The effects of COVID-19 on Chinese commuting patterns in early 2020

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Abstract. *We build mobility networks from Chinese commuting data and track network metrics for the two months before the WHO pandemic announcement. The Wuhan travel ban on 23 January imposed changes to the level of importance of some central cities in the commuting patterns. While Beijing was the most important city in both the inflows and outflows, Wuhan and other cities became more relevant after the transition.*

1. Introduction

The World Health Organization (WHO) declared the COVID-19 pandemic on 11 March 2020, after the cases of the new Coronavirus increased about 13-fold outside China [Cucinotta and Vanelli 2020, Li et al. 2020]. Wuhan (province of Hubei) is the city of patient zero, whose notification date back to 11 January 2020, followed by cases in Beijing, Shenzhen, and Shanghai in the following days. As of 10 September 2022, China had confirmed about 2,615,600 cases and 15,000 deaths [Dong et al. 2020].

Evidences suggest that the people commuting patterns are behind the spread of viral diseases [Freitas et al. 2020a, Kraemer et al. 2020], and the outbreaks might trigger individual and governmental-induced mobility restrictions [Freitas et al. 2020b]. It is of paramount importance to quantify and qualify the changes in mobility patterns during such events.

A Complex Network is a graph, a set of nodes (elements) and edges (relations between elements) representing a Complex System: a system with several elements with non-trivial relations. The Complex Network approach emerges as a natural mechanism to handle mobility data, taking areas as nodes and movements between origins and destinations as edges [Santos et al. 2019].

In this paper, we build several networks with the commuting of each day between 01 January 2020 and 29 February 2020. We monitor how their topological indexes change over time, emphasizing four important dates: the beginning of the Spring festival travel rush (*Chunyun* - 10 January), the Wuhan travel ban (23 January), the Lunar new year (25 January), and the end of the Spring Festival travel rush (18 February) [Tan et al. 2021].

Our results show that the travel ban imposed changes in Chinese commuting patterns. While before the restrictions Beijing was the most important in both the in and outflows of people between cities, Wuhan and other central cities assumed an important role in the following days. We also observe this transition from shortest paths-based network metrics.

This paper is organized as follows: Section 2 presents the methodology, followed by the results and discussion of Section 3. The conclusions are in Section 4.

2. Methodology

This section presents the data and methods[1].

2.1. Mobility and geographical data

We use the Baidu Mobility Data [China Data Lab 2020, Hu et al. 2020] from Jan 1 to Feb 29, 2020, two months prior to the WHO pandemic announcement. The dataset contains the daily inflows and outflows of people between origins and destinations within 340 Chinese cities. The inflows and outflows compose two separate adjacency matrices. The former presents the percentage of people that moves from i to j, concerning j. Node j tracks the relative inflows from every other node and its inflows sum up to one. The outflows behave similarly, but with the distribution of outflows concerning j. Moreover, each node has at most 100 neighbors.

As a preprocessing step, we remove from the analysis the cities with unavailable city codes and geographical coordinates [China Data Lab 2020, Lab 2020] and end up with the daily flows between 303 cities over the aforementioned 60 days.

2.2. Network analysis

Based on mobility data, we build 60 networks, where nodes are places and connections are flows of people commuting from one place to another within a day.

A network is a graph $G(V, E)$ with $N = |V|$ nodes and $L = |E|$ links. We use here weighted networks, whose link weights W_{ij} between pairs of nodes i and j are the flows [Barabási and Pósfai 2016].

We characterize the networks through their average weighted betweenness b_w, weighted closeness c_w, and diameter l_{max}.

Since the flows of people are the weights in the network representation, the concept of distance when computing the shortest paths must have a different interpretation: the higher the weights between two nodes, the closer they are. Thus, we use the inverse of link weights to compute the shortest path lengths l_{ij}.

[1]Data and source code are available at: `https://github.com/vanderfreitas/chinese_commuting_patterns`

The weighted betweenness quantifies the node's importance in the shortest paths of the network. The higher its value, the more shortest paths pass through it. The weighted closeness states how close a node is to the others. Mathematically, it is the inverse of the average shortest path lengths between i and the other nodes. The network diameter is the highest shortest path, or simply the highest possible distance (geodesic) between any pairs of nodes.

3. Results and discussion

Figure 1 shows the mobility networks with the inflows and outflows of 2 January 2020 and 2 February 2020. The node colors correspond to the weighted betweenness and edge colors represent the weights (flows). Note that the weights are in terms of percentages and have comparable magnitudes in the four subfigures. What changes from one subfigure to another is their disposition. Thus, one cannot infer the number of travelers, but the rates of incoming/outgoing people from/to point A to/from point B.

Regarding the inflow networks, the higher betweenness centralities emerge in cities that contribute more by sending people to other places, since they monopolize the percentages and serve as a distribution hub. On the other hand, those with higher b_w in the outflow networks are preferred destinations, because they receive a higher percentage of people that leaves other cities.

Figure 1a and 1b shows that Beijing fits the role of a node that is important in the shortest paths for distributing and receiving flows of people, before the travel ban. The situation changes after the travel ban, with Wuhan becoming an important local bridge within the Hubei province. About 11 cities from the same province received more than 20% of their incoming flow from Wuhan in the period. It does not mean that more people commuted from Wuhan, but that most travelers that reached the mentioned cities came from Wuhan.

Figure 2 presents the time series of a few selected network metrics: weighted betweenness b_w, weighted closeness c_w, and diameter l_{max}. The latter is inherently global whilst the others are node-wise, which justifies showing their average. We decided to use only weighted network metrics and, although others present transitions in the period of the travel ban, their amplitudes are comparable and not worth showing.

All metrics present a transition between the Wuhan travel ban on 23 January, and the Lunar new year, on the 25th, especially in the inflow networks. Recall the differences between nodes of Figure 1a and 1c, that correspond to the inflow networks of before and after the travel ban. The nodes of the first seem to have similar importance in the shortest paths (Beijing is an exception with higher b_w than the others). In contrast, in the second network one sees more nodes with higher importance (redder colors), increasing the average. Interestingly, Beijing is not in the top three anymore, in agreement with [Tan et al. 2021], that states that the outflow from the big cities decreased faster than others in the transition. The weighted closeness has a similar behavior as observed with b_w and the diameter follows the trends observed in b_w and c_w, although in a more wiggling fashion.

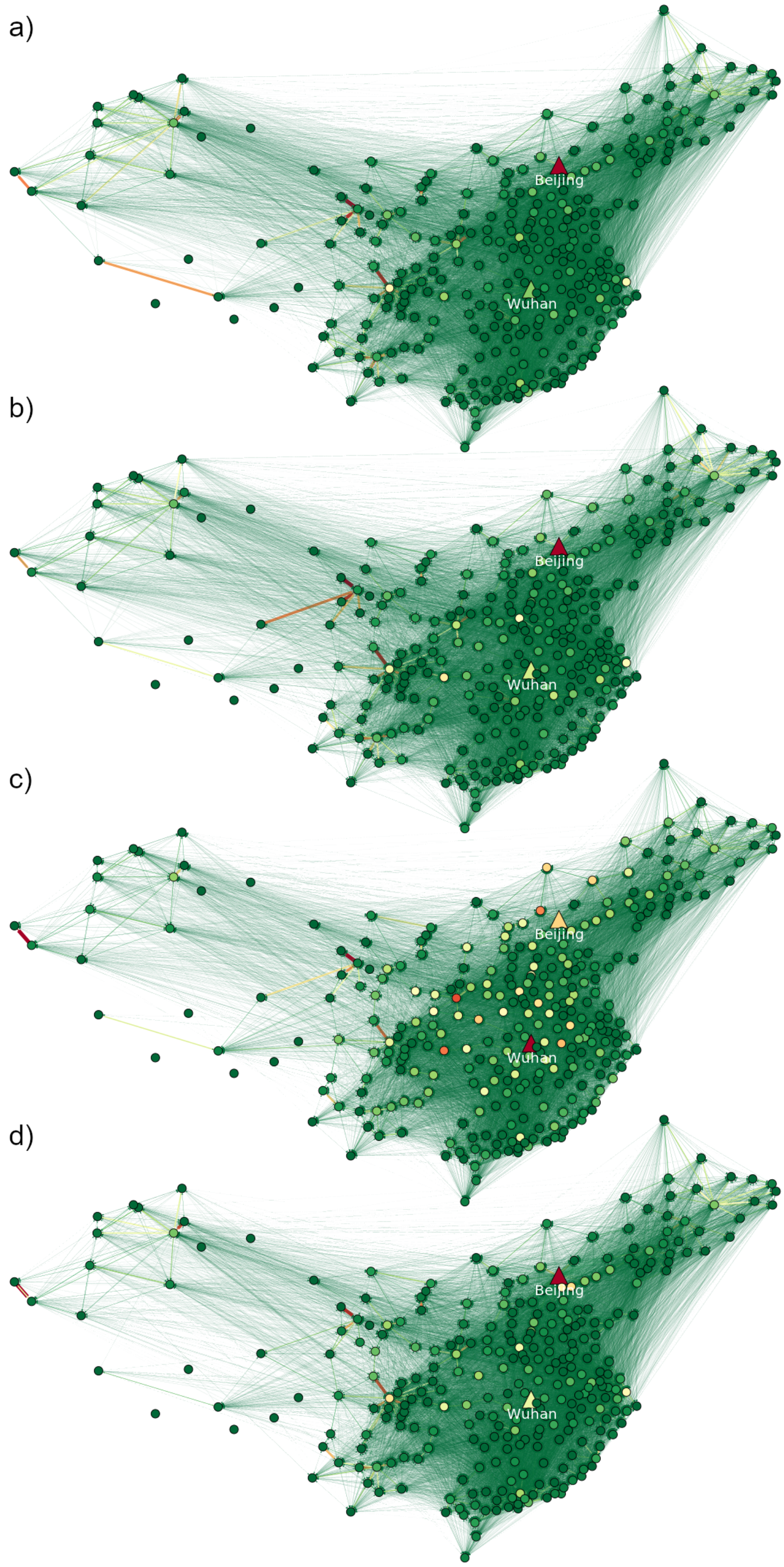

Figure 1. Mobility networks for: a) inflows and b) outflows of 2 January 2020; c) inflows and d) outflows of 2 February 2020. Points represent cities' centroids, and edges represent the flow of people between cities. Edge colors and widths are the flow intensities. Node colors are the weighted betweenness. Higher values are in red and lower in green.

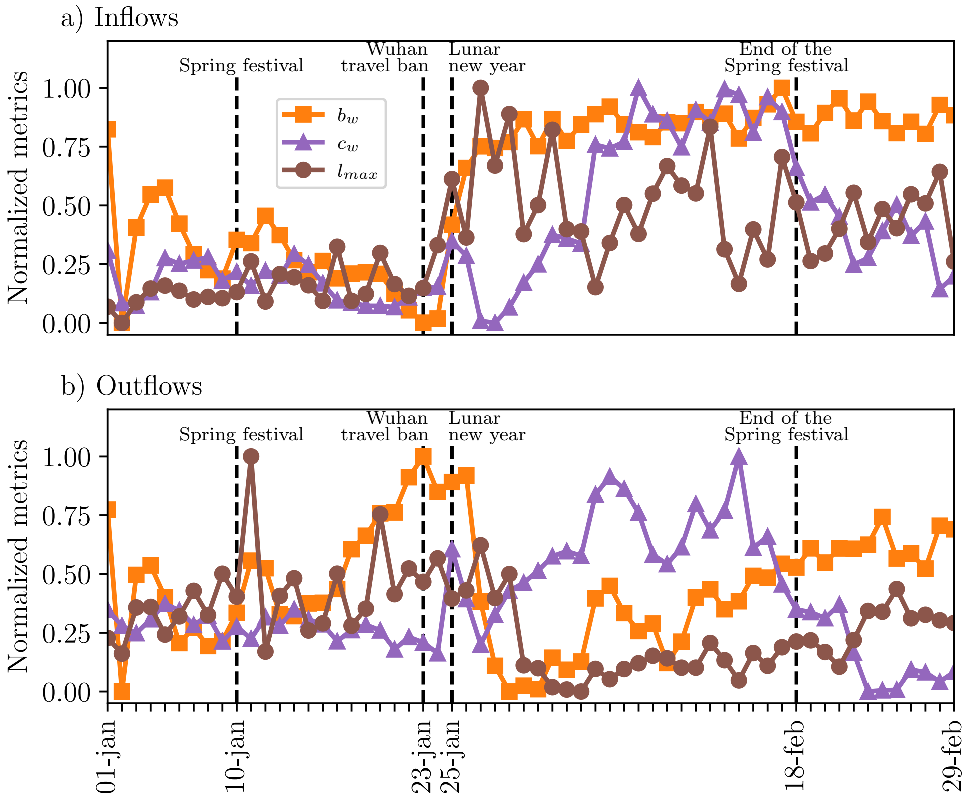

Figure 2. Time series of normalized network metrics for the a) inflow and b) outflow data. Their values lies within the following intervals a) $1,326.5 \leq b_w \leq 2,151.0$**,** $0.82 \leq c_w \leq 0.99$**,** $3.13 \leq l_{max} \leq 7.78$**; b)** $1,434.12 \leq b_w \leq 2,225.57$**,** $0.74 \leq c_w \leq 0.98$**,** $3.36 \leq l_{max} \leq 11.28$**.**

4. Conclusions

We discuss the changes in the Chinese commuting network during the first two months of 2020, before the COVID-19 announcement by the World Health Organization. The data we use consists of two matrices for each day, one with the normalized inflow and another with the outflow between cities. Of all the people that arrive in a city (inflow), the data maps the contribution of all other cities in relative numbers (percentage). The same is valid for the people that leaves the city (outflow).

We show that the Wuhan travel ban on 23 January imposed changes to the level of importance of some central cities in the commuting patterns. While Beijing was the most important city in both the inflows and outflows, Wuhan and other cities became more relevant in the following days.

As future work, we intend to quantify correlations between the cities that are more central in the networks with the pandemic numbers.

5. Acknowledgement

The authors thank the Conselho Nacional de Desenvolvimento Científico e Tecnológico, CNPq, Brazil (process: 441016/2020-0) and Coordenação de Aperfeiçoamento de Pessoal de Nível Superior, CAPES, Brazil (process: 88887.506931/2020-00).

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