Differential impact of non-pharmaceutical public health interventions on COVID-19 epidemics in the United States

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Research article

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Differential impact of non-pharmaceutical public health interventions on COVID-19 epidemics in the United States

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Abstract

The widespread pandemic of novel coronavirus disease 2019 (COVID-19) poses an unprecedented global health crisis. In the United States (US), different state governments have adopted various combinations of non-pharmaceutical public health interventions (NPIs) to mitigate the epidemic from February to April, 2020. Quantitative assessment on the effectiveness of NPIs is in great need to assist in guiding the individualized decision making for adjustment of interventions in the US and around the world. However, the impact of these approaches remain uncertain. Based on the reported cases, the effective reproduction number (R_t) of COVID-19 epidemic for 50 states in the US was estimated. The measurement on the effectiveness of eight different NPIs was conducted by assessing risk ratios (RRs) between R_t and NPIs through a generalized linear model (GLM). Different NPIs were found to have led to different levels of reduction in R_t. Stay-at-home contributed approximately 51% (95% CI 46%-57%), gathering ban (more than 10 people) 19% (14%-24%), non-essential business closure 16% (10%-21%), declaration of emergency 13% (8%-17%), interstate travel restriction 11% (5%-16%), school closure 10% (7%-13%), initial business closure 10% (6%-14%), and gathering ban (more than 50 people) 6% (2%-11%). This retrospective assessment of NPIs on R_t has shown that NPIs played critical roles on epidemic control in the US in the past several months. The quantitative results could guide

individualized decision making for future adjustment of NPIs in the US and other countries for COVID-19 and other similar infectious diseases.

Keywords: COVID-19; non-pharmaceutical public health interventions; reproduction number; epidemic control; the United States

Introduction

Coronavirus disease 2019 (COVID-19), caused by the severe acute respiratory syndrome coronavirus 2 (SARS-COV-2), has become a pandemic around the world. Currently, the epidemic in the United States (US) is still of serious concern. As of June 27, 2020, there have been 2,596,537 reported cases in the US, with 128,152 deaths. The daily number of reported new cases is increasing yet again recently after a period of decreasing. From February to April, 2020, various non-pharmaceutical public health interventions (NPIs) have been adopted in different states of the US. However, they were challenged from time to time by governments and the public, given their high economic and lifestyle costs.[1-3] Notably, since April 20, 2020, all the 50 states have been relaxing NPIs gradually. However, due to the lack of data support for the actual effect of each NPIs, unsuitable relaxing policy might cause an even more serious pandemic. For example, a substantial increase of daily new cases was observed recently in Texas which had relaxed stay-at-home since April 30. Therefore, a retrospectively quantitative assessment for the impacts of individual interventions on epidemic control is of great importance, which could assist policymakers and health care providers to make informed intervention decisions on future adjustment of NPIs for COVID-19 and other infectious diseases transmitted via similar routes. This study leveraged the combined NPIs being executed in different states to estimate the effects of

individual NPIs employed on containment of the epidemic among the states of the US, including declaration of emergency, school closure, gathering ban (more than 10 or 50 people), initial business closure (e.g., dine-in service and retail), non-essential business closure, interstate travel restriction and stay-at-home.

Methods

The number of reported cases in the US (50 states) from January 21 to May 31 were collected for this study.[4] Considering the time delay between infection time and reporting time, including an incubation period (assumed to follow a gamma distribution with mean=5.1 days and SD=3.0 days[5]) and a reporting delay (assumed to follow a gamma distribution with mean=4.9 days and SD=3.3 days[6]), the infection epidemic curves were inferred by randomly selecting samples from the two gamma distributions. The total daily number of reported new cases and inferred new infection cases of the 50 states during this period were shown in Fig. 1a, along with the timeline of federal NPI responses. Due to the fact that the states have been relaxing the interventions gradually since April 20, the inferred infection number of each states before April 19 were finally used to estimate the daily effective reproduction number (R_t). The relationships among these time-related concepts are shown in

Supplemental Fig. 1a. The method proposed by Thompson R et al[7] were applied to estimate the time varying R_t for each state (R software package EpiEstim) from the inferred infection epidemic curves over seven-day sliding windows. The generation time used for the calculation of R_t was obtained from the time lag between the 133 collected infector/infectee pairs through a gamma distribution using maximum likelihood estimation (mean: 5.9, SD: 3.9, Supplemental Fig. 1b, Supplemental Table 3, R software package R0). To examine the association between R_t and NPIs, the timeline of the most widely executed NPIs for each state from February 29 to April 24 were collected (Fig. 1b, Supplemental Table 1, 2). Note that inclusion relations exist for certain selected interventions, meaning that one intervention would be implemented by default if another more aggressive intervention was issued. Here, three such relations were identified: 1) gathering ban (more than 50 people) is included in gathering ban (more than 10 people); 2) initial business closure is included in non-essential business closure; 3) stay-at-home covers all other interventions, except declaration of emergency and interstate travel restriction. The generalized linear model (GLM) with ridge regression for the gamma distribution (glmGamma) was developed to estimate the impacts of different interventions on R_t (R package H2o). For each state, the population density (number of people per square mile),[8] per capita GDP,[9] median age,[10] testing rate, and testing positive rate[4] were considered as potential

confounders. The risk ratios (RRs) of different interventions were then calculated from the coefficients, representing the impact of interventions on R_t.

Results

The infection epidemic curves were first estimated for all the 50 states, by considering the incubation period and reporting delay, based on the number of daily reported new cases from January 21 to May 31. R_t of each state was calculated accordingly, from the first inferred case to April 19 (exemplified by New York state in Fig. 2; others in Supplemental Fig. 2). Some states started with high R_t value in the early phase, which were then reduced to below 1.0 on April 19 (Supplemental Fig. 3), after implementation of aggressive NPIs. Taking NY as an example, R_t was decreased from 3.25 (95% CI 3.17-3.32) on March 7 (declaration of emergency) to 1.52 (1.50-1.53) on March 22 (stay-at-home), and decreased to below 1.0 on April 4.

When constructing the GLM model for effect estimation, only population density was statistically significant ($p<0.0001$), while P-values of the other pre-defined confounders were above 0.1 (per capita GDP ,0.52; median age, 0.31; testing rate, 0.90; testing positive rate, 0.35). In the final model, only population density was selected as a confounder. Based on the constructed GLM model (R-squared =

0.78), risk ratios (RRs) of each NPI with respect to R_t were assessed (Fig. 3). Due to the inclusion relation of some interventions, the actual RR of a more aggressive intervention was recalculated by accumulating the multivariable adjusted RRs of the included interventions (Supplemental Table 4). Based on the constructed GLM model, stay-at-home exhibited the lowest RR value of 0.49 (95% CI 0.43-0.54), indicating that the execution of this NPI could reduce the current R_t by about 51% (46%-57%). The reduction in R_t generated by gathering ban (more than 10 people), non-essential business closure, and declaration of emergency were 19% (14%-24%), 16% (10%-21%), and 13% (8%-17%), respectively. Interstate travel restriction, school closure, and initial business closure achieved reductions in R_t corresponding to 11% (5%-16%), 10% (7%-13%) and 10% (6%-14%), respectively. Gathering ban (more than 50 people) had the minimum effect (R_t (6%, 2%-11%) among the eight interventions.

Discussion

This study quantitatively estimated the impacts of different NPIs on R_t in the US and ranked the eight selected interventions on the potential capacities of decreasing R_t and controlling the COVID-19 epidemic. It has been demonstrated that the selected eight interventions had substantially reduced R_t,

which represents the control of an outbreak of COVID-19. The analysis in this study reveals which interventions were more effective in epidemic control in the US.

All 50 states in the US have begun to reopen in some way since April 20. However, some states are facing with increasing daily new cases recently. The findings of this study are valuable for states in making individual plans for intervention adjusting to control the epidemic and avoid the potential for a second wave of cases. For states which currently have R_t>1.0, relaxation is not recommended[6] and more NPIs should be re-implemented based on current R_t as well as the different effect of the NPIs to reduce R_t. Otherwise, the infection size could grow rapidly, and the epidemic would lead to more severe losses in terms of human health and the economy. For states with R_t<1.0 at present or in the future, it is important to comprehensively evaluate the impacts on R_t (keeping R_t below 1.0 based on the RRs of our model), infection size, and the burden on the healthcare system and a gradual lifting plan should start with interventions that have a lower impact on R_t (high RRs) and then be extended to more aggressive interventions.

This study has several limitations. First, the four parameters for estimating R_t, i.e., incubation time, reporting delay and generation time, were not estimated by using the US data, because of the limited data availability. Second, there are other confounders that have not been taken into account in

evaluating the association between R_t and NPIs, such as climate factors and medical resources. Third, the enforcement intensity of NPIs in the different states has not been taken into account. More detailed data are required to consider the impact of enforcement. Finally, in this study, it was postulated that the impact of NPIs on R_t would remain fixed over time, and the average R_t over a period was used as the response value. Incorporating the time factor into the modeling requires more data on the diversity of policies.

Declarations

Funding

None

Conflicts of interest

The authors declare that they have no competing interests.

Availability of data and material

The data used in the study are included in the supplementary material or in the manuscript.

Code availability

The code used in the study are available from the corresponding author on reasonable request.

Authors' contributions

Linqi Zhang, Guotong Xie, and Xiang Li conceptualised the study; Xiaoshuang Liu, Xiao Xu, and Guanqiao Li conducted the statistical analysis and interpreted the study results; Xian Xu and Yuyao Sun acquired the data and created figures; Xiao Xu and Xiaoshuang Liu drafted the manuscript, compiled and addressed comments from coauthors; Guanqiao Li, Fei Wang and Xuanlin Shi revised the manuscript and provided intellectual advice. All authors reviewed and approved the final version of the manuscript.

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Fig. 1 Daily number of reported and inferred new cases in the US and execution dates of main NPIs among 50 states. a. Daily number of reported new cases and inferred new infection cases (up to April 19) in the US (50 states). b. Execution dates of the selected main NPIs among 50 states in the US from February 29 to April 19. Interventions that started on the same day are represented in one rectangle. The full names of the state abbreviations were shown in Supplemental Table 1.

Fig. 2 Time varying R_t and inferred infection epidemic curve for New York state(a) and risk ratios of each variable to R_t(b). a. Time varying R_t and inferred infection epidemic curve of New York state(NY). The blue bars represent the daily number of infections, the orange lines show the trends of R_t (standard deviation less than 0.5), and the grey shading refers to the 95% confidence intervals of R_t. The dates of the main NPIs executed by NY from February 22 (one week before the first state emergency on February 29) to April 19 were shown in different colors of triangles. b. Risk ratios(dot) and 95% confidence intervals(bars) of each variable to R_t.

Figures

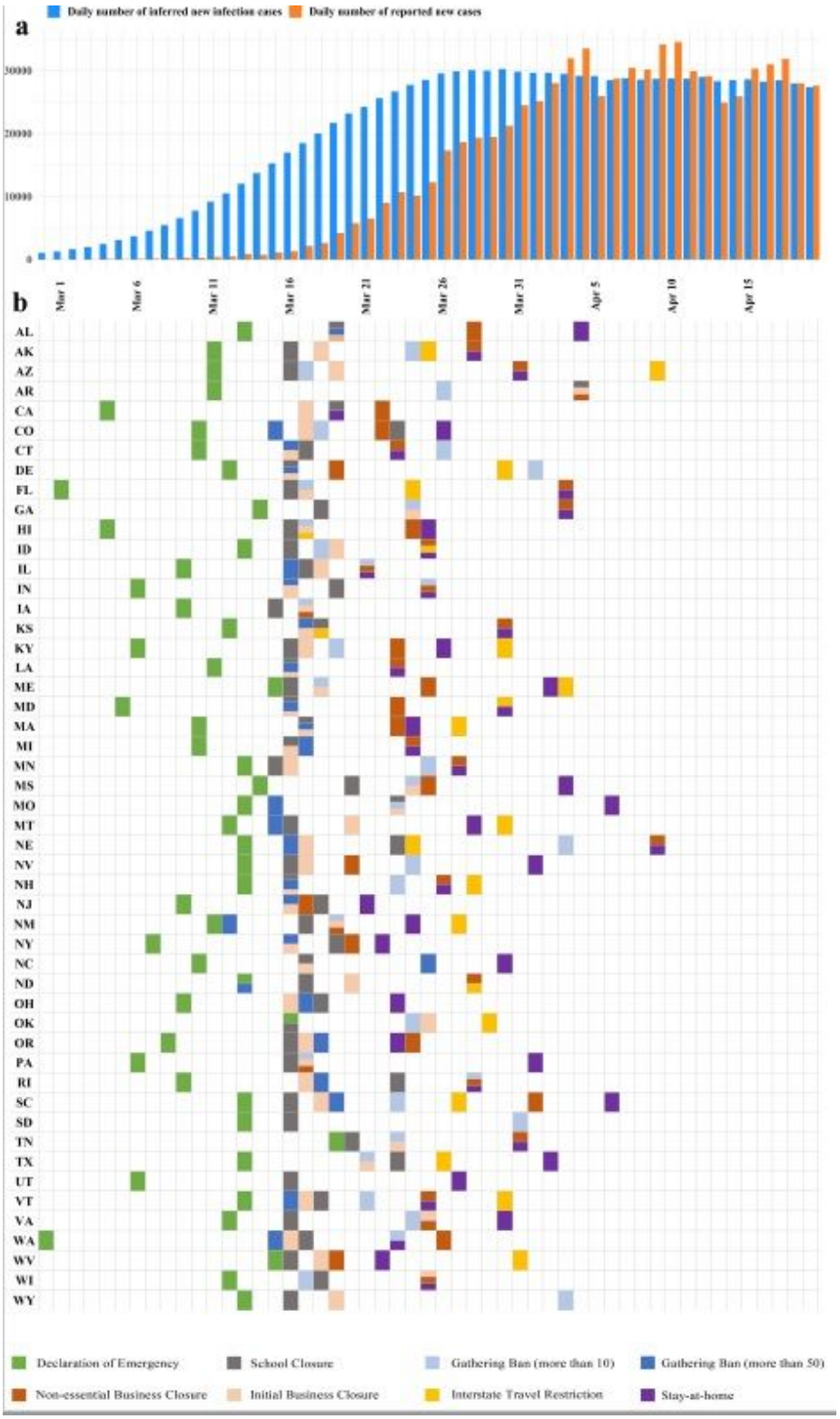

Figure 1

Daily number of reported and inferred new cases in the US and execution dates of main NPIs among 50 states. a. Daily number of reported new cases and inferred new infection cases (up to April 19) in the US (50 states). b. Execution dates of the selected main NPIs among 50 states in the US from February 29 to

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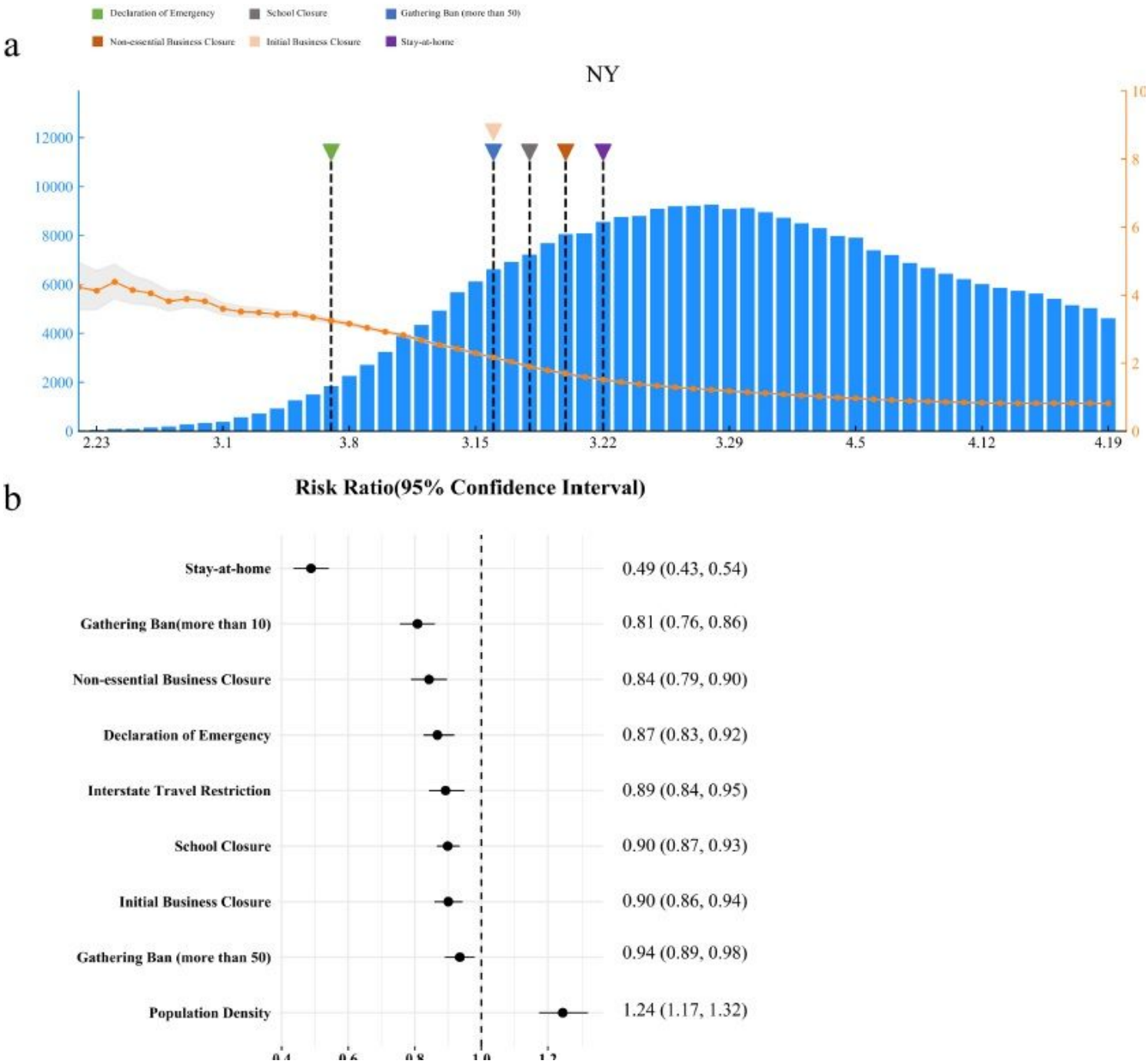

Figure 2

Time varying R_t and inferred infection epidemic curve for New York state(a) and risk ratios of each variable to R_t(b). a. Time varying R_t and inferred infection epidemic curve of New York state(NY). The blue bars represent the daily number of infections, the orange lines show the trends of R_t (standard deviation less than 0.5), and the grey shading refers to the 95% confidence intervals of R_t. The dates of the main NPIs executed by NY from February 22 (one week before the first state emergency on February

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Supplementary Files

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- SupplementaryTable.pdf
- Supplementaryfigure.pdf