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Structural changes in intercity mobility networks of China during the COVID-19 outbreak: A weighted stochastic block modeling analysis

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\textbf{ARTICLE INFO}

Keywords: COVID-19
Intercity mobility network
Network structure
Weighted stochastic block model (WSBM)
China

\textbf{ABSTRACT}

This study focuses on a mesoscale perspective to examine the structural and spatial changes in the intercity mobility networks of China from three phases of before, during and after the Wuhan lockdown due to the outbreak of COVID-19. Taking advantages of mobility big data from Baidu Maps, we introduce the weighted stochastic block model (WSBM) to measure and compare mesoscale structures in the three mobility networks. The results reveal significant changes to volume and structure of the intercity mobility networks. Particularly, WSBM results show that the intercity network transformed from a typical core-periphery structure in the normal phase, to a hybrid and asymmetric structure with mixing core-peripheries and local communities in the lockdown phase, and to a multi-community structure with nested core-peripheries during the post-lockdown phase. These changes suggest that the outbreak of COVID-19 and the travel restrictions deconstructed the original hierarchy of the intercity mobility network in China, making the network more locally or regionally fragmented, even at the recovery stage. This study provides new empirical and methodological insights into understanding mobility network dynamics under the impact of COVID-19, helping assess the emergency-induced impact as well as the recovery process of the mobility network.

1. Introduction

Human mobility dynamics during emergencies caused by epidemic outbreak and other critical events, e.g., earthquake and flood, have been recognized in great distinction with the mobility patterns under a normal condition (Kenett & Portugali, 2012). Thus, the study of mobility patterns under emergencies is imperative to the understanding of emergency-induced impacts and the making of impact mitigation strategies that aims to reduce damages, fatalities, and economic loss. The outbreak of COVID-19 has significantly changed human mobility around the world (Nouvéllet et al., 2021). The mobility change is largely associated with non-pharmaceutical interventions implemented by most countries, such as China, France, Germany, Italy, Japan, England, United States, to reduce the rates of disease contagion and infection (Fang, Wang, & Yang, 2020; Flaxman et al., 2020; Hsiang et al., 2020; Imai et al., 2020; Lai et al., 2020; Siedner et al., 2020). In China, a lockdown was in place at Wuhan on January 23rd, the epicenter of the outbreak, and travel restrictions were also implemented nationally to control the spread of the disease. It was in the middle of the \textit{chunyun} period for the Chinese Spring Festival (January 25th 2020), which features massive domestic travels for family reunion. As reported, there were about 76.22 million trips per day from January 10 to 24, while it was reduced to 13.48 million trips per day from January 25 to February 14 due to the lockdown and the related interventions (The Ministry of Transport of the People’s Republic of China, 2020).

One of the main themes around assessing the impact of emergencies is to monitor human mobility before and after the critical events in order to understand how the social system of human movements respond to}

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https://doi.org/10.1016/j.compenvurbsys.2022.101846

Received 6 August 2021; Received in revised form 7 June 2022; Accepted 8 June 2022
Available online 14 June 2022
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external shocks (Bagrow, Wang, Si, & Szlo, 2011; Yabe et al., 2020). Yet, existing literature on COVID-19 related mobility change has limited discussion of the impacts over a three-phase process, namely, normal, intervention, and recovery (Kim & Kwan, 2021; Hu et al., 2021). Recent research found that human movements tend to develop alternative patterns and regularities in response to disruptive emergencies during natural disasters such as earthquakes, contrasting with their patterns and regularities in the normal condition. However, it remains understudied whether this finding can be extended to epidemic outbreaks, especially, whether alternative structural regularities will emerge in human mobility networks that are under the impact of epidemic and in the process of recovery.

Most existing research focused on general mobility trends at the national level and confirmed an overall reduction in mobility in various countries due to the COVID-19 related travel restrictions (Galeazzi et al., 2021; Jeffrey et al., 2020; Lee et al., 2020; Pullano et al., 2020; Schlosser et al., 2021; Yabe et al., 2020); others investigated mobility change for individual critical cities (e.g., Wuhan) at the micro-level (Fang et al., 2020; Gibbs et al., 2020; Jia et al., 2020). Although attention has been paid to the impact of COVID-19 related travel restrictions on the structural changes of mobility networks (Galeazzi et al., 2021; Schlosser et al., 2021), only limited research took a perspective of the mesoscale structure of mobility networks (Rombach, Porter, Fowler, & Mucha, 2014) and studied its changes under the pandemic. By considering network structure or spatial proximity or both, these studies detected the ‘communities of cities’ existing in mobility networks with network analysis or community detection methods. As they neglected the relations between communities of cities, they failed to capture more complex mesoscale network structures, for instance, the grouping of cities exhibiting roles and positions of cities in urban hierarchies.

In this study, we seek to contribute to the following two aspects. First, it focuses on examining the dynamics in mesoscale structural change of intercity mobility network before, during, and after the Wuhan lockdown in order to answer whether alternative structural regularities emerge in human mobility networks under the emergency of a pandemic. To fulfill this goal, we obtained real intercity mobility data from January 2020 to April 2020 from Baidu Maps, one of the largest online mapping and location-based service providers in China. Second, this study adopted a weighted stochastic block model (WSBM) to detect the mesoscale structure of mobility network without presuming any prior knowledge about the underlying network structure. This approach aims to capture more complex mesoscale network structures including not only communities but also city hierarchies and hybrid ones of both. Without presuming a particular structure, the WSBM also avoids the pitfall of methodological determinism (Zhang & Thill, 2019; Zhang, Zhu, & Zhao, 2021); thus, it can detect the “true” mesoscale structures embedded in the national city networks.

The rest of this paper is organized as follows. The second section reviews the related research on the impact of COVID-19 on human mobility. In Section 3, we conceptualize mesoscale structure of mobility network and describe the materials and methods, including the data and the weighted stochastic block model. Section 4 shows the general trend of mobility networks during the study period. Section 5 illustrates the dynamic of the mesoscale structure of mobility networks. Finally, we conclude and discuss potential future works.

2. Literature review

2.1. Impact of emergencies on human mobility

Human mobility dynamics during emergencies due to critical events, such as epidemic outbreak, tsunami, earthquake, flood, blackout, nuclear disaster, or terrorist attack, has been well recognized in the literature in contrast with the mobility patterns under normal and familiar conditions, where regular daily routines of individuals are captured (Kenett & Portugali, 2012). The impact of such emergencies tends to become large-scale and destructive in modern society, as massive human movements, communications and interactions take places in urban areas where more than 50% of the world population lives. A better understanding of the emergency-induced impacts on human mobility can be greatly helpful to mitigate the catastrophic damages, such as injuries, fatalities, and economic loss (Wang & Taylor, 2016).

One of the main themes around assessing the impact of emergencies is to monitor human mobility before and after the critical events in order to understand how the social system of human movements respond to external shocks (Bagrow et al., 2011; Yabe et al., 2020). There were theoretical grounding and empirical evidences for the spatial regularities of human movement under the normal and routinized daily conditions; that is, the predictability of human mobility (Bagrow et al., 2011; Lu, Bengtsson, & Holme, 2012). Recent research also found that people tend to develop alternative routines and movement patterns in response to disruptive emergencies, which means that new regularities emerge and rejects the long-held hypothesis that human mobility deviates from its normal steady states during large-scale critical events with purely irregular patterns while people fleeing unrest and searching for material support (Lu et al., 2014; Wang & Taylor, 2014, 2016). For instance, in the study of population movement after the 2010 Haiti earthquake, Lu et al. (2012) demonstrated that people move with patterns that are familiar to them; that is, patterns are highly influenced by their historic behavior and their social ties. However, most existing studies are limited to mobility during the natural disasters such as tropical cyclones, wildfires, earthquakes, or flooding. It remains unclear whether the findings of these studies can be extended to other critical events such as epidemic outbreaks; especially, whether alternative structural regularities will emerge in human mobility networks under the impact of a pandemic and in response to it for recovery. This study aims to bridge this gap.

2.2. Human mobility under the impact of COVID-19

Thanks to the widespread use of location-based service enabled mobile devices, there has been a proliferation of human mobility related studies based on real-time big data generated from these sources, e.g., mobile phone or social media data (Bengtsson et al., 2015; Finger et al., 2016; Louail et al., 2015; Tizzoni et al., 2014). Seminal work has highlighted the important role of mobile device data on human mobility in informing public health decision making, especially during epidemic outbreak response (Dong, Wang, & Liu, 2021; Grantz et al., 2020; Oliver et al., 2020). Firstly, one thread of research takes advantage of such data for modeling the spatiotemporal spread of diseases and supporting contact tracing (Chang et al., 2021; Grantz et al., 2020; Oliver et al., 2020; Tian et al., 2020). A second thread focuses on the impact of COVID-19 pandemic and related non-pharmaceutical interventions (NPI) measures on the human mobility (Galeazzi et al., 2021; Wang, Wei, Lin, & Li, 2020), which is under the umbrella of the emergency induced mobility impact discussed in Section 2.1. The NPI related policies include a wide range of both top-down (i.e., governmental) and bottom-up (i.e., self-initiated) measures aimed at interrupting infection chains by altering key aspects of human behavior (Perra, 2021), for example, border closure, travels ban, curfew, social distancing, ban of social gathering, face masking, increased hygiene, remote working, school closure, and lockdown. Mobile device data thus provide an unprecedented opportunity to quantify, evaluate, and understand how human movement behaviors are influenced by those NPI measures. A third body of research is a combination of the aforementioned two approaches focusing on the interrelation of mobility and disease transmissions given the implementation of NPI policies. For instance, it has been reported that mobility reduction is likely instrumental in reducing the effective reproduction number in many countries (Badr et al., 2020; Fang et al., 2020; Schlosser et al., 2021; Siedner et al., 2020; Xiong, Hu, Yang, Luo, & Zhang, 2020; Nouvellet et al., 2021).

This study is in line with the second stream of research in the
literature discussed above and focuses on the travel related NPIs’ impact on human mobility and on how human mobility responds to interventions to recover. However, only a few studies tried to develop a thorough empirical examination of the impacts over a three-phase process, including normal, intervention, and recovery (Li, Wang, Huang, Yang, & Chen, 2021; Wei & Wang, 2020). On the one hand, it may be because little attention was paid to the investigation of emerging regularities of human mobility under the disruptive impact of the disease and in the recovery process. On the other hand, many countries were still experiencing a series of lockdowns by the end of 2021 and few have managed to enter the recovery phase (Looi, 2020). China is an exception. The extremely strict lockdown in Wuhan, the epicenter of the outbreak, was lifted on April 8, 2020, as the epidemic was largely under control at that time. Since February 17, 2020, travel and work resumed gradually outside Hubei Province and the industrial production in China surged in April more than twice as fast as most economists expected (Bradsher, 2020), showing a sign that China was already in a recovery mode in late April. The mobility recovery in this phase is worth for an examination in order to assess how the return-to-work response in mobility adapted to the relaxed travel restrictions while coping with the continuous impact of the disease.

Most existing research focused on general mobility trends at the national level and confirmed an overall reduction in mobility in various countries comparing the lockdown phase with the pre-lockdown phase (Galeazzi et al., 2021; Jeffrey et al., 2020; Lee et al., 2020; Pullano et al., 2020; Schlosser et al., 2021; Yabe et al., 2020). A few studies examined structural changes of mobility network across cities. Galeazzi et al. (2021) compared the connectivity, efficiency, and resilience of human mobility networks in France, Italy and UK. Schlosser et al. (2021) found that a strong reduction of long-distance travels rendered mobility network in Germany more local and a decreasing “small-world” effect. On the other hand, some studies investigated mobility change for individual critical cities at the micro-level. For example, inbound and outbound movement flows of Wuhan, or cities with a large number of infectious cases have been examined carefully to evaluate the effectiveness of NPI measures (Fang et al., 2020; Gibbs et al., 2020; Jia et al., 2020). Between the national scale and the individual city scale, there are several studies taking a perspective of mesoscale, i.e., grouping of cities (Gibbs et al., 2020; Li, Wu, Zhu, Liu, & Zhang, 2021; Wei & Wang, 2020). By considering network structure or spatial proximity or both, they detected the ‘communities of cities’ existing in mobility networks with network analysis or community detection methods. As these studies neglected the relations between communities or groupings of cities, they failed to capture more complex mesoscale network structures, for instance, the grouping of cities based on intercity mobility patterns exhibiting roles and positions of cities in urban hierarchies.

3. Analytical framework, methods and data

3.1. Conceptualizing mesoscale structure of mobility network

We define the mesoscale structure of a mobility network as a partition of cities into groups based on the pattern and strength of intercity connections. Cities are divided into the same group mainly because of similar relational patterns between groups, instead of similar attributes of city nodes. The mesoscale structure is a concept from the field of network science, representing the role and position of each city node and cluster in a network (Rombach et al., 2014). Even though two cities may be weakly connected to each other, they can be in the same cluster due to their similar positions in a network (Zhang & Thill, 2019). The general forms of the mesoscale structure of an intercity mobility network may comprise three prototypes, including core-periphery, community, and flat-world (i.e., random) structures (Fig. 1).

The first prototype of mesoscale structure is core-periphery (CP, Fig. 1A), in which cities in the core group have much stronger mobility linkages within and between groups than other cities at the periphery. Cities in periphery groups are weakly linked with each other but relatively well connected with the core cities. This structure is comparable to the scalar hierarchies found in traditional world system research (Lloyd, Mahutga, & De Leeuw, 2009; Snyder & Kick, 1979) and Friedmann’s (1986) world city hypothesis. The CP structure is often observed in scale-free networks, whereas the community structure is often seen in small-world networks. Here, the community structure is another prototype (Fig. 1B), where connections within communities are significantly stronger than those linkages between communities. The third prototype is a flat-world structure in random or complete networks, which shows no significant partitions (Fig. 1C). In a random network, we rarely identify either hierarchies or communities. In addition, the true mesoscale structure in mobility networks may be more complex than the three prototypes as described above, such as one having a hybrid structure of both core-periphery and community clusters (Fig. 1D). By detecting mesoscale structures of mobility networks

Fig. 1. Hypothetical and schematic mesoscale structures in the intercity mobility networks before, during and after the outbreak of COVID-19. (Notes: The blocks represent the groups of nodes, and the colors represent the strength of linkages among blocks. Nodes represent city divisions, and links represent the connections between cities.)

However, our network-based understandings on the CP structure are different from the Friedmann’s (1986) – that emphasized the spatial organization of international division of labor – as well as from the Krugman’s (1991), which developed a core-periphery model under the umbrella of new economic geography in the literature of regional science and spatial economics.
before, during, and after the lockdown, we can measure the structural changes in networks.

3.2. Weighted stochastic block model

This study employs weighted stochastic block models (WSBM) to measure and compare patterns and structures in mobility networks at the three stages before, during and after (i.e., the recovery stage) the lockdown regulation. Although the WSBM has been increasingly used in city network studies (e.g., Zhang, Fang, Zhou, & Zhu, 2020; Zhang, Zhu, & Zhao, 2021; Zhang & Thill, 2019), to the best of our knowledge, it has not been used to study the changes in mesoscale structures of city networks under the impact of external interventions. Notably, using cluster analysis and community detection methods, some recent research explores community structures in China’s mobility network during the COVID-19 pandemic (Gibbs et al., 2020; Li, Wang, et al., 2021; Wei & Wang, 2020). However, these approaches are subject to the “methodological determination” (Zhang & Thill, 2019); that is, the methods pre-determine a mesoscale structure while excluding other potential structure. For example, most community detection approaches postulate the existence of a community structure in a network but fail to detect a core-periphery structure, even though the network truly has one. As structures of mobility networks could be variant and hybrid, it requires a data-driven approach to learn the true mesoscale structure. The WSBM approach can resolve this issue without assuming a specific mesoscale structure and thus enables us to search for an optimal mesoscale structure from data.

The mobility networks in this study are directed and weighted graphs, in which cities are nodes, human movement flows are directed edges, and the number of flows is the weight of each edge. In the model, given the adjacency matrix of the mobility network \( W = \{ w_{ij} \}_{N \times N} \), each city node \( i = 1, 2, 3, \ldots, N \), is assigned to a latent group membership \( \alpha_i \in \{ 1, 2, 3, \ldots, K \} \), where \( N \) and \( K \) denote the number of cities and groups, and \( \alpha_i \) is the index of group \( i \). In a stochastic block model, \( w_{ij} \) is stochastic instead of deterministic, and being distributed by following an edge distribution \( \theta_{ij} \) that depends on group memberships of cities \( i \) and \( j \). This paper assumes \( \theta \) as a normal distribution. Suppose the normal distribution \( \theta | \mu, \sigma^2 \) has a mean \( \mu = (\mu_k)_{1 \times K} \) and a variance \( \sigma^2 = (\sigma^2_{kk})_{K \times K} \). The objective of WSBM is to infer an optimal grouping \( \alpha \) and a stochastic block matrix \( \theta = (\theta_{ij})_{n \times K} \) through a maximum likelihood approach. The likelihood function is written as follows (Zhang & Thill, 2019):

\[
P(\mathbf{W} | \theta, \sigma^2) = \prod_{i,j} \exp \left( \frac{w_{ij}}{\sigma^2_{ij}} - \frac{1}{2\sigma^2_{ij}} \frac{w_{ij}^2}{2\sigma^2_{ij}} - \frac{1}{2\sigma^2_{ij}} \log \sigma^2_{ij} \right)
\]

Aicher, Jacobs, and Clauset (2015) applied a Bayesian regularization to solve the problem that the parameters \( \mu, \sigma^2 \) suffer from degenerate solutions under continuous unsigned weights. In Bayesian approach, parameters are treated as random variables and assigned an appropriate prior distribution \( P(\cdot, \theta) \). Then, the posterior distribution \( P(\cdot | \theta | W) \) can be obtained through the Bayes’ law:

\[
P(\cdot | \theta | W) \propto P(W | \cdot, \theta) P(\cdot, \theta)
\]

Furthermore, we followed Aicher et al. (2015) to develop a factorizable distribution \( q(\cdot, \theta) = q(\cdot) q(\theta) \) to estimate \( P(\cdot | \theta | W) \) using a machine learning method. The WSBM algorithm was implemented in MATLAB 2019a (https://www.mathworks.com/) and the visualization of results done in MATLAB and Gephi 0.9.2 (https://gephi.org/).

After the estimation of WSBMs, we introduce an incremental fit index (IFI) as developed by Zhang and Thill (2019) to compare mesoscale structures in different periods of pandemic. \( IF_{xy} \) measures how similar a given partition \( x \) is to the optimal partition \( y \) detected by the WSBM. The larger the value, the higher the similarity. The \( IFI \) value ranges from 0 to 1. If \( IFI_{xy} = 0 \), the partition \( x \) is close to a null model (without partition, \( K = 1 \)). If \( IFI_{xy} = 1 \), the partition \( x \) is equal to the optimal partition \( y \). The equation of \( IFI_{xy} \) is given as:

\[
IFI_{xy} = \frac{LL_y - LL_0}{LL_y - LL_x}
\]

here, we define \( LL_0 \) as the log-likelihood score without any partition \( (K = 1) \), as computed in Eq. (1); \( LL_y \) is the log-likelihood score of the optimal partition \( y \); \( LL_x \) is the log-likelihood value of the given partition \( x \) for comparison.

3.3. Data source

Location-based service (LBS) is regarded as an effective data source that can reveal real-time and dynamic human travels patterns (Zhang et al., 2021; Oliver et al., 2020). In this study, we obtain intercity mobility data from Baidu Maps, one of the biggest map service providers in China (Wei & Wang, 2020). Baidu Maps aggregate and map intercity mobility data collected from anonymous and privacy-protected mobile devices based on LBS. Our intercity flows data has following advantages. First, the LBS of Baidu serves hundreds of thousands of software apps and covers 1.1 billion mobile devices (about 60% of the total domestic market) according to the report of Baidu. Baidu Maps responds to more than 120 billion global location service requests everyday. The representation of the data is one of the best in China. Second, regarded as a trustworthy data source, Baidu’s LBS data has been widely used in research to help understand human mobility patterns, study regional spatial structures, and monitor the spreading of infectious diseases, especially during the COVID-19 pandemic (Gibbs et al., 2020; Kraemer et al., 2020; Li, Wu, et al., 2021; Wei & Wang, 2020). Third, it is noteworthy that we obtained from Baidu Maps the real daily mobility flows between cities in China, which is of much better quality than the Baidu Migration data (scaled index data for only top 100 cities and publicly available via Baidu Maps API) subject to several limitations and used by most existing studies (Fang et al., 2020; Gibbs et al., 2020).

In this paper, we obtained the real daily mobility data between 366 prefecture-level cities in mainland China covering pre- to post-lockdown periods. To effectively monitor the dynamics of the mobility networks before and after the lockdown, we select three weekly durations in 2020, including a week from January 10 to 16, from February 7 to February 13, and from April 17 to April 23. To reduce the daily bias of intercity mobility due to daily variability, we select weekly aggregate data rather than daily data to construct the mobility network, in which a flow between two cities represents the amount of movements in a week. As the lockdown of Wuhan took place on January 23 and the lockdown was lifted on April 8, the three weeks selected here represent the phases of pre-lockdown (January 10–16), lockdown (February 7–13), and post-lockdown (April 17–23), respectively. It is well reported in the literature that people’s travels and activities present significant periodicity of weekly cycles (Goulet-Langlois, Koutsopoulos, Zhao, & Zhao, 2017). Many studies used weekly Baidu Maps data or similar dataset to describe weekly patterns of intercity mobility networks, e.g., Gibbs et al. (2020), Chang et al. (2021), Schlosser et al. (2021), and Li, Wang, et al. (2021).

Thus, weekly period is a reasonable time frame to explore the structural changes in intercity mobility networks during the first wave of COVID-19 outbreak.

Appendix Table A1 presents the macroscale properties of three mobility networks in pre- to post-lockdown phases, including the average degree centrality, weighted degree centrality, diameter, density, cluster coefficient and average path length. The changes in spatial patterns of mobility networks are depicted Fig. A1 in the Appendix.

4. Mesoscale structures in mobility networks from pre- to post-lockdown

In order to search for the best-fit WSBMs, we change the number of
partitions $K$ from 6 to 20, and see how the marginal log-likelihood value (as defined in Eq. (1)) varies accordingly. The optimal number of partitions can be obtained when the maximum log-likelihood value is achieved. The optimal numbers of groups in the three phases from pre- to post-lockdown are identified as 9, 11, and 10, respectively. Fig. 2 presents the results of WSBMs by 3-dimensional charts of block matrices. Figs. 4–6 visualize the mesoscale structure and network position of critical city nodes.

According to the WSBM results, the mesoscale structure of nationwide mobility networks experienced significant structural changes, from a typical CP structure in the pre-lockdown phase, to a hybrid structure of CP and community during the lockdown, and to a multi-community structure with a CP nested within each community at the stage of post-lockdown (Fig. 2). This tendency indicates that the COVID-19 lockdown makes the national mobility network less hierarchical but more locally/regionally fragmented.

4.1. Mesoscale structure of pre-lockdown

Before the outbreak of COVID-19, the top intercity linkages are mainly concentrated in major megaregions or urban agglomerations of China (see in Appendix Fig. A1). For instance, Beijing-Tianjin-Hebei, Shanghai, and Pearl River Delta.

A. Pre-lockdown: A standard core-periphery structure. This is a typical hierarchical structure of nationwide mobility network. There are two hierarchical core clusters, $\alpha$-core and $\beta$-core. All the rest are peripheral groups.

B. Lockdown: An asymmetric structure mixed with core-peripheries and local communities. The mesoscale structure consists of two horizontal and separated core communities, such as $\alpha$-Core and $\beta$-Core, and a peripheral community.

C. Post-lockdown: A hybrid structure of global community mixed with local core-peripheries. Nationwide mobility network is partitioned into four communities, and each presents a CP structure.

Fig. 2. Block-matrix visualization of mesoscale structures in intercity mobility networks of China from pre-to-post lockdown based on the WSBM. (Notes: X or Y axis represents the indexes of groups, and the value in the Z axis at the grid $(x, y)$ represents the average strength of flows from cities in group $x$ to cities in group $y$.)
Yangtze River Delta (YRD), Pearl River Delta (PRD), and Chengdu-Chongqing areas are highly connected by daily mobility, formulating the top hierarchy (i.e., a diamond region) of the mobility network (Li, Wang, et al., 2021). According to the results of WSBM (Fig. 2A), the mobility network presents a standard core-periphery structure, as conceptualized in Fig. 1A. In detail, the mesoscale structure in the pre-lockdown network has two hierarchical core clusters: α-core group (including Beijing and Shanghai, Chengdu, and Xi’an, i.e., Group 1 in Fig. 2A) and β-core group (including Guangzhou, Shenzhen, Chongqing, and Wuhan, i.e., Group 2 in Fig. 2A) with particularly regional influences in the South China. These two cores are not at the same position in the network, and the α-core is the premier in controlling national mobility, because the linkages between the two cores are even larger than those within the β-core. As shown in Fig. 2A, the mobility volume within the α-core accounts for 20% of total trips in the mobility network, while the β-core has about 9%; the aggregate mobility linkages between these two cores account for 12%. All the rest are peripheral groups, because they are well connected with one or two of the core groups, while having relatively weak connections with other peripheral groups (Fig. 2A).

Fig. 4 further visualizes topological (4A) and geographical (4C) features of the mesoscale structure in the pre-lockdown mobility network, with focuses on subnetworks of the core groups (4B). There is a distinctive hierarchical structure or a hub-and-spoke structure inside the two core groups. The subnetworks show that the mobility network before the pandemic has scale-free and hierarchical properties. In the α-core, Beijing is a dominant mobility center, with intensive connections with other mobility centers such as Shanghai, Tianjin, Xi’an, Chengdu, Jinan, Zhengzhou, which are all important transportation hubs and regional economic centers. β-core plays a sub-center role, with Guangzhou-Shenzhen as the dominant hubs and Wuhan, Chongqing, and Hangzhou as regional centers. They are well-connected with cities in the α-core. In summary, the pre-lockdown network is a typical CP structure, consistent with the hierarchical urban system and rank-size urban scaling properties (Pan & Lai, 2019).

4.2. Mesoscale structure during lockdown

During the lockdown period (Fig. 2B), the CP structure is broken down, and the network changes to a hybrid and asymmetric structure mixed with core-peripheries and local communities, differing from our assumption during the lockdown-the community structure (Fig. 1B), as found in some existing studies of mobility network in China by using cluster analysis or community detection algorithms (Li, Wang, et al., 2021; Wei & Wang, 2020). This suggests that WSBM can avoid the pitfall of methodological determinism and detect a more accurate mesoscale structure than traditional clustering approaches. By comparing the network before and after the Wuhan Lockdown, we find that the changes of average degree centrality and average weighted degree centrality are significant, with a sharp drop from 318 to 236 by 25.85% and from 260 to 51 thousand by 80.27%, respectively (Table A1 in the Appendix). It demonstrated that the outbreak of COVID-19 distinctly cut down most of intercity flows in China, and many city dyads even lost connections. According to Fig. 2B, the mesoscale structure consists of two core communities and a peripheral community. Cities in core groups of the two core communities are similar to those in the two cores of the pre-lockdown network. They are α-Core including Beijing, Shanghai and its surrounding cities e.g., Suzhou, Hangzhou, and Ningbo (i.e., Group 1 in Fig. 2B) and β-Core including Guangzhou, Shenzhen, Chengdu, Chongqing, and Changsha (i.e., Group 5 in Fig. 2B). However, these two core groups are neither hierarchical nor well-connected as those in the pre-lockdown network (Fig. 2B). They look more like two horizontal and separated communities. In the lockdown phase, the two cores have similar roles and positions. The two cores are regional centers with their own hinterland cities, instead of a national core with all the rest of cities as hinterland (Fig. 5A).

As shown in Fig. 2B, we calculated that 19% of total trips were accounted for in α-Core while about 12.3% of total trips accounted for in β-Core, and only 2.5% of total trips accounted for between the two cores. The connection between these two cores become very weak (Fig. 5B), and even weaker than the link strength between the core and periphery groups within each core community. This is also verified by the spatial pattern of mobility network (Appendix Fig. A1). We found that the diamond structure of the mobility network is dissolved and the linkages among megaregions are disappear. Another significant change of the mobility network is the fade-out of Wuhan and surrounding cities in the Hubei Province; the mobility linkages between Wuhan and the four megaregions turn weak. The rank of mobility in Wuhan dropped from the 13rd to the 75th and the aggregate amount of Wuhan sharply decreases by 94%, from 2.3 to 0.14 million trips. Notably, Wuhan was assigned to a peripheral group during the lockdown (Fig. 5), while it was in a core group during the pre-lockdown period (Fig. 4).

The structural changes may mainly result from a sharp decrease in long-distance mobilities (i.e., flows between megaregions) as national and regional mobility intervention policies were in place after the outbreak of COVID-19. To illustrate this point, we calculated how shares of decreased mobility volume vary with distance between cities (Fig. 3). As expected, after the lockdown, the percentage of decreased mobility volume grows with the distance between two cities. On average, the amount of daily mobility drops by about 79% for short-distance city dyads, the distance of which lies below 20% of total distance ranges, that is, smaller than 665 km. When the distance between two cities is above 665 km, the decreased percentage rises to above 83%. Moreover, we compared small-world property of mobility networks between pre-lockdown and lockdown (Table A1 in the Appendix). It indicated that both changes of average clustering coefficient and average path length indicate that the small-world property of mobility network become weak during the lockdown (Table A1 in the Appendix). These tendencies are consistent with the findings in Germany (Schlosser et al., 2021), which also found a moderation of the small-world effect in mobility networks.

Another distinct feature of the network structure in the lockdown stage (Fig. 2B versus 5A) is that the network becomes asymmetric. The amount of mobility flows from core cities to peripheral cities within each community cluster becomes much smaller than those from peripheries to cores. The trips from cores to peripheries is only about one third from peripheries to cores. This finding reflects an asymmetric impact of the lockdown on mobility flows: the pandemic may distinctively cut off the flows from cores to peripheries while retaining the essential flows from peripheries to cores. This trend may be driven by the changing economic or social dynamics. For example, it could be explained by the fact that the COVID-19 disease is severe in large and highly urbanized core cities, which demand more people and resource supports from peripheral cities, than smaller cities (Mu, Yeh, & Zhang, 2021). In addition, we believe that, similar as intracity travels (Hamidi & Zandiatsashbar, 2021), intercity mobility can be divided into essential (part of business/ commuting travel; logistic of daily necessities and medical supplies) and non-essential travels (friends-visit, relatives-visit and leisure flow) based on the trip purposes during the pandemic. Intercity trips from small cities to core cities are mainly indispensable business/commuting flows, whereas trips from cores to peripheries are often more flexible, such as tourist and family-visit travel (Li, Wang, Huang, & Gao, 2020). Another explanation is related to the return of migrant workers from small to large cities after the Spring Festival since the late January (Ren, 2020), which reinforces the asymmetric trend of mobility networks.

4.3. Mesoscale structure of post-lockdown

In the post-lockdown period, we found that the average intercity flows in the network rebounded to about 300,000 daily trips, about 3 times the lockdown stage and 60% of the pre-lockdown phase. The mesoscale structure presents a typical hybrid structure of global
Compared to the pre-lockdown phase, the changes of blue bars indicate that percentages of decreased mobility volume grow with the distance during the lockdown. Similarly, during early post-lockdown stage, the changes of orange bars indicate that percentages of decreased mobility volume grow with the distance. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 3. Percentage changes of mobility amount from pre-lockdown to lockdown and post-lockdown that distributed across the intercity distance ranges. (Notes: Compared to the pre-lockdown phase, the changes of blue bars indicate that percentages of decreased mobility volume grow with the distance during the lockdown. Similarly, during early post-lockdown stage, the changes of orange bars indicate that percentages of decreased mobility volume grow with the distance.)

The aggregate mobility volume inside these four communities account for 40%, 26%, 12%, and 11% of total trips, respectively, while the amount of inter-megaregion mobility remains small (Appendix Fig. A1). Although the mobility levels have been recovered, most of the recovered mobilities occur within certain distances and within regions, rather than between regions. We compared the mobility volumes in between pre- and post-lowdown phases and found that the mobility level drops less as to shorter-distance city dyads. The increased amount of inter-megaregion mobility from lock-down to post-lock-down is the largest at the first deciles (i.e., below 445 km between two cities). This distance range is proximity to the distance between cities within urban agglomerations or the center cities of two adjacent megaregions in China (e.g., from Wuhan to Changsha, Hangzhou to Shanghai, Xi’an to Zhengzhou, Chongqing to Chengdu, Xining to Lanzhou, and from Beijing to Jinan). Moreover, compared to the lockdown phase, the mobility network become more symmetric, implying that the flows from core to peripheral cities have been recovered.

The formulation of regionally fragmented structure may be related to the late lifting of long-distance and cross-province travel restrictions. As socio-economic activities in China have a clear regional/provincial concentration and usually a close proximity to regional centers or provincial capitals (Rodriguez-Pose & Crescenzi, 2008), short-distance local travels were resumed first by local governments to support the recovery of regional economic activities depending on how well the disease was controlled locally (Liu, Ma, & Mu, 2021). Subsequently, the resumption of long-distance travel between center cities of different megaregions was allowed. Another possible explanation may be that the short-distance mobility within megaregion is more resilient than those long-distance trips between megaregions under the extreme events (Roy, Cebrian, & Hasan, 2019). Therefore, the recovery time of long-distance travel is longer than the short-distance.

5. Conclusions

This study employs WSBMs to explore the structural changes in intercity mobility networks of China under the COVID-19 pandemic from pre-lockdown to post-lockdown periods based on a large set of real-time intercity mobility data from the company of Baidu Migration. We
**Pre-lockdown Phase**

**Fig. 4.** Network and spatial features of the mesoscale structure detected in the pre-lockdown phase. (Notes: The topological feature of intercity pre-lockdown mobility network illustrates a typical core-periphery structure, including \( \alpha \)-core, \( \beta \)-core and other peripheral groups (A). There is a distinctive hierarchical structure in subnetwork of two core groups, \( \beta \)-core plays a sub-center role. C, Beijing and Shanghai are dominant mobility centers of \( \alpha \)-core, Guangzhou and Shenzhen are the dominant hubs of \( \beta \)-core (B). Notably, Wuhan is located in \( \beta \)-core group in the pre-lockdown phase (C).)
Fig. 5. Network and spatial features of the mesoscale structure detected in the lockdown phase. (Notes: The topological mobility network presents a hybrid structure mixed with core-peripheries and local communities, including two core communities and a peripheral community (A). Subnetwork of two core communities is horizontal and separated. Core cities in two core communities are neither hierarchical nor well-connected as those in the pre-lockdown network (B). Compared with Wuhan in pre-lockdown, Wuhan as the epicenter of the outbreak in lockdown, is attributed to the peripheral community (C).)
Fig. 6. Network and spatial features of the mesoscale structure detected in the post-lockdown phase. (Notes: The mesoscale structure of mobility network is partitioned into four communities, and each presents a CP structure (A). Reduced subnetwork in post-lockdown reveals the geographical proximity of intercity linkages and regionalization feature of the mobility network (B). Core cities in four communities are distributed in different geographical regions in China. Wuhan plays a prime role in central China (C).)
found that mesoscale structures of the national mobility networks significantly changed during the impact and recovery phases of the pandemic, from a typical core-periphery (CP) structure in the normal phase, a hybrid structure with both core-peripheries and local communities during lockdown, and a multi-community structure with nested CPs in the post-lockdown phase. These findings confirm that alternative structural regularities do emerge in mobility networks under the emergency of pandemic, which is also consistent with findings in other related studies (Schlosser et al., 2021; Wang et al., 2020; Wei & Wang, 2020).

This study also contributes to the theoretical discussions on structural changes of intercity networks by conceptualizing prototypes of mesoscale structures under external interventions. The theoretical framework of mesoscale structures helps us discover the localized, asymmetric, and mixing clustering features of mobility networks in China during the pandemic and confirm the structural dynamics and adaptation of intercity mobility networks. With these findings, this study also demonstrates the advantage of the WSBM approach to detecting mesoscale structures in dynamic city networks over other community detection and clustering methods. The methodology and analytical perspectives developed in this paper can be generalized to the research of human-mobility and network dynamics during other emergencies.

This study can provide meaningful policy implications for the pandemic prevention and mobility intervention during a public health emergency as well as resilient regional planning in a post-COVID era. First, at the early stage of a pandemic outbreak, mobility restriction policies should pay more attention to restricting long-distance trips between core cities in order to mitigate the spread of virus. Second, the property of asymmetry during the lockdown also suggest that the change of intercity mobility is heterogenous in the direction of flows, and precise mobility interventions should be more targeted on the flows from peripherical to core cities than on those in the opposite direction. At the early recovery phase, the short-distance flows were rebounded faster than the long-distance ones. This suggests that the pandemic-prevention policies during the recovery focus more on the local or regional level, and the flows surrounding a city exhibit better resilience than those farther away from the city. Third, a resilient intercity network during the pandemic presents a regionally fragmented urban system structure. An adaptive regional planning thus should aim to improve the essential functions of production and accessibility to daily needs within a mega-city region or megaregion (Kleinman, 2020), in order to save the moving costs of essential trips during the pandemic.

This paper has some limitations. First, the outbreak period of COVID-19 coincided with the traditional Spring Festival in 2020 China, when the scale of intercity mobility increases in the period of Chunyun. Although we have considered the effect of the Chunyun, future studies could control for such effect by considering mobility data of 2019 (Fang et al., 2020). Second, future work should focus on the mechanisms behind the structure changes in mobility networks (Li, Wu, et al., 2021), and empirical studies for other countries, in order to reach more generalized findings. Third, although the real-time intercity mobility data from the Baidu Migration used in this study are more accurate than the migration index scale (ratio) data widely applied in the literature, there remain representation issues in term of obtaining a whole picture of the entire intercity population movements in China. Thus, future studies can incorporate multiple sources of mobility big data, such as the Tencent mobility data, cellphone big data, and movements estimated from geotagged social media data (Huang et al., 2020; Pan & Lai, 2019; Zhang, Fang, Zhou & Zhu, 2020).

CRediT authorship contribution statement

Wenjia Zhang: Conceptualization, Supervision, Writing – review & editing. Zhaoyua Gong: Resources, Writing – review & editing. Caicheng Niu: Data curation, Writing – original draft & editing. Pu Zhao: Visualization, Software.

Data availability

Data will be made available on request.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (42171201), Natural Science Foundation of Guangdong Province Of China (2020A1515010847), the Shenzhen Municipal Natural Science Foundation (Key Project) (GXWD20201231165807007-20200810223326001), and the Shenzhen Municipal Natural Science Foundation (JCYJ20190808173611341).

Appendix

Table A1 presents the macroscale topological properties of three directed and weighted mobility networks from pre- to post-lockdown. According to the changes of average degree centrality and weighted degree centrality, the average range and strength of urban connectivity dropped by 20.30% (from 318 to 236) and 80.28% (from about 260 to 51 thousand) during the lockdown, respectively. Both changes of average clustering coefficient and average path length illustrate that the small-world property of mobility network become weak by the lockdown.

| Network metrics          | Definition                                                                 | Pre-lockdown | Lockdown | Post-lockdown |
|--------------------------|---------------------------------------------------------------------------|--------------|----------|--------------|
| Average degree centrality| $C_0 = \frac{1}{n(n-1)} \sum_{i \neq j} a_{ij}$ where $a_{ij}=1$ when a direct edge exists between nodes $i$ and $j$, $a_{ij}=0$ otherwise. | 318          | 236      | 295          |
| Average weighted degree centrality| $C_0 = \frac{1}{n(n-1)} \sum_{i < j} E_{ij}$ where $E_{ij}$ is the strength of connection from nodes $i$ to $j$, $E_{ij}=0$ otherwise. | 259,262      | 51,130   | 149,452      |
| Diameter                 | $D = \max d_{ij}$ where $d_{ij}$ is the number of edges by the shortest path from node $i$ to $j$. The diameter $D$ is the maximum $d_{ij}$. | 2            | 3        | 2            |
| Density                  | $N_d = \frac{2L}{n(n-1)}$ where $L$ is the actual number of the edges in network; $n$ is the number of nodes of network. | 0.87         | 0.65     | 0.81         |
| Cluster coefficient      | $C = \frac{1}{n(n-1)} \sum_{i \neq j} E_{ij} / E_i$ where $E_i$ is the number of edges of node $i$ and $E_i$ is the average of all nodes’ cluster coefficient ($C_i$); $C_i$ is the portion of actual edges ($E_i$) between the nodes within its neighborhood divided by the maximal possible edges $n(n-1)$ between them (Watts & Strogatz, 1998). | 0.91         | 0.79     | 0.87         |
| Average path length      | $L = \frac{1}{N(N-1)} \sum d_{ij}$ where $L$ is the average number of edges along the shortest paths for all possible node-pairs in the network (Watts and Strogatz, 1998). | 1.13         | 1.36     | 1.19         |

This paper was supported by the National Natural Science Foundation of China (42171201), Natural Science Foundation of Guangdong Province Of China (2020A1515010847), the Shenzhen Municipal Natural Science Foundation (Key Project) (GXWD20201231165807007-20200810223326001), and the Shenzhen Municipal Natural Science Foundation (JCYJ20190808173611341).
Fig. A1. Spatial distribution of intercity mobility patterns and networks in China from pre-lockdown to post-lockdown phrases affected by the COVID-19. (Notes: Only the city dyads with top 1% strength of intercity linkages are shown. Node size and line width indicate that the magnitude of connections of cities and links. The top intercity linkages are mainly concentrated in major megaregions or urban agglomerations of China (A). During the lockdown, the diamond structure of the mobility network is dissolved, while the linkages among megaregions are disappear, and the mobility linkages between Wuhan and the four megaregions turn weak, compared with that before the lockdown (B). The strength of intercity connections within megaregions have been restored at the early phase of post-lockdown, while the inter-megaregion mobility remains weak (C).
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