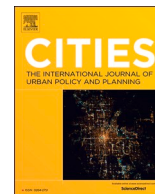




Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.



Spill-over effect of Wuhan travel ban on population flow in the outbreak stage of COVID-19 in China

Zhudan Pang^a, Zhao Zhang^{b,*}, Chuanqi Zhu^c, Jinghua Wang^b

^a *Tourism and Urban-Rural Planning College, Chengdu University of Technology, Chengdu 610059, China*

^b *School of Transportation Science and Engineering, Beihang University, Beijing 100191, China*

^c *Lingnan College, Sun Yat-Sen University, Guangdong 510275, China*

ARTICLE INFO

Keywords:

Population flow
COVID-19
Wuhan travel ban
Spill-over effect

ABSTRACT

This paper investigates the impact of COVID-19 travel restrictions on population flow in the People's Republic of China. We discover an “unreasonable” surge in population flow after the Wuhan travel ban. We further find out that such a surge of population flow is attributed to the “spill-over” effect of the Wuhan travel ban. We utilize a logistic regression model to quantify that the spill-over effect linearly decays with the travel distance to the Pandemic center city. Because of the “spill-over” effect of the travel ban policy, government authorities should design redundancy policy to simultaneously implement a travel ban for the pandemic center city and its neighboring cities to restrain human movement and pandemic transmission.

1. Introduction

The spread of COVID-19 has impacted 192 countries or regions with billions of people in the world (Johns Hopkins University & Medicine, 2021). As of 13 Apr 2021, more than 136 million people globally have been confirmed to be infected with the novel coronavirus, and 2,946,568 people among them died of such disease (Dong et al., n.d.; Johns Hopkins University & Medicine, 2021; World Health Organization, 2020). Obviously, population flow from heavily infected areas to other regions may bring viruses and cause transmission of pandemics. Because pandemics such as COVID-9 never destroy the transportation system's infrastructures, traffic restrictions could be the most effective method to restrain human movement, thus constrain the spread of COVID-19.

Most of the current research efforts on COVID-19 focus on the mechanism or structure of the novel coronavirus (Chan et al., 2020; Cui et al., 2019; Gao et al., 2020; Huang et al., 2020; Zhou et al., 2020), the outbreak process (Sun et al., 2020; Wang et al., 2020), transmission models, and travel restrictions on COVID-19 (Buckee et al., 2020; Chinazzi et al., 2020; Jia et al., 2020; Kraemer et al., 2020; Li et al., 2020; Tian et al., 2020). Among these research efforts, it is believed that COVID-19 is closely correlated to population flow. Because the movement of infected people could bring viruses and high risk to other places, researchers believe that a travel restriction policy would decrease the

transmission risk of COVID-19. Thus, many researchers started to analyze the impact of travel restriction policy on population flow.

Among the research efforts on COVID-19 and population flow, Engle et al. (2020) combine GPS data with COVID-19 case data and other demographic information to estimate how human activity is affected by COVID-19 and restriction orders to stay-at-home. They find that a rise of the local infection rate from 0% to 0.003% is associated with reduced mobility by 2.31%. An official stay-at-home restriction order corresponds to reducing mobility by 7.87%. Lv et al. (2020) study the traffic and emission variations during the Beijing lockdown period. It is statistically revealed that during the COVID-19 lockdown period, the traffic flow in freeways and urban roads dropped by 37% to 60% compared to the pre-lockdown period, while the traffic speed increased by 14% to 31%. Another traffic index, such as average daily vehicle kilometers of travel (VTK) of light-duty vehicles (LDV), heavy-duty vehicles (HDV), and light-duty trucks (LDT), decreased by 28%, 61%, and 37%, respectively. Saha et al. (2020) study the change of mobility in India after the lockdown policy during the COVID-19 outbreak period. It is shown that retail and recreation endures the most significant decline, i. e., -73.% and the park has a minor change, i. e., -46.3%. On the contrary, visits to residential place mobility increase by about 24%, indicating that 24% more people prefer to stay at home under the pandemics than average conditions. Hien et al. (2020) investigate the positive impact of the Wuhan travel ban on restraining the spread of COVID-19 in

* Corresponding author.

E-mail addresses: zhaozhang@buaa.edu.cn (Z. Zhang), zhuchq3@mail.sysu.edu.cn (C. Zhu).

<https://doi.org/10.1016/j.cities.2021.103404>

Received 24 May 2021; Received in revised form 16 June 2021; Accepted 27 July 2021

Available online 2 August 2021

0264-2751/© 2021 Elsevier Ltd. All rights reserved.

China based on air traffic data and COVID-19 infection data. They find out that strict traffic control measurement would better confine the spread of COVID-19. These research outcomes are pretty robust that the city lockdown and travel restriction policies play an important role in restraining population flow and COVID-19 spreading. However, very few research efforts discovered the impact of travel restriction policy on population flow in the very early outbreak stage of COVID-19.

2. Methodology

To study the impact of the Wuhan travel ban on population flow in the very early outbreak stage of COVID-19 in Hubei Province, China, we draw the cumulative departure curve of population flow based on mobile phone data and then use the regression method to fit the response curve. Finally, we try to find the correlations between travel ban implementation, population flow, and geographic location.

2.1. Data description

Hubei Province is set as the epidemic center (red area in Fig. 1) and the neighboring Zhejiang Province as a connected node to Hubei (green area in Fig. 1). Mobile phone roaming data provided by the Big Data Center of China Mobile Group, Zhejiang Corporation, Ltd., calculates the population flow between Hubei and Zhejiang.

Fig. 2 exhibits Hubei—Zhejiang population flow ratio was kept around 3% before the Wuhan travel ban. Subsequently, a sharp rise in the coming week after the ban is witnessed, but it finally decreases to less than 0.05% in the last days, while the Zhejiang—Hubei ratio follows a long-time decrease till 2 Mar 2020.

We have reason to assume the public anxiety of not leaving Wuhan after the ban may trigger the rise of the Hubei population outflow at the early COVID-19 outbreak stage. However, it is still unknown why there was a short-time surge of population flows from Hubei to Zhejiang as the travel ban should have completely cut off all population outflow from Hubei.

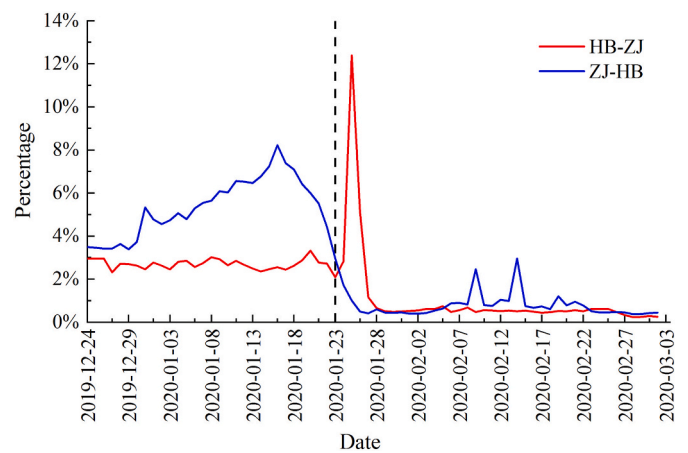


Fig. 2. The ratio of Hubei—Zhejiang population flows, and Zhejiang—Hubei population flows.

2.2. Spill-over effect

We classify the cities in Hubei as “Wuhan” and “Other cities” in Fig. 3, which demonstrates that such surge of population outflow in Hubei is attributed to the rise of that in the other 13 cities in Hubei. We find out that the other 13 towns all had a surge of outflow on 24 Jan 2020 (Table 1). Because the date when these people left Hubei is one day earlier than the date they arrived in Zhejiang, the increase of Hubei cities’ outflow happened on 23 Jan, before the other 13 towns implemented their travel restriction. Thus, we conclude that the surge of population outflow from the “Other cities” in Hubei province is attributed to the Wuhan travel ban rather than the travel ban in these cities.

We further identify the population outflow surge of the other cities in Hubei as a “spill-over” effect of the Wuhan travel ban. We draw the daily cumulative percentage of population outflow (response curve) from the

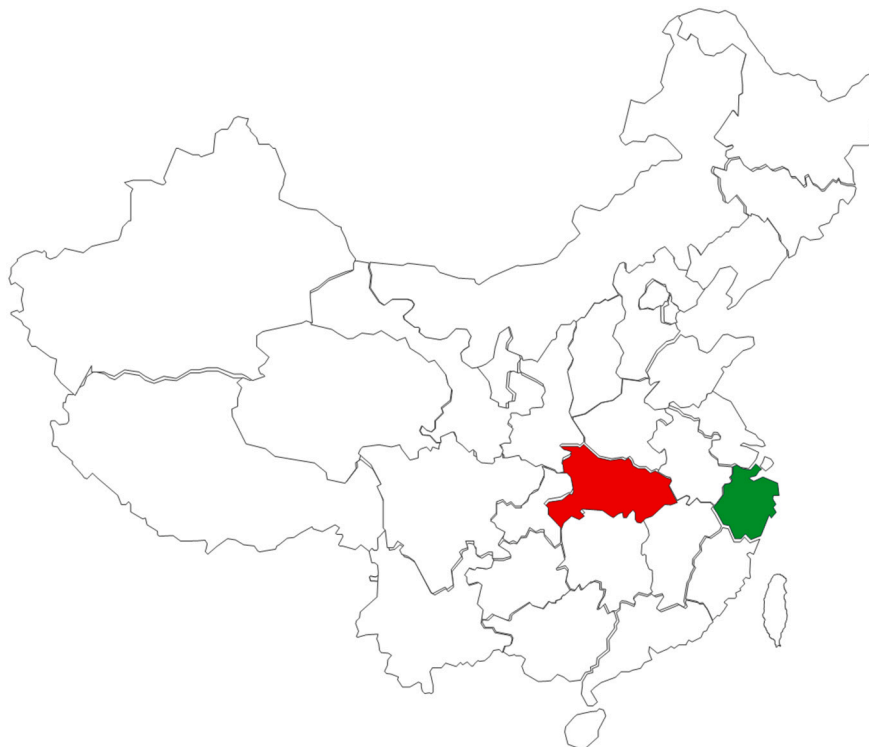


Fig. 1. The geographic location of Hubei province and Zhejiang province. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

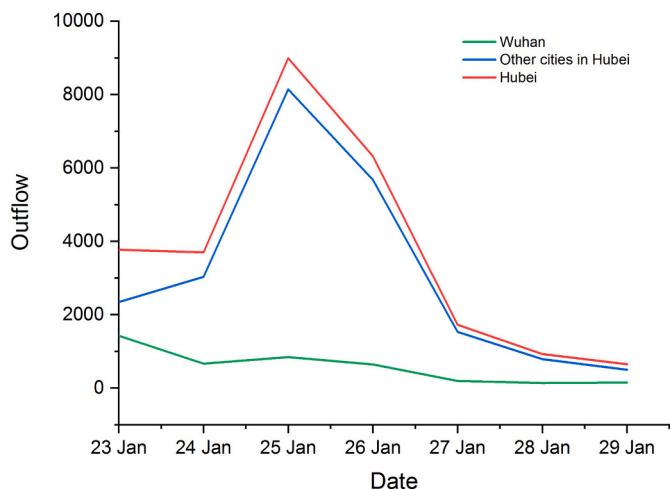


Fig. 3. Daily population outflow of Wuhan and the other 13 cities in Hubei from 23 Jan 2020 to 29 Jan 2020.

Table 1
Travel ban issue time and outflow pattern of 14 cities in Hubei province.

Division	Start date	Surge of outflow	Maximum outflow day	Drop of outflow
Wuhan	1/23	No	1/23	1/23
Huanggang	1/24	1/24	1/25	1/26
Ezhou	1/24	1/24	1/25	1/26
Huangshi	1/24	1/24	1/25	1/26
Xianning	1/24	1/24	1/25	1/26
Tianmen	1/24	1/24	1/25	1/26
Xiaogan	1/24	1/24	1/25	1/26
Suizhou	1/25	1/24	1/25	1/26
Jingzhou	1/24	1/24	1/25	1/26
Jingmen	1/25	1/24	1/25	1/26
Xiangyang	1/26	1/25	1/26	1/27
Yichang	1/24	1/24	1/25	1/26
Shiyan	1/25	1/25	1/25	1/26
Enshi	1/26	1/24	1/26	1/27

other 13 Hubei cities to Zhejiang between 23 Jan 2020 and 29 Jan 2020 in Fig. 4. The response curve follows an S-shape, which is very similar to the growth curve models in economics (Vieira & Hoffmann, 1977) and the evacuation response curve under other emergencies (Gudishala &

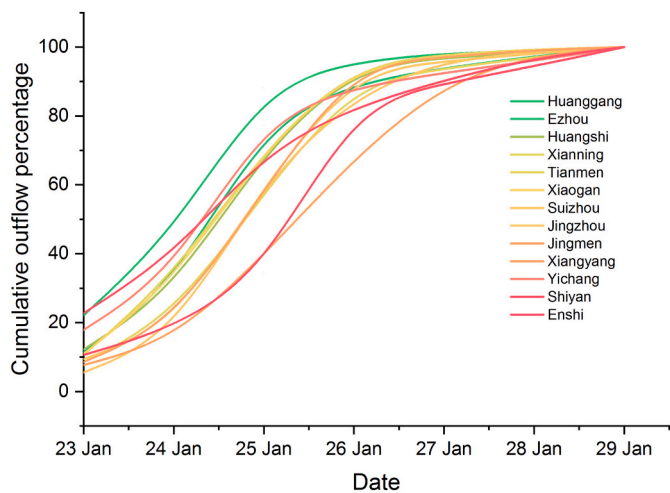


Fig. 4. The response curve of 13 cities in Hubei. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

Wilmot, 2012; Zhang et al., 2013). Fig. 4 also demonstrates that cities further from Wuhan (dark red) have a relatively later response than those nearer to Wuhan (light green).

We fit the response curve for each of the 13 cities with the growth curve function, i.e., the Logistic model in Eq. (1).

$$Y(t) = \frac{1}{1/s + r \cdot a^t} \tag{1}$$

In this model, parameter s is the saturation level, set as 100, meaning 100% of population outflow. Parameter α and r determine response pattern and response speed, respectively. As each of the 13 cities has a similar response pattern, we set the same α for each municipality. After multiple fitting tries, $\alpha = 0.22$, and the fitted parameter r for each city are shown in Table 2. Based on the fitted function, the response curve can be visualized. The response curve of Huanggang city is shown in Fig. 5, while the curves for the other 12 cities are illustrated in Fig. 11.

3. The role of geographic location

As Fig. 4 shows, cities further from Wuhan have a relatively later response than those nearer to Wuhan; we further analyze the relationship between spill-over effect and geographic location. We fit the response curve's speed parameter r with the transportation distance (minimum highway distance and highspeed rail distance) to Wuhan (the pandemic center). The fitted lines are shown in Fig. 6. Interestingly, there is a linear relationship between response speed and transportation distance from the pandemic center (Wuhan). The parameter r of the Logistic function is shown below.

$$r = \beta x + c \tag{2}$$

In this formula, c is the intercept term, β is the slope, and x is the transportation distance. The fitted results show that all the 12 cities except Shiyan are seen a linear relationship between response speed and transportation distance. Besides, all the cities can be clustered into two groups, i.e., 5 cities to the west of Wuhan (green squares in Fig. 6) and 8 other cities (red squares in Fig. 6). The slope parameters β and intercept c for the cities to the West of Wuhan are 0.0026 and 0.048. In contrast, the parameters β and c of the other 7 cities are 0.0051 and 0.0145, indicating the people from the cities to the West of Wuhan have a slower response than those from the other cities in Hubei. We have reasons to infer such a slower response speed is attributed to the transportation mode to Zhejiang. The 5 cities lying to the West of Wuhan all have access

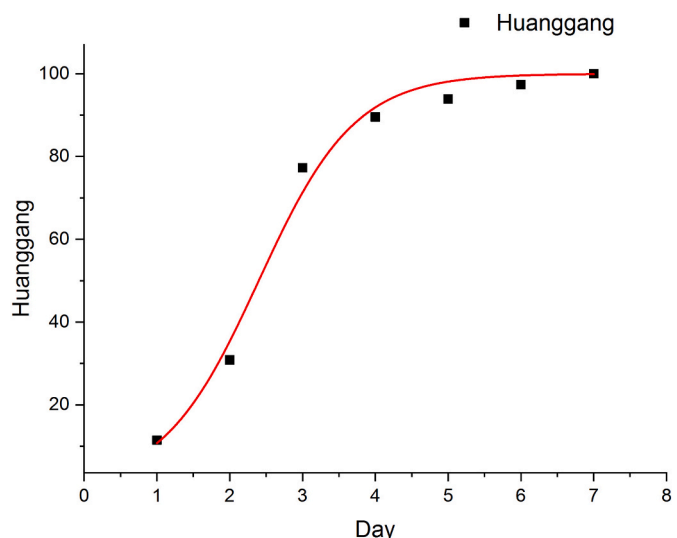


Fig. 5. The response curve for Huanggang city of Hubei Province.

Table 2
Estimation of the cumulative response curve.

City	Parameter value	Standard error	R ²
Huanggang	0.378	0.043	0.989
Ezhou	0.195	0.020	0.988
Huangshi	0.428	0.029	0.996
Xianning	0.676	0.046	0.996
Tianmen	0.391	0.016	0.999
Xiaogan	0.405	0.019	0.998
Suizhou	0.719	0.069	0.994
Jingzhou	0.646	0.068	0.992
Jingmen	0.643	0.073	0.991
Xiangyang	1.622	0.173	0.992
Yichang	0.321	0.047	0.979
Shiyan	0.342	0.075	0.942
Enshi	1.316	0.230	0.978

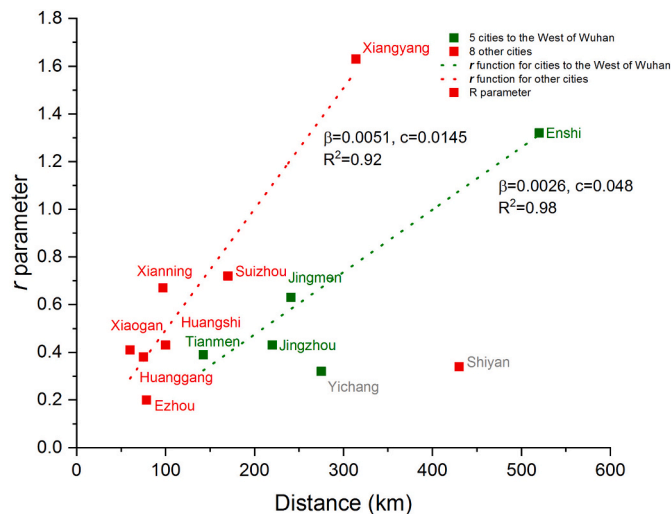


Fig. 6. The relationship between response speed (Logistic parameter) and transportation distance. (For interpretation of the references to color in this figure, the reader is referred to the web version of this article.)

to the direct high-speed train to Hangzhou, Zhejiang's provincial capital. In contrast, the other 7 cities, i.e., red square in Fig. 6, do not have the direct high-speed train to Hangzhou.

These model outcomes verify the spill-over effect of the Wuhan travel ban: 1) Wuhan travel ban has an indirect impact on the population flow of the other 13 cities in Hubei Province; 2) and such spill-over effect decays with the increase of distance from Wuhan. However, it is still unclear why the city, Shiyan, lying the second furthest to Wuhan, has a rapid response (parameter $r = 0.34$ in Table 1).

Combing Eqs. (1) and (2), the response curve function is depicted below.

$$Y(t) = \frac{1}{1/s + (\beta x + c) \cdot a^t} \quad (3)$$

4. Conclusion

This paper investigates the impact of the Wuhan travel ban on population flow in the early outbreak stage of the COVID-19 Pandemic in China. Unlike the previous research efforts (Hien et al., 2020; Lv et al., 2020; Saha et al., 2020) find out that travel ban will always constrain human movement, we find out that a travel ban policy may stimulate human movement if it's not properly designed. For pandemics like the COVID-19, the travel ban policy of the pandemic center city has a spill-over effect, which may trigger a short-term surge of human movement of its neighboring cities, making the risk of virus transmission to other

regions. Thus, the travel ban policy should be simultaneously implemented in the pandemic center city as well as its neighboring cities in other countries. Overacting in response to the COVID-19 pandemic may not be bad, as we need more redundancy policy design to restrain human movement.

Future research may be put forward to analyze the outbound, and inbound population flows in Hubei province for a more extended time range to better explain the spill-over effect. Besides, testing if such spill-over effect exists in other regions or countries will also bring new sights to the research community to design more effective travel constrain policy worldly.

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.cities.2021.103404>.

Declaration of competing interest

None.

Acknowledgements

This work is supported by the National Science Foundation of China under Grant #61773035, U1764265. The authors would also like to thank the insightful and constructive comments from anonymous reviewers

References

Buckee, C. O., et al. (2020). Aggregated mobility data could help fight COVID-19. *Science*. <https://doi.org/10.1126/science.abb8021>.

Chan, J., Yuan, S., et al. (2020). A familial cluster of pneumonia associated with the 2019 novel coronavirus indicating person-to-person transmission: A study of a family cluster. *The Lancet*. [https://doi.org/10.1016/S0140-6736\(20\)30154-9](https://doi.org/10.1016/S0140-6736(20)30154-9).

Chinazzi, M., et al. (2020). The effect of travel restrictions on the spread of the 2019 novel coronavirus (COVID-19) outbreak. *Science*. <https://doi.org/10.1126/science.aba9757>.

Cui, J., Li, F., & Shi, Z. (2019). Origin and evolution of pathogenic coronaviruses. *Nature Reviews Microbiology*, 17, 181–192. <https://doi.org/10.1038/s41579-018-0118-9>.

Ensheng Dong, Hongru Du, Lauren Gardner, "An interactive web-based dashboard to track COVID-19 in real time". *The Lancet Infectious Diseases*, doi:10.1016/S1473-3099(20)30120-1.

Engle, S., Stromme, J., & Zhou, A. (2020). Staying at home: Mobility effects of COVID-19. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.3565703>.

Gao, Y., et al. (2020). Structure of the RNA-dependent RNA polymerase from COVID-19 virus. *Science*. <https://doi.org/10.1126/science.abb7498>.

Gudishala, R., & Wilmot, C. (2012). Comparison of time-dependent sequential logit and nested logit for modeling hurricane evacuation demand. In *Transportation research record: Journal of the transportation research board*, No. 2312 (pp. 134–140). Washington, D.C: Transportation Research Board of the National Academies.

Hien, L., Veria, K., Piotr, K., Agata, M., Justyna, S., Jacek, B., et al. (2020). The positive impact of lockdown in Wuhan on containing the covid-19 outbreak in China. *Journal of Travel Medicine*, 3, 3.

Huang, C., Wang, Y., et al. (2020). Clinical features of patients infected with 2019 novel coronavirus in Wuhan, China. *The Lancet*. [https://doi.org/10.1016/S0140-6736\(20\)30183-5](https://doi.org/10.1016/S0140-6736(20)30183-5).

Jia, J. S., Lu, X., Yuan, Y., et al. (2020). Population flow drives spatio-temporal distribution of COVID-19 in China. *Nature*. <https://doi.org/10.1038/s41586-020-2284-y>.

Johns Hopkins University & Medicine. (2021). Coronavirus COVID-19 global cases by the Center for Systems Science. <https://coronavirus.jhu.edu/map.html>, 13 Apr.

Kraemer, M. U. G., et al. (2020). The effect of human mobility and control measures on the COVID-19 epidemic in China. *Science*. <https://doi.org/10.1126/science.abb4218>.

Li, Q., Guan, X., Wu, P., Wang, X., Zhou, L., Tong, Y., & Feng, Z. (2020). Early transmission dynamics in Wuhan, China, of novel coronavirus-infected pneumonia. *The New England Journal of Medicine*. <https://doi.org/10.1056/NEJMoa2001316>.

Lv, Z., Wang, X., Deng, F., Ying, Q., & Liu, H. (2020). Significant reduced traffic in Beijing failed to relieve haze pollution during the covid-19 lockdown: implications for haze mitigation. arXiv:2006.07297.

Saha, J., Barman, B. B., & Chouhan, P. (2020). Lockdown for covid-19 and its impact on community mobility in India: An analysis of the covid-19 community mobility reports. *Children and Youth Services Review*, 116, 105160.

Sun, K., Chen, J., & Viboud, C. (2020). Early epidemiological analysis of the coronavirus disease 2019 outbreak based on crowdsourced data: A population-level observational study. *Lancet Digital Health*, 2, e201–e208.

Tian, H., et al. (2020). An investigation of transmission control measures during the first 50 days of the COVID-19 epidemic in China. *Science*. <https://doi.org/10.1126/science.abb6105>.

- Vieira, S., & Hoffmann, R. (1977). Comparison of the logistic and the gompertz growth functions considering additive and multiplicative error terms. *Applied Statistics*, 26, 143. <https://doi.org/10.2307/2347021>.
- Wang, C., Horby, P., Hayden, F., & Gao, G. (2020). A novel coronavirus outbreak of global health concern. *The Lancet*. [https://doi.org/10.1016/S0140-6736\(20\)30185-9](https://doi.org/10.1016/S0140-6736(20)30185-9).
- World Health Organization. (2020). Rolling updates on coronavirus disease (COVID). <https://www.who.int/emergencies/diseases/novel-coronavirus-2019/events-as-they-happen>, 12 May.
- Zhang, Z., Spansel, K., & Wolshon*, B. (2013). Megaregion network simulation for evacuation analysis. *Transportation Research Record: Journal of the Transportation Research Board*, 2397(1), 161–170.
- Zhou, P., Yang, X., Wang, X., et al. (2020). A pneumonia outbreak associated with a new coronavirus of probable bat origin. *Nature*, 579, 270–273. <https://doi.org/10.1038/s41586-020-2012-7>.