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The changing patterns of COVID-19 transmissibility during the social unrest in the United States: A nationwide ecological study with a before-and-after comparison

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A B S T R A C T

Nationwide mass social unrest has emerged in the US since May 25 and raised broad concerns about its impacts on the local COVID-19 epidemics. We compared the COVID-19 transmissibility between May 19–May 25 and May 29–June 4 for each state of the US. We found that social unrest is likely associated with the rebound of the COVID-19 transmissibility, which might raise difficulties in the pandemic control.

1. Introduction

The pandemic of the coronavirus disease 2019 (COVID-19) caused tremendous impacts on public health and the global economy, comparable to the 1918 influenza pandemic [1]. As of November 23, 2020, the United States (US) has over 12.2 million COVID-19 cases, and approximately 0.25 million deaths [2]. The growth of epidemic curve seems to slow down in the US after a series of social distancing restrictions [3]. However, nationwide mass demonstrations have emerged since May 25, which raised broad concerns about whether the protests would affect the COVID-19 pandemic control. In this study, we explore the temporal changes of the COVID-19 transmissibility associated with the mass demonstrations in the US.

2. Methods

The COVID-19 cases data were collected via public domain https://guangchuangyu.github.io/nCov2019/, where the US part was collected from the New York Times (link of data: https://github.com/nytimes/covid-19-data/blob/master/us-states.csv). The time-varying reproduction numbers (R_t) are constructed to quantify the instantaneous COVID-19 transmissibility of each state ($n = 47$, excluding Connecticut, Hawaii, and North Dakota due to missing data) in the US. The daily percentage change (η) in the R_t series is estimated, which quantifies the changing rate of the COVID-19 transmissibility. A negative η is desired when the outbreak control measures are effective, under which the COVID-19 transmissibility decreases steadily. By using the generalized linear discontinuity design, we examined the structural break in the trends of R_t and then estimated ηs before and after the time window of social unrest.

2.1. Estimate the time-varying reproduction number (R_t)

We adopt the R_t to quantify the instantaneous COVID-19 transmissibility. Referring to previous studies [4–7], the epidemic growth is modeled as a branching process, and thus the R_t can be expressed as a ratio of $C(t)$ over $\int_0^\infty w(k)C(t-k)dk$. Here, the function $w(\cdot)$ is the distribution of the generation time (GT) of COVID-19. The $C(t)$ was the

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numbers of COVID-19 cases at the t-th date, which is modeled to obey a Poisson process with the rate determined by the R_t. As such, the likelihood-based parameter estimation of R_t can be carried out. To set up, we considered the distribution function of GT (w) as a Gamma distribution having mean (±SD) values of 5.3 (±2.1) days [8–11], which is obtained by averaging the GT estimates from the existing literature. We note that slight variations in the settings of the GT will not affect our main findings.

2.2. Regression discontinuity design on the time-varying R_t

We suspect the R_t series pattern may be different between May 19–May 25 and May 29–June 4, since numerous protests were outbroken in a time window from May 26 to May 28. By using the generalized linear discontinuity design, we examine a structural break in the trends of R_t. We fit the following discontinuity model to the R_t series against the time index t.

$$\mathbf{E}[ln(R_t)] = c + a\cdot t + b\cdot \mathbf{I}(t > t_0)\cdot(t - t_0)$$

Here, $\mathbf{E}[\cdot]$ is the function of the expectation. The $\mathbf{I}(\cdot)$ is an indicator function taking the binary variable (0 or 1) that is 1 if variable t is larger than the threshold value t_0, or 0 otherwise. The c is the constant parameter, and the a and b are the slope parameters. Specially, term b is the parameter that measures the structural break in the changing patterns. In our study, we fix term t_0 to be May 25, 2020. The daily η of R_t can be calculated directly from the slope parameters, i.e., a and b. For the dates before social unrest, we have $\eta = [\exp(a) - 1] \times 100\%$. Similarly, for the dates after social unrest, we have $\eta = [\exp(a + b) - 1] \times 100\%$. Thus, a significant estimate of term b, if occurs, indicates that the structural break is likely to occur at threshold t_0, which warrants further investigation. The 95%CIs of the regression parameters are estimated by their point estimates plus and minus a Student's-t-distributed quantile multiplied by their standard errors. Since η and the slope parameters are one-to-one mappings, the 95%CI of η can also be directly calculated from the 95%CI of slope parameter.

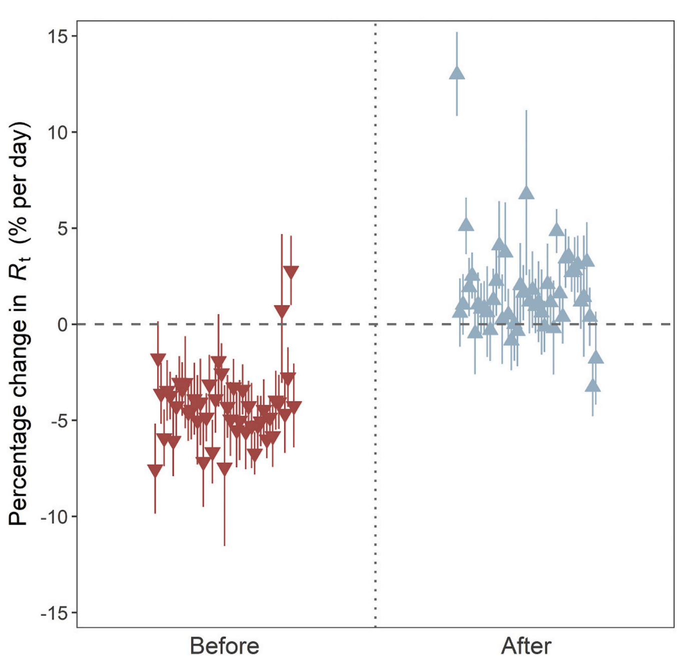

Fig. 1. The daily percentage change (η) in the R_t series of each state in the US (n = 47). The η estimates in red are for the period from May 19 to 25, 2020 (labeled as 'Before'), and the η estimates in cyan are for the period from May 29 to June 4, 2020 (labeled as 'After'). The triangular dots are the point estimates, and the bars are the 95% confidence intervals (CI).

3. Results and discussion

During May 19–May 25, significantly negative ηs are estimated in 43 out of 47 (91%) states, see Fig. 1. During May 29–June 4, we find a significant increase in η in 41 (87%) states, and η estimates are positive in 39 states (83%), which indicates the transmissibility has increased steadily between the two periods.

Our findings indicate that social unrest is likely associated with the rebound of the COVID-19 transmissibility in many states. The COVID-19 rebound, caused by the large gatherings and proximity, would raise the difficulty in the pandemic control and exacerbate social rifts. The dominated modes of COVID-19 transmission includes respiratory, aerosol, and contact transmissions, which mainly occurs in specific settings, particularly in indoor, crowded and inadequately ventilated spaces. Although people in outdoor spaces may have a lower risk of infection than those in enclosed spaces, exposure population would increase exponentially when largely gathering, such as the protests. The outdoor gathering would increase the population risk of COVID-19 infection, probably because of the elevating exposure population instead of increased individual risk. A nationwide cross-sectional study shows that African and Latino American residents experience higher odds of seropositivity than others [12]. This might accelerate the speed of the COVID-19 rebound during the protests. African and Latino Americans have been hit hard disproportionally by the COVID-19 so far, due to complicated underlying reasons [13,14]. This rebound of COVID-19 transmissibility could also increase this disparity. Other reasons behind this rebound could be the relaxation of restrictions, public behavioral reaction to the slowing down of the pandemic in the US. Studies suggested that the large indoor political rally without social distancing would be an extremely high-risk activity for COVID-19 contagion [15]. However, our study only focused on the two little periods (May 19–May 25 vs. May 29–June 4), which cannot evidence the influence of the political rally. Considering that it is largely gathering and is mainly established in indoor spaces, the contribution of these political rallies to the COVID-19 rebound would be unparalleled. Other studies are warranted to follow.

There is no denying that COVID-19 also indirectly promotes the series of protests. With uncertainty and unpredictability, long-time physical distancing or lockdown result in unemployment, social isolation, increased access to alcohol and online gambling, as well as decreased social support [16]. These known risk factors for mental health problems may exaggerate personal emission to public events, weaken resistance to inflammatory remarks, and accelerate aggressive behaviors during protests. Therefore, accessible mental health services and remote community supports, provided by local health-care workers, may contribute to both the protest alleviation and the pandemic control [17].

Cautions should be exercised when interpreting our results. First, reported cases could not be representative of the whole population, because sampling has not been random, and most of asymptomatic are missed. Testing protocols might differ between countries and even within countries, especially at different points in time. However, since we only restricted in a short period (May 19–May 25 vs. May 29–June 4), the mission of asymptomatic patients was assumed to be balanced across the period. And since we preferred to observing the R_t variation between the two different periods for each state of the US, the influence of testing protocols across states could be less significant. Second, our data were collected from the New York Times, and we acknowledge that there might be minor inconsistency in the information from different sources, such as Johns Hopkins University COVID-19 surveillance platform. However, we assumed that the minor inconsistency was negligible, and it could be covered by our R_t estimation approach to some extent. The limitation is unlikely to affect our main conclusion. Last but not least, this is an ecological study. As such, our results is not equivalent to a causal relationship, which requires more exhaustive and sophisticated exploration, because they may be confounded by unmeasured factors, such as the increased testing capacity. We have not adjusted for the testing capacity in the two periods in each state because relevant data are unavailable. However, the protest was the most impactive event occurring on May 26–May 28 in the US, which might largely influence the COVID-19 transmission. Studies are also warranted to explore further if other factors, such as the possible increased testing capacity, would contribute to the observed COVID-19 rebound when data is available.

Although the social unrest leads to large gatherings and proximity and may inevitably result in a spread of the virus during the protests, self-protection should be more noticed and promoted to minimize the risk of infection. We advocate attendees to utilize compensatory behaviors to protect themselves, such as frequently washing hands, wearing masks, avoiding human contact, maintaining distance from each other, and using megaphone instead of shouting during the protests.

Ethics approval and consent to participate

The COVID-19 cases data were collected via public domain https://guangchuangyu.github.io/nCov2019/, and thus neither ethical approval nor individual consent is applicable.

Availability of materials

All data used in this work are publicly available via https://guangchuangyu.github.io/nCov2019/. Technique details are available in the supplementary materials.

Consent for publication

Not applicable.

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Author statement

JR and SZ conceived the study, conducted the analyses, and drafted the manuscript. LH, MC, YQ, YY, JW, YW, MJ, MW and DH critically revised the manuscript and all authors approved the submission.

Conflict of interests

D. He received support from an Alibaba (China) Co. Ltd. Collaborative Research grant. M. H. Wang is a shareholder of Beth Bioinformatics Co., Ltd. Other authors have no conflict of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.onehlt.2020.100201.

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