Impact of state reopening on COVID-19 transmission, United States, 2020

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Abstract

The novel coronavirus disease (COVID-19) pandemic resulted in an unprecedented lock-down of the United States. After weeks of lock-down, State's Reopening has raised concerns about potential exacerbation of the epidemic. We developed a Bayesian hierarchical model to analyze the impact of reopening on COVID-19 transmission in four states and cities. We showed that reopening significantly increased COVID-19 transmission. Our results indicate that additional control measures are needed to mitigate disease transmission, as states are reopening.

Keywords: COVID-19; Reopening; Intervention analysis; Prediction

The novel coronavirus disease, COVID-19, which was first reported in the United States (US) on January 20th, 2020 has now become one of the main public health threats in all states across the nation. The steep early increase of COVID-19 cases in the US inevitably led most states government authorities to issue strict social distancing restrictions such as stay-at-home orders in the hope of flattening the epidemic curve. These restrictions on population movement did not only suppress people's mobility but also froze the national economy, which resulted in an upsurge of the unemployment rate [6] and a contraction of the gross domestic product [1, 9], among others. About one and a half months after the stay-at-home orders, states began to ease their restrictions to allow reopening of businesses to revitalize their economy. However, states' reopening has raised concerns about a potential surge of COVID-19 cases as population mobility and physical contacts increase.

A topical question, arising in intervention analysis [2], is whether or not state' reopening has so far had an impact on the spread of COVID-19. The intervention analysis governing rationale suggests that if COVID-19 transmission in a state was affected by the reopening then the infection trajectory will correspondingly respond by showing jump upward (or

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possibly downward) in infected cases shortly after the reopening date (as case reporting usually take place several days after the initial infection [7]). Such intervention analysis is paramount for estimating the potential impact of a given intervention on epidemic dynamics and providing valuable information to policy-makers for a swift and well-informed decision needed to ensure the control of the epidemic.

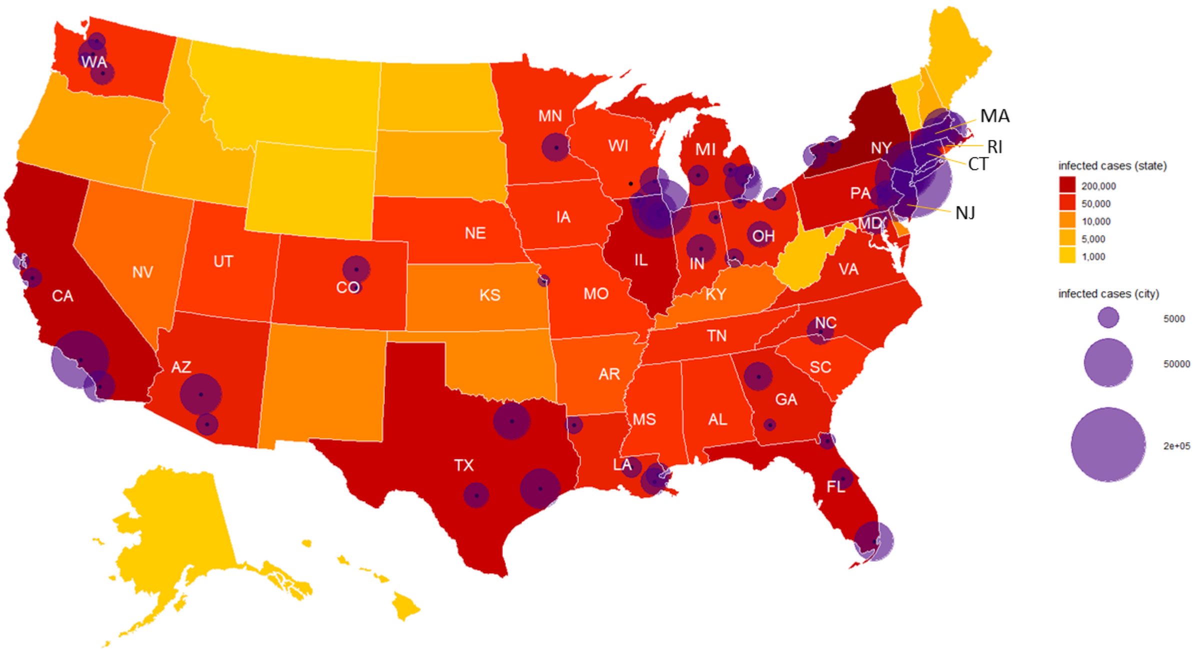

Figure 1: . Infection map for the 35 states (named on the map) 62 cities (dotted on the map) included in the hierarchical model. (cumulative cases reported as of June 22nd, 2020)

To determine whether or not state' reopening has so far had an impact on the spread of COVID-19, we developed a Bayesian hierarchical Richards model [8] to analyze daily trajectories of COVID-19 infected cases [3]. The hierarchical state- and city-level models used dataset from 35 states and 62 major cities, respectively, shown on the Figure 1. (See Supplemental materials for the full lists of states/cities.) For each state/city, we evaluated the predictive ability of our model during the stay-at-home order period using short-term forecasts (two weeks into the future) of reported infection cases. A two-week period was used as it represents the maximum incubation period [7]. Let t_{IV} denotes a reopening date, which can be different for different states/cities. We employed a *2-week moving window prediction* (where cumulative numbers of infected cases for the next 2-week are predicted given past 2-week information for time-varying covariates and the daily trajectories) at each of the time points t_{IV}, $t_{\mathrm{IV}} \pm 1 \times$ (2-week), $t_{\mathrm{IV}} \pm 2 \times$ (2-week), and $t_{\mathrm{IV}} + 3 \times$ (2-week) (See Supplemental materials for a technical description for the *2-week moving window prediction*). Four daily time series data considered in our model include: (1) change in mobility from baseline [10]; (2) change in non-essential visits from baseline [10]; (3) change in encounterdensity from baseline [10]; and (4) number of COVID-19 tests (covidtracking.com/-). Daily number of tests as a covariate to account for possible increase in cases from increase testing. To evaluate our model's predictions, we used the Brier Score which measures the accuracy of probabilistic forecast [4, 5]. (See Supplemental Materials for a detail on the Brier Score.) We used our model to analyze the impact on reopening on COVID-19 cases in four states (Texas, Florida, North Carolina, Arizona) and cities (Houston, Miami, Charlotte, Phoenix).

We show that prior to reopening date the model accurately predicted the cumulative number of cases in each state and city (Figure 2) with Brier Score of 0 (Table 1). Over the first two weeks following reopening date, our model accurately predicted the cumulative number of new COVID-19 cases in the four states and cities, with the exception of Texas where the model under-estimated the number of cases during the second week (Figure 2 and Table 1). After the first two weeks, the model consistently under-estimated the number of cases with high Brier Score in the state of North Carolina, and Arizona and the city of Charlotte, and Phoenix (Figure 2 and Table 1). In Texas, Florida, Houston, and Miami consistent under-estimations with high Brier Score were obtained after the fourth weeks following reopening (Figure 2 and Table 1).

In the four states/cities, the impact of reopening on COVID-19 cases was initially observed at least 14 days after the reopening dates. This time delay may be due to several factors such as the time-lag between infection and case reporting and progressive increase in human contacts following state/city reopening. Our results indicate that state/city reopening had a significant impact on COVID-19 transmission. That increase in cases cannot be explained by increase testing or a simple increase in population mobility, as these factors were accounted for in our model. This implies that an increase in mobility coupled with an increase in risky behavior (non-compliance with face-mask recommendations, six feet physical distancing, or hygiene practices) may better explain the resurgence of cases following reopening. As states continue to ease their social distancing restrictions, non-essential businesses reopen, more workers return to regular in-person office hours, and schools/colleges plan for reopening and face-to-face lectures in the forthcoming Fall semester, we anticipate that these various events may exacerbate the spread of COVID-19 if implemented without corresponding infection risk mitigation measures. Though the present approach provides qualitative information on the impact of reopening on the spread of COVID-19, further analysis is required to quantify the impact of such events on COVID-19 transmission.

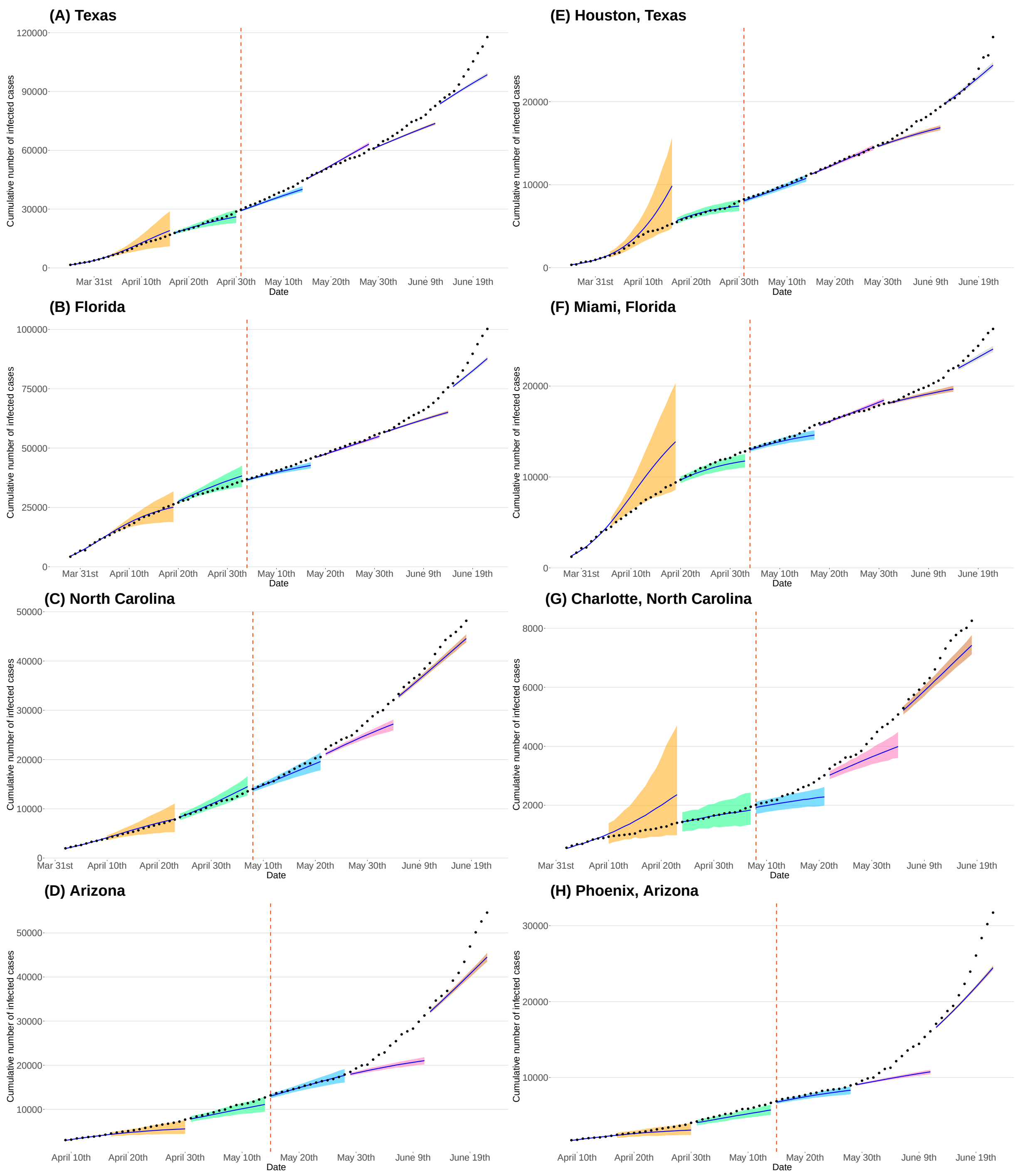

Figure 2: **2-week moving window prediction results for infected cases**: observations (black dots); predictive posterior mean (black curves); pointwise 95% predictive posterior intervals (colored regions); reopening dates (red vertical dotted lines).

Table 1: Prediction diagnosis on the 2-week moving window prediction based on Brier Score over each time interval for the states and cities on the Figure 2.

State/city	I_1	I_2	I_3	I_4	I_5	I_6
Texas	0	0	0.7857	0.5000	0.9286	1.0000
Florida	0	0	0.2143	0.2143	0.8571	1.0000
North Carolina	0	0	0.0000	1.0000	0.9286	NA
Arizona	0	0	0.0000	0.9286	1.0000	NA
Houston	0	0	0.0000	0.0000	0.8571	0.3636
Miami	0	0	0.0714	0.1429	0.7857	0.8750
Charlotte	0	0	0.2143	0.7143	0.6429	NA
Phoenix	0	0	0.0000	0.9286	1.0000	NA

NOTE: A lower value for the Brier Score indicates a better predictive accuracy. NA represents 'Not Applicable'. Interval notations I_1, I_2, I_3, I_4, I_5, and I_6 represent time intervals $[t_{IV} - 4W, t_{IV} - 2W)$, $[t_{IV} - 2W, t_{IV})$, $[t_{IV}, t_{IV} + 2W)$, $[t_{IV} + 2W, t_{IV} + 4W)$, $[t_{IV} + 4W, t_{IV} + 6W)$, $[t_{IV} + 6W, t_{IV} + 8W)$, respectively. t_{IV} is the reopening date. The interval $[t_{IV} - 4W, t_{IV} - 2W)$ is interpreted as a 2-week time period spanning from the '4-week before the reopening date' through the '2-week before the reopening date'. Other interval notations can be similarly interpreted. For more detail about the Brier Score see the Supplemental materials.

Conflict of interest

We declare that we have no conflict of interest.

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