, *6*(2), 261–278. https://doi.org/10.1108/IJTC-08-2019-0123

Robins, G., & Pattison, P. (2001). Random graph models for temporal processes in social networks. *The Journal of Mathematical Sociology*, *25*(1), 5–41. https://doi.org/10.1080/0022250X.2001.9990243

Rodrigues, V., Carneiro, M. J., Eusébio, C., Madaleno, M., Robaina, M., Gama, C., Oliveira, K., Relvas, H., Lopes, M., & Monteiro, A. (2021). How important is air quality in travel decision-making? *Journal of Outdoor Recreation and Tourism*, *35*, 100380. https://doi.org/10.1016/j.jort.2021.100380

Seth, A. K., Barrett, A. B., & Barnett, L. (2015). Granger causality analysis in neuro- science and neuroimaging. *Journal of Neuroscience*, *35*(8), 3293–3297. https://doi.org/10.1523/JNEUROSCI.4399-14.2015

Shafiee, S., Ghatari, A. R., Hasanzadeh, A., & Jahanyan, S. (2019). Developing a model for sustainable smart tourism destinations: A systematic review. *Tourism Management Perspectives*, *31*, 287–300. https://doi.org/10.1016/j.tmp.2019.06.002

Shareef, R., & McAleer, M. (2008). Modelling international tourism demand and uncertainty in Maldives and Seychelles: A portfolio approach. *Mathematics and Computers in Simulation*, *78*(2–3), 459–468. https://doi.org/10.1016/j.matcom.2008.01.025

Stienmetz, J. L., & Fesenmaier, D. R. (2019). Destination value systems: Modeling visitor flow structure and economic impact. *Journal of Travel Research*, *58*(8), 1249–1261. https://doi.org/10.1177/0047287518815985

Tang, L., Li, J., Du, H., Li, L., Wu, J., & Wang, S. (2022). Big data in forecasting research: A literature review. *Big Data Research*, *27*, 100289. https://doi.org/10.1016/j.bdr.2021.100289

Volchek, K., Liu, A., Song, H., & Buhalis, D. (2019). Forecasting tourist arrivals at attractions: Search engine empowered methodologies. *Tourism Economics*, *25*(3), 425–447. https://doi.org/10.1177/1354816618811558

Vu, H. Q., Li, G., Law, R., & Ye, B. H. (2015). Exploring the travel behaviors of inbound tourists to Hong Kong using geotagged photos. *Tourism Management*, *46*, 222–232. https://doi.org/10.1016/j.tourman.2014.07.003

Wang, L., Fang, B., & Law, R. (2018). Effect of air quality in the place of origin on outbound tourism demand: Disposable income as a moderator. *Tourism Management*, *68*, 152–161. https://doi.org/10.1016/j.tourman.2018.03.007

Wang, J., Huang, J., & Du, F. (2020). Estimating spatial patterns of commute mode preference in Beijing. *Regional Studies, Regional Science*, *7*(1), 382–386. https://doi.org/10.1080/21681376.2020.1806104

Wang, X., Zhou, Q., Yang, J., You, S., Song, Y., & Xue, M. (2019). Macro-level traffic safety analysis in Shanghai, China. *Accident Analysis & Prevention*, *125*, 249–256. https://doi.org/10.1016/j.aap.2019.02.014

Wu, F., & Li, Z. (2005). Sociospatial differentiation: Processes and spaces in subdistricts of Shanghai. *Urban Geography*, *26*(2), 137–166. https://doi.org/10.2747/0272-3638.26.2.137

Wu, Y., Wang, L., Fan, L., Yang, M., Zhang, Y., & Feng, Y. (2020). Comparison of the spatiotemporal mobility patterns among typical subgroups of the actual population with mobile phone data: A case study of Beijing. *Cities*, *100*, 102670. https://doi.org/10.1016/j.cities.2020.102670

Xu, J., Choi, H. C., Lee, S. W., & Law, R. (2022). Residents' attitudes toward and intentions to participate in local tourism during and after the COVID-19 pandemic. *Asia Pacific Journal of Tourism Research*, *27*(5), 473–488. https://doi.org/10.1080/10941665.2022.2091945

Xu, P., Li, W., Hu, X., Wu, H., & Li, J. (2022). Spatiotemporal analysis of urban road congestion during and post COVID-19 pandemic in Shanghai, China. *Transportation Research Interdisciplinary Perspectives*, *13*, 100555. https://doi.org/10.1016/j.trip.2022.100555

Yang, Y., & Wong, K. K. F. (2012). A spatial econometric approach to model spillover effects in tourism flows. *Journal of Travel Research*, *51*(*6*), 768–778. http://doi.org/10.1177/0047287512437855

Yang, Y., & Zhang, H. (2019). Spatial-temporal forecasting of tourism demand. *Annals of Tourism Research*, *75*, 106–119. https://doi.org/10.1016/j.annals.2018.12.024

Yu, R., Wang, X., Yang, K., & Abdel-Aty, M. (2016). Crash risk analysis for Shanghai urban expressways: A Bayesian semi-parametric modeling approach. *Accident Analysis & Prevention*, *95*, 495–502. https://doi.org/10.1016/j.aap.2015.11.029

Zenker, S., & Kock, F. (2020). The coronavirus pandemic–A critical discussion of a tourism research agenda. *Tourism Management*, *81*, 104164. https://doi.org/10.1016/j.tourman.2020.104164

Zhang, T. (2002). Urban development and a socialist pro-growth coalition in Shanghai. *Urban Affairs Review*, *37*(4), 475–499. https://doi.org/10.1177/10780870222185432

Zhang, K., Chen, Y., & Li, C. (2019). Discovering the tourists' behaviors and perceptions in a tourism destination by analyzing photos' visual content with a computer deep learning model: The case of Beijing. *Tourism Management*, *75*, 595–608. https://doi.org/10.1016/j.tourman.2019.07.002

Zhang, X., Deng, Y., Li, Q., Skitmore, M., & Zhou, Z. (2016). An incident database for improving metro safety: The case of Shanghai. *Safety Science*, *84*, 88–96. https://doi.org/10.1016/j.ssci.2015.11.023

Zhao, X., Lu, X., Liu, Y., Lin, J., & An, J. (2018). Tourist movement patterns understanding from the perspective of travel party size using mobile tracking data: A case study of Xi'an, China. *Tourism Management*, *69*, 368–383. https://doi.org/10.1016/j.tourman.2018.06.026.

Zheng, L., Long, F., Chang, Z., & Ye, J. (2019). Ghost town or city of hope? The spatial spillover effects of high-speed railway stations in China. *Transport Policy*, *81*, 230–241. https://doi.org/10.1016/j.tranpol.2019.07.005

Zhou, X., & Chen, Z. (2023). Destination attraction clustering: segmenting tourist movement patterns with geotagged information. *Tourism Geographies*, *25*(2–3), 797–819. http://doi.org/10.1080/14616688.2021.2006769

Zhou, Y., Jiang, X., Fu, C., Liu, H., & Zhang, G. (2022). Bayesian spatial correlation, heterogeneity and spillover effect modeling for speed mean and variance on urban road networks. *Accident Analysis & Prevention*, *174*, 106756. https://doi.org/10.1016/j.aap.2022.106756

Zhou, B., Yang, B., & Liu, Y. (2019). Compatible effect or competitive effect: An investigation of attraction spatial interdependency. *Tourism Economics*, *25*(8), 1182–1199. https://doi.org/10.1177/1354816618816188

Zhu, N., Zeng, G., Li, X., & Zhong, Z. (2022). Optimum spatial scale of regional tourism cooperation based on spillover effects in tourism flows. *Tourism Economics*, *29*(2), 409–436. https://doi.org/10.1177/13548166211052810