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Evaluating the impact of the travel ban within mainland China on the epidemic of the COVID-19



Ling Xue^{a,1}, Shuanglin Jing^a, Wei Sun^{a,1}, Maoxing Liu^b, Zhihang Peng^c, Huaiping Zhu^{d,*}

^a College of Mathematical Sciences, Harbin Engineering University, Harbin, Heilongjiang, 150001, China

^b School of Sciences, North University of China, Taiyuan, Shanxi, 030051, China

^c Department of Epidemiology and Biostatistics, School of Public Health, Nanjing Medical University, Nanjing, Jiangsu, 210029, China

^d Lamps and Canadian Centre for Disease Modelling (CCDM), Department of Mathematics and Statistics, York University, Toronto, ON, M3J 1P3, Canada

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ABSTRACT

Objectives: The ongoing COVID-19 pandemic expanded its geographic distribution through the movement of humans and caused subsequent local outbreaks. Hence, it is essential to investigate how human mobility and travel ban affect the transmission and spatial spread while minimizing the impact on social activities and national economics.

Methods: We developed a mobility network model for spatial epidemics, explicitly taking into account time-varying inter-province and inner-province population flows, spatial heterogeneity in terms of disease transmission, as well as the impact of media reports. The model is applied to study the epidemic of the dynamic network of 30 provinces of mainland China. The model was calibrated using the publicly available incidence and movement data.

Results: We estimated that the second outbreak occurred approximately on February 24, 2020, and the cumulative number of cases as of March 15, 2020, increased by 290.1% (95% CI: (255.3%, 324.9%)) without a travel ban in mainland China (excluding Hubei and Tibet). We found that intra-province travel contributes more to the increase of cumulative number of cases than inter-province travel.

Conclusion: Our quantitative and qualitative research results suggest that the strict travel ban has successfully prevented a severe secondary outbreak in mainland China, which provides solutions for many countries and regions experiencing secondary outbreaks of COVID-19.

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Introduction

The global outbreak caused by the severe acute respiratory syndrome coronavirus-2 (SARS-CoV-2) has been declared a pandemic by the World Health Organization (WHO). The number of imported SARS-CoV-2 cases in many countries has been rising due to large-scale geographic spread (Candido et al., 2020; Li et al., 2020). The ongoing epidemic of COVID-19 presents significant challenges to the development of the economy. As of November 15, 2020, the COVID-19 epidemic has caused 53.7 million confirmed cases and 1.3 million deaths worldwide (2020f). However, by the beginning of March 2020, the COVID-19 epidemic was already under control in mainland China (Xu and Li, 2020), and most provinces had gradually resumed work and production.

The Spring Festival was coming when the COVID-19 outbreak became a public health concern in China. To prevent the further spatial spread of COVID-19 caused by the massive population movement during the most important traditional holiday period, Wuhan of Hubei province started lockdown on January 23, 2020 (Tian et al., 2020). Soon afterwards, other provinces also implemented travel bans between provinces, suspended local public transportation such as buses and subways, closed schools and entertainment places, banned public gatherings, encouraged the public to wash their hands, wear masks, and suggested other personal preventive actions (Lai et al., 2020). In addition to the travel ban implemented in each province, Chinese public health authorities have also reinforced screening, identification, diagnosis, timely reporting and contact tracing of suspected or confirmed cases, isolation of infected individuals, quarantine of exposed individuals to minimize the risk of SARS-CoV-2 infection (Chen et al., 2020). China has allocated medical resources among more than 30 provinces, municipalities, and districts to optimize limited healthcare facilities and achieved centralized treatment of severely

* Corresponding author at: 4700 Keele Street, Toronto, Ontario, M3J1P3, Canada.
E-mail address: huaiping@yorku.ca (H. Zhu).

¹ Contributed equally.

affected areas through unified adjustment, deployment, and mobilization (2020e).

Implementing these non-pharmaceutical interventions (NPIs) has led to a rapid decline in daily new cases across the country. Therefore, it is crucial to understand how China successfully curbed the spread of the COVID-19 epidemic, which will provide valuable experiences and guidance for other countries suffering from the epidemic and prevent the second wave of the COVID-19 outbreak in China.

Many previous mathematical models have studied the impact of non-pharmaceutical interventions (NPIs) on the spread of COVID-19 (Candido et al., 2020; Chinazzi et al., 2020; Gatto et al., 2020; Jia et al., 2020; Kraemer et al., 2020; Lai et al., 2020; Li et al., 2020; Song et al., 2020; Sun et al., 2020; Tian et al., 2020; Wells et al., 2020; Xia et al., 2020). As this highly infectious disease rapidly spreads, media reports have been active in community education on COVID-19 by disseminating useful information on pathogenesis, prevention, and mitigation (Liu et al., 2020a). To the best of our knowledge, very few works have simultaneously taken into account the delay and strength of media reports, variation of isolation rates, the infection caused by asymptomatic infection, as well as inter-province and inner-province travel bans.

To evaluate the impact of media reports, variation of isolation rates, and inter-province and intra-province travel bans on the epidemics in mainland China, we developed a network model consisting of 30 provinces of the country. We considered the heterogeneity among provinces in terms of population size, the timing and strength of initiating NPIs, and the mobility rate of humans.

We fitted the reported COVID-19 data to the models and computed the effective reproduction number for every 30 provinces. We conducted the comparative analysis to quantify the impact of travel restriction, media reports, and detection and isolation of cases on the dynamics of the COVID-19 epidemic using the Baidu travel data and Baidu Index data to project the corresponding effective containment strategy for each province. We also assessed the risk of postponing the travel ban on the spread of COVID-19.

Method

Data collection and analysis

To parameterize the mathematical model for the transmission dynamics of COVID-19 in mainland China, we used the observations of reported cases within 30 provinces (excluding Tibet) from January 10 to March 15, 2020, provided by the Chinese Center for Disease Control and Prevention (2020c) (CCDC) and National Health Commission (NHC) of China (2020d) as shown in Figure A1 of Appendix A. The official website of the CCDC reported the number of daily confirmed cases, deaths, and recovered cases in each province. The Center for Disease Control and Prevention (CDC) and Health Commission (HC) in each province reported detailed information on the patients infected by COVID-19, including gender, age, the timing of symptom onset, and hospitalization. We focused on the number of daily new cases.

Public health authorities are increasingly advocating the use of virtual social networks to spread information about infectious diseases. Although it is difficult to measure the effectiveness of such strategies, many researchers have found that disease information has dramatically changed the awareness and behavior of online users and the public (Vance et al., 2009). The awareness of the public and the prevention of diseases can be reflected by the active acquisition of relevant information. The Baidu Search Index is provided by Baidu, which represents the levels of Internet users' attention to keyword searches that vary with time (Liu et al., 2020b). To characterize the impact of media reports on the COVID-19 outbreak, we collected the Baidu Search Index (2020b) shown in Figure A1 of Appendix A by searching SARS-CoV-2 or COVID-19 in Chinese, representing the public's concerns on the COVID-19 epidemic.

Large-scale population movements may cause further spread of the epidemic (Meloni et al., 2011). We collected real-time travel data using the Baidu Migration server (2020a) from January 10, 2020, to March 15, 2020, which provides real-time travel patterns in China based on mobile-phone positioning services. These data include the daily migration ratio and Baidu Migration Index between provinces, as shown in Figure A2 of Appendix A. The explicit relationship between the population size and the Baidu

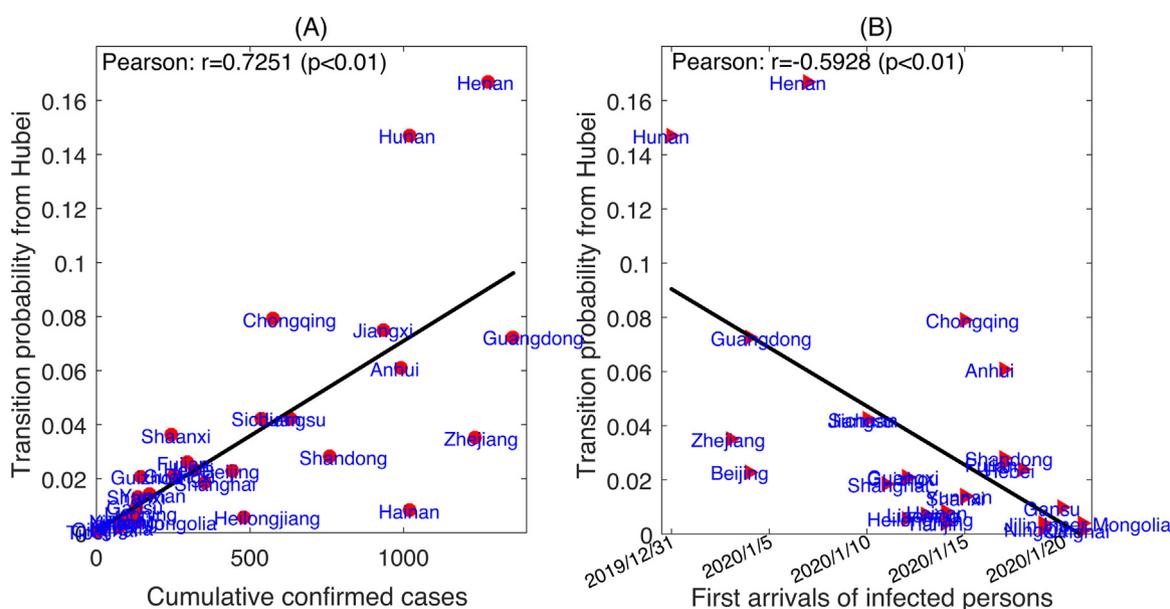


Figure 1. (A) Correlation between the cumulative number of cases in each province (excluding Hubei) and transition probability from Hubei province. (B) Correlation between the dates of documented first arrivals of infected persons in 26 provinces (excluding Hubei, Shaanxi, Jiangxi, and Xinjiang) and transition probability from Hubei province.

Migration Index was not explained explicitly. [Sanche et al. \(2020\)](#) estimated that one unit of the Baidu Migration Index corresponds to approximately 44520 migrants, and we estimated the travel flow between the provinces of mainland China using this approximation.

To study the relationship between media reports and the COVID-19 epidemic, we used the cross-correlation analysis ([Wei, 2006](#)) to reveal the statistically significant correlation between the Baidu Search Index and the number of daily new cases from January 10, 2020, to March 15, 2020. Cross-correlation is a standard method of estimating the degree to which two series are correlated. We used the collected data to reveal the range of cross-correlation coefficients and determine the specific value of the time lag when the cross-correlation coefficient reaches its maximum.

We derived the cross-correlation function between the number of daily new cases and the Baidu Search Index in each province, as shown in Figure A3 of Appendix A. The results show a statistically significant correlation between the number of daily new cases and the Baidu Search Index in each province. Figure A3 shows that the local maximum cross-correlation coefficient occurs at lag = 1 in Tianjin, Liaoning, Hainan, and Ningxia. For Beijing, Inner Mongolia, Gansu, and Xinjiang, the local maximum cross-correlation coefficient occurs at lag = 0. The local maximum cross-correlation coefficient occurs at lag < 0 in other provinces.

Population flow from Hubei can be hypothesized to export the virus to other provinces, where local outbreaks are produced thereafter ([Jia et al., 2020](#)). We found that there is a highly positive correlation between the cumulative number of cases in each province (excluding Hubei) as of March 15, 2020, and the transition probability from Hubei province (average of daily migration rates from Hubei to each province from January 10 to January 23, 2020) as shown in Figure 1(A). Meanwhile, we also found that there is a moderately negative correlation between the dates of first documented arrivals of infected persons in 26

provinces (excluding Hubei, Shaanxi, Jiangxi, and Xinjiang) and transition probability from Hubei province (average of daily migration rates from Hubei to each province from January 10 to January 23, as shown in Figure 1(B)).

Model formulation

The total population of each province is divided into six classes, namely, $S_n(t)$, $E_n(t)$, $A_n(t)$, $I_n(t)$, $H_n(t)$ and $R_n(t)$ representing the number of susceptible, exposed, asymptomatic infected, symptomatic infected, hospitalized, and recovered individuals in the n -th province. The total population in the n -th province at time t is denoted by $N_n(t)$. The model describing the dynamics of the epidemic in the n -th province is as follows

$$\left\{ \begin{aligned} \frac{dS_n}{dt} &= -\beta_n(t)e^{-\alpha_n M_n(t-\tau_n)} S_n \left(\frac{I_n}{N_n} + \theta_n \frac{A_n}{N_n} + \delta_n \frac{E_n}{N_n} \right) + \sum_{m \neq n} \eta_m(t) P_{mn}(t) S_m \\ &\quad - \sum_{m \neq n} \eta_n(t) P_{nm}(t) S_n, \\ \frac{dE_n}{dt} &= \beta_n(t)e^{-\alpha_n M_n(t-\tau_n)} S_n \left(\frac{I_n}{N_n} + \theta_n \frac{A_n}{N_n} + \delta_n \frac{E_n}{N_n} \right) - \sigma_n E_n \\ &\quad + \sum_{m \neq n} \eta_m(t) P_{mn}(t) E_m - \sum_{m \neq n} \eta_n(t) P_{nm}(t) E_n, \\ \frac{dA_n}{dt} &= \rho_n \sigma_n E_n - \gamma_{an} A_n + \sum_{m \neq n} \eta_m(t) P_{mn}(t) A_m - \sum_{m \neq n} \eta_n(t) P_{nm}(t) A_n, \\ \frac{dI_n}{dt} &= (1 - \rho_n) \sigma_n E_n - P_n^{ir} \gamma_i I_n - P_n^{ih} \varepsilon_n(t) I_n \\ &\quad + \sum_{m \neq n} \eta_m(t) P_{mn}(t) I_m - \sum_{m \neq n} \eta_n(t) P_{nm}(t) I_n, \\ \frac{dH_n}{dt} &= P_n^{ih} \varepsilon_n(t) I_n - \gamma_{hn} H_n, \\ \frac{dR_n}{dt} &= \gamma_{an} A_n + P_n^{ir} \gamma_i I_n + \gamma_{hn} H_n + \sum_{m \neq n} \eta_m(t) P_{mn}(t) R_m \\ &\quad - \sum_{m \neq n} \eta_n(t) P_{nm}(t) R_n. \end{aligned} \right. \tag{1}$$

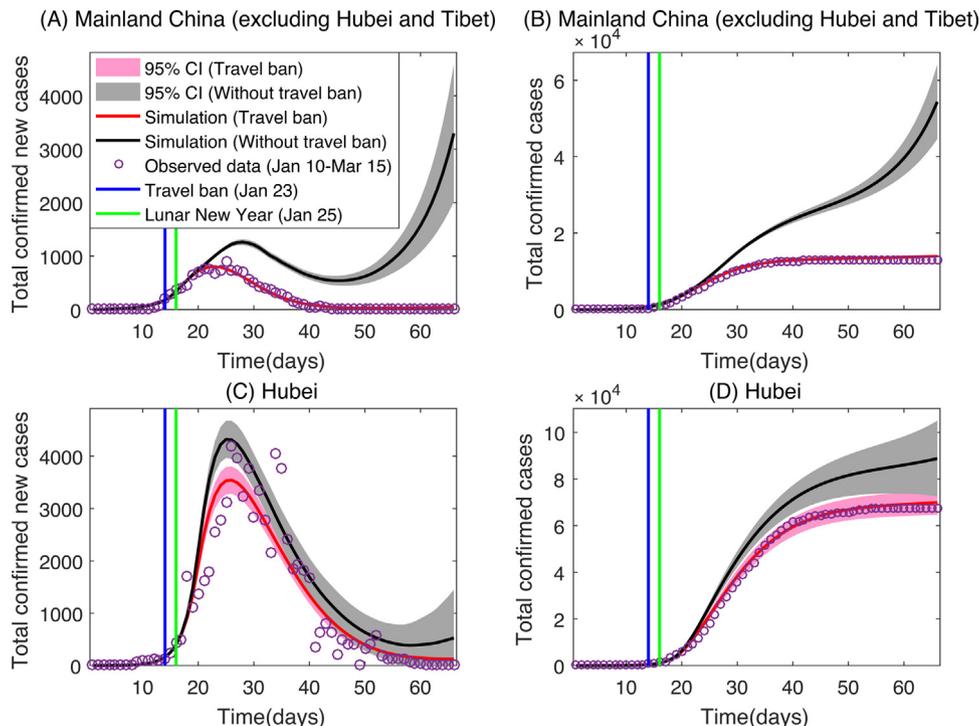


Figure 2. The impact of travel bans on the dynamics of COVID-19 outbreak. (A) The impact of the travel ban on the number of daily new cases in mainland China (excluding Hubei and Tibet). (B) The impact of the travel ban on the cumulative number of cases in mainland China (excluding Hubei and Tibet). (C) The impact of the travel ban on the number of daily new cases in Hubei Province. (D) The impact of the travel ban on the cumulative number of cases in Hubei Province.

The detailed description of Model (1) is in Appendix B.

Parameter estimation

Using Model (1), we quantified the impact of non-pharmacological interventions on the dynamics of the COVID-19 epidemic using the Baidu travel data, Baidu Index data, and the isolation rate to project the corresponding effective containment strategy for each province, as well as the possibility of further spread after lifting the travel ban and the delayed travel ban. We simulated the epidemic for each province from January 10, 2020, taking into account the underreported cases at the beginning of the epidemic in Hubei. Since daily numbers of new cases were not reported in Hubei Province from December 1, 2019, to January 18, 2020, we assumed that the initially daily number of newly infected individuals is 0 in simulations. Detailed parameter estimation and fitting results are in Appendix B.

Results

Impact of the absence of the travel ban

We quantified the spread of COVID-19 without any travel ban. As of March 15, 2020, the cumulative number of COVID-19 cases in mainland China (excluding Tibet) increased by 70.6%, and the cumulative number of COVID-19 cases in Mainland China (excluding Tibet and Hubei) increased by 290.1%. The second outbreak occurred approximately On March 1, 2020, and February 24, 2020, in mainland China (excluding Tibet) and mainland China (excluding Tibet and Hubei), respectively (see Figure 2).

Impact of the inter-province travel ban

We quantified how the transmission of COVID-19 varied with the inter-province travel ban, as well as the possibility of further spread of COVID-19 in each province after the inter-province travel ban was lifted on January 23, 2020 (see Figure C3 and Figure C4 of Appendix C). We simulated the scenarios when the inter-province travel ban is not implemented as is shown in Figure C5 of Appendix C. The peak size of the number of daily new cases increased by 29.67% in mainland China (excluding Hubei and Tibet). The peak time for the number of daily new cases was delayed by three days in mainland China (excluding Hubei and Tibet) after implementing the travel ban. As of March 15, 2020, the cumulative number of cases increased by 48.69% in mainland China (excluding Hubei and Tibet). The impact of the inter-province

travel ban on the peak size, peak time, and cumulative cases of each province is summarized in Table C1 of Appendix C.

Impact of the intra-province travel ban

We quantified how the transmission of COVID-19 varied with the inner-provincial travel ban, as well as the possibility of further spread of COVID-19 in each province after the inner-provincial travel ban was lifted on January 23, 2020 (see Figure C6 and Figure C7 of Appendix C). When there was no travel ban within the province, the peak size of the first wave increased by 5.85% in the country (excluding Hubei and Tibet). After the first peaks, the number of daily new cases continued decreasing until the trough appeared on February 21; afterwards the rebound of daily new cases was very serious in mainland China (excluding Hubei and Tibet). As of March 15, the cumulative number of cases increased by 143.19% in mainland China (excluding Hubei and Tibet). The peak size of the first wave increased by 28.76% in Hubei. The trough appeared on March 9. As of March 15, the cumulative number of cases increased by 40.30% in Hubei (see Figure C8 of Appendix C).

Impact of the delayed travel ban

The timing of the travel ban in the early stages of the COVID-19 outbreak was critical; we quantified the possibility of the spread of COVID-19 in each province for the period after a travel ban was implemented on January 27, 2020, and January 30, 2020, respectively. Figure C9 of Appendix C and Table 1 show the spreading of the epidemic when the travel ban was delayed. The peak size of daily new cases increased by 23.02% and 26.91% in mainland China (excluding Tibet) when the travel ban was postponed by 4 days and 7 days, respectively, and as of March 15, 2020, the cumulative number of cases increased by 22.30% and 26.25% in mainland China (excluding Tibet). If we exclude Hubei and Tibet, due to the same delays, the peak size of daily new cases increased by 15.82% and 27.90%, and as of March 15, 2020, the cumulative number of cases increased by 18.15% and 36.64% in mainland China. However, in Hubei province, the peak size of daily new cases increased by 24.00% and 24.90% when the travel ban was delayed by 4 days and 7 days, respectively; also by March 15, 2020, the cumulative number of cases increased by 23.12% and 24.18%, respectively.

Impact of media reports

Previous work revealed that media coverage significantly delayed and reduced the peak and final size of the epidemics

Table 1
The peak number of new cases, peak time, and final size with the delayed travel ban.

Mainland China (excluding Tibet)	Peak size (95%CI)	Peak time (95%CI)	Final size (95%CI)
No delay	4293(4029,4557)	25(25,25)	83896(78596,89196)
4 days delay	5281(4926,5636)	25.50(24.52,26.48)	102602(95365,109839)
7 days delay	5448(5066,5830)	25.95(25.50,26.39)	105917(97882,113952)
Mainland China (excluding Hubei and Tibet)	Peak size (95%CI)	Peak time (95%CI)	Final size (95%CI)
No delay	804(788,821)	23(23,23)	13934(13670,14197)
4 days delay	932(910,953)	24(24,24)	16462(16096,16829)
7 days delay	1029(1001,1057)	25.02(24.74,25.30)	19039(18517,19561)
Hubei	Peak size (95%CI)	Peak time (95%CI)	Final size (95%CI)
No delay	3542(3280,3804)	25.92(25.37,26.46)	69962(64680,75245)
4 days delay	4392(4041,4743)	26(26,26)	86140(79009,93270)
7 days delay	4424(4052,4796)	25.99(25.81,26.17)	86878(79089,94667)

The final size refers to the cumulative number of cases as of March 15, 2020.

Table 2
The peak number of new cases, peak time, and final size varying with the behavioral parameter α_n .

Mainland China (excluding Hubei and Tibet)	Peak size (95%CI)	Peak time (95%CI)	Final size (95%CI)
$0.6\alpha_n$	1066(1039,1093)	24(24,24)	21985(21066,22904)
$0.8\alpha_n$	902(882,922)	23.00(22.92,23.09)	16540 (16133, 16946)
α_n	804(788,821)	23(23,23)	13934(13670,14197)
$1.2\alpha_n$	737(722,751)	22.75(21.92,23.60)	12413 (12190, 12636)
$1.4\alpha_n$	688(675,702)	22.09(21.54,22.64)	11407 (11196, 11617)
Hubei	Peak size (95%CI)	Peak time (95%CI)	Final size (95%CI)
$0.6\alpha_n$	4883(4488,5279)	26.31(25.40,27.21)	110668(96150,125185)
$0.8\alpha_n$	4092(3782,4402)	26(26,26)	83615(76541,90690)
α_n	3542(3280,3804)	25.92(25.37,26.46)	69962(64680,75245)
$1.2\alpha_n$	3129(2892,3366)	25.44(24.46,26.41)	61019(56514,65524)
$1.4\alpha_n$	2803(2577,3029)	25.06(24.59,25.53)	54350(50263,58438)

The final size refers to the cumulative number of cases as of March 15, 2020.

Table 3
The peak number of new cases, peak time, and final size varying with the initial isolation rate ϵ_{n0} .

Mainland China (excluding Hubei and Tibet)	Peak size (95%CI)	Peak time (95%CI)	Final size (95%CI)
ϵ_{n0}	804(788,821)	23(23,23)	13934(13670,14197)
$2\epsilon_{n0}$	808(791,826)	20.57(19.60,21.54)	12685 (12448,12923)
$3\epsilon_{n0}$	777(757,797)	19.28(18.40,20.16)	11835 (11611,12059)
$4\epsilon_{n0}$	741(720,762)	19(19,19)	11187(10972,11402)
$5\epsilon_{n0}$	703(680,726)	18.14(17.46,18.82)	10672 (10465,10879)
Hubei	Peak size (95%CI)	Peak time (95%CI)	Final size (95%CI)
ϵ_{n0}	3542(3280,3804)	25.92(25.37,26.46)	69962(64680,75245)
$2\epsilon_{n0}$	4352(4047,4656)	23.74(22.88,24.60)	64245(59477,69014)
$3\epsilon_{n0}$	4627(4278,4976)	22.99(22.84,23.15)	60040(55567,64514)
$4\epsilon_{n0}$	4695(4300,5090)	22.06(21.60,22.51)	56707(52464,60950)
$5\epsilon_{n0}$	4686(4274,5097)	22(22,22)	53989(49938,58041)

The final size refers to the cumulative number of cases as of March 15, 2020.

(Cui et al., 2008). We used Model (1) to quantify the spread of COVID-19 with media reports. We further confirmed that the intensity of different media reports played an important role in the spread of COVID-19 (see Figure C10, and Figure C11 of Appendix C, Table 2). Due to the relaxation of awareness, the behavioral parameter α_n was reduced by 40%, the peak occurred about one day later, the peak size increased by 32.59%, and the final epidemic size increased by 57.78% in mainland China (excluding Hubei and Tibet) as of March 15, 2020. Due to the improvement of self-protection awareness, the behavioral parameter α_n increased by 40%, the peak occurred about one day earlier, the peak size reduced by 14.43%, and the final epidemic size reduced by 18.14% in mainland China (excluding Hubei and Tibet) as of March 15, 2020. Due to the relaxation of awareness, the behavioral parameter α_n was reduced by 40%, the peak occurred about half a day later, the peak size increased by around 37.86%, and the final epidemic size increased by 58.18% in Hubei as of March 15, 2020. Due to the improvement of self-protection awareness, the behavioral parameter α_n increased by 40%, the peak occurred about one day earlier, the peak size was reduced by around 20.86%, and the final epidemic size was reduced by 22.31% in Hubei as of March 15, 2020 (see Figure C10 of Appendix C and Table 2).

Impact of initial isolation rate

The initial isolation rate reflects how soon the NPIs are implemented after infected cases are detected. We quantified the impact of different initial isolation rates on the dynamics of COVID-19 transmission. When the initial isolation rate ϵ_{n0} was increased twice by expanding test capacity, the peak occurs about

two days earlier, and the final epidemic size was reduced by around 8.96% in mainland China (excluding Hubei and Tibet) as of March 15, 2020. When the initial isolation rate ϵ_{n0} was increased by four times by expanding test capacity, the peak occurred about four days earlier, and the final epidemic size was reduced by around 19.71% in mainland China (excluding Hubei and Tibet) as of March 15, 2020. When the initial isolation rate ϵ_{n0} was increased twice by the strengthening of testing capability, the peak occurred about two days earlier, and the final epidemic size reduced by around 8.17% in Hubei as of March 15, 2020. When the initial isolation rate ϵ_{n0} was increased four times by strengthening the testing capability, the peak occurred about four days earlier, and the final epidemic size was reduced by around 18.95% in Hubei as of March 15, 2020 (see Figure C12 of Appendix C and Table 3).

Discussion

Highly virulent emergent pathogens are more likely to spread with the progressing global urbanization and growing connectivity among metropolitan centers (Brockmann et al., 2006; Moore et al., 2003; Vespignani, 2009). Application of Georeferenced epidemiological data and modeling tools supply insights that inform decision-making for emergency management (Gatto et al., 2020).

To understand how human mobility between and within provinces, other factors including media reports, and the initial isolation rate of quarantine influence the dynamics of the spread of SARS-CoV-2, we developed a meta-population disease transmission model, where human mobility is characterized by a dynamic directed network. The model takes into account the heterogeneity between different provinces, such as the timing of implementing

NPIs, the hospitalization rate due to the availability of health care resources, and population behavior changes.

We only analyzed the epidemic in mainland China for the period from January 10 to March 15, 2020, since the epidemic was almost dying out throughout the whole country. Although scattered outbreaks occurred in Heilongjiang province due to imported cases, and in Beijing City and Dalian City caused by seafood, the scales of these outbreaks were small and thus were soon contained by mass screening, contact tracing, and quarantine within the regions.

Our model has incorporated major key factors responsible for the temporal and spatial spread of COVID-19, such as media reports publicity, travel ban between and within provinces, and the rate at which infected individuals are isolated at the beginning of an outbreak within a province. People were quarantined when there was a travel between provinces, but the quarantine policy did not apply for people traveling within a province. This may be the reason that the intra-province travel ban is more crucial in containing an epidemic which is consistent with that in the available literature (Lai et al., 2020). We found that enhancing media reports and increasing isolation rates could significantly reduce the final size of the epidemics, although the impact varies for different locations. Our findings provide insights that help support the planning of emergency management and decision-making for public health authorities. However, our work still has limitations. The efficacy of disease control relies on the availability of data needed for modeling and quantifying human mobility (Tizzoni et al., 2014). We did not consider the imported cases from overseas and the role of environmental factors and their variations in different provinces in the transmission of COVID-19, which we keep as future work when such data become available.

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Ethical approval

This article does not contain any studies involving animals or humans performed by any of the authors.

Conflicts of interest

The authors declare that they have no conflicts of interest.

Author contributions

LX, WS, and HZ conceived the study. SJ, WS, and LX designed and analyzed the model. LX and SJ programmed the model and made the figures and tables. LX, SJ, and WS worked on statistical aspects of the study. All authors interpreted the results, contributed to writing the article, and approved the final version for submission.

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:<https://doi.org/10.1016/j.ijid.2021.03.088>.

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