The shortage of hospital beds for COVID-19 and non-COVID-19 patients during the lockdown of Wuhan, China

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Background: The 76-day lockdown of Wuhan city has successfully contained the first wave of the coronavirus disease 2019 (COVID-19) outbreak. However, to date few studies have evaluated the hospital bed shortage for COVID-19 during the lockdown and none for non-COVID-19 patients, although such data are important for better preparedness of the future outbreak.

Methods: We built a compartmental model to estimate the daily numbers of hospital bed shortage for patients with mild, severe and critical COVID-19, taking account of underreport and diagnosis delay.

Results: The maximal daily shortage of inpatient beds for mild, severe and critical COVID-19 patients was 43,960 (95% confidence interval: 35,246, 52,929), 2,779 (1,395, 4,163) and 196 (143, 250) beds in early February 2020. An earlier or later lockdown would have greatly increased the shortage of hospital beds in Wuhan. The overwhelmed healthcare system might have delayed the provision of health care to both COVID-19 and non-COVID-19 patients during the lockdown. The second wave in Wuhan could have occurred in June 2020 if social distancing measures had waned in early March 2020. The hospital bed shortage was estimated much smaller in the potential second wave than in the first one.

Conclusions: Our findings suggest that the timing and strength of lockdown is important for the containment of the COVID-19 outbreaks. The healthcare needs of non-COVID-19 patients in the pandemic warrant more investigations.

Keywords: Coronavirus disease 2019 (COVID-19); mathematical modelling; hospital beds

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Introduction

An ongoing pandemic of coronavirus disease 2019 (COVID-19), caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), has spread throughout China and to over 200 countries since December 2019 (1). The rapid spread of COVID-19 in the early stage was largely facilitated by the traffic rush of the Lunar New Year holiday in China, when around 3 billion trips were expected from January 10 to February 18, 2020 (1). By January 24, 2020, 76 exported cases from Wuhan were found in 15 regions/cities of China and 6 overseas countries (2). In order to contain the COVID-19 outbreak, the Chinese government implemented a series of massive and unprecedented control measures (3).

The rapidly increased cases soon overburdened the healthcare system in Wuhan in the early stage of the outbreak. At the same time, suspension of non-emergency healthcare services and implementation of stringent traffic restrictions might have seriously delayed the hospitalization of non-COVID-19 patients, some of whom might have been in critical condition (4). Here non-COVID-19 patients refer to those who had acute or chronic diseases not directly caused by SARS-CoV-2 infection. Moreover, it was found that the lockdown could have increased anxiety and stress of local residents, thereby increasing their susceptibility to infection (5,6). In addition, many cases exported from Wuhan had been reported in other cities in China and overseas weeks before the lockdown, suggesting the need to evaluate the optimal timing of lockdown implementation. Some studies have evaluated the effects of the lockdown and social distancing measures on the COVID-19 outbreak in and outside of Wuhan (3,7,8), and one estimated the hospital bed shortage for COVID-19 patients in Wuhan (9). However, none have evaluated the healthcare demands of non-COVID-19 patients during the lockdown, when the healthcare system was overwhelmed by COVID-19 patients.

In this study, we used a mathematical model to simulate the epidemic curves of COVID-19 in Wuhan and 50 other cities in mainland China during the lockdown, after adjustment for temporal variation in reporting rates. We estimated the shortage of inpatient and ICU beds for patients with mild, severe and critical SARS-CoV-2 infection. In addition, we proposed a simple model based on the social media posts to estimate hospital bed shortages for non-COVID-19 patients. We present the study in accordance with the MDAR reporting checklist (available at http://dx.doi.org/10.21037/atm-20-5248).

Methods

Data sources

We retrieved daily numbers of laboratory-confirmed cases and deaths of SARS-CoV-2 infection in Wuhan , from the daily reports of the National Health Commission of China (http://www.nhc.gov.cn/) and published data during December 22, 2019 to February 11, 2020 (10). Considering that intra- and inter-city transmissions had occurred before the Wuhan lockdown, we also retrieved daily numbers of COVID-19 cases in Wuhan and 50 other cities in mainland China with more reported cases than other cities/regions by the end of January 2020. A map of these cities is shown in Figure S1. The daily numbers of hospital beds designated for COVID-19 cases, as well as the proportion of inpatient beds in isolation wards for severe patients and ICU beds for critical patients, were retrieved from the published data and the Wuhan Municipal Health Commission (WMHC) (9,11) (Figure S2). Detailed descriptions of data sources can be found in the Supplementary material. The dates cited hereafter in this paper were all in 2020.

Statistical analysis

We built a susceptible-exposed-infected-recovered (SEIR) model to simulate the inter-city transmission of SARS-CoV-2 viruses, considering of underreport and test delay in the early stage of the epidemic. We also incorporated into the model the implementation of individual and governmental control measures, the population inflow/outflow between Wuhan and 50 other cities in mainland China, and a higher transmission risk in public transportation. Details of the model's structure, parameters, descriptions and ranges can be found in the Supplementary material and Table S1.

We assumed that the lockdown and traffic restrictions had reduced 99% of the population flow from and within Wuhan since January 23. The daily number of diagnosed cases of SARS-CoV-2 infection in China was assumed to follow a Poisson distribution. Underreport of COVID-19 cases in the early pandemic has been widely reported but it is nearly impossible to get the true reporting rates. We therefore estimated the reporting rates according to previous studies (12-16) and the public available data: 1.8% on January 3, 3.0% on January 18, 14.0% on January 23, 34.0% on February 8 and 35.3% on February 18 (*Table 1*). The daily reporting rates between these dates were interpolated by a linear regression.

We built the second model to simulate the occupancy of hospital beds designated for COVID-19 cases, based on the clinical data of mild, severe and critical cases from previous clinical and epidemiological studies (Table S2). The daily hospital bed shortage for COVID-19 patients was calculated from the daily number of COVID-19 patients in the mild, severe and critical stages deducted by the total number of designated inpatient and ICU beds. Details of estimation for hospital bed shortages of non-COVID-19 patients are shown in Tables S3,S4.

During the lockdown, most hospitals in Wuhan suspended non-emergency services due to manpower

Table 1 Estimated reporting rates in Wuhan

Date	Rate	Source
January 3	1.8% (0.9%, 3.3%)	Wu *et al.* (14)
January 18	3.0% (1.2%, 12.1%)	Imai *et al.* (15)
January 23	14.0% (10.0%, 18.0%)	Li *et al.* (16)
February 8	34.0% (30.3%, 37.7%)	Verity *et al.* (12)
February 18	35.3% (29.3%, 42.3%)	Wang *et al.* (13)

shortages and allocation of inpatient hospital beds to COVID-19 patients. However, there are no official reports about the numbers of non-COVID-19 patients or hospital bed availability during the Wuhan lockdown. Previous work has demonstrated the feasibility of using social media posts and news to monitor and assess unexpected disease outbreaks (17,18). Here we adopt a simple model utilizing social media posts to estimate hospital bed shortages of non-COVID-19 patients. We first retrieved posts on the social media platform Weibo and then sort for posts relevant to online medical consultations, or complaints about hospital bed shortages and suspension of non-emergency healthcare services (19). We retrieved all relevant posts before February 29 and found that the earliest date for such posts was February 3. We then deleted repeated posts from the same Weibo users, and narrowed down the search to Weibo users located in Wuhan to increase specificity. After screening the contents, we retrieved the posts by COVID-19 patients (i.e., mentioned they had confirmed and suspected SARS-CoV-2 infection), and by non-COVID-19 patients (mentioned they did not have SARS-CoV-2 infection). Daily numbers of these posts are plotted in Figure S3. We assumed that COVID-19 and non-COVID-19 patients had the same probability of posting messages on social media. Hence, the daily ratio of hospital beds needed by COVID-19 patients to those needed by non-COVID-19 patients was estimated in proportion to the daily ratio of the posts by these two groups. Given the higher attention and perceived risk to COVID-19, we also repeated the estimation by assuming that COVID-19 patients were 2 or 10 times more likely to post messages. Because the earliest post about hospital bed shortages appeared on February 3 and most hospitals in Wuhan had gradually resume normal services by early March, we only calculated the hospital bed shortage for non-COVID-19 patients in February.

Simulation scenarios

The Wuhan lockdown began on January 23 and nearly all inter- and intra-city traffic was suspended. To study the impact of traffic restrictions, we simulated three additional scenarios: 80% and 50% decrease of traffic volume, and no traffic restriction (0% decrease) under different assumptions of reporting rates. In addition, the Wuhan lockdown was implemented in the exponential phase of this outbreak, therefore it would be interesting to examine the change in efficacy if the implementation date were 20 days earlier/later than the actual date (January 3 or February 12). We simulated the transmission of COVID-19 under these different scenarios, and subsequently calculated the cumulative number of cases by February 11 and the final epidemic size of the first wave. We quantified the relative efficiency of different traffic restriction levels and timing by comparing these estimates to the estimated real cumulative cases in Wuhan and 50 other Chinese cities. We also estimated the shortage of hospital beds in Wuhan under these scenarios.

The experience of the 2009 influenza pandemic suggested that infection control measures and human behaviour change could disrupt the rapid spread of novel viruses, but the gradual relaxation of these measures could result in multiple waves of epidemics over months or years (20-22). Similarly, during the lockdown, aggressive social distancing measures and traffic restrictions could have gradually waned as well. Hence, we also investigated the possibility of the second wave based on different assumptions of gradual relaxation of personal mitigation measures in Wuhan.

All data analyses were conducted using the R version 3.6.1. The datasets and codes used in this study can be found at https://github.com/Larryzza/The-shortage-of-hospital-beds-for-COVID-19-Wuhan.

IRB approval

The study was conducted in accordance with the Declaration of Helsinki (as revised in 2013). The IRB approval is exempted since this study used only the public available data.

Results

The model well fits the daily numbers of newly reported cases and cumulative numbers by February 11 in Wuhan

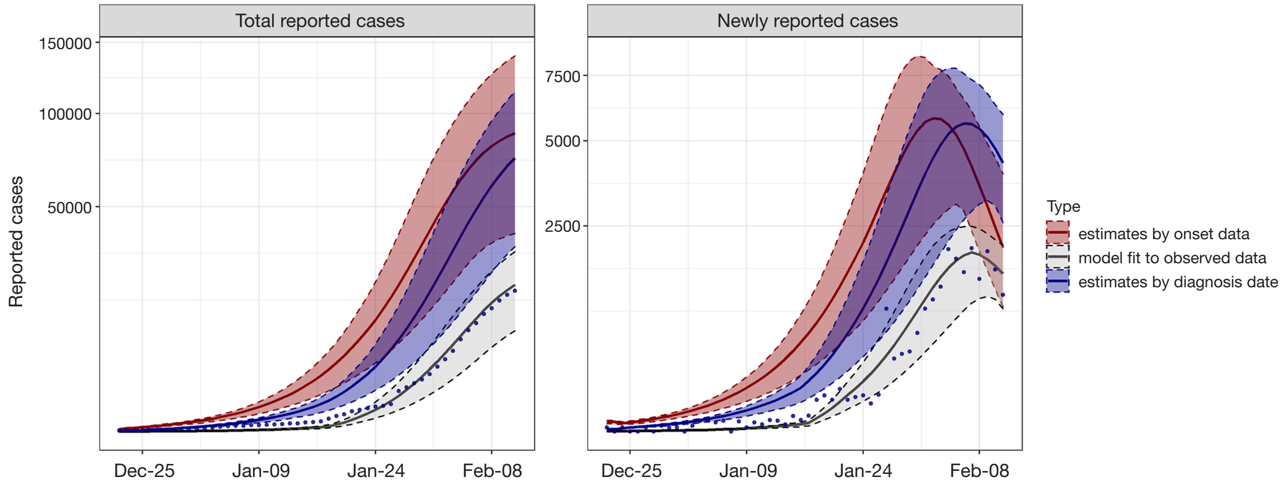

Figure 1 Plots of the observed data and model estimates for (I) the cumulative numbers and (II) the daily numbers of SARS-CoV-2 infection in Wuhan, December 22, 2019–February 11, 2020. Each panel contains the observed data of actual reported numbers (blue dots), the fitted line (gray line), the model estimates by onset date (red line) and by diagnosis date (blue line) with 95% confidence intervals (bars in the same color).

(*Figure 1*). After adjustment for underreport and diagnosis delay, we estimated that there were a total of 88,083 [95% confidence interval (CI): 38,929, 139,796] symptomatic COVID-19 cases in Wuhan as of February 11. These numbers are much higher than the reported number of 19 601 laboratory-confirmed cases, suggesting that 77.7% (95% CI: 49.6%, 86.0%) of cases were unreported. Daily numbers of newly onset cases peaked on February 2 and February 3, and gradually declined afterwards. Correspondingly, the daily hospital bed shortages were estimated to have peaked on February 6, February 9 and February 11, with estimates of 43,960 (95% CI: 35,246, 52,929), 2,779 (95% CI: 1,395, 4,163) and 196 (95% CI: 143, 250) beds for mild, severe and critical cases, respectively (*Figure 2*). The daily average shortage of hospital beds for mild, severe and critical cases was 41,241 (95% CI: 32,852, 49,797), 1,498 (95% CI: 553, 2,563) and 160 (95% CI: 108, 215) in early February, 18,238 (95% CI: 13,824, 23,100), 1,553 (95% CI: 451, 3,072) and 143 (95% CI: 100, 187) in mid-February, and 0 (95% CI: 0, 92), 0 (95% CI: 0, 0) and 39 (95% CI: 16, 69) in late February (Table S5).

We retrieved a total of 1,215 Weibo posts relevant to hospital bed demands for COVID-19 and non-COVID-19 patients. More than 90% of the posts were about the hospital bed needs of COVID-19 cases, with the first found on February 3. The daily numbers of posts about COVID-19 peaked on February 5 and gradually decreased until February 29 (Figure S3). This pattern coincides with the gradual increase of designated hospital beds and reveals that healthcare services in Wuhan nearly broke down in early February. A small number of posts about the hospital bed needs of non-COVID-19 patients were retrieved, and the maximal daily number was observed on February 18, nearly 4 weeks after the start of the lockdown.

From the model, we estimated that the proportion of mild, severe and critical cases in COVID-19 patients who posted social media messages of seeking help was 1.6% (95% CI: 1.4%, 2.2%) and 0.09% (95% CI: 0.01%, 0.1%), and 20% (95% CI: 10%, 30%), respectively. On average, the daily numbers of hospital bed shortages for mild cases of non-COVID-19 patients were 919 (95% CI: 63, 5,087), 1,838 (95% CI: 127, 10,177) and 9,187 (95% CI: 639, 50,899) during February 3 to 10. The numbers slightly increased during February 11 to 20, and decreased during February 21 to 29 (Table S6). The corresponding numbers of severe and critical non-COVID-19 cases were 13 (95% CI: 1, 336), 26 (95% CI: 3, 675) and 126 (95% CI: 15, 3,408) in early February, doubled in mid-February and then decreased to the similar level of early February (Table S6).

The estimates of the total cases and relative changes under 5 different traffic restriction scenarios in Wuhan are shown in Figure S4. Compared to the real situation (lockdown since January 23 and 99% traffic restriction),

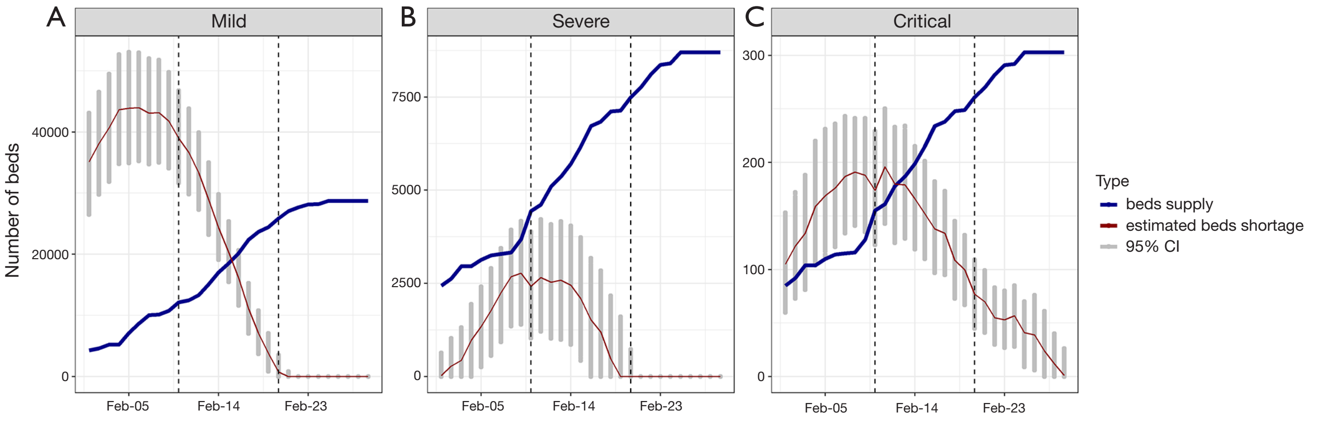

Figure 2 Daily numbers of hospital beds designated for COVID-19 cases (blue line) and estimated hospital bed shortages (red line) with 95% confidence intervals (gray bars), February 1 to 29, 2020, Wuhan. The numbers allocated to mild (A), severe (B) and critical cases (C) are plotted separately.

Table 2 Comparison of the effects of traffic restrictions in Wuhan under different scenarios

Variable	Total numbers and percentage change compared to the current situation				
	Late start on February 12	Early start on January 3	Reduced traffic volume by 80%	Reduced traffic volume by 50%	No restrictions
Other 50 cities	5,275 (2,397, 9,645); 26.4% (12.9%, 40.7%)	−14,476 (−26,512, −7,142); −70.3% (−70.8%, −69.5%)	975 (454, 1,775); 4.9% (2.5%, 7.6%)	2,552 (1,176, 4,654); 12.8% (6.3%, 19.8%)	5,283 (2,396, 9,655); 26.4% (12.9%, 41.1%)
Wuhan	9,150 (3,988, 15,376); 10.8% (3.8%, 18.2%)	12,848 (8,115, 19,524); 14.6% (13.9%, 15.2%)	1,686 (745, 2,841); 2% (0.7%, 3.4%)	4 456 (1,954, 7,524); 5.3% (1.8%, 9%)	9 381 (4,064, 15,889); 11.1% (3.8%, 19.1%)
All 51 cities	14,425 (6,386, 25,022); 13.7% (5.1%, 23.2%)	−1,628 (−8,044, 3,633); −1.4% (−5.7%, 2.8%)	2,661 (1,199, 4,616); 2.5% (1%, 4.3%)	7,008 (3,131, 12,178); 6.7% (2.5%, 11.4%)	14,663 (6,460, 25,544); 13.9% (5.2%, 23.9%)

if there were no traffic restriction, by April 8 the number of COVID-19 cases would have increased by 9,381 (95% CI: 4,064, 15,889) in Wuhan, 5,283 (95% CI: 2,396, 9,655) in the other 50 cities, and 14,663 (95% CI: 6,460, 25,544) in all cities combined, respectively (*Table 2*). The increased numbers correspond to 11.1%, 26.4% and 13.9% of the actual observed numbers. Earlier implementation of traffic restriction on January 3 would have increased the total number of cases in Wuhan to 12,848 (95% CI: 8,115, 19,524) (14.6% of the actual cases), but dramatically reduced cases in other cities by 14,476 (95% CI: 7,142, 26,512) (70.3% of the actual cases). The total number of cases in all 51 cities would have decreased by 1,628 (95% CI: −3,633, 8,044) (1.4% of the actual number) by February 11. If there were later implementation of restriction on February 12, 9,150 (95% CI: 3,988, 15,376) more cases would have been observed in Wuhan, 5,275 (95% CI: 2,397, 9,645) in other cities, and 14,425 (95% CI: 6,386, 25,022) in all 51 cities by April 8.

Compared to the real scenario, the hospital bed shortage for mild, severe and critical COVID-19 patients would have increased under all the five simulated scenarios (*Figure 3* and Table S5). The greatest increase would have occurred if the lockdown and traffic restrictions were enforced on January 3, or if there were neither traffic restrictions nor lockdown. Earlier implementation would have increased the shortage of hospital beds earlier than February 21, whereas completely no lockdown would have delayed the ICU shortage peak, compared to the real scenario.

We simulated the second wave based on the assumption that social distancing measures had gradually waned by the daily ratio of 1/30, 1/40 after February 11. The larger the waning weight, the earlier the second wave would have started. The onset date of the second wave would have

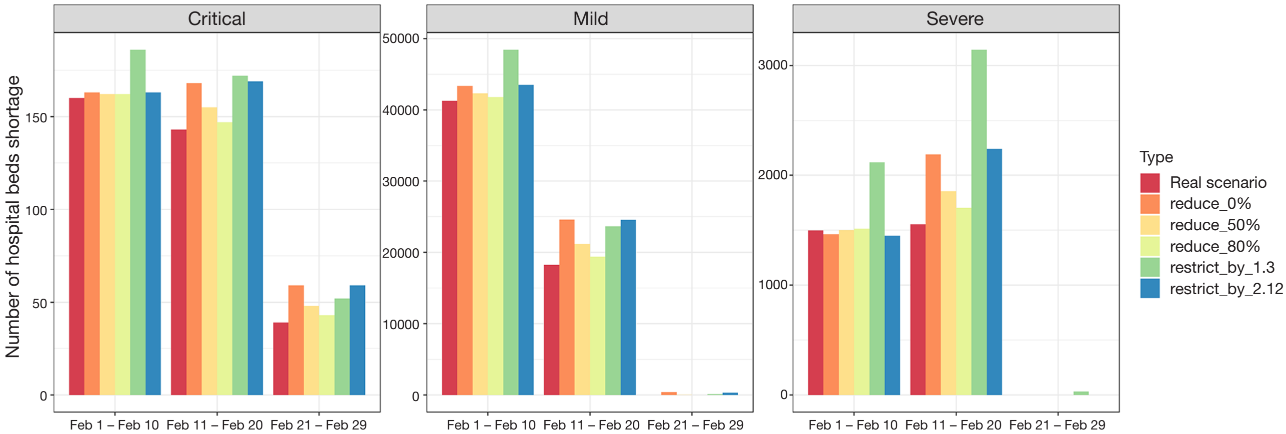

Figure 3 Estimated daily numbers of hospital bed shortages for mild, severe and critical COVID-19 cases in Wuhan, during three periods of 1 to 10 February, 11–20 February, 21–29 February 2020. The estimates are from different scenarios: the real scenario of lockdown since 23 January 2020 with 99% traffic restriction (red bar); the simulation scenario of lockdown since 23 January 2020 with 0% traffic restriction (orange bar); the simulation scenario of lockdown since 23 January 2020 with 50% traffic restriction (yellow bar); the simulation scenario of lockdown since 23 January 2020 with 80% traffic restriction (light green bar); the simulation scenario of no traffic restriction; the simulation scenario of late lockdown since January 3, 2020 with 99% traffic restriction (green bar); and the simulation scenario of early lockdown since February 12, 2020 with 99% traffic restriction (blue bar).

been as early as in June if social distancing measures were relaxed soon after the end of the lockdown (Figure S5). We estimated that the second wave would have reached the maximum (2,894, 95% CI: 523, 3,635) that were nearly half of the peak numbers in the first wave (5,812, 95% CI: 2,531, 7,911, when the waning weight was assumed 1/30). But the second wave would have lasted longer than the first wave. A shortage of ICU beds would have occurred in critical cases under the scenario that social distancing lasted for 30 and 40 days (Table S7). Overall, if the same number of hospital beds were designated to COVID-19 as in the first wave, it would have met the needs of mild and severe cases in the second wave.

Discussion

In response to the COVID-19 outbreak, Wuhan had been locked down for 67 days from January 23 to April 8. In line with other studies, we demonstrated the Wuhan lockdown and stringent control measures had effectively mitigated the regional and national COVID-19 epidemics (3,23-25). In this study, we did a further investigation on the shortage of inpatient and ICU beds for COVID-19 patients across the spectra of mild, severe and critical cases. We also adopted a simple approach to estimate non-COVID-19 patients hospital bed shortage by retrieving social media posts of seeking help with medical consultations and hospital beds.

The health authority in Wuhan recently updated the death toll of COVID-19, bringing the number of cases during the first wave to 50,333 and the death toll to 3,869, which were 325 and 1,290 more than the previously reported numbers (26). Our model estimates demonstrated that the serious underreport of the deaths had most likely occurred in February, when the reporting rate was low and there was a great gap of hospital beds for severe and critical cases (*Figure 2* and Figure S6). According to our estimates, as of April 8, when Wuhan reopened, there had been a total of 4,037 (95% CI: 3,465, 4,642) deaths, which is largely consistent with the total number of reported deaths after adjustment for temporal change in reporting rates. In addition, we estimated a final epidemic size of 95,336 (95% CI: 41,762, 158,606) infected cases, twice as high as the officially reported number. This result is consistent with the underreporting rate estimated by Wang *et al.* (59% as of February 18) (13). The daily shortage of ICU beds for critical COVID-19 patients remained at the level of 100 beds during the entire first wave, although the shortage was nearly resolved for severe cases in the late stage. This could explain why such a large number of deaths were not captured in surveillance.

Previous studies have suggested a high risk of virus transmission while traveling in buses, trains and airplanes, due to increased direct and indirect human-to-human contact (27,28). Compared to the real situation of city lockdown and stringent traffic restrictions, no traffic restrictions could have increased the total number of cases by 11.1% (95% CI: 3.8%, 19.1%) and 26.4% (95% CI: 12.9%, 41.1%) in Wuhan and 50 other mainland Chinese cities, respectively. This is not surprising, as in the early stages of the COVID-19 epidemic, most of the cases in other cities were imported from Wuhan (29). Our results support that traffic restrictions in Wuhan were effective in containing the spread of COVID-19 to other cities, despite that the outbreak within Wuhan slightly escalated soon after the restriction. This immediate surge could have been explained by two reasons. First, many people rushed to the designated hospitals and waited for a few hours to get throat swabs for lab tests. This could have increased the transmissions within the city. Second, all the infected cases in their latent period were forced to stay in the city due to traffic restrictions, leading to more sources of transmission. However, it is of note that complete suspension of public and private traffic creates problems in daily life and delays access to critical and routine healthcare services. This is particularly of concern for vulnerable populations, such as the elderly and those with disabilities or chronic conditions who need regular medication. To date, a few countries and regions outside of China have been locked down in order to mitigate the COVID-19 outbreak, and most have adopted voluntary home quarantines. Hence, we investigated the scenarios of partial traffic restrictions (80% and 50% reduction), which would have only slightly increased the final epidemic size and the hospital bed shortage compared to the complete lockdown. Taken together, partial traffic restrictions might have achieved a better balance between the social and medical needs of different populations.

Our results demonstrate that the timing of the lockdown had a greater effect than the intensity of the traffic restrictions. It is interesting to find that January 23 now appears to have been a better time point to lock down Wuhan than January 3 and February 12, according to our estimates. The implementation of traffic restrictions as early as January 3 would have been more effective in reducing the regional spread of the COVID-19 epidemic, but significantly increased the case numbers inside Wuhan. This would have overwhelmed the healthcare system in Wuhan to a greater extent. Ai *et al.* (30) estimated that 1,420 (95% CI: 1,059, 1,833) cases would have been prevented if the city lockdown policy had been implemented 2 days earlier. Nevertheless, our simulation shows early implementation on January 3 would also have increased case numbers in Wuhan by 14.6% (95% CI: 13.9%, 15.2%) of total cases estimated under the real scenario (as of April 8). This would have placed even more unbearable burden on the local healthcare system. Our results further suggest that an earlier traffic restriction in Wuhan would have not changed the local and regional epidemics, but later implementation on February 12 would probably have significantly increased the final size of the epidemic by 13.7% (95% CI: 5.1%, 23.2%) as of April 8, 2020.

The daily number of posts on social media that sought for online medical consultations or complained about the shortage of hospital beds or suspension of clinics, had reached a peak in early February. This pattern was similar to that of the hospital bed shortage for COVID-19 patients in Wuhan. It is of note that our estimates of hospital bed shortages for non-COVID-19 patients might need a cautious interpretation. We assumed that the probability of sending posts to seek for help via social media in non-COVID-19 patients was the same as that in COVID-19 cases, which might not hold due to different risk perceptions and media attention to the COVID-19 outbreak and chronic diseases. Also, high-risk populations such as the elderly might not be familiar with social media. Nevertheless, we observed that a large proportion of posts were posted by relatives and friends for older people. As suggested by previous studies (31,32), crowdsourcing from online sources and social media could be an alternative approach in the absence of reliable and timely data.

Conclusions

The overwhelmed healthcare system in Wuhan might have delayed the provision of health care to both COVID-19 and non-COVID-19 patients during the lockdown. However, earlier or later lockdowns of Wuhan would have caused more serious shortages. Although the city lockdown is an effective mitigation measure to control the regional and national COVID-19 epidemics, such stringent control measures require considerable manpower and economic costs, making them unlikely to be sustainable or affordable in many cities or countries. As we demonstrated in this study, the suspension of routine healthcare services might have seriously delayed the hospitalization of patients without SARS-CoV-2 infection. The decision to lock down a city in future should ensure equality of access to healthcare services among vulnerable populations, with careful consideration of societal and economic costs.

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Ethical Statement: The authors are accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved. The study was conducted in accordance with the Declaration of Helsinki (as revised in 2013). The IRB approval is exempted since this study used only the public available data.

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Supplementary

The shortage of hospital beds for COVID-19 patients during the lockdown of Wuhan, China

Data sources

We retrieved daily numbers of laboratory-confirmed cases and deaths of SARS-CoV-2 infection from the daily reports of the National Health Commission of China (http://www.nhc.gov.cn/), for the period from January 17 to February 11, 2020 in Wuhan and 50 other cities in mainland China (*Xiaogan*, *Huanggang*, *Suizhou*, *Jingzhou*, *Xiangyang*, *Huangshi*, *Ezhou*, *Yichang*, *Jingmen*, *Xianning*, *Shiyan*, *Chongqing*, *Wenzhou*, *Xiantao*, *Shenzhen*, *Beijing*, *Guangzhou*, *Shanghai*, *Tianmen*, *Xinyang*, *Changsha*, *Nanchang*, *Enshi*, *Hangzhou*, *Ningbo*, *Hefei*, *Haerbin*, *Taizhou*, *Nanyang*, *Bengbu*, *Yueyang*, *Fuyang*, *Zhengzhou*, *Zhumadian*, *Chengdu*, *Shangrao*, *Xinyu*, *Xian*, *Tianjin*, *Jiujiang*, *Bozhou*, *Shaoyang*, *Qianjiang*, *Zhuhai*, *Shangqiu*, *Nanjing*, *Yichun*, *Anqing*, *Suzhou*, *Foshan*) (Figure S1). We did not use the data after February 12, 2020 because of changing diagnosis criteria, which caused an unusually dramatic increase in the number of confirmed cases(1). The officially reported numbers before January 17, 2020 have been criticized for serious underreporting(2), therefore we exported the data of early cases with onset dates from December 8, 2019 to January 3, 2020 from a recent study(3). These data were lagged for 14 days to account for the delay of symptom onset to laboratory test, and subsequently combined with the official data to replace the official data released before January 17, 2020 (Figure S2).

We also obtained daily population flow data from Wuhan to the selected cities from the Baidu migration database (https://qianxi.baidu.com/) during the Lunar New Year traffic rush periods: January 1 to February 28, 2019, and December 22, 2019 to February 17, 2020. The data after February 17 were not available at the time of analysis, so we extrapolated from the average population flow in the preceding 10 days.

The daily numbers of hospital beds designated for COVID-19 cases in Wuhan from January 23 to February 25, 2020 were retrieved from the published data and the official reports of the Wuhan Municipal Health Commission (WMHC),(4, 5) and the number was assumed to be unchanged after February 25, 2020. We also retrieved the proportion of inpatient beds in isolation wards for severe patients and ICU beds for critical patients, from the WMHC (5).

Mathematical modeling to estimate daily numbers of COVID-19 patients

We built a SEIR model to simulate the inter-city transmission of SARS-CoV-2 viruses driven by population inflow/outflow between the epicenter, Wuhan, and 50 other cities in mainland China. The structure of this SEIR model is as follows:

http://dx.doi.org/10.21037/atm-20-5248

$$
\begin{cases}
\vec{S}' = -\vec{S} * (\beta * G * \vec{J} + \frac{\vec{N}'}{\vec{N}}) \\
\vec{E}' = -\vec{E} * (\sigma + \frac{\vec{N}'}{\vec{N}}) + \vec{S} * (\beta * G * \vec{J} + \frac{\vec{N}'}{\vec{N}}) \\
\vec{I}' = -\vec{I} * (\gamma + \frac{\vec{N}'}{\vec{N}}) + \vec{E} * (\sigma + \frac{\vec{N}'}{\vec{N}}) \\
\vec{Z}' = \vec{I} * (\gamma + \frac{\vec{N}'}{\vec{N}}) - \vec{Z}/q \\
\vec{R}' = \vec{Z}/q \\
\vec{D}' = \vec{Z}/q * d \\
\vec{N}' = \vec{K}_{colsum} - \vec{K}_{rowsum} \\
\vec{C} = m * \gamma * \vec{I} \\
G = \left(1 - \frac{D_{Wuhan}}{N_{Wuhan}}\right)^{p} \\
\vec{J} = \left[\left(\frac{\vec{I}}{\vec{N}}\right) + \delta * \left(\frac{K}{\vec{N}}\right)^{T} * \left(\frac{\vec{I}}{\vec{N}}\right)\right]
\end{cases}
\quad (1)
$$

In equation (1), $\vec{S}$ is the susceptible population in each city; $\vec{E}$ is the latent population; $\vec{I}$ is the currently infected population; $\vec{R}$ is the cumulative number of confirmed cases; $\vec{Z}$ denotes the post-symptom onset patients who were not admitted to hospital. $\vec{D}$ is the cumulative number of deaths from COVID-19 and D_{Wuhan} represents total number of deaths in Wuhan; $\vec{N}$ is the total population of each city and $\vec{N}'$ is the daily population change of each city; N_{Wuhan} is the current population in Wuhan; $\vec{C}$ is the daily officially reported cases in each city; and K_{ij} is a 51*51 matrix of daily population flow between city i and city j. Please note that K_{ij} changes with time and $K_{ii} = 0$; $\vec{K}_{rowsum/colsum}$ is the total population inflow/outflow of each city; $\vec{J}$ is the city-specific transmission rate adjustment of newly imported cases from other cities; δ is the transmission rate change during the transportation process; G represents the control measures other than traffic restrictions implemented since January 11, 2020, when the number of COVID-19 cases was officially reported to the public for the first time, and G is determined by public awareness of the epidemic, which is represented by the death rate in the epicenter.

We assumed that the lockdown and traffic restrictions had reduced 99% of the population flow from and within Wuhan since January 23, 2020. The daily number of diagnosed cases of SARS-CoV-2 infection in China was assumed to follow a Poisson distribution, as in equation $\vec{C}_{obs(t)} = \text{Poisson}(\vec{C}_t)$. $\vec{C}_{obs(t)}$ is the number of new cases reported in each city on day t, and $\vec{C}_t$ is the expected number of new cases reported on day t. Appendix Table 1 lists the range of key parameters assumed in the model.

Due to the overburdened healthcare system and limited laboratory testing capacity at the beginning of the outbreak, it is widely believed that COVID-19 cases were seriously underreported in the early stages of the outbreak in Wuhan. We therefore estimated the reporting rates according to previous studies (6-10): 1.8% on January 3, 3.0% on January 18, 14.0 % on January 23, 34.0% on February 8 and 35.3% on February 18 (Table 1). The daily report rates between these dates were interpolated by linear regression. We also considered the delay of laboratory tests from symptom onset in our model by adding a parameter, q, which was assumed to be roughly 14 days before January 17, and decreased this to q days on February 11 according to published epidemiological studies in Wuhan (11) (Figure S2). The length of delay between January

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17 and February 11 was imputed by a linear regression. The parameter q in other cities outside Wuhan was fixed as q, which was same as the value in Wuhan on February 11, due to the relatively greater sufficiency of supplies in those cities.

$$l(\lambda) = \log \mathcal{L}(\lambda) = \sum_{i=1}^{k} \log f\left(\vec{N}, \vec{C}_{obs}, D_{obs\_Wuhan}, K_{ij}, \gamma, \sigma, \beta, m, q, d; I_0, \delta, p\right) \quad (2)$$

where $l(\cdot)$ is the total log-likelihood for the daily number of new cases and deaths; D_{obs_Wuhan} is the daily reported number of deaths; k is the total observation days. We estimated the parameters by using the maximum likelihood estimation approach with the likelihood framework (Table S4). The within-city transmission rate β was derived by the daily proportion of infectious individuals losing infectiousness multiplied by the basic reproduction number ($\beta = R_0 * \gamma$).

The 95% confidence interval (CI) of log-likelihood l was calculated from a Chi-square quantile and then 95% CI of individual parameters was calculated accordingly.

Estimation of hospital bed shortage for COVID-19 patients in Wuhan

The designated inpatient and ICU beds for mild, severe, and critical COVID-19 cases in Wuhan increased gradually from 1 766, 999 and 35 on January 23 to 28 739, 8 704, and 303 on 25 February 2020. In particular, two emergency hospitals, Huoshenshan and Leishenshan hospitals, were fully operational after February 10. Sixteen Fangcang shelter hospitals provided more than 10 000 beds for mild cases after February 20.(12) It is of note that the Fangcang shelter hospitals admitted only mild COVID-19 cases, but the designated hospitals and two emergency hospitals admitted mainly severe and critical cases as well as a small number of mild cases.

We built a simple model to simulate the occupancy of hospital beds designated for COVID-19 cases. Based on clinical and epidemiological studies, we assumed that 81%, 14%, and 5% of total cases were classified into mild, severe, and critical cases respectively.(13) The days of progression for severe and critical cases, as well as the length of stay in inpatient wards and ICUs, were obtained from two clinical studies.(14, 15) The length of hospital stay was assumed to follow a normal distribution, with means and standard deviations for mild, severe, and critical cases obtained from previous clinical studies.(14-16) We also assumed that severe cases had priority of admission over mild cases. The assumptions of disease progression probability and length of hospital stay for mild, severe and critical cases are summarized in Appendix Table 2. We also assumed that critical cases were admitted first, followed by severe cases, and that mild cases had the lowest priority. The following equations were used to evaluate the shortage of hospital beds for COVID-19 cases in Wuhan:

$$\begin{cases} P' = I_{new} - P_{admitted} \\ H' = P_{admitted} - P_{discharged} \\ H_T = \text{total number of patients admitted in day } T^{\cdot} \\ P_T = \text{Shortage of hospital beds in day } T \end{cases} \quad (3)$$

Here H_T is the number of patients who were admitted to hospital on day T, with the maximum equal to the total number of beds on that day (Fangcang hospitals were included but only for mild cases). I_{new} is the daily number of new onset cases

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estimated from the SEIR model in Equation (1). $P_{admitted}$ and $P_{discharged}$ are the daily numbers of patients newly admitted to and discharged from designated hospitals, respectively. P denotes the number of COVID-19 patients at the mild, severe and critical stages minus the total number of designated inpatient and ICU beds in day T, which is used to quantify the hospital bed shortage for COVID-19 patients. Then we simulate 1000 time to estimate the hospital bed shortage for mild, severe and critical cases. We obtained 95% Confidence interval by calculating 2.5% to 97.5% quantile of the estimated results. The median of the results is set as the estimation of hospital bed shortage.

Estimate of hospital bed shortage for non-COVID-19 patients in Wuhan

During the lockdown, most hospitals in Wuhan suspended non-emergency services due to a shortage of manpower and because many inpatient hospital beds were designated for COVID-19 patients. There are no official reports about the numbers of non-COVID-19 patients and hospital bed availability for them during the Wuhan lockdown. We proposed a simple model to estimate non-COVID-19 patients hospital bed shortages through social media posts. Appendix Table 3 presents the flowchart of the process of estimating hospital bed shortage for non-COVID-19. We retrieved all relevant posts before February 29 and found that the earliest date for such posts to appear was February 3 (17). We further deleted repeat posts from same Weibo users and narrowed down the search to Weibo users located in Wuhan to increase specificity. By screening the contents, we separated them into two groups: posts from those who mentioned they had confirmed and suspected SARS-CoV-2 infection, and posts from those who mentioned they did not have SARS-CoV-2 infection.

We first built a model to estimate the correlation between the hospital bed needs for mild, severe and critical cases of SARS-CoV-2 infection and the posts seeking help on the Weibo platform:

$$\begin{cases} P_{severe\ and\ critical} = P_{severe} + P_{critical} \\ W_{severe\ and\ critical} = \text{Binomial}\ (P_{severe\ and\ critical}, \zeta_{severe\ and\ critical}) \\ W_{mild} = \text{Binomial}\ (P_{mild}, \zeta_{mild}) \\ W_{total} * k = \mathrm{W}_{severe\ and\ critical} \\ W_{total} * (1-k) = \mathrm{W}_{mild} \end{cases} \tag{4}$$

Here we assumed that the probability that COVID-19 patients would have post messages related to their hospital bed demands, represented by ζ, followed a binomial distribution. P is the hospital bed shortage, and $W_{mild}\ and\ W_{severe\ and\ critical}$ represents the total number of posts by mild, severe and critical COVID-19 cases, respectively. k is the proportion of severe and critical cases in COVID-19 patients who posted social media messages seeking help. Specifically, the following equations were used to calculate ζ and k based on the estimates for COVID-19 patients from Equation (3):

$$l(\lambda) = \log \mathcal{L}(\lambda) = \sum_{i=1}^{3} \log f(\ W_i, P_{severe\ and\ critical}, P_{mild}; \zeta_{severe}, \zeta_{mild}, k). \tag{5}$$

where $l(\cdot)$ is the total log-likelihood for COVID-19 patients to post messages related to hospital beds on Weibo (Equation (4)). We estimated the parameters $\zeta_{severe}, \zeta_{mild}, k$ by using the maximum likelihood estimation approach with the likelihood

http://dx.doi.org/10.21037/atm-20-5248

framework.

Then we assumed three scenarios: 1) same proportions of patients with and without COVID-19 had posted messages on social media; 2) proportion of patients with and COVID-19 had posted messages on social media is 2 times as that of non-COVID-19 patients; 3) proportion of patients with and COVID-19 had posted messages on social media is 10 times as that of non-COVID-19 patients; so the daily ratio of hospital bed needs by COVID-19 patients to those by non-COVID-19 patients was estimated a quantitative relation to daily ratio of these two groups of posts.

In Equation (6), we further applied the estimated parameters $\zeta_{severe}, \zeta_{mild}, k$ to estimate the hospital bed shortage for non-COVID-19 patients:

$$l(\lambda) = \log \mathcal{L}(\lambda) = \sum_{i=1}^{3} \log f(W_i, \zeta_{severe}, \zeta_{mild}, k; P_{severe\ and\ critical}, P_{mild}). \qquad (6)$$

where $l(\cdot)$ is the total log-likelihood for non-COVID-19 patients to post messages related to hospital beds on Weibo (Equation (4)) and the 95% confidence intervals (CI) based on a Chi-square quantile. We estimated the parameters $P_{severe\ and\ critical}, P_{mild}$ and 95% CI by using the maximum likelihood estimation approach, to calculate the hospital bed shortage for severe and mild cases of non-COVID-19 patients.

Because the earliest post about hospital bed shortages appeared on February 3 and most hospitals in Wuhan gradually resumed normal services in early March, we calculated the hospital bed shortage for non-COVID-19 patients for February 2020 only. We separated daily estimates into three periods due to the greatly increased number of designated hospital beds on February 10 and on February 20 (Figure 2). We expected the relative likelihood of patients posting messages between mild, severe/critical COVID-19 cases to be different across these three periods. In equation (5), i denotes three periods: February 3-10, when there was a serious shortage of designated beds; February 11-20, when the most severe cases were admitted; and February 21-29, when bed vacancies gradually increased.

Simulation scenarios

The Wuhan lockdown since January 23 dramatically reduced the volume of intra-city traffic (99% reduction in our assumption). However, most countries/cities outside China adopted less stringent traffic restrictions, and home quarantine was voluntary. Hence the traffic volume reduction was probably much lower than 99%. To compare, we simulated three additional scenarios: decrease of traffic volume by 80% and 50%, and no traffic restriction (0%). In addition, the Wuhan lockdown was implemented in the stage of exponential growth of this outbreak, therefore it would be interesting to examine the predicted efficacy of an earlier enforcement on January 3 and later implementation on February 12 (20 days earlier/later than the actual implementation date). We simulated the transmission of SARS-CoV-2 infection under these different scenarios, calculating the cumulative number of cases by February 11, 2020 and the final epidemic size of the first wave. We quantified the relative efficiency of traffic restriction levels and timing by comparing these estimates to the estimated cumulative cases of real scenarios in Wuhan and 50 cities outside of Wuhan. We also estimated the hospital bed shortage in Wuhan under these scenarios.

 http://dx.doi.org/10.21037/atm-20-5248

The experience of the 2009 influenza pandemic suggested that infection control measures and human behavior changes could interrupt the rapid spread of novel viruses, but the gradual relaxing of these measures could result in multiple waves of epidemics over months or years(18-20). Similarly, during the lockdown, aggressive social distancing measures and traffic restrictions could gradually wane as well. Hence we also investigated the possibility of a second wave based on different waning levels of these personal mitigation measures in Wuhan. We replaced G in equation (1) by the following equation to forecast the second wave:

$$\begin{cases} G = \left(1 - \frac{D^*_{\text{Wuhan}}}{N_{\text{Wuhan}}}\right)^p \\ {D^*}'_{\text{Wuhan}} = q * \vec{Z}_{Wuhan} \times d - \varepsilon \times D_{Wuhan} \end{cases} . \tag{6}$$

where ε is the waning weight of control measures (for example, $\varepsilon = \frac{1}{30}$ if social distancing measures were sustained for 30 days after 11 February 2020). To simplify the calculation, we did not consider cases imported from overseas in our model, since strict border controls and quarantine measures were in place and all travelers from overseas were required to take laboratory tests for SARS-CoV-2 (21).

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Table S1 Parameter descriptions and a prior value (or range) assumed or adopted from references

Parameter	Description	Value (range)	Sources
q_{Wuhan_early}	test delay in Wuhan before 17 January (in days)	14	Assumed
q	test delay in Wuhan on 11 February (in days) and other cities outside Wuhan (in days)	(1,3)	Assumed*
R_0	reproduction number of SARS-CoV-2	(2.3, 3)	Reference (22)*
β	within-city transmission rate	R_0* γ	Calculated
γ	rate of infectious individuals losing infectiousness per day	(0.13, 0.3)	Reference (22, 23)*
I_0	initial number of infected patients at day zero in Wuhan (22 Dec. 2020)	(1,100)	Assumed*
σ	rate of exposed individuals showing infectiousness per day	(0.14, 0.5)	Reference (24)*
p	intensity of social distancing measures by the government and individuals	(0, 15000)	Assumed*
δ	transmission rate adjustment during transportation process	(0, 30)	Assumed*
d	crude case-fatality-ratio	4.5%	Reference (25-27)

* parameter needs to be estimated within a given range

Table S2 The assumptions of disease progression probability and length of hospital stay (days) for mild, severe and critical cases

	stage1: mild	stage2: severe	stage3: critical	stage4: severe	percentage of total cases
Critical cases (survive)	6	5.5	6.5	3	3.6%
Critical cases (dead)	6	5	7.5	0	1.4%
Severe cases	6	7	0	0	14.0%
Mild cases	11	0	0	0	81.0%

Table S3 Steps of estimating hospital bed shortages for non-COVID-19 patients

Stage	Process
1	Screened the contents, separated them into two groups: posts from those who mentioned they had confirmed and suspected SARS-CoV-2 infection, and posts from those who mentioned they did not have SARS-CoV-2 infection.
2	Based on our previous estimates for COVID-19 patients, calculated the probability, , that COVID-19 patients would post messages and the proportion k of severe and critical cases in COVID-19 patients who posted social media messages seeking help.
3	Applied the estimated parameters, and k, to estimate the hospital bed shortage for non-COVID-19 patients by using the maximum likelihood estimation approach with the likelihood framework.

Table S4 Maximum likelihood estimates and 95% CI of parameters estimated from the model

Parameter	Estimate	95% CI
R_0	2.92	(3.00, 2.70)
γ	0.24	(0.23, 0.27)
I_0	23	(16, 28)
σ	0.48	(0.43, 0.49)
p	13 200	(12 300, 14 700)
δ	4	(3,5)
q	2.81	(2.41, 2.91)

Table S5 Estimated hospital bed shortages for COVID-19 patients

N (95% confidence interval)	Hospital bed shortage for mild COVID-19 cases			Hospital bed shortage for severe COVID-19 cases			Hospital bed shortage for critical COVID-19 cases		
Time period	February 1 – 10	February 11 – 20	February 21 – 29	February 1 – 10	February 11 – 20	February 21 – 29	February 1 – 10	February 11 – 20	February 21 – 29
Current scenario	41241 (32852, 49797)	18238 (13824, 23100)	0 (0, 92)	1498 (553, 2563)	1553 (451, 3072)	0 (0, 0)	160 (108, 215)	143 (100, 187)	39 (16, 69)
Restricted on 5 February	43531 (34238, 52874)	24576 (18952, 30452)	341 (0, 1124)	1450 (502, 2639)	2242 (744, 3985)	0 (0, 241)	163 (110, 220)	169 (122, 218)	59 (28, 92)
Restricted on 11 January	48435 (38622, 58508)	23668 (18202, 29141)	119 (0, 574)	2119 (939, 3398)	3143 (1417, 4965)	31 (0, 407)	186 (126, 250)	172 (124, 223)	52 (23, 84)
Restricted 80% of traffic	41794 (32989, 50576)	19384 (14290, 24643)	0 (0, 188)	1513 (519, 2652)	1703 (484, 3333)	0 (0, 38)	162 (109, 219)	147 (104, 194)	43 (17, 73)
Restricted 50% of traffic	42312 (33459, 51056)	21195 (16160, 26289)	55 (0, 467)	1501 (526, 2576)	1855 (575, 3444)	0 (0, 67)	162 (109, 220)	155 (111, 202)	48 (21, 82)
no restriction	43341 (34560, 52205)	24616 (18716, 30447)	397 (0, 1231)	1463 (540, 2589)	2190 (804, 3924)	0 (0, 241)	163 (111, 220)	168 (122, 217)	59 (29, 93)

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Table S6 Estimated hospital bed shortages for non-COVID-19 patients

N (95% confidence interval)	February 3 – 10 *			February 11 – 20			February 21 – 29		
Weight of non-COVID-19 patients send posts compare to COVID-19 patients	1	0.5	0.1	1	0.5	0.1	1	0.5	0.1
Estimated hospital bed shortage for severe non-COVID-19 patients	13 (1, 336)	26 (3, 675)	126 (15, 3408)	26 (2, 298)	51 (5, 601)	252 (25, 3 022)	13 (1, 336)	26 (3, 675)	126 (15, 3408)
Estimated hospital bed shortage for mild non-COVID-19 patients	919 (63, 5087)	1838 (127, 10177)	9 187 (639, 50899)	1 838 (371, 7166)	3 675 (743, 14336)	18 373 (3714, 71694)	919 (63, 5087)	1 838 (127, 10177)	9187 (639, 50899)

*Estimations start from 3 February, since the earliest post to the Weibo platform was on 3 February.

Table S7 Estimated daily hospital bed shortage for COVID-19 cases in the second wave in Wuhan

Waning weight	1/30	1/40
Onset of the second wave	late-June	early-August
Maximum shortage for critical cases (95% CI)	66 (27, 111)	53 (9, 92)
Maximum shortage for serve cases (95% CI)	0 (0, 0)	0 (0, 0)
Maximum shortage for mild cases (95% CI)	0 (0, 0)	0 (0, 0)

 http://dx.doi.org/10.21037/atm-20-5248

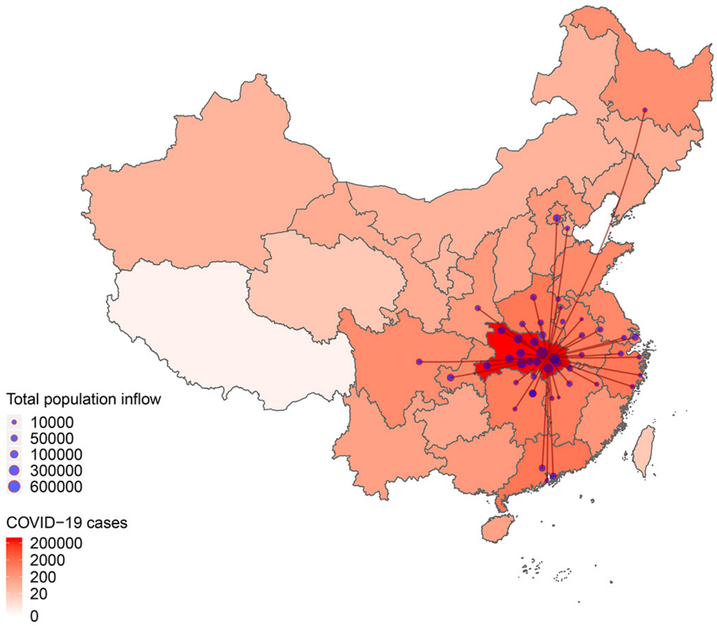

Figure S1 Cumulative numbers of COVID-19 cases in China as of 11 February 2020. Red lines show population flow between Wuhan and 50 other cities. The diameter of the blue points presents levels of total outflow from Wuhan to those cities from December 22, 2019 to January 23, 2020.

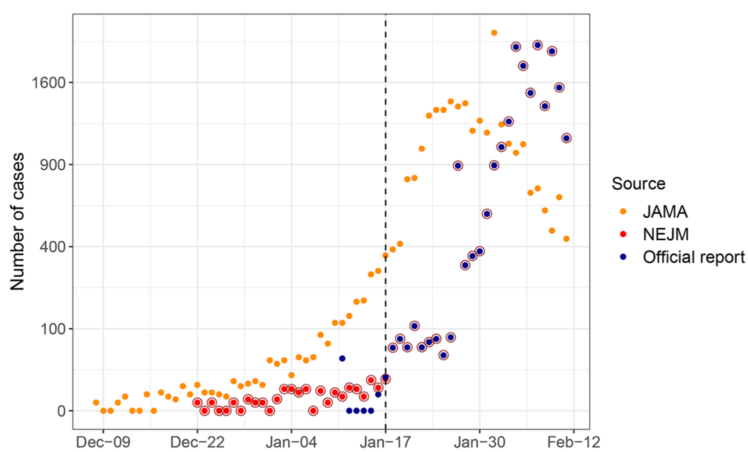

Figure S2 Daily numbers of new COVID-19 cases by diagnosis date (brown circles) used in this study to fit the model. The data were combined from the published data of early cases (red dots) from reference (3) (lagged for 14 days to account for the delay between symptom onset and laboratory testing) and officially reported numbers (blue dots) (28). Orange dots are number of onset cases (13).

 http://dx.doi.org/10.21037/atm-20-5248

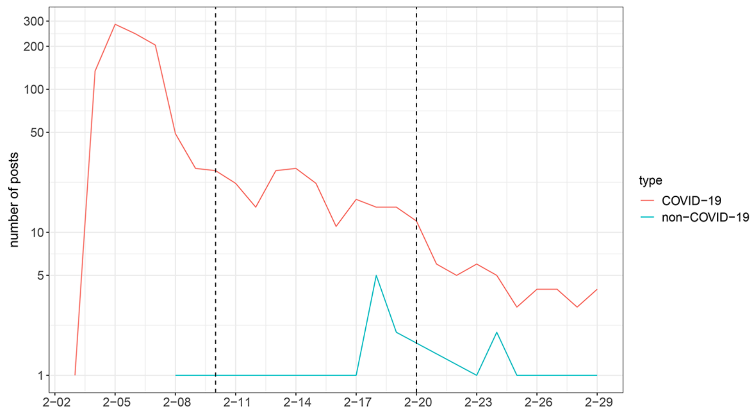

Figure S3 Daily numbers of different types of social media messages posted by the Wuhan users to the Weibo, seeking online medical consultations or complaining about limited hospital beds or the suspension of healthcare services.

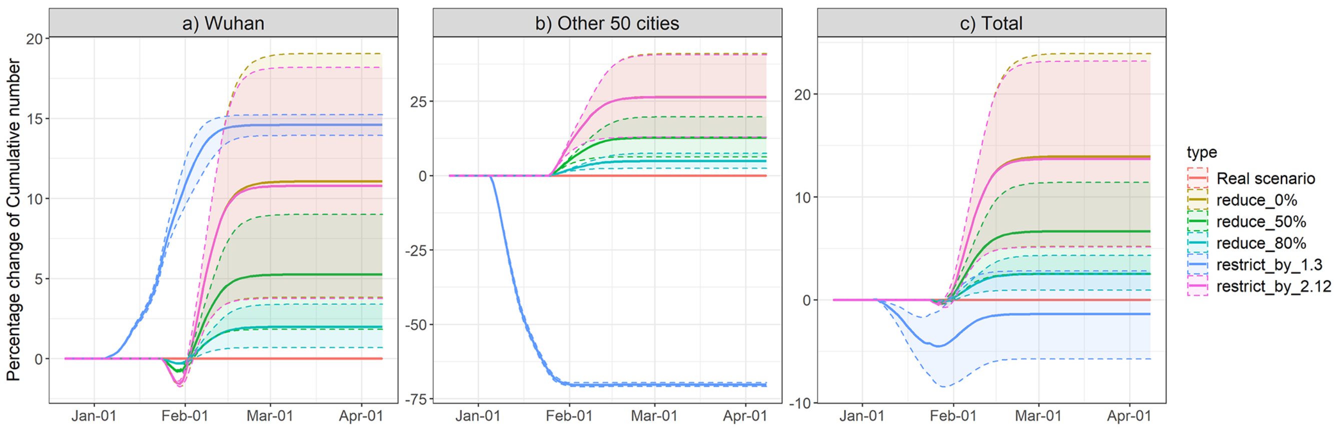

Figure S4 Prospective evaluation of the traffic restriction policy under different scenarios by April 8, 2020. (a) relative change of total cumulative cases in Wuhan with 95% confidence intervals; (b) relative change of total cumulative cases in 50 cities (excluding Wuhan) with 95% confidence intervals; (c) relative change of total cumulative cases in all cities with 95% confidence intervals. We considered the current policy, which reduced traffic volume by 99% (red), together with five other scenarios: traffic volume reduced by 80% (cyan), by 50% (green), and no traffic restrictions (brown), as well as traffic restrictions implemented on January 3, 2020 (blue) and February 12, 2020 (pink).

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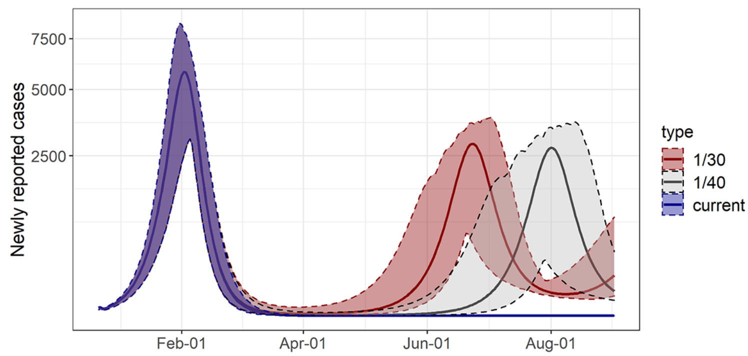

Figure S5 Possible multiple infection waves analysis. Forecast of the effect on newly reported cases with 95% confidence intervals by July 1, 2020, under different public and government reaction waning weights.

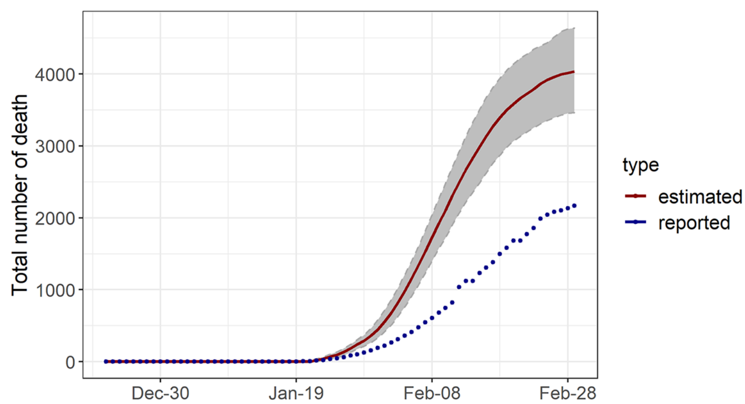

Figure S6 Daily numbers of reported COVID-19 death cases (blue lines) and estimated death cases (red lines) with 95% confidence intervals (gray bar), 22 December 2019 to 29 February 2020, Wuhan.

http://dx.doi.org/10.21037/atm-20-5248