Estimating the Effect of Social Distancing Interventions on COVID-19 in the United States

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Running head: Estimating Social Distancing Effects on COVID-19

Since its global emergence in 2020, severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) has caused multiple epidemics in the United States. Because medical treatments for the virus are still emerging and a vaccine is not yet available, state and local governments have sought to limit its spread by enacting various social distancing interventions such as school closures and lockdown, but the effectiveness of these interventions is unknown. We applied an established, semi-mechanistic Bayesian hierarchical model of these interventions on SARS-CoV-2 spread in Europe to the United States, using case fatalities from February 29, 2020 up to April 25, 2020, when some states began reversing their interventions. We estimated the effect of interventions across all states, contrasted the estimated reproduction number, R_t, for each state before and after lockdown, and contrasted predicted future fatalities with actual fatalities as a check on the model's validity. Overall, school closures and lockdown are the only interventions modeled that have a reliable impact on R_t, and lockdown appears to have played a key role in reducing R_t below 1.0. We conclude that reversal of lockdown, without implementation of additional, equally effective interventions, will enable continued, sustained transmission of SARS-CoV-2 in the United States.

Bayesian hierarchical model; intervention effect size; severe acute respiratory syndrome coronavirus 2; social isolation; reproduction number

Abbreviations: IFR, infection fatality ratio; SARS-CoV-2, severe acute respiratory syndrome coronavirus 2; R_t, time-varying reproduction number; COVID-19, coronavirus disease 2019.

Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) causes coronavirus disease 2019 (COVID-19). Discovered in Wuhan, China in December 2019, SARS-CoV-2 rapidly spread to the rest of the world, initially through travelers from Wuhan, but later through community transmission in Asia, Europe, Australia, and North America, until it was declared a pandemic by the World Health Organization on March 11, 2020. The rapid spread of SARS-CoV-2 is attributable to its transmissibility by aerosol and fomites[1,2], by presymptomatic/asymptomatic carriers[3,4], and by the relatively mild clinical characteristics of symptomatic carriers, which often include fever, cough, and fatigue[5]. However, approximately 20% of confirmed cases develop severe or critical forms of COVID-19, including complications of respiratory failure, myocardial dysfunction, and acute kidney injury, with approximately 50% mortality for critically-ill patients[6].

As of July 2020, outbreaks or epidemics of SARS-CoV-2 have emerged in all 50 states, with over 2.5 million confirmed cases reported. Because medical treatments and vaccines are still emerging, state and local governments have sought to limit the virus's spread by enacting various social distancing interventions. Social distancing interventions have varied widely within states and across states. Within states, interventions typically begin with public health directives like washing hands and staying home if sick, followed by restrictions on or closures of places housing vulnerable populations like nursing homes or schools, followed by successive, increasingly restrictive bans on gathering in groups, culminating in stay-at-home orders or so-called lockdown. Across states, interventions have been adopted with different speeds, such that some states moved rapidly to lockdown and others never entered lockdown at all. Likewise, states are currently lifting lockdown and reversing social distancing interventions at different rates.

To explore the association between social distancing interventions and fatalities, we applied an established, semi-mechanistic Bayesian hierarchical model of these interventions on SARS-CoV-2 spread in Europe[7,8] to the United States. We estimated the effect of interventions and the time-varying reproduction number (R_t) for each state using state-level daily case fatality counts.

METHODS

Data

We used data from three different sources: state-level intervention data, infection fatality rate data, and confirmed case fatality data.

State-level intervention data. We created a dataset[9] of state-level intervention dates by inspecting the executive orders, public health directives, and official communications (e.g., press releases) from state governments. For each intervention date, we used the effective date, unless the timing of the intervention was so close to midnight as to only practically take place the next day. Interventions were only counted if they targeted the general population. The interventions themselves closely parallel those in the European model we used, but with slightly different operationalizations which we describe in turn. Self-isolating if ill is a recommendation to stay home if sick. Social distancing encouraged is a recommendation to avoid nonessential travel and/or contact; the mere words "social distancing" were not counted unless elaborated with examples of what social distancing entails. Schools or universities closing is the date at which schools partly or completely close; the earlier of schools or universities closing was used. Sport is the banning of sporting events or public gatherings of more than 1000 persons. Public events is the banning of public gatherings of more than 100 participants. Finally, lockdown includes banning of non-essential gatherings or business operations, which is sometimes formalized as a stay-at-home or safer-at-home order. Notably some more restrictive interventions imply others, e.g., lockdown implies all other interventions, and public events implies sport.

Infection fatality rate data. The infection fatality rate (IFR), or ratio of fatalities to true infections, was derived via the methods outlined in Flaxman et al. Briefly, IFR estimates from Verity[10] et al were adjusted using an age-specific UK contact matrix to account for non-uniform attack rates across age groups (see Ferguson et al.[11] for details and previous US application). The resulting IFRs were weighted by state-level age demographics and averaged to produce estimates adjusted for both age and location. Demographic data were obtained from the 2018 ACS survey 5-year estimates[12].

Confirmed case fatality data. SARS-CoV-2 fatality data was obtained from the New York Times public data repository[13], which describes the data collection process along with subtle issues in counting cases, e.g. cruise ship passengers. In general, the dataset counts confirmed cases according to where they were treated and on the days they were reported up to midnight Eastern Time. Because this dataset provides cumulative counts, we transformed these into daily counts by taking the difference between successive daily cumulative counts (setting this difference to zero in the rare instances where cumulative counts decreased due to reporting corrections).

Model

We applied an established, semi-mechanistic Bayesian hierarchical model of interventions on SARS-CoV-2 spread in Europe to the United States, and the design and details of this model are presented elsewhere[7,8] (see the Web Appendix for a brief overview). Notably, a recent variant of this model has been applied to the United States at the state level, but this variant uses mobility data rather than interventions as the basis of predictions[14]. Briefly stated, daily death counts in the model follow a negative binomial distribution such that their expectation is a function of infections on previous days. The model is semi-mechanistic in the sense that it incorporates classical Susceptible-Infected-Removed concepts[15] in a Bayesian framework. The number of infected is modeled using a discrete renewal process, and death counts are similarly linked to the number of infected based on the state country IFR and the distribution of times from infection to death. Importantly, the model assumes the effect of intervention is that same regardless of location and that the implementation of an intervention instantaneously reduces R_t. Making these assumptions allows pooling of data from states for estimating intervention effects. The model was specified using Stan[16], and model inference was performed using adaptive Hamiltonian Monte Carlo. We fit our model with a time series for each state 30 days before the state has experienced seven deaths, from February 29, 2020 up to April 25, 2020, when some states began reversing their interventions. Seven deaths is a somewhat arbitrary threshold for excluding imported cases, and other work has used five[14] or ten[8] deaths for this threshold. We chose seven because it is the highest number we can use and still obtain valid data for states like Alaska, which had a relatively low case count during this period.

RESULTS

States implemented the six interventions at different rates. The mean period between the first and last intervention of a state was 18.64 days (*SD*=6.51, range: 4-31). The mean number of directives (e.g., executive orders) implementing interventions in a state was 4.32 (*SD*=0.94, range: 2-6), and the mean number of interventions per order was 1.40 (*SD*=0.35, range 1-3). Some interventions were more likely to co-occur in a single directive than others, with <u>sport</u> (*M*=1.08, *SD*=0.83) and <u>public events</u> (*M*=1.04, *SD*=0.81) occurring the most frequently with other interventions and <u>schools or universities closing</u> (*M*=0.40, *SD*=0.81) and <u>lockdown</u> (*M*=0.14, *SD*=0.50) occurring the least frequently with other interventions. Despite these differences, 96.33% of the interventions were implemented across states, with <u>lockdown</u> being the least implemented (*n*=43). The decision to implement <u>lockdown</u> was not clearly data-driven across states: on the date of the last intervention, there was no significant difference between states that implemented <u>lockdown</u> and those that did not in the cumulative case rate (P=0.052) or the cumulative death rate (P=0.059) using 2-sided rank-sum tests.

The mean IFR across states was 1.11% (*SD*=0.12%, range: 0.76-1.35%). Because confirmed case fatality data across states increased dramatically over the time period examined, similar statistics are not reported for these data.

Estimated national intervention effects on R_t are shown in Table 1. It is evident that only schools or universities closing and lockdown have a nontrivial impact on R_t, with mean relative reductions of 23.7% and 54.4% respectively. Moreover, schools or universities closing and lockdown are the only interventions whose 95% credible interval is not close to zero.

<Table 1 about here>

State-level measures and estimates of the model are shown in Table 2 (see also Web Figure 1). Of primary interest are R_t estimates before and after lockdown and corresponding forecasted death counts 2 weeks into the future. Across states, the mean R_t before lockdown was 1.86 (*SD*=0.56, range: 1.00-3.37) and the mean R_t after lockdown was 0.88 (*SD*=0.25, range: 0.50-1.41). Notably, no state had a mean R_t below 1.0 pre-lockdown, but 29 states had a R_t below 1.0 after lockdown. While lockdown was associated with reduced R_t in all states that underwent lockdown (a 54.4% reduction, see Table 1), in these 29 states, lockdown appears to have been the single critical intervention allowing containment of the disease. In the remaining states, pre-lockdown R_t was too high (i.e., greater than 2.2) for lockdown to bring R_t below 1.0.

Predicted deaths vs. actual deaths two weeks into the future in each state serve as a validity check on the model's estimates of intervention effects (see also Web Figure 2). Forty-five states (90%) had actual deaths that were within the 95% CI of predicted deaths. Notably, the mean predicted deaths were well above actual (>100 deaths) for Connecticut, New Jersey, Massachusetts, and New York. The mean absolute error of mean predicted deaths was 50.80, and without these four states the mean absolute error was 10.08. As expected, the model fit to actual deaths was even closer on the observed data, with mean absolute error at 5.90 (N=2951).

<Table 2 about here>

DISCUSSION

Social distancing interventions are important for limiting the spread of SARS-CoV-2, because medical treatments for COVID-19 are still emerging and a vaccine is not available. To our knowledge, we are the first to apply an established, semi-mechanistic Bayesian hierarchical model of these interventions on SARS-CoV-2 spread in Europe to the United States. We estimated the effect of interventions across all states, contrasted the estimated R_t for each state before and after lockdown, and contrasted predicted fatalities with actual fatalities as a check on the model's validity. Overall, school closures and lockdown are the only interventions modeled that have an estimated effect where the 95% credible interval is not close to zero, i.e. no effect. No state had an estimated R_t below 1.0 before lockdown, but 29 states reached an R_t below 1.0 after lockdown. The model's ability to successfully predict deaths supports the validity of estimated intervention effects. These results suggest that reversal of lockdown, without implementation of additional, equally effective interventions, will enable continued, sustained transmission of SARS-CoV-2 in the United States.

Our study has several limitations. First, the assumption that all interventions have the same implementation and effect in all states is a strong assumption. For example, the public events intervention banning gatherings of 100 persons or more could be met by a ban on 10 persons or more or 50 persons or more; it is unlikely that such bans are truly equivalent. Schools or universities closing treats primary, secondary, and higher education the same, though emerging evidence suggests that younger children may be less effective at spreading the virus than adults[17]. This limitation has since been partially addressed in the European model by allowing random effects for lockdown only. Second, the assumption that interventions are binary, instantaneous, and non-harmful are strong assumptions and oversimplifications that do not account for time-varying compliance with intervention or unintended consequences. Using mobility data as a measure of population mixing[14,18,19] partially addresses this. Third, the parameters of the model are estimated using reasonable, but still uncertain, assumptions about prior distributions. We have used the same assumptions as in the European model, but these assumptions may be contradicted by future empirical work.

Modeling of SARS-CoV-2 is emerging and rapidly diversifying, including classical SEIR models and derivatives[20], deep learning[21], and piecewise models for sub-exponential growth[22]. State and local governments are likewise rapidly adjusting policy decisions regarding interventions based on case data and economic concerns. As the United States adopts an increasingly fragmented response to SARS-CoV-2, modeling approaches like ours that focus on shared interventions may not be tenable. While our results give valuable insights into which interventions did and which did not change the transmission rate substantially, we recommend that future studies measure the change in behaviors resulting from interventions and then strengthen the predictive relationships between these behaviors and disease transmission.

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Table 1. Intervention Effects on the Time-Varying Reproduction Number, United States, February 29 to April 25, 2020

Intervention	Mean relative % reduction	95% CI[a]
Self-isolating if ill	1.2	0.0, 5.7
Sport	2.1	0.0, 9.7
Social distancing encouraged	3.2	0.0, 15.0
Public events	9.8	0.0, 31.5
Schools or universities closing	23.7	0.7, 40.4
Lockdown	54.4	44.7, 62.7

Abbreviations: CI, credible interval

[a] The model assumes reductions in R_t are non-negative. See Web Appendix for details.

Table 2. State-level Measures and Estimates of Infection, Fatality, and Lockdown Intervention, United States, February 29 to April 25, 2020

State	IFR (%)	Pre-Lockdown R_t	Pre-Lockdown 95% CI	Lockdown[a] R_t	Lockdown[a] 95% CI	Predicted Deaths[b]	95% CI[b]	Actual Deaths[c]
Alabama	1.076	1.334	1.083, 1.619	0.610	0.476, 0.767	5.618	0, 15	7
Alaska	0.813	1.224	0.176, 2.466	0.558	0.081, 1.110	0.067	0, 1	0
Arizona	1.147	1.667	1.373, 1.998	0.762	0.603, 0.942	8.993	1, 23	15
Arkansas	1.125	1.005	0.715, 1.336			2.081	0, 8	0
California	0.986	2.290	1.869, 2.786	1.042	0.913, 1.178	84.400	23, 201	82
Colorado	0.955	1.887	1.536, 2.294	0.859	0.723, 1.011	24.600	6, 60	7
Connecticut	1.190	3.100	2.575, 3.722	1.411	1.227, 1.617	287.897	76, 707	58
Delaware	1.221	2.542	1.902, 3.311	1.157	0.891, 1.457	9.387	1, 28	8
Florida	1.353	1.726	1.465, 1.988	0.789	0.650, 0.942	40.651	10, 97	46
Georgia	0.938	1.345	1.154, 1.548	0.614	0.511, 0.732	19.987	4, 48	2
Hawaii	1.260	1.524	0.547, 2.608	0.695	0.247, 1.172	0.331	0, 2	0
Idaho	1.035	1.684	1.066, 2.509	0.674	0.450, 0.944	1.069	0, 5	0
Illinois	1.070	2.781	2.272, 3.409	1.265	1.102, 1.438	192.095	51, 461	100
Indiana	1.062	2.210	1.811, 2.676	1.007	0.845, 1.183	42.399	10, 104	43
Iowa	1.160	1.409	1.110, 1.744			17.357	2, 51	9
Kansas	1.087	1.750	1.281, 2.348	0.704	0.521, 0.919	2.850	0, 9	5
Kentucky	1.090	1.799	1.406, 2.255	0.820	0.645, 1.015	6.422	0, 18	8
Louisiana	1.036	1.968	1.657, 2.329	0.897	0.772, 1.034	55.047	14, 133	40
Maine	1.353	1.729	1.180, 2.390	0.790	0.528, 1.090	1.899	0, 7	1
Maryland	1.057	2.451	2.029, 2.928	1.119	0.913, 1.345	74.977	18, 191	54
Massachusetts	1.127	3.366	2.694, 4.238	1.379	1.183, 1.580	402.458	108, 942	138
Michigan	1.149	2.338	1.960, 2.777	1.065	0.923, 1.223	204.275	55, 481	133
Minnesota	1.081	2.491	1.977, 3.091	1.136	0.906, 1.390	21.938	4, 58	24
Mississippi	1.063	1.449	1.175, 1.762	0.662	0.523, 0.828	6.381	1, 17	12
Missouri	1.138	1.436	1.183, 1.720	0.656	0.523, 0.809	9.949	1, 26	11
Montana	1.215	1.533	0.525, 2.658	0.698	0.237, 1.201	0.424	0, 3	0
Nebraska	1.071	1.384	0.967, 1.885			8.851	0, 30	3
Nevada	1.026	1.420	1.131, 1.739	0.648	0.505, 0.814	4.370	0, 12	5
New Hampshire	1.215	1.871	1.293, 2.572	0.854	0.586, 1.167	2.519	0, 9	10
New Jersey	1.117	2.949	2.437, 3.556	1.342	1.184, 1.512	746.096	207, 1782	164
New Mexico	1.145	2.578	1.887, 3.412	1.174	0.876, 1.505	8.435	1, 26	10
New York	1.126	2.487	2.082, 2.942	1.132	0.995, 1.277	1225.995	345, 2892	226
North Carolina	1.087	2.183	1.754, 2.684	0.996	0.787, 1.227	20.463	4, 53	17
North Dakota	1.072	1.310	0.617, 2.139			2.445	0, 12	2
Ohio	1.149	2.333	1.912, 2.828	1.063	0.899, 1.243	44.063	11, 110	25
Oklahoma	1.057	1.950	1.468, 2.578	0.783	0.608, 0.982	4.921	0, 14	4
Oregon	1.141	1.534	1.147, 1.995	0.700	0.527, 0.903	1.342	0, 5	3
Pennsylvania	1.235	2.332	1.997, 2.693	1.065	0.883, 1.271	165.470	44, 408	69
Rhode Island	1.188	2.155	1.631, 2.758	0.982	0.756, 1.236	13.197	2, 36	19
South Carolina	1.150	1.303	1.082, 1.544	0.596	0.464, 0.744	4.460	0, 13	10
South Dakota	1.120	1.264	0.337, 2.316			1.525	0, 9	3
Tennessee	1.088	1.149	0.900, 1.437	0.525	0.403, 0.666	2.642	0, 8	1
Texas	0.862	1.632	1.393, 1.894	0.746	0.616, 0.893	23.321	5, 56	27
Utah	0.755	1.416	1.037, 1.860			6.216	0, 22	5
Vermont	1.268	1.095	0.751, 1.525	0.500	0.340, 0.696	0.342	0, 2	0
Virginia	1.054	2.173	1.822, 2.569	0.993	0.810, 1.200	27.818	6, 69	15
Washington	1.032	1.191	1.012, 1.392	0.543	0.467, 0.626	5.496	0, 14	10
West Virginia	1.290	2.045	1.184, 3.057	0.931	0.546, 1.361	2.020	0, 8	1
Wisconsin	1.144	1.600	1.258, 2.001	0.729	0.581, 0.899	5.382	0, 15	14
Wyoming	1.093	1.365	0.267, 2.531			1.690	0, 11	0

Abbreviations: CI, credible interval; IFR, infection fatality ratio; R_t, time-varying reproductive number

[a] Lockdown effects presented for states that implemented lockdown, otherwise blank

[b] Forecasted daily deaths on May 9th, 2020

[c] Actual daily deaths on May 9th, 2020