Looking into mobility in the Covid-19 'eye of the storm': simulating virus spread and urban resilience in the Wuhan city region travel flow network

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Looking into mobility in the Covid-19 'eye of the storm': Simulating virus spread and urban resilience in the Wuhan city region travel flow network

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ABSTRACT

Recent urban and regional studies have focused on identifying positive spillover effects from intensifying flows of people in city region networks. However, potential negative spillover effects have lacked attention. The article addresses this research gap focusing on the negative spillover effects represented by Covid-19 contagion in the Wuhan regional travel flow network, China. Drawing on central place theory and central flow theory, Covid-19 spatial spread simulation scenarios are explored using a combined micro-level epidemic compartment model and urban network approach. It is found that not only centrally positioned primate but secondary cities are highly risk exposed to contagion. In addition, these cities have enhanced transmission capacity in a balanced, well-connected travel flow network, whereas a centralised or locally clustered network would be more spread resilient. Both hierarchical position and horizontal flows are found relevant for explaining Covid-19 uneven spread and for informing mobility interventions for a potential future outbreak.

1. Introduction

Since the December 2019 outbreak of Covid-19 in Wuhan City, China, many studies have investigated the part played by mobility and travel in the ensuing global pandemic (Gibbs et al., 2020; Jia et al., 2020; Kraemer et al., 2020; Liu et al., 2021; Xiong et al., 2020; Zhou et al., 2020). Most of these studies have either focused on the application of epidemic compartment (EC) models in local contexts or have traced international travel flows to predict virus spread across global cities. However, the dramatic spread of contagion within the Wuhan city region (WCR) before the introduction of lockdown policy measures, has lacked attention in the academic literature. This article puts the travel flows in the WCR 'eye of the storm' in Covid-19 and their implications for urban planning and policy, centre stage in this special edition of *Cities*. The virus spread is conceived of as a negative spillover effect interlinking proximate urban centres in the analysis, inspiring new understanding of the spatial organisation of urban mobility relations at a city region scale.

Attempts to understand the underlying spatial organisation of relations between cities in urbanised regions were long influenced by Christaller's (1933/1966) central place theory (CPT) (Hall & Pain, 2006,

pp. 4–5). However, with advances in ICT technologies since the late twentieth century, attention shifted to the need to make sense of evolving city relations in the networked 'space of flows' described by central flow theory (CFT) (Castells, 1996; Meijers, 2007; Taylor et al., 2010). European research has found intense cross-cutting flows of people travelling between urban centres of different sizes in functionally interconnected city regions (Hall & Pain, 2006, p. 17). Other research has suggested that resultant positive spillovers of labour, knowledge, innovation and capital from large cities allow proximate smaller cities to 'borrow' valuable 'agglomeration size' in regional networks of cities (Meijers et al., 2016; Meijers & Burger, 2015).

Reflecting this research, the renewed European Union twenty-year policy commitment to boosting economic growth, urged policymakers to build linkages "with neighbouring cities and towns in order to 'borrow' size and quality, to create a stronger critical mass and ensure positive spillover effects for the development of wider regions" (ESPON, 2020, p. 2). Following the footsteps of Europe, Chinese regional planning strategy has sought to promote economic development and spatial rebalancing through major investment in time-efficient passenger services (Guo et al., 2020; Luo et al., 2010; Wu et al., 2017). Reduction of regional inter-urban travel times has been a renewed objective in China's

2021–25 'Fourteenth Five-Year Plan'[1] to further boost national economic growth. However, there has been a general lack of research or policy enquiry into potential negative spillover effects from intensifying human travel flows within a city region.

As the largest economic agglomeration in central China, Wuhan is the leading primate city in a city region with the designated role in the Chinese central government planning system of promoting inland development (CSC, 2016; NDRC, 2016). State investment in the region's infrastructure to facilitate inter-city human mobility has therefore been a central plank in government policies to develop the city region economically. However, the resultant intensification of travel flows in a city region presents a concomitant risk of the geographical distribution of contagious human virus infection. Since the first case of Covid-19 was officially reported in Wuhan in December 2019, the virus spread rapidly across the region, as illustrated in Fig. 1. The 68,135 cases reported in the WCR to May 2020 represented 81% of China's total infections nationally. Regardless of a slight decline in national cases, the WCR remained the most severely affected region in China until 2022, yet the proportions of the epidemic crisis within the city region have attracted little attention in or beyond China.

The worldwide spread of Covid-19 has led to international recognition of the catastrophic social and economic impacts of the transmission of human infectious disease between urban centres of population in a hypermobile society (Helbing, 2013; Jia et al., 2020; Liu et al., 2021). The 2019 Wuhan outbreak "is unlikely to be the last of its kind" (Bailey et al., 2020, 1163) but, to the best of our knowledge, the analysis presented in this article is the first to consider how city region planning and policy can be better prepared to mitigate travel flow contagion risk when a future virus outbreak is detected.

Important for informing our analytical approach is the longstanding conundrum of how to reconcile the spatial contradiction noted by Castells (1996), between territorially administered spatial planning and policy, and the networked space of contemporary inter-city flows. Reflecting this spatial contradiction, we refer to both CPT and CFT in our analysis of the WCR travel flow network. The principles underpinning modern transport planning have their roots in CPT (Hall & Pain, 2006). The CPT predictive capability was based on the (k = 4) 'transport principle' (Goodall, 1987),[2] which established what would be an efficient transport network interconnecting proximate urban places of different sizes servicing a predominantly rural hinterland. However, travel flows in contemporary functional city regions have become increasingly multi-directional and multi-dimensional, overriding the CPT two-dimensional logic of a proximity and service hierarchy order of places.[3] To understand the spatial organisation of the Covid-19 spread in the WCR travel flow network and draw inferences for city region planning and policy, we therefore examine the multi-directional human flows represented by CFT in relation to the urban hierarchical positions represented by CPT.

Our research questions ask:

- First, what is the association between *city positions* and virus spread in the WCR travel flow network?

- Second, what is the association between *network structures* and virus spread in the WCR travel flow network?
- Third, what lessons can be learned for *planning and policy mobility interventions* to mitigate regional virus contagion risk in the event of a future infectious disease outbreak?

The new contribution of the article to existing literature is that by means of innovatively combining a micro-level EC model and macro-level urban network approach, the scenario projections we develop shed light on the part played by complex multi-directional travel flows in the WCR network of cities. Furthermore, the analysis puts an overdue spotlight on planning and policy considerations from a pre-lock-down intervention perspective in the city region where the epidemic outbreak originated. Generic CFT and CPT urban processes are drawn on to explore the planning and policy implications of negative city region spillover effects represented by the spread of a mobile disease.

The remainder of the article is organised as follows. First, we review notable theoretical and empirical contributions to relevant literature. Second, the method, data processing and model specification used in the analysis are elaborated. Third, the results are presented and discussed. Fourth, the conclusion and implications for urban mobility planning and policy are considered.

2. City region Covid-19 mobility puzzles in central place and central flow relations

Unravelling the Covid-19 virus spread in the WCR is rooted in understanding the way that urban relations are spatially organised, which is explicitly discussed in CPT and CFT. The CPT representation of a hierarchical spatial order of cities servicing hinterlands based on the 1920s development pattern of southern Germany (Christaller, 1933/1966), remained dominant in urban and transport planning thinking until the late twentieth century (McLoughlin, 1969; Mulligan, 1984). The turn of millennium 'Global Research Proposal' unveiled by Taylor (1997) in *Cities*, was distinctive in introducing a method of quantifying city relations in the emergent networked space of flows described by Castells (1996). Addressing the CPT reliance on over-simplified urban relational assumptions (Meijers et al., 2016; Neal, 2011), development of the quantitative 'interlocking network model' (INM) (Taylor, 2004), was followed by the specification of its conceptual premises in the theory of 'central flows' (Taylor et al., 2010).

While the INM has been applied in a swathe of 'global city' studies (Sassen, 1991), it has also been adapted and applied in city region studies. Regional INM applications have explored 'global city region' connectivity in valuable economic networks and flows of people and capital at different spatial scales (Scott, 2001; Hall & Pain, 2006; Taylor et al., 2006; Taylor & Pain, 2007; Pain & Hall, 2008; Mahroum et al., 2008; Zhu et al., 2021). Regional development literature has illustrated the contribution of intra-regional knowledge and capital flows to regional 'network capital' (Huggins & Thompson, 2014; McCann, & van Oort., F., 2009; Shi et al., 2021). Studies investigating the concept of agglomeration borrowed size, have indicated the potential for city region network externalities to assist 'levelling up' and counter uneven spatial development (Burger & Meijers, 2016; Meijers et al., 2016; Van Meeteren et al., 2016). In theory, positive spillovers from globally networked cities facilitated by intra-regional flows of people, allow proximate smaller cities to exploit agglomeration knowledge and innovation advantages, flattening traditional CPT hierarchical urban relations. Aligned with this argument, cities may also borrow the negative spillover effects of Covid-19 infection via human mobility from proximate cities in a networked city region. Investigating the "inherent complexity and multidimensionality involved" in the spread of a "networked disease" (Ali & Keil, 2008, xxi; Zhang et al., 2020), remains a critical analytical gap for informing planning and policy.

While critiques of INM analyses in the literature have cited the exclusiveness of their prioritisation of urban relations associated with

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[1] In Chinese: http://www.xinhuanet.com/politics/2021-03/11/c_11272 00766.htm.

[2] In central place theory, the k value is used to define the geographical relationship between different orders of urban places. With a k = 4 relationship, each market area of a higher-order place contains four market areas of a lower order place. Settlements were assigned to the midpoints of six sides of a hexagonal configuration to minimise the total length of roads between central places.

[3] There are two important assumptions with regard to transportation in central place theory: residents choose the nearest market to purchase goods and services; transport cost is evenly proportionate to geographical distance in all directions. These assumptions are weak with respect to a more complex contemporary transportation network.
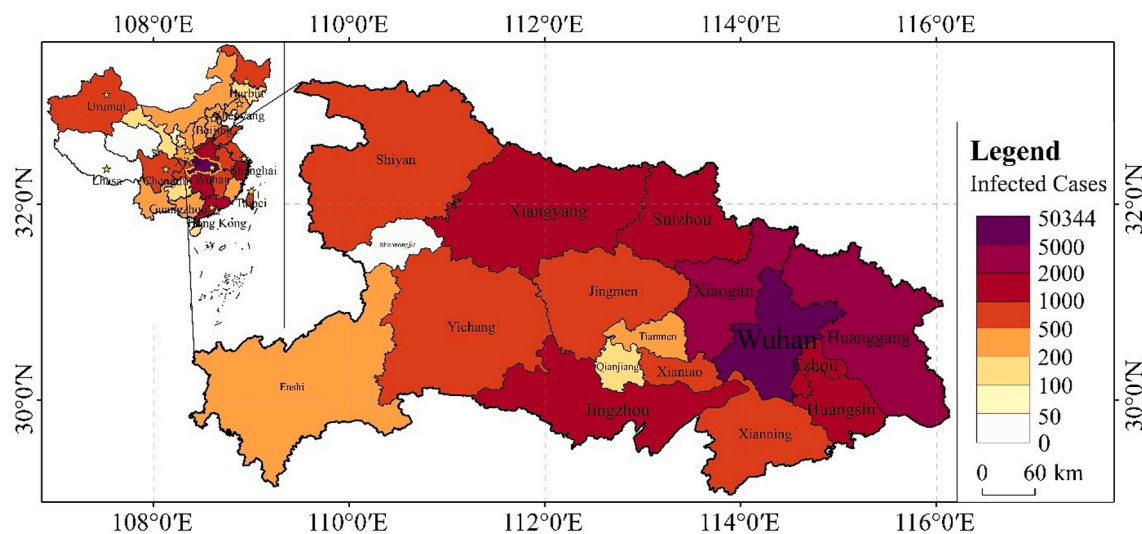
Fig. 1. The spatial distribution of Covid-19 infected cases in the Wuhan city region (source: NHC).

corporate networks operating in and through leading global cities, leaving 'ordinary' cities 'off the map' in international analysis (Brown et al., 2010; Robinson, 2006). Some studies have speculated that urban hinterland 'middle places' not represented in global city analysis, can 'connect' other hinterland cities to valuable regional flow networks (Doran & Fox, 2016; Humer & Granqvist, 2020). A recent study of the capital flow network in the WCR, observed that despite the regional primacy of Wuhan, multi-directional horizontal relations are rising, interlocked by non-primate, ordinary regional cities (Shi & Pain, 2020). This finding raises the question whether 'middle places' also exist in the WCR travel flow network and are associated with negative Covid-19 spillovers. Thus, in addition to the importance of complex multi-directional flows, the importance of city network positions is also recognised in network contagion incidents. For example, a 'knife-edge' risk presented by network 'central players' has been identified in corporate interlocking defaults, value chain disruptions and commercial real estate market volatility (e.g. Beck & Walker, 2013; Hałaj & Kok, 2013; Lizieri & Pain, 2014; Nier et al., 2007). If the findings from these studies apply to functionally networked city regions, when an infectious disease suddenly breaks out in centrally positioned cities (players) in a well-connected regional travel flow network, a knife-edge risk of systemic contagion, could result.

Thus far, academic literature on Covid-19 and urban mobility has generally focused on long distance inter-city and local intra-city human flows, and their impact on virus spread (Alessandretti, 2022, 12). This is illustrated explicitly by several Covid-19 spread simulation studies using mobility data within or between the major cities in China and internationally (Gibbs et al., 2020; Jia et al., 2020; Kraemer et al., 2020; Liu et al., 2021; Xiong et al., 2020; Zhou et al., 2020). These studies are inadequate for explaining the virus spread associated with complex multi-directional inter- and intra-city travel flows. For instance, Zhou et al. (2020) employed various EC models to uncover the virus spread within cities, whereas their study ignored inter-city travel flows. Kraemer et al. (2020) and Jia et al. (2020) calculated one-way outbound travel flows from Wuhan to other Chinese cities but did not address the virus spread implications of multi-directional two-way inter-city travel flows. While Xiong et al. (2020) and Liu et al. (2021)'s more comprehensive empirical approach did not consider the simultaneity of intra-city and inter-city transmission and the network positions of cities, which may lead to biased risk exposure. However, Ali and Keil's (2006) study of Severe Acute Respiratory Syndrome (SARS), concluded that urban resilience to epidemics is embedded in a network structure that

reflects the unique positions of cities which are determined by complex multi-directional travel flows and the simultaneity of intra- and inter-city travel flows. The study focused on the network relations of just one global city, the case of Toronto, leaving a research gap in studying city networks involving less globalised and smaller cities such as Wuhan and its neighbouring cities.

Correspondingly, the ability of urban planning and policy to promote travel flows maintaining continuity and resilience, requires a capacity to adapt to shocks caused by the spread of infectious disease and Long Covid morbidity (Kelly & Gulati, 2022). There has been increasing attention in the academic literature to the policy implications of the Covid-19 virus spread for the design of interventions that could avoid full lockdown measures (Chinazzi et al., 2020; Kraemer et al., 2020; Zhang et al., 2021). Gibbs et al.'s (2020) study cautioned that travel interventions imposed early in China's Covid-19 outbreak had a temporary effect on containment of the virus spread and warned that spatial spread from major agglomerations may shift healthcare service pressure to places with limited capacity. Alessandretti (2022) cautioned that studies suggesting that the spread of infection can be limited despite reduced travel restrictions, are dependent on the successful implementation of place-based mobility measures. Nevertheless, the lessons for future urban planning and policy from the spread of Covid-19 from Wuhan to smaller proximate cities in the WCR, have so far not been considered.

The novel contribution of this article is that it addresses the foregoing analytical gaps in the existing literature. Theoretically, the article contributes to increasing scholarly debate noted by Van Meeteren et al. (2016) about the relative power of CFT and CPT. In doing so, it fills the present gap in enquiry into whether the negative Covid-19 spillovers of human mobility follow the same spreading mechanism of positive network capital noted by Shi and Pain (2020). Furthermore, the investigation of multi-directional two-way travel flows in the WCR, sheds long overdue light on the underlying complexity of the spatial spread of a contagious disease, called for by Ali and Keil (2008). This can assist international academic and policy understanding of the "specifics of *how* cities impact regional development" (Clark et al., 2018, 1025), which is required to inform advanced mobility intervention planning for unexpected epidemic outbreaks. Empirically, the analysis focuses on the singular city region in China where the Covid-19 outbreak occurred without warning and during the high vulnerability period prior to government lockdown interventions being imposed, allows planners and policymakers to learn from observations on the spontaneous travel flow

influence on virus spatial spread. Methodologically, the inclusion of simultaneous intra-city and inter-city transmission between Wuhan and multiple proximate, non-primate cities reduces the bias in existing network risk estimation.

3. Method and data

In order to unravel the underlying negative spillovers embedded in complex place-flow relations, the method builds on Openshaw and Veneris (2003) by combining a micro-level epidemic Susceptible-Infectious (S—I) model and a macro-level urban network approach to test virus spread scenarios and inform city region policy for a sudden contagious disease outbreak. EC models generally take a whole population as the observational basis for predicting viral contagion trajectories at an enclosed spatial scope and thereby fail to reveal risk exposure related to heterogeneities within a city region scope (Wu, 2020).[4] Urban network approach in INM, generally regards a whole city as a network node and uses aggregated linkages to represent a functional connection between two cities (Taylor, 2004; Taylor et al., 2008; Taylor et al., 2010). However, this approach to analysis cannot explicitly reflect micro-level human-to-human transmission characteristics of Covid-19 infection (Jia et al., 2020). Consequently, in the present analysis, mobile people are the 'agents' or nodes interlocking networked cities, expressed by both inter-city and intra-city human mobilities in the regional travel flow network. By innovatively combining the S—I model and urban network approach, their respective shortcomings for shedding light on city region virus spatial spread are overcome.

The methodological quasi-experimental design simulates the spatial spread of the Covid-19 virus in the regional travel flow network. On one hand, people are assigned as infected cases (treatment groups) following the S—I epidemic model with an infectious rate; on the other hand, the directions and the total number of inter-city travel flows are controlled following actual migration data. The combined micro-level epidemic model and macro-level regional travel flow network generate Covid-19 viral contagion simulations in the WCR. The design allows potential contagious risks under different scenarios to be detected by varying origin cities and network structures. The analysis adopts a structured approach to examine the association of city position and network flow relations with Covid-19 spatial transmission. First, a regional travel flow network is constructed based on Baidu commuting data. Second, an epidemic S—I model is employed to simulate the spatial spread of Covid-19 initiated by different cities ceteris paribus, in order to estimate the association between city positions and virus spread. Third, the simulation model is implemented by re-organising inter-city human flows ceteris paribus, in order to estimate the role of network structures in virus spread.

3.1. Data

The source of the travel flow data is the Baidu human mobility big data platform (qianxi.baidu.com) which tracks daily commuting flows covering more than 300 cities in China. Data on inter-city human flow direction, inter-city human flow scale and intra-city human flows are taken from the Baidu map app that is widely used in China as a navigation application and other apps that use Baidu's Location-based Service (LBS). The Baidu map has 320 million users covering 1.1 billion terminal devices and processes 120 billion daily LBS requests from 0.5 million mobile applications (source: lbsyun.baidu.com).[5] In order to shed light on regional spontaneous travel flows, the period from 1st January to 23rd January 2020 is selected as the time window for analysis because Wuhan was locked down on 23rd January and other cities in the region followed suit.[6] Imposition of lockdown has been found largely effective in reducing the basic infection reproduction rate in China (Tian et al., 2020). And human interactions are changed considerably when people become fully aware of the risk of infection (Imai et al., 2020).

3.2. The construction of the regional travel flow network

The regional travel flow network is comprised of nodes (human individuals) and linkages (human interactions). The human-to-human transmission of Covid-19 can thus be mirrored by node-to-node linkages distributed in the network. To provide a better fit with the dynamic micro-level process of human-to-human viral transmission, population units are assigned as network nodes according to population size (one node represents 10,000 individuals). For data privacy and technological limitation reasons, it is not possible to track every individual's travel itineraries to assign linkages. Instead, with a fixed number of linkages, intra-city linkages are distributed across nodes within the same city; inter-city linkages are assigned to two nodes that are located in different cities following the direction of inter-city travel flows. Although the randomisation of intra-city linkage assignments simplifies realistic scenarios to some extent, it improves the overall robustness of scenario simulations compared to former studies that neglect the simultaneity of inner- and inter-city transmission (e.g. Liu et al., 2021). In order to improve the robustness of the model, the assignment process is iterated 100 times to compensate for randomisation-induced information loss while the number of nodes and linkages is unchanged. Consequently, a complex mega-size regional travel flow network is constructed comprising 5911 nodes, 29,897 intra-city linkages and 1057 inter-city linkages, as illustrated in Fig. 2.

3.3. Calculation of city network relations

City network relations are estimated by nodal degree and structural positions, reflecting CFT horizontal and CPT hierarchical relations respectively. Nodal degree measures the direct linkages between cities to reflect the individual capacity of nodes to build interactions with others through indegree, outdegree and self-degree, according to the directions of the flows. Indegree is a measure of the total number of linkages a city receives, indicating its 'attractiveness' to other cities. Outdegree concerns the total number of linkages that a city originates, reflecting its centrifugal forces to expand its influence in the network. Structural positions take 'indirectness' into account, reflecting that a node's centrality not only depends on how many direct connections it has individually but also on how many connections its neighbor nodes have. As Derudder (2019) highlighted, it is structural positions derived from 'beyond first-order neighbours' that add conceptual relevance to urban network approach. The incorporation of 'indirect' network
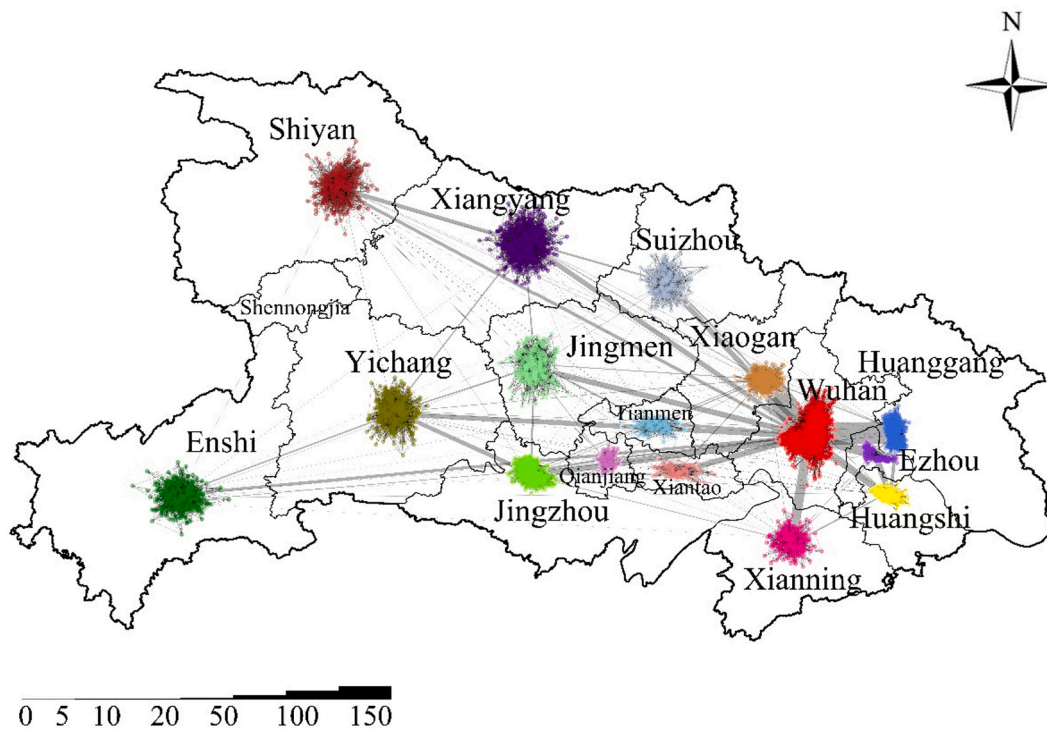

Fig. 2. The spatial pattern of the travel flow network in the Wuhan city region (note: the tie strength indicates the number of connections across cities; the number of nodes indicates the population size i.e. one node represents 10,000 individuals) (source: Baidu Commuting Data).

positions fills the gap in this regard left by other Covid-19 urban network studies that focus on 'direct' travel flows (e.g., Jia et al. (2020) and Liu et al. (2021)).

Following this line of reasoning, structural positions are measured by 'betweenness' and 'closeness' in the present analysis. Betweenness is used to measure how often a given city appears on the shortest paths between other cities, reflecting its bridging function in the network. Referring to Burt (2009)'s structural hole theory, network actors that are positioned in others' shortest paths exert power to affect the whole network. The measure of betweenness (C_B) of network node (v) is formally written as:

$$C_B(v) = \sum_{s \neq v \neq t \in V} \frac{\sigma_{st}(v)}{\sigma_{st}} \tag{1}$$

where σ_{st} is the total number of shortest paths from node s to node t and $\sigma_{st}(v)$ is the fraction of shortest paths from node s to node t passing through node v.

The other structural measure, closeness, represents the reciprocal of the sum of a node's geodesic functional distances from all other nodes. It serves as a gauge for how centrally positioned nodes are in the overall network. In contrast with betweenness that focuses on nodes' bridge role between certain dyads, closeness can reflect a holistic view concerning how long it takes to spread information from one node to all others sequentially. More formally, the closeness of node x ($C(x)$) is formulated as:

$$C(x) = \frac{n-1}{\sum_y d(y,x)} \tag{2}$$

where $d(y,x)$ is the shortest functional distance between node x and all other nodes y.

3.4. Implementation of the susceptible-infectious model in dynamic network modelling

The S—I model imposes assumptions on the regional travel flow network formulated to allow for the transmission of Covid-19 to specific connected nodes.[7] The model divides the whole network of nodes into two subgroups, susceptible and infected respectively. Susceptible nodes are not immune to the virus, and once infected, they are unable to recover during the observation period[8]; susceptible nodes turn into infected counterparts via contact with confirmed cases according to a certain transmission rate. The transmission rate is constant and no super-transmission individuals are assumed; once infected, secondary transmission starts immediately regardless of incubation period (see Nishiura et al., 2020). The S—I model is implemented using a Python iterative algorithm to simulate the dynamic spread of Covid-19 throughout the constructed network until all nodes are eventually infected (see Fig. 3). Formally, the number of newly infected nodes (I) is written in the form of an ordinary differential equation as:

$$\frac{dI_k}{d_k} = \beta \bullet A \bullet I_{k-1}$$

$$I_k = N - S_k$$

The iterative process is converged until:

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[7] There are two reasons why the basic S—I model is chosen: 1) other EC models (such as SIR, SIS and SEIR etc.) require more assumptions concerning transmission dynamics based on local demographic characteristics which are generally heterogeneous across cities; 2) rather than calculating a realistic reproduction number, the quasi-experimental design is used intentionally in order to capture hidden network risks under different scenarios.
[8] This assumption is justified since this study focuses on investigating the initial outbreak period without strong interventions and effective medical treatments.
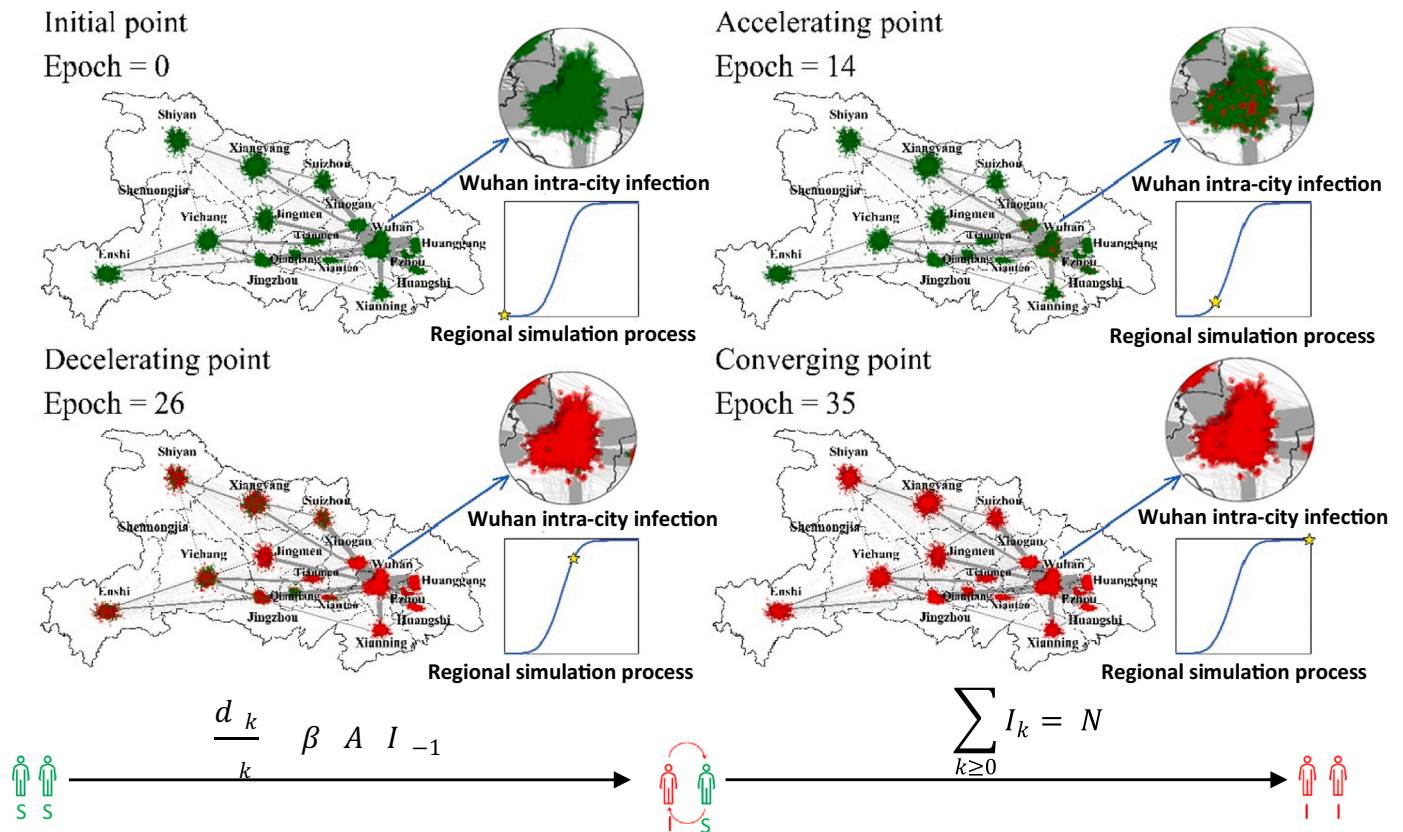
Fig. 3. The dynamic process of the Covid-19 infection in the Wuhan regional travel flow network (note: the epoch reflects the number of iterative steps needed to reach the infection status in the Wuhan city region; transmission is occurring within and across cities; the initial infected node is located in Wuhan; accelerating and decelerating points are determined by the width of the fitted Gaussian function).

$$\sum_{k \geq 0} I_k = N$$

where I_k is the number of infected network nodes at the kth epoch; β is the probability rate of transmitting disease from an infected node to its linked counterparts[9]; A is the adjacency matrices of infected network nodes in the last step I_{k-1}; N is the total number of network nodes and S is the number of susceptible nodes.

Last, in order to test the association between network structures and viral contagion, inter-city linkages are re-organised to different benchmark network structures, i.e. 'uniform networks', 'small world networks', 'scale free networks' and 'nearest neighbour networks' by controlling for the number of nodes and linkages. This analysis estimates to what extent these benchmark network structures are exposed to network viral contagion in comparison to the existing regional travel flow network, thus opening up potential to provide insights into novel adaptive planning and policy interventions. Uniform networks follow the law of uniform distribution, that is all city nodes have the same probability of being linked, indicating a balanced network structure. Small world networks describe a network structure where most cities are reached within a small number of steps regardless of insufficient direct

linkages, representing a well-connected network structure. A scale-free network is conceived of as a centralised network structure in which linkages are concentrated in a limited number of large cities, while other cities are weakly linked. In a nearest neighbor network, several locally clustered subgroups exist in which subgroup member cities are well-connected while connections across subgroups are relatively weak.

4. Results

First, as shown in Table 1, in terms of nodal degrees, Wuhan outperforms other cities in the urban travel flow network in both intra-city and inter-city flows. In addition, Wuhan is the only city whose outdegree outweighs its indegree, indicating its uniquely 'expansive' position in the network. In terms of structural positions which add weight to indirect linkages, Wuhan dominates in both betweenness and closeness, indicating that it not only has a hub position role but is also centrally clustered with other cities. Yichang is notable as a hub city interlinking regional eastern and western cities; while associated with its geographically central location, Xiaogan also stands out as a centrally positioned node in the network. In contrast to other Covid-related urban network studies that solely focus on primate cities (Jia et al., 2020; Liu et al., 2021), this analysis identifies these examples of non-primate cities that have vital roles in regional virus spread. Reflecting their high network centrality, they have potential importance as foci for government interventions to mediate cost- and time-efficient virus-alert travel flows (Ali & Keil, 2006). We find that the regional travel flow network is characterised by a centralised hierarchical structure in which Wuhan is

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[9] The value of β is characterised by strong spatial heterogeneity worldwide due to different social and cultural contexts (for instance, Imai et al., 2020; Lee et al., 2020; Shim et al., 2020). Our analysis therefore refers only to medical studies that have investigated the transmission of Covid-19 in China before the initiation of lockdown measures. Instead of pathological inferences on confirmed cases, Bi et al. (2020) directly surveyed close contacts via contact tracing and found that the average secondary attack rate is 6.6% in a sample population, providing a more direct reliable β for use in our analysis.

Table 1

City positions and viral contagion simulation results in Wuhan city region human flow network. (Note: the unit of Population is million persons; the unit of GDP per capita is 10,000 yuan annually; the amplitude reflects the maximum intensity of Covid-19 transmission at one step; the centroid indicates the least steps to reach the peak of Covid-19 transmission; the full width of half maximum measures the duration of outbreak; actual cases are sourced from NHC).

City	Population	GDP per capita	Self-degree	Indegree	Outdegree	Betweenness centrality	Closeness centrality	Actual cases	Iteration number	Gaussian Amplitude	Gaussian Centroid	Gaussian Width
Wuhan	11.08	13.4	5249	240	458	0.00108	0.219	50,340	35	0.0780	20.4859	11.9899
Huanggang	6.33	3.22	3133	113	64	0.00061	0.190	2907	40	0.0599	23.4116	14.6626
Xiangyang	5.67	7.6	3051	57	43	0.00068	0.188	1175	41	0.0729	24.6350	12.3109
Jingzhou	5.59	3.72	2755	84	64	0.00069	0.192	1580	42	0.0672	24.1156	13.6329
Xiaogan	4.92	3.89	2377	115	82	0.00062	0.197	3518	38	0.0778	23.2370	11.7691
Yichang	4.14	9.83	2217	56	47	0.00071	0.191	931	41	0.0679	23.9437	13.5287
Enshi	3.38	2.58	1878	28	15	0.00062	0.174	252	44	0.0676	26.8571	13.4175
Shiyan	3.41	5.13	1789	29	23	0.00064	0.177	672	54	0.0610	26.8465	14.0731
Jingmen	2.90	6.38	1521	49	38	0.00067	0.195	928	39	0.0745	23.3206	12.8356
Xianning	2.54	5.36	1417	45	34	0.00054	0.186	836	43	0.0739	25.4746	12.3084
Huangshi	2.47	6.42	1316	59	54	0.00058	0.186	1015	41	0.0679	23.9642	13.7062
Suizhou	2.22	4.56	1069	37	21	0.00058	0.183	1307	44	0.0693	25.9413	13.2972
Tianmen	1.27	4.65	648	31	19	0.00053	0.183	496	42	0.0690	25.1957	13.4698
Xiantao	1.14	7.02	521	36	25	0.00052	0.186	575	49	0.0620	24.7518	14.4402
Ezhou	1.08	9.33	467	53	50	0.00046	0.190	1394	44	0.0598	24.0596	15.6734
Qianjiang	0.97	7.82	447	23	18	0.00050	0.179	198	48	0.0629	27.0192	14.8920

the primate city[10] displaying comprehensive influence in the network, while other regional cities have discrete specific network positions.

Second, as illustrated in Fig. 4, the simulation results indicate that Wuhan requires the least iterations (35 steps) to converge the simulation process, followed by Xiaogan (38 steps) and Jingmen (39 steps); while if the outbreak initiates from Qianjiang, Xiantao or Shiyan, the simulation process requires relatively longer steps to converge. This result indicates that without policy interventions, Wuhan, Xiaogan and Jingmen are the most risk-exposed cities to human contagious disease, while Qianjiang, Shiyan and Xiantao are relatively temporally lagged during the virus spread process. Furthermore, since the number of iterations can only indicate the overall period taken to converge the simulation process, we use a Gaussian function to fit the simulation process in order to explore outbreak intensity, speed and duration respectively.[11] Regarding outbreak intensity, Wuhan and Xiaogan stand out, which indicates that the number of newly infected people at one iterative step can reach the maximum point. Regarding outbreak speed, Wuhan substantially out-paces other regional cities, indicating that effective policy and planning interventions are most needed at the initial stage of a contagious disease outbreak in Wuhan (followed by Huanggang and Ezhou). In terms of outbreak duration, Wuhan and Xiaogan outperform other cities, which indicates that once these cities enter into the intensive spread phase, it takes the least time for the virus to spread to the majority of other regional cities. Considering all three parameters, it is not surprising that the primate city Wuhan is most exposed to unexpected contagious shocks due to its dominance in the network. However, we find that Xiaogan and Jingmen, both of which are non-primate ordinary cities in terms of population size and economic development level, stand out as unexpectedly high contagion risk-exposed cities. This result accords with and extends the proposition that hinterland middle places (Doran & Fox, 2016), or cities described by Derudder (2019) as 'beyond first-order

neighbours', can act as 'connectors' in urban systems.

Third, as presented in Table 2, a pairwise correlation analysis is implemented in order to explore the underlying association between network relations and the simulated results.[12] As expected, outdegree is strongly associated with iteration steps, while both indegree and out-degree are highly correlated with the Gaussian centroid, reflecting that cities that are most active in circulating direct human flows are more exposed to viral contagion. When indirect network effects are included, closeness is found to be most correlated with the Gaussian centroid, which means that the more centrally positioned a city is in the regional travel flow network, the faster is its capability of spreading the virus to the rest of city region. This result corroborates the potential systemic contagion risk posed by network central players that are functionally closer to other cities in corporate networks (Beck & Walker, 2013). Lastly, the overall iteration steps and the Gaussian centroid are generally associated with actual cases reported in the city region, while the Gaussian amplitude and width are less associated. This may suggest that the 2020 lock-down interventions were imposed before the virus spread entered an intensive accelerating stage (see Jia et al., 2020; Tian et al., 2020). This implies the significance of intervention timing and rapid responses for building regional adaptivity to unexpected viral shocks, particularly in terms of improving the efficiency of collective inter-city responses.

Finally, inter-city travel flows are re-organised into distinctive benchmark network structures to simulate the viral contagion (see Fig. 5). It is shown that viral contagion is generally faster in balanced, well-connected networks (uniform and small world networks), while relatively centralised or locally clustered networks (scale-free and nearest neighbor networks) are more resilient. For instance, among benchmark network structures, Wuhan is most risk exposed in a uniform network but most resilient in a nearest neighbor network. For a potential future infectious virus outbreak, this finding draws attention to the importance of adopting policy and planning interventions to improve the structural flexibility/adaptability of network responsiveness to city region development specifics (Boschma, 2015). Overall, city region risk exposure in an emergent health crisis, is highly associated with both city horizontal flows and structural positions, which are spatially uneven,

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[10] A primate city refers to a city that is overwhelmingly larger than its peer cities in terms of population, economy, politics, culture, education etc. at a certain geographical scale such as a country or a region.

[11] The discrete results produced by every iterative step are transformed into continuous information by fitting the Gaussian function (see details in Conder, 2015), formally written as: $y = a \cdot \exp\left(-\left(\frac{x-b}{c}\right)^2\right)$, where y is the proportion of newly infected nodes to the total number of nodes; X is the number of iteration steps; a, b, c are parameters determining the amplitude, the centroid, and the width of the curve to indicate outbreak intensity, speed and duration respectively.

[12] Multiple regression modelling is not feasible in this study because simulated results are endogenously determined by human flows themselves and variables confront a multi-collinearity issue. In addition, regression models assume independence of observations, which omits the characteristics of human-to-human interactions for viral transmission.
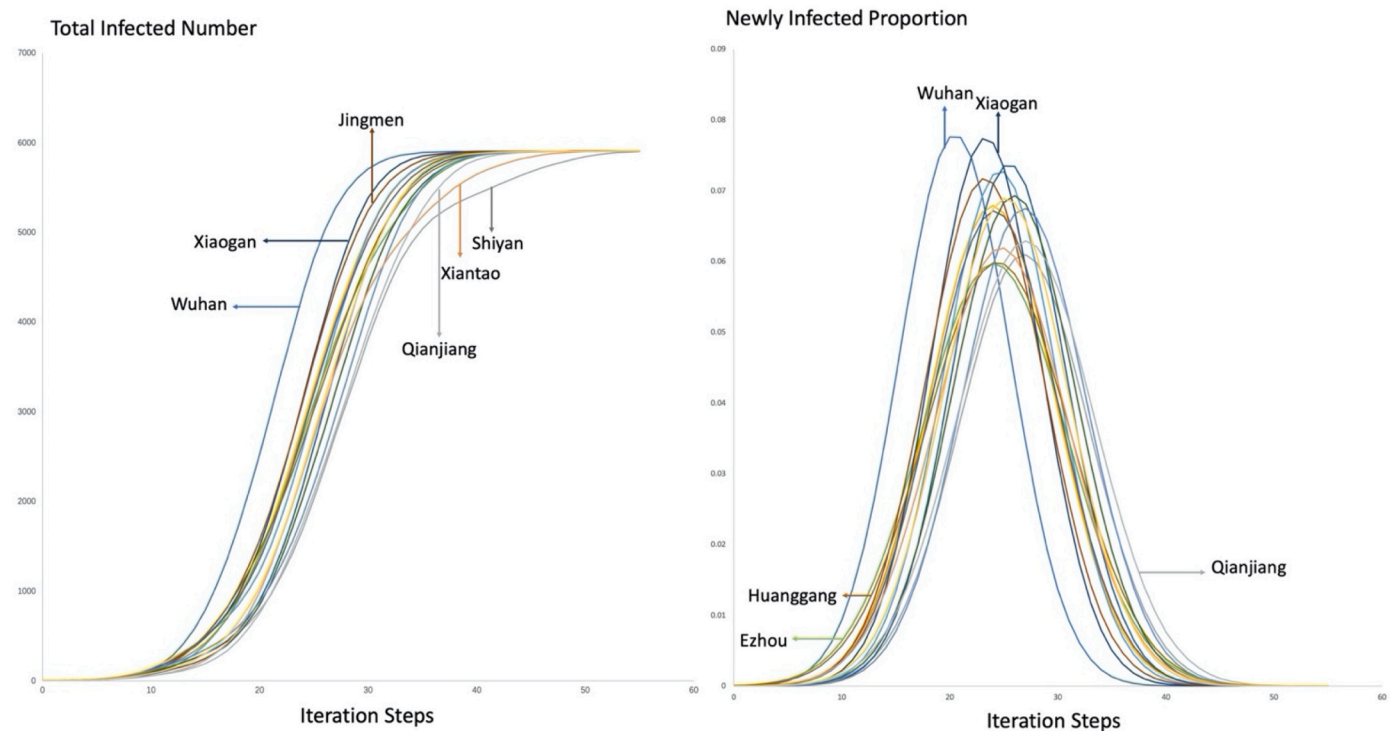
Fig. 4. The simulation results of the spatial spread of Covid-19 in the Wuhan region (note: the different curves represent the simulation process that is initiated in different cities; the average fitness of the Gaussian function R2 is 99.3%).

Table 2
The Correlation Matrix between Network Positions and Simulated Viral Contagion (Note: a nonparametric Spearman correlation test is implemented as a robustness check, however no significant changes are found).

Experiment results:	Iteration steps		Gaussian amplitude		Gaussian centroid		Gaussian width	
Network positions	Coefficient ρ	p value	Coefficient ρ	p value	Coefficient ρ	p value	Coefficient ρ	p value
Self-degree	0.65	0.01	0.32	0.22	0.45	0.08	0.39	0.13
Indegree	0.66	0.01	0.28	0.28	0.84	0.00	0.21	0.42
Outdegree	0.82	0.00	0.15	0.58	0.86	0.00	0.08	0.76
Betweenness	0.73	0.00	0.45	0.07	0.47	0.06	0.53	0.04
Closeness	0.56	0.02	0.38	0.15	0.92	0.00	0.33	0.21
Actual cases	0.75	0.01	0.28	0.49	0.81	0.00	0.25	0.58

instead of network size. The results point to the importance of both tailored place-specifics and indirect network effects considerations in city region viral risk mitigation planning.

5. Conclusion and policy implications

The analysis has contributed to new understanding of the spatial organisation of Covid-19 spread in an urbanised region by examining multi-directional human flows represented by CFT in relation to the urban hierarchical positions represented by CPT in the WCR travel flow network. The combination of a micro-level EC model and macro-level urban network approach to simulate Covid-19 spatial spread scenarios in the WCR is novel in providing for not only the simultaneity of intra-city and inter-city flows but also for multi-directional transmission feedback loops within a regional network of cities. In response to our research questions, we now turn to consider what can be learned from the results and the inferences for city region planning and policy,

First, what is the association between *city positions* and virus spread in the Wuhan regional travel flow network?

It is found that the negative spillovers of Covid-19 virus spread are highly associated with the centrality of city positions in the regional travel flow network. The risk exposure of Covid-19 virus spread is

disproportionately distributed to the cities with central and intermediary positions. Specifically, Wuhan's dominant centrality in the network makes it the most influential node in the expansion of the contagion across the entire region. In addition, the outstanding centrality of Xiaogan and Jingmen, both in terms of their direct relations and hierarchical positions (Taylor et al., 2010, 21), indicates that these cities are not only exposed to contagion but are also key network intermediaries in the virus spread. This finding highlights the need for strategic urban policies that are attuned to the unique positions of cities in a given city region travel flow network.

Second, what is the association between *network structures* and virus spread in the Wuhan regional travel flow network?

It is found that a well-connected, balanced network structure, can accelerate the spread of Covid-19 and vice versa, whereas a centralised or locally clustered network structure would be more spread resistant. The existing travel flow network is generally hedged between well-connected small-world and balanced uniform network structures, indicating a high-level regional contagion risk. This finding draws attention to the significance of the structural adaptive capacity of urban networks for the mitigation of infection spread and consequently the need for effective inter-city coordination and multilateral relations overriding administrative boundaries. Overall, both CPT hierarchical and CFT
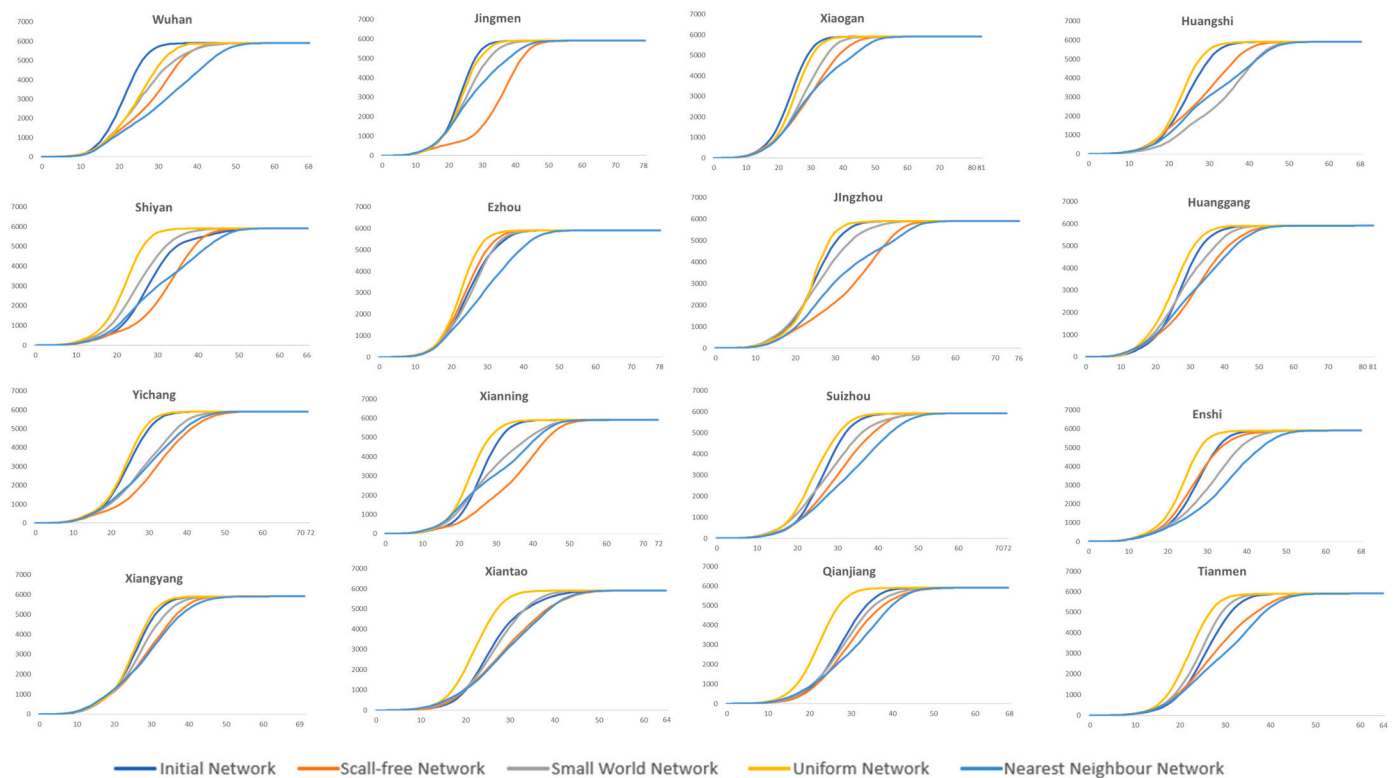
Fig. 5. The spatial spread patterns of Covid-19 transmission in different network structures (note: the x-axis represents iteration steps; the y-axis represents the accumulated number of infected nodes).

horizontal city relations have been found relevant for understanding the spatial organisation of Covid-19 as a negative network externality. We take from this that the Wuhan regional "model of urbanisation is at the same time both old and new", as in the case of European city regions, according to Castells (2010, 2738). The WCR results may therefore also have relevance for negative spillover effects in European city regions in a future sudden communicable disease outbreak.

Third, what lessons can be learned for *planning and policy mobility interventions* to mitigate regional virus contagion risk in the event of a future infectious disease outbreak?

The intensity and complexity of travel flows in the WCR indicate that while shutting down inter-city travel in a blanket lockdown would limit the risk exposure of urban centres throughout the region, this intervention would result in high economic and social costs by limiting mobility important for positive spillovers to these centres. The juxtaposition between city CPT positions and CFT relational structures for the Covid-19 virus spread, endorses Beer et al.'s (2020, 9) view that place-based regional solutions remain generally relevant for pandemic "economic and social bounce-back". In consequence, we conclude that future WCR urban planning and policy interventions should reflect the heterogeneity of specific local place and network flow interactions at a granular level to avoid spatially uneven 'bounce-back' (Eraydin & Taşan-Kok, 2012; Tian et al., 2020).

The examples of the Xiaogan and Jingmen network positions revealed by CPT in our study, indicate that intervention measures in functionally networked city regions in other parts of the world might beneficially focus on similar intermediary cities in regional travel flow networks. A place-based policy is recommended to reflect the dual role of these 'middle place' cities in connecting peripheral cities both to positive and negative externalities. For such place-based interventions to be deliverable in a specific government jurisdiction internationally, city and regional authority cooperation supported by coordinated monitoring systems, would be needed.

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transmission in other complex city region network internationally, would also need to be informed by vigilant real-time mobility observations to mediate negative contagion and positive social-economic interactions. Gibbs et al. (2020) found that travel interventions imposed early in China's Covid-19 outbreak, had a temporary effect on the containment of contagion. Interactive human mobility data platforms could track real-time travel flows and identify central players dynamically. These platforms should allow LBS providers and government transportation departments to share and integrate their individual databases, we suggest. The analysis of the regional travel flow network suggests that smart data informed network restructuring to manage travel flows, could reduce risk exposure to virus spread in the advent of a future local outbreak. Complex human behaviors, virus pathological characteristics, and health service capacity considerations which were outside the scope of the present analysis, would also demand monitoring and information sharing. For example, our findings on infection risk in the travel flow network can serve as an alarm bell for how healthcare demand may shift to places with relatively low service capacity, leading to potential public health service system shock (Bailey et al., 2020; Gibbs et al., 2020). This risk is likely to apply in other city regions internationally. Advanced travel flow network mobility observation systems could inform agile policy, for example, on medical resource allocations to mitigate mortality and Long Covid morbidity negative spillover effects.

Finally, despite Western 'new regionalism' and Chinese modernized subnational governance models both arguably encouraging regional and local territorial institutional cooperation (Dong & Kübler, 2021, 507), sceptics have observed that such cooperation is compromised by territorially competitive regional scale-building interventions (Brenner, 1999, 2004; McCann, 2016; Wu, 2020). Uncoordinated cross-jurisdictional policy responses to communicable disease outbreaks have also been blamed on nation state competitive economic growth agendas at the international level (Ali & Keil, 2006; Eaton & Humphreys, 2020). In consequence, a conclusion for both Chinese and

international 'Western' style planning and policy models is that non-competitive, coordinative practices are essential to control the spatial spread of a networked, mobile infectious disease. The politics of Covid-19 mobility interventions in a disrupted world remain to be addressed in other contributions to research.

CRediT authorship contribution statement

Declaration of competing interest

Acknowledgments

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cities.2022.103675.

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