Article

Association of anti-contagion policies with the spread of COVID-19 in United States

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Abstract

Background: The outbreak of a novel coronavirus, known as severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), or COVID-19, raised worldwide concern. The present study investigates the association between anti-contagion policies and the spread of COVID-19 across the United States.

Design and methods: We selected the most frequently implemented COVID-19 anti-contagion policies in all the U.S. states issued from 29 February 2020. Accordingly, we modified an epidemiological model and combined it with a comprehensive statistical analysis to evaluate the policies' individual and overall likely impact.

Results: For the first time, a novel index, evaluates the associations between policy implementation and COVID-19 spread at both statewide and national levels. Our results indicate that governmental policies requiring mask use, businesses social distancing, and quarantining travelers may be most effective for controlling COVID-19 spread. Simultaneously, widespread orders like school closure and safer-at-home that can be particularly disruptive to the economy and social fabric of society may be unnecessary given their lack of association with reducing infection.

Conclusions: The absence of any COVID-19 vaccines during the first several months of its pandemic necessitated using governmental policies to help stop the spread of this disease. Our index showed the association between implemented policies and COVID-19 spread, highlighting the specific policies with the greatest association - mandatory quarantine upon entering a state, businesses implementing social distancing, and mandatory mask use - and those with less association like school closure and safer-at-home orders. This study provided evidence to inform policy choices for the current global crisis and future pandemics.

Introduction

In the United States (U.S.), there were nearly 39,960,000 confirmed cases and over 656,000 deaths of people who tested positive for severe acute respiratory syndrome coronavirus 2 (COVID-19) as of August 31, 2021.[1] The first COVID-19 case in the U.S. was reported in Washington State on January 22, 2020.[2] By March of 2020, states and federal governments were implementing public health interventions to reduce the growth rate of COVID-19 across the nation (Table 1).[3-6]

To study the impact of policy implementation, investigating the evolution of COVID-19 is crucial; thus, well-known compartmental mathematical models (*e.g.,* SIR, SEIR) have often been applied.[7-9] Using those models, previous studies predicted the spread of COVID-19 in Europe,[10] China,[11] Germany,[12] and various communities in South Korea, India, Australia, and the U.S.[13] However, these research studies deployed simplified models incapable of producing reliable estimates since such models consider the transmission rate to be constant, imposing limitations on predicting other parameters (*e.g.,* daily susceptible and infected cases).[14] Furthermore, COVID-19 epidemiological studies mostly used reported infected cases as the response value, which comprises primarily diagnosed symptomatic infections[15] but does not take diagnosed asymptomatic and non-diagnosed cases into account.[16] In investigating the effect of policies, previous studies mainly focused on evaluating one[17-19] or a few implemented orders.[20] According to Hsiang *et al.*,[5] developing epidemiological simulations to investigate the effect of policies is not merely sufficient for policies impact evaluation since the actual effects of policies on the number of infected cases in the ongoing pandemic are unknown[21-24] and more analytics methods (e.g., statistical analysis) are required to be implemented to support the findings. In this regard, Chaudhry *et al.*'s[16] study on 50 countries highlighted that except for the days to lockdown, no other association between reducing the number of cases and the rest of studied variables (lockdown and border closure) was found. The number of confirmed cases as the response value was used during their analysis; however, as discussed, the number of confirmed cases is not a well-representative of total infected cases. Above-mentioned studies failed to report all policies' overall associations, or the most important policies in effect, with COVID-19 spread which can help policy makers to curb the pandemic more effectively.

To address these shortcomings for the U.S., we first modified

Significance for public health

The absence of any COVID-19 vaccines during the first several months of its pandemic necessitated using nonpharmaceutical interventions to help stop the spread of this very contagious and lethal disease. We examine all major anti-contagion policies across the 50 U.S. states and combine this with a comprehensive epidemiological and statistical analysis to develop a novel policy ratio index. Our index shows the association between implemented policies and COVID-19 spread, highlighting the specific policies with the greatest association - mandatory quarantine for travelers, businesses implementing social distancing, and mandatory mask use - and those with less association like school closure and safer-at-home orders. This article presents a novel index to evaluate the associations between policy implementation and novel coronavirus spread statewide and nationally and provides evidence to inform policy choices for the current global crisis and future pandemics.

the SEIR model by updating the model parameters on a daily basis using the daily death statistics reported for every state. Accordingly, we used our predicted number of daily infected cases (included all the infected categories) for every state produced by the modified SEIR model as the response value and the implemented anti-contagion policies as predictors in a comprehensive statistical analysis. As a result, we evaluated the individual and overall effects of the most frequently implemented anti-contagion policies. For the first time in the COVID-19 literature, we present a novel index (policy ratio) highlighting the associations between policy implementation and COVID-19 spread for every state of the U.S.

To perform the present research, we selected the most frequently implemented COVID-19 anti-contagion policies in the U.S. The study data includes policy activity, policy implementation duration, and the number of implemented policies in each of the 50 U.S. states for the study period, as presented in Figure 1.

Design and methods

Data collection

We selected the most frequently implemented COVID-19 anti-contagion policies in the U.S. out of more than 50 policies issued from February 29, 2020 (Table 1). The study data includes policy activity in each of the 50 U.S. states from March 1, through July 31, 2020 (Figure 1).[25-27] We chose the end of July as the cut-off time because COVID-19 policy activity became relatively stable in the U.S. The number of daily COVID-19 cases, deaths, and tests were obtained and cross-checked from multiple sources, including the Centers for Disease Control and Prevention (CDC),[28] Johns Hopkins Coronavirus Resource Center,[29] The New York Times COVID data repository,[30] and Worldometers data center[31] to ensure data integrity and consistency. The study used COVID-19 outcome measures (cases and deaths) starting two weeks after each policy was implemented and suspended to account for the response lag.

Table 1. Most frequently implemented anti-contagion policies across the U.S. Table is sorted based on the implementation date.

No.	Policies	Description	First time implemented in
1	Relaxed regulations to become a caregiver	Extends the licensing for doctors and assistants, removes requirements for medical students to join the workforce	February 29, 2020 WA
2	Suspended provisions requiring in-person notarization of legal documents (driver's license, marriage license etc.)	Digital notarization is allowed for documents	March 1, 2020 NY
3	Insurance coverage for all diagnosis testing and partial treatment for COVID-19	Insurance companies cover telehealth meetings and co-pay for COVID-19 testing and treatment	March 5, 2020 CA-WA-NV
4	Temporarily suspend evictions	Renters and homeowners cannot lose their house or apartment due to COVID-19 complications	March 6, 2020 IN
5	Restaurant dine-in restrictions	Restaurants can only do delivery and takeout	March 9, 2020 RI
6	Mandatory quarantine for travelers into the state	Anyone traveling into the state must avoid contact with others for 14 days	March 11, 2020 AK
7	Prohibiting visitation in hospitals and extended living facilities	Visitors aren't allowed in hospitals or nursing homes	March 13, 2020 NH
8	Schools closure	K-12 schools closed for the remainder of the school year	March 16, 2020 AK, AZ, DE, FL, IA, KY, LA, MD, MI, MT, NV, NH, NM, NC, ND, OR, PA, SC, UT, VA, WV, WY
9	Travel restriction/advisory to/from states	Warning against or restrictions to travel between states	March 17, 2020 AK
10	Ceasing non-emergency medical and dental procedures	Any surgeries, evaluations, etc. that aren't to save lives are canceled	March 18, 2020 OH
11	Non-essential business closure (stay-at-home order)	Any business that is not essential should be closed	March 19, 2020 CA
12	Safer-at-home order	Usually enacted as a less extreme stay-at-home, non-essential businesses can open	March 19, 2020 CA
13	Mandatory social distancing protocols for businesses	If businesses are to open, they must provide personal protection equipment for workers, adhere to social distancing policies, restrict the number of people inside the facilities, and alert the Public Health Department if workers test positive. Also, all workers who can perform their jobs from home should work remotely	March 24, 2020 VA
14	Social distancing/gatherings and meetings restrictions	Gatherings with members outside the household are prohibited	April 4, 2020 AL
15	Re-opening guidelines	Guidelines for child care facilities, entertainment venues, tourist attractions, and camps serving children and teens	April 16, 2020 WV
16	Face covering requirement outdoor and indoor (public) areas	Everyone over an acceptable age is required to wear a cloth face covering in	April 17, 2020 NY

Epidemiological analysis

Compartmental models are frequently used to model infectious diseases.[32] One such model, the Susceptible-Infectious-Recovered (SIR) model, has been used since the beginning of the COVID-19 pandemic to predict the spread[13,33-35] and simulate the progress of COVID-19.[36,37] However, the SIR model fails to consider the latent phase - when the individual is infected but not yet infectious - which is an important period in the case of COVID-19.[38] Adding a latent/exposed population can incorporate the latent phase within the SIR model. In this way, infected individuals move from susceptible to exposed to infected.[39,40] As such, the Susceptible-Exposed-Infectious-Recovered (SEIR) model is defined by four coupled nonlinear ordinary differential equations (ODEs) as below:[41]

$$\frac{dS(t)}{dt} = -\frac{\beta S(t)I(t)}{N} \quad \text{(eq. 1)}$$

$$\frac{dE(t)}{dt} = \frac{\beta S(t)I(t)}{N} - \sigma E(t) \quad \text{(eq. 2)}$$

$$\frac{dI(t)}{dt} = \sigma E(t) - \gamma I(t) \quad \text{(eq. 3)}$$

$$\frac{dR(t)}{dt} = \gamma I(t) \quad \text{(eq. 4)}$$

where N, S, E, I, and R represent the number of individuals in the population who are susceptible, exposed, infectious, and removed (recovered/deceased), respectively. Also, b, s, and g are the contact, infection, and recovery rates, respectively. In the present study, to perform the SEIR model, we recall the ODEs (eqs. 1-4) in python[TM] and initialize the parameters E_0, I_0, and R_0. In this regard, for every simulation, we assumed the number of susceptible individuals equals the corresponding regional population collected from the U.S. Census Bureau.[42] Also, the number of exposed, infected, and recovered individuals on the first day of the study period was set at 1, 0, and 0, respectively. It should be noted that these assumptions are used to merely initialize the values in the model and all the values are updated during the iteration based on the real data.

To provide a reliable result for each state, the general SEIR model needed to be trained for every state using the corresponding reported state data. Otherwise, there would have been no differentiation among the contact rates (b). To train the model based on the available death data, we added the case fatality rate (CFR, the proportion of people who die from a specified disease among all individuals diagnosed with the disease over a certain period). Based on the CFR estimations for COVID-19 reported in the literature, we initialized the CFR to be 0.01% of the total population.[43,44] Later, we implemented an optimizer using the least squares method to minimize the difference between the predicted and actual daily death rate for every state. In reality, due to the implementation of anti-contagion policies, the contact rate (b) and basic reproduction number (R_0, the number of secondary cases an individual would produce in a completely susceptible population[45,46]) are not constant. Therefore, we defined b as time-dependent, representing the effective reproduction number (R_t, the number of secondary cases an individual would produce at any specific time[46,47]). Having a time-dependent contact rate increases the reliability of the model with the real-life situation.[48] Moreover, to estimate the values of incubation periods (i.e., the period of the days from the time the individual is exposed to the virus to the onset of symptoms) and infectious periods (i.e., the period in which an individual is infectious), we examined several studies[49-52] and considered the corre-

sponding values to be 3 days and 10 days, respectively. Accordingly, both infection (s) and recovery rates (g), which are defined as the reciprocal of incubation and infectious periods, were calculated. As a result, the daily total number of susceptible, exposed, infected, and recovered cases for every state were estimated. We used the total numbers of daily infected cases for every state as response values to perform the statistical analysis.

There are four categories of infected cases, including non-diagnosed symptomatic, non-diagnosed asymptomatic, diagnosed symptomatic, and diagnosed asymptomatic.[53] According to previous studies[54-56] and the CDC,[57] most people who were infected with COVID-19 were asymptomatic, and daily reported cases mainly included those symptomatic since they were the individuals more likely to get tested.[58] To perform comprehensive modeling, our modified SEIR model considered all those categories and represents the total number of daily infected cases for every state. We used this number as the response values for performing our statistical analysis. Also, to evaluate the overall effect of anti-contagion policy implementation, we used the SEIR model in two different scenarios. First, we considered every state's total population to predict the daily number of infected cases if there were no policies in effect. Next, we evaluated the daily number of infected cases
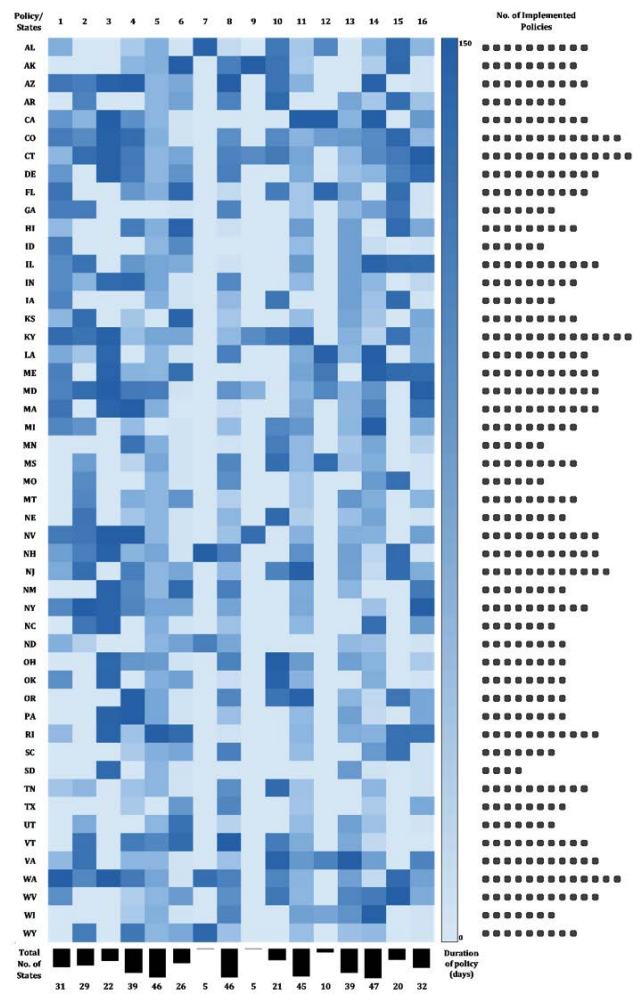

Figure 1. The duration of every policy in every state during the study period. States are ordered alphabetically based on their abbreviations.

with the policies in effect. Implementing the anti-contagion policies impacts both the number of daily cases and daily deaths. Since the reported number of infected cases (i.e., number of infected cases reported on data sources for each state) was not an accurate representation of the total infected cases, we used the daily reported deaths data to optimize the SEIR model. As a result, having the data of both scenarios, we calculated the policy ratio, or the average ratio of total infected cases when no policy was in effect compared to when policies were implemented, as follows:

$$Policy\ Ratio\ (PR) = \frac{\sum_{March\ 1}^{July\ 31} \frac{I_{np} - I_p}{I_{np}}}{period\ of\ time} \qquad (eq.\ 5)$$

where I_{np} is the total number of daily infected cases when there is no policy in effect and I_p is the total number of daily infected cases when policies are implemented. The larger policy ratio represents the greater potential effect of policies in controlling COVID-19.

Figure 2 shows the flow diagram of the modified SEIR model developed in this study.

Statistical analysis

To perform the statistical analysis, we defined the predictors (implemented anti-contagion policies) as categorical variables either in-effect or suspended. We used our modified SEIR model outcomes (i.e., the daily number of total infected cases) as response values to investigate every policy's potential effect in each U.S. state using statistical analysis. To find a statistically significant association between our predictors and response values, the appropriate regression modeling, either Negative Binomial Regression Modeling (NBRM) or Poisson Regression Modeling (PRM), was selected depending on data equidispersion or overdispersion.[59,60] All the analyses were performed considering 95% confidence intervals (95% CI). We evaluated both tolerance and the variance inflation factors to diagnose the collinearity in multiple regression by observing the R^2 of regressing one predictor on all other predictors throughout the analysis. Accordingly, we removed all statistical noise (i.e., random irregularity). To investigate the effect of any probable noise and outlier, we examined the models using Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). All statistical analyses were performed using SPSS (International Business Machines Corporation (IBM), Armonk, NY, USA). As a result, after removing noises and checking all the criteria [e.g., p-value (<0.05), CI (95%)], we determined which policies and to what extent they decreased the number of daily infected cases for every state of the U.S. throughout the study period. Accordingly, we demonstrated the most effective anti-contagion policies in control of COVID-19 across the nation.

Results

The most effective policies

Our findings reveal that among all policies, mandatory quarantine upon entering a state (order No. 6; see Table 1), businesses implementing social distancing protocols (order No. 13), and mandatory mask use (order No. 16) are the policies associated with reducing COVID-19 spread. There was a significant association between policy implementation and reduction in the total number of infected cases in the country for 55%, 75%, and 45% of the states that implemented mandatory quarantine upon entering a

state, businesses implementing social distancing protocols, and mandating mask use, respectively.

To reveal specific policy action that may help explain slowing the spread of infection, Figure 3 demonstrates the states which showed a significant decrease in the number of infected cases after implementing orders 6, 13, and 16. The findings suggested that implementing those policies is associated with an average 40%
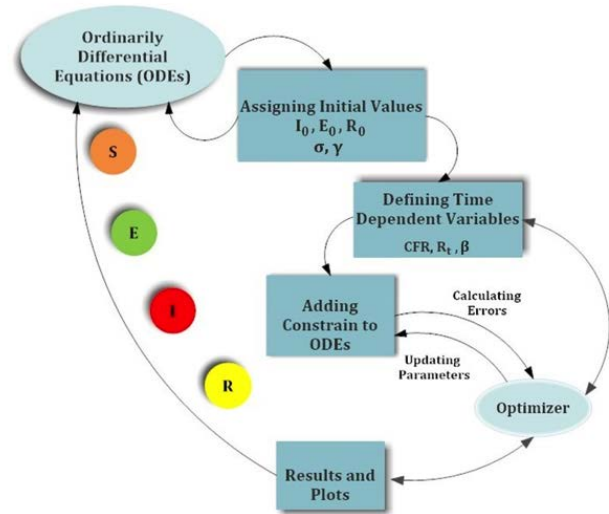

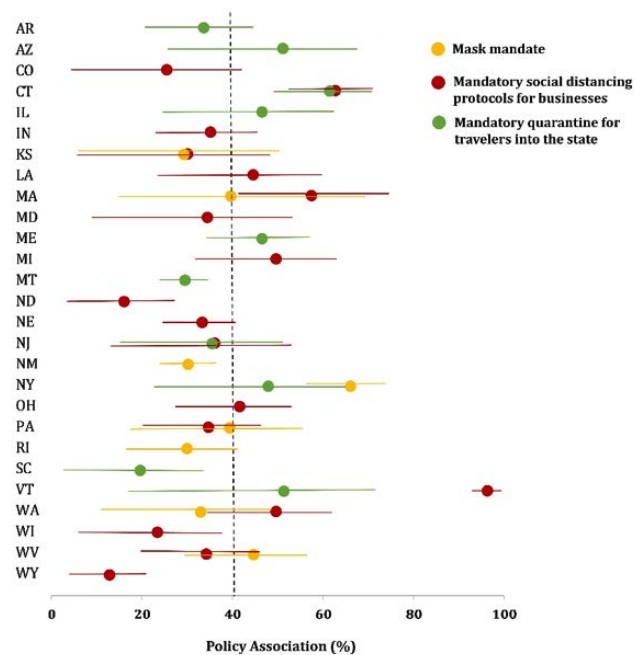**Figure 2. Flow diagram of modified SEIR model.**

Figure 3. The association of each of three policies (mandating mask use, businesses implementing social distancing protocols, and mandatory quarantine upon entering a state) with a reduction in the number of COVID-19 infected cases. The colored lines represent the upper and lower bounds of the association. Also, the vertical dashed line demonstrates the average value of association for all states shown here.

reduction in the total number of infected cases. Zeroing in on one state, for example, New York, shows that mandating mask use was associated with a 66% decrease in the total number of infected cases. Similarly, implementing the mandatory quarantine upon entering a state was associated with a 48% reduction in the total number of infected cases in New York. Supplementary Table S1 presents the details of the multivariable binomial regression analyses, including the incidence rate ratio (i.e., the exponents of coefficients in the multiplicative Poisson model) and standard error for orders 6, 13, and 16.

Novel policy ratio index

We defined and calculated a policy ratio (the average ratio of total infected cases when no policy was in effect compared to when policies were implemented - see Methods) for every state to represent the overall association of policy implementation with controlling the spread of COVID-19. Figure 4 demonstrates the value of the policy ratio calculated for each U.S. state. Alaska had the greatest impact (policy ratio: 3666), and South Dakota had the least impact (policy ratio: 17) from policy implementation, respectively. Also, this figure shows policies are more effective in states with less population density since the probability of getting infected in populated areas is higher than areas with less population density (this is mainly because the COVID-19 is highly infectious). As a result, the virus can rapidly spread compared to areas with lower population density.

Figure 5 compares the cumulative number of infected cases considering two different scenarios - one if there were no policies in effect (Figure 5a) and one with policies implemented (Figure 5b). Considering our calculated policy ratio and the cumulative number of infected cases reported by the end of July,[30] we estimated the total number of infected cases when no policies were in effect. We estimate that implementing policies was associated with an average 58% reduction in the total number of infected cases (average of the column titled "Estimated reduction in the number of infected cases due to implementing policies (%)" in

Supplementary Table S2). Figure 5, indicates that the implementation of anti-contagion policies was associated with nearly 10.8 million fewer Americans becoming infected by July 31, 2020 which highlights the importance of policies in controlling the spread of the virus.

According to research by Ioannidis,[61] the COVID-19 infection fatality ratio (IFR; i.e., the proportion of deaths among all infected individuals) for the locations with mortality rates less than the global average (i.e., <118 deaths/million) and high death rate (i.e., more than 500 deaths per million) is 0.20 and 0.57%, respectively. Johns Hopkins Coronavirus Resource Center[29] reported that the mortality rate of COVID-19 in the U.S. is more than 500 deaths per million. Therefore, considering the total number of infected cases when no policies were in effect (predicted by the present study) and 0.57% as the IFR, implementing the examined policies was associated with 61,560 fewer deaths nationwide as of July 31, 2020. Based on other estimations of IFR by Russel et al.[62] at 1.3% for all the ages combined and Brazeau et al.[63] at 1.15% (for high-income countries), the number of fewer deaths nationally associated with implementing the policies may have been as many as 140,000. Supplementary Table S2 presents the cumulative number of reported and predicted infected cases and deaths considering two policy implementation scenarios.

We evaluated the relation between our policy ratio and both normalized reported number of cases and deaths across the nation. Results demonstrated a significant negative association between policy ratio and those two criteria. This means the higher policy ratio is associated with fewer infected cases and deaths, which confirms the association of policy implementation with reducing COVID-19 spread (p<0.05). Additionally, we investigated the relationship between the state policy ratio and population density. The correlation analysis exhibited a significant negative association (p<0.05), demonstrating that policies have a greater association with reducing COVID-19 spread in the states with less population density. To test this correlation, using the modified SEIR model developed here, we calculated the effective reproduction number
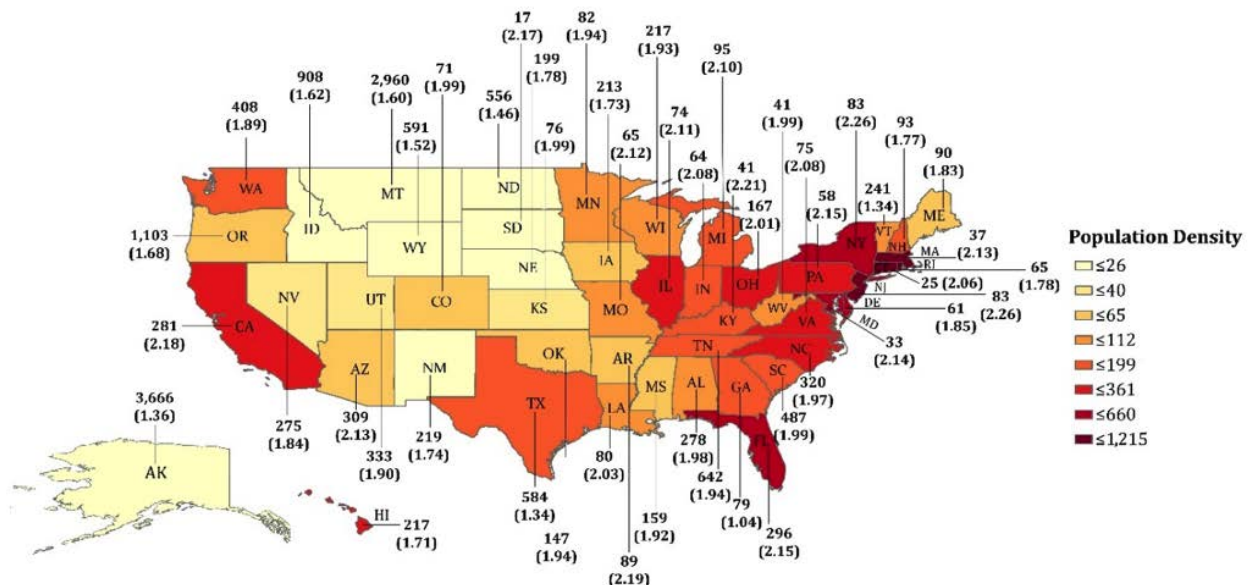

Figure 4. The distribution of policy ratio and population density over the study period (March 1 to July 31, 2020). The average effective reproduction number (R_t) for every state is presented in parenthesis.

(R_t) over the study period in the states with greatest population density, including New Jersey (2.26), Rhode Island (1.78), and Massachusetts (2.13), and the least population density, including Montana (1.60), Wyoming (1.52) and Alaska (1.36). Our findings indicated that, on average, the effective reproduction number was 40% higher in states with the largest population density. This confirms an increase in the probability of becoming infected in more populated areas and, accordingly, a decrease in the potential of anti-contagion policies controlling COVID-19 in these areas. This finding is consistent with other research study by Hu *et al.* that showed that contact rates tend to increase with density.[64] Figure 4 presents the population density distribution, the policy ratio, and the average effective reproduction number for each state.

Discussion and Conclusions

We have presented COVID-19 case outcomes as they relate to the top 16 anti-contagion policies implemented in each of the U.S. states from March 1, 2020 through July 31, 2020. This study differs from other COVID-19 epidemiology and policy studies in that we modified the SEIR model and combined it with a comprehensive statistical analysis to better capture symptomatic and asymptomatic cases and examine, for the first time, the association of all the major policies implemented in the U.S. states with COVID-19 spread during the first six months of the pandemic. Additionally, we predicted the total number of COVID-19 infected cases and deaths if no policies were implemented to highlight the potential impact of anti-contagion policies in controlling COVID-19 in the U.S. Moreover, we calculated the average effective reproduction number for every U.S. state, indicating the number of secondary infections likely to occur from a single infection in every state.

Our findings show the policies of mandating mask use, businesses implementing social distancing protocols, and mandatory quarantine upon entering a state were associated with an average 40% reduction in the total number of infected cases. Additionally, policies implemented across the states may have saved nearly 10.8 million people from being infected. Considering different IFRs reported by other research studies and our estimated number of infected cases, results demonstrated that policies may have been associated with 140,000 fewer deaths nationwide. Note that previous studies based reported IFR values based on symptomatic cases only.[65] Yet, the majority of COVID-19 infected cases are asymptomatic.[28] Therefore, using the previously reported values of IFR, we expected the number of estimated deaths (Supplementary Table S2) to be more than the reported number of deaths for all the U.S. states; however, it is not. The lower-than-expected reported number of deaths could be due to various other factors, such as population density, age, race, and ethnicity. We also calculated the average effective reproduction number for all U.S. states, and our results demonstrated a direct association between the population density and the effective reproduction number. This finding is not surprising given that when individuals are in closer proximity to one another, the droplet transmission and airborne transmission increase causing an acceleration in the spread of the virus.[66] The policies of mask-wearing and businesses implementing social distancing found potentially effective in this study are consistent with other U.S. anti-contagion policy observational studies.[67,68] However, our study provides even greater evidence for these policies because our epidemiological and statistical analysis accounted for many infected cases not included in other studies, which depended only on reported COVID-19 rates.

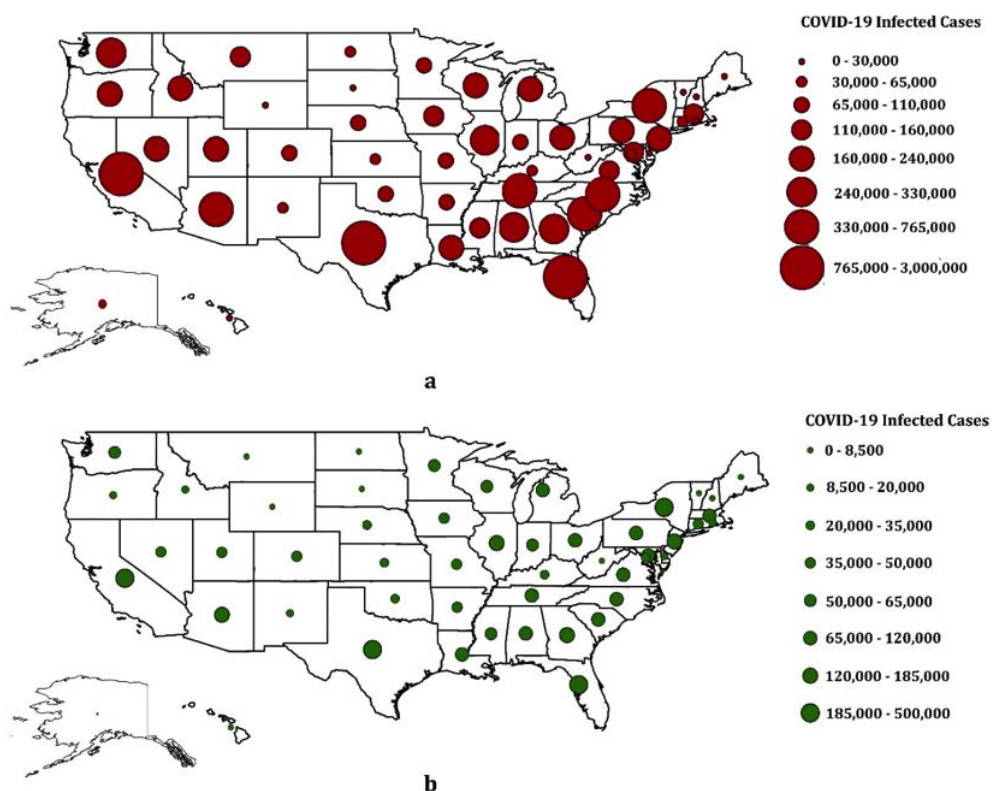Several policies examined in this study did not show signifi-

Figure 5. The cumulative number of infected cases: a) no policies; b) policies in effect.

cant associations with reducing the number of infected cases across the U.S. One such policy that stands out is school closure which has sparked much debate throughout the COVID-19 pandemic.[69] Research based on previous influenza viruses indicated children would be major spreaders of the coronavirus.[70] However, the evidence produced since states first implemented school closure in mid-March 2020 supports our findings and indicates children are at significantly less risk for COVID-19 infection.[71,72] However, children's role in spreading the disease remains unclear.[73]

Further evidence that school closure may not be significantly linked to increasing infection rates can be seen in Europe when, throughout the fall of 2020, in contrast to the widespread canceling of in-person education in the U.S., schools remained opened using safety precautions like mask-wearing and ventilation without it significantly accelerating disease spread.[74] Experts have criticized school closures, arguing that closing schools may have caused social, economic, and health problems even more common and more severe than those due to COVID-19,[75] including increased risk of loneliness, addiction to videogames and binge-watching, alteration of circadian rhythms, direct or assisted domestic violence, and academic achievement gaps.[76-78] In learning from past pandemic research, a 2014 review by Mangtani[79] commissioned by the Department of Health in England (now known as the Department of Health and Social Care) concluded that "the benefit of school closure in reducing clinically important outcomes needs to be balanced against secondary adverse effects."

Social distancing (i.e., prohibiting gatherings with members outside the household), non-essential business closure (stay-at-home order), and safer-at-home orders were three other prominent policy areas not associated with a significant reduction in COVID-19 spread. One reason for these findings may be the difficulty with grouping the many types and levels of social distancing measures or restricting people to their homes into just one or two categories. The various aspects such as geographic level of examination, COVID-19 incidence rates at the time of implementation, duration, frequency, and intensity of such orders make evaluative studies on these policies difficult to compare to one another. For example, Thu et al.[80] reported a wide variation in the effectiveness of social distancing measures between ten highly infected countries. Additionally, the timing of social distancing, business closure, and safer-at-home orders in terms of how soon after the first reported case and how frequently (continuous versus intermittent) the policy is implemented can impact their effectiveness in reducing infection spread.[81]

The lack of accurate data about COVID-19 cases, especially asymptomatic cases, in the U.S.,[82] posed a challenge to verifying our epidemiologic model's case and death values. While we used existing data to estimate these values, we can further analyze their precise association with policy implementation as more accurate retrospective case data becomes available over time. A limitation of this study is that the data does not account for the interactions between policies. We recommend future investigation into the interplay of policies to determine potential synergies and conflict, rollout approach, and communication strategies to emphasize prioritization. This analysis focuses mainly on COVID-19 infected cases and also considers deaths. However, we did not examine hospitalizations. Future investigations should include hospitalizations to represent severity and, together with health system capacity data, identify inadequacies in medical care to inform medical response-related policies.

The ultimate goal of this research is to help inform discussion about further policy actions state and national governments can take to curb infection spread now and during future pandemics.

With 3 out of 16 (19%) of the examined policies accounting for the majority (about 75%) of positive policy-related impact on COVID-19, Pareto's principle,[83] or the "80/20 rule," surfaces here. As the country continues reopening businesses and schools, decision-makers should focus on policies emphasizing mask-wearing, social distancing, and quarantining travelers as they may have the greatest chance of preventing the spread of COVID-19.

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References

1. Centers for Disease Control and Prevention; COVID Data Tracker 2021 [cited 2021 Feb. 1]. Available from: https://covid.cdc.gov/covid-data-tracker/#datatracker-home

2. Holshue ML, DeBolt C, Lindquist S, et al. First case of 2019 novel coronavirus in the United States. N Engl J Med 2020;382:929-36.

3. Porcher S. Response2covid19, a dataset of governments' responses to COVID-19 all around the world. Sci Data 2020;7:423.

4. Hale T, Petherick A, Phillips T, Webster S. Variation in government responses to COVID-19. BSG Working Paper 2020;31:2020-11.

5. Hsiang S, Allen D, Annan-Phan S, et al. The effect of large-scale anti-contagion policies on the COVID-19 pandemic. Nature 2020;584:262-7.

6. Korolev I. Challenges with estimating the effect of anti-contagion policies on the COVID-19 pandemic. (2022). Available from: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3659623

7. Liao Z, Lan P, Liao Z, et al. TW-SIR: time-window based SIR for COVID-19 forecasts. Sci Rep 2020;10:1-15.

8. Bizzarri M, Di Traglia M, Giuliani A, et al. New statistical RI index allow to better track the dynamics of COVID-19 outbreak in Italy. Sci Rep 2020;10:22365.

9. Rădulescu A, Williams C, Cavanagh K. Management strategies in a SEIR-type model of COVID 19 community spread. Sci Rep 2020;10:21256.

10. Bhanot G, DeLisi C. Predictions for Europe for the Covid-19 pandemic from a SIR model. medRxiv 2020.

11. Peng L, Yang W, Zhang D, et al. Epidemic analysis of COVID-19 in China by dynamical modeling. 2020. arXiv preprint arXiv:200206563.

12. Barbarossa MV, Fuhrmann J, Meinke JH, et al. Modeling the spread of COVID-19 in Germany: Early assessment and possible scenarios. PloS One 2020;15:e0238559.

13. Cooper I, Mondal A, Antonopoulos CG. A SIR model assumption for the spread of COVID-19 in different communities. Chaos Solitons Fractals 2020;139:110057.

14. Wang J. Mathematical models for COVID-19: Applications, limitations, and potentials. J Public Health Emerg 2020;4:9.

15. Centers for Disease Control and Prevention. Ending isolation and precautions for people with COVID-19: Interim guidance. 2021. [cited 2021 Feb. 1]. Available from: https://www.cdc.gov/coronavirus/2019-ncov/hcp/duration-isolation.html

16. Chaudhry R, Dranitsaris G, Mubashir T, et al. A country level analysis measuring the impact of government actions, country preparedness and socioeconomic factors on COVID-19 mortality and related health outcomes. EClinicalMedicine 2020;25:100464.

17. VoPham T, Weaver MD, Hart JE, et al. Effect of social distancing on COVID-19 incidence and mortality in the US. MedRxiv 2020.

18. Chinazzi M, Davis JT, Ajelli M, et al. The effect of travel restrictions on the spread of the 2019 novel coronavirus (COVID-19) outbreak. Science 2020;368:395-400.

19. Fowler JH, Hill SJ, Levin R, Obradovich N. The effect of stay-at-home orders on COVID-19 cases and fatalities in the United States. medRxiv 2020.

20. Giordano G, Blanchini F, Bruno R, et al. Modelling the COVID-19 epidemic and implementation of population-wide interventions in Italy. Nat Med 2020;26:855-60.

21. Tang B, Wang X, Li Q, et al. Estimation of the transmission risk of the 2019-nCoV and its implication for public health interventions. J Clin Med 2020;9:462.

22. Kraemer MU, Yang C-H, Gutierrez B, et al. The effect of human mobility and control measures on the COVID-19 epidemic in China. Science 2020;368:493-7.

23. Ferguson N, Laydon D, Nedjati-Gilani G, et al. Report 9: Impact of non-pharmaceutical interventions (NPIs) to reduce COVID19 mortality and healthcare demand. Imperial College London 2020;10:77482.

24. Li R, Pei S, Chen B, et al. Substantial undocumented infection facilitates the rapid dissemination of novel coronavirus (SARS-CoV-2). Science 2020;368:489-93.

25. STATESIDE. Introducing State Snapshot: A COVID-19 Report 2020. [cited 2020 Jul. 31]. Available from: https://www.stateside.com/blog/introducing-state-snapshot-covid-19-report

26. Multistate [Internet]. COVID-19 Policy Dashboard 2020 [cited 2020 Jul. 31]. Available from: https://www.multistate.us/research/covid/public/

27. Kaiser Family Foundation. State COVID-19 Data and Policy Actions 2020 [cited 2020 Jul. 31]. Available from: https://www.kff.org/coronavirus-covid-19/issue-brief/state-covid-19-data-and-policy-actions/

28. Centers for Disease Control and Prevention 2020 [cited 2020 Jul. 31]. Available from: https://www.cdc.gov/

29. Johns Hopkins Coronavirus Resource Center 2020 [cited 2020 Jul. 31]. Available from: https://coronavirus.jhu.edu/

30. The New York Times Coronavirus (Covid-19) Data in the United States 2020 [cited 2020 Jul. 31]. Available from: https://github.com/nytimes/covid-19-data/

31. Worldometer [Internet]. Real time world statistics 2020 [cited 2020 Jul. 31]. Available from: https://www.worldometers.info/coronavirus/

32. Tolles J, Luong T. Modeling epidemics with compartmental models. JAMA 2020;323:2515-6.

33. Anand N, Sabarinath A, Geetha S, Somanath S. Predicting the spread of COVID-19 using SIR model augmented to incorporate quarantine and testing. Trans Ind Natl Acad Eng 2020;5:141-8.

34. Chen Y-C, Lu P-E, Chang C-S, Liu T-H. A time-dependent SIR model for COVID-19 with undetectable infected persons. IEEE Trans Netw Sci Eng 2020;7:3279-94.

35. Jia W, Han K, Song Y, et al. Extended SIR prediction of the epidemics trend of COVID-19 in Italy and compared with Hunan, China. Front Med (Lausanne) 2020;7:169.

36. Das S. Prediction of covid-19 disease progression in india: Under the effect of national lockdown. 2020. arXiv preprint arXiv:200403147.

37. Nguemdjo U, Meno F, Dongfack A, Ventelou B. Simulating the progression of the COVID-19 disease in Cameroon using SIR models. PloS One 2020;1):e0237832.

38. Kaddar A, Abta A, Alaoui HT. A comparison of delayed SIR and SEIR epidemic models. Nonlinear Analysis Modelling Control 2011;16:181-90.

39. Biswas MHA, Paiva LT, De Pinho M. A SEIR model for control of infectious diseases with constraints. Math Biosci Eng 2014;11:761.

40. Sun C, Hsieh Y-H. Global analysis of an SEIR model with varying population size and vaccination. Appl Math Modell 2010;34:2685-97.

41. Li MY, Muldowney JS. Global stability for the SEIR model in epidemiology. Math Biosci 1995;125:155-64.

42. U.S. Census Bureau. 2020 [cited 2020 Jul. 31]. Available from:

https://www.census.gov/data.html

43. Carcione JM, Santos JE, Bagaini C, Ba J. A simulation of a COVID-19 epidemic based on a deterministic SEIR model. 2020. arXiv preprint. arXiv:200403575.

44. Wilson N, Kvalsvig A, Barnard LT, Baker MG. Case-fatality risk estimates for COVID-19 calculated by using a lag time for fatality. Emerg Infect Dis 2020;26:1339-41.

45. Dietz K. The estimation of the basic reproduction number for infectious diseases. Stat Methods Med Res 1993;2:23-41.

46. Daley DJ, Gani J. Epidemic modelling: an introduction: Cambridge University Press; 2001.

47. Nishiura H, Chowell G. The effective reproduction number as a prelude to statistical estimation of time-dependent epidemic trends. In: G Chowell, JM Hyman, LMA Bettencourt, C Castillo-Chavez, Editors. Mathematical and statistical estimation approaches in epidemiology. Springer: 2009; p. 103-21.

48. Grimm V, Heinlein A, Klawonn A, et al. Estimating the time-dependent contact rate of SIR and SEIR models in mathematical epidemiology using physics-informed neural networks. 2020. Available from: https://kups.ub.uni-koeln.de/12159/

49. Lauer SA, Grantz KH, Bi Q, et al. The incubation period of coronavirus disease 2019 (COVID-19) from publicly reported confirmed cases: estimation and application. Ann Int Med 2020;172:577-82.

50. Lei S, Jiang F, Su W, et al. Clinical characteristics and outcomes of patients undergoing surgeries during the incubation period of COVID-19 infection. EClinicalMedicin. 2020;21:100331.

51. McAloon C, Collins Á, Hunt K, et al. Incubation period of COVID-19: a rapid systematic review and meta-analysis of observational research. BMJ Open 2020;10:e039652.

52. World Health Organization. Transmission of SARS-CoV-2: implications for infection prevention precautions: scientific brief. 2020. Available from: https://www.who.int/news-room/commentaries/detail/transmission-of-sars-cov-2-implications-for-infection-prevention-precautions

53. Giordano G, Blanchini F, Bruno R, et al. Modelling the COVID-19 epidemic and implementation of population-wide interventions in Italy. Nat Med 2020;26:855-60.

54. Kim G-u, Kim M-J, Ra SH, et al. Clinical characteristics of asymptomatic and symptomatic patients with mild COVID-19. Clin Microbiol Infect 2020;26:948.e1-e3.

55. Wu Z, McGoogan JM. Asymptomatic and pre-symptomatic COVID-19 in China. Infect Dis Poverty 2020;9:72-3.

56. Yang R, Gui X, Xiong Y. Comparison of clinical characteristics of patients with asymptomatic vs symptomatic coronavirus disease 2019 in Wuhan, China. JAMA Netw Open 2020;3:e2010182.

57. Centers for Disease Control and Prevention. COVID-19 Science Update released 2020. [cited 2020 Nov. 17]. Available from: https://www.cdc.gov/library/covid19/111720_covidupdate.html/

58. Buitrago-Garcia D, Egli-Gany D, Counotte MJ, et al. Occurrence and transmission potential of asymptomatic and presymptomatic SARS-CoV-2 infections: A living systematic review and meta-analysis. PLoS Med 2020;17:e1003346.

59. Lawless JF. Negative binomial and mixed Poisson regression. Can J Statistics 1987;15:209-25.

60. Consul P, Famoye F. Generalized Poisson regression model. Commun Stat-Theor M 1992;21:89-109.

61. Ioannidis J. The infection fatality rate of COVID-19 inferred from seroprevalence data. Bull World Health Organ 2021;99:19-33F.

62. Russell TW, Hellewell J, Jarvis CI, et al. Estimating the infection and case fatality ratio for coronavirus disease (COVID-19) using age-adjusted data from the outbreak on the Diamond Princess cruise ship, February 2020. EuroSurveillance 2020;25:2000256.

63. Brazeau N, Verity R, Jenks S, et al. Report 34: COVID-19 infection fatality ratio: estimates from seroprevalence. Imperial College London 2020. Available from: https://www.imperial.ac.uk/media/imperial-college/medicine/mrc-gida/2020-10-29-COVID19-Report-34.pdf

64. Hu H, Nigmatulina K, Eckhoff P. The scaling of contact rates with population density for the infectious disease models. Math Biosci 2013;244:125-34.

65. Basu A. Estimating the infection fatality rate among symptomatic covid-19 cases in the united states: study estimates the covid-19 infection fatality rate at the us county level. Health Affairs 2020;39:77-84.

66. Bahl P, Doolan C, de Silva C, et al. Airborne or droplet precautions for health workers treating COVID-19? J Infect Dis 2020;jiaa189. Online ahead of print.

67. Lyu W, Wehby GL. Community use of face masks and covid-19: evidence from a natural experiment of state mandates in the us: study examines impact on covid-19 growth rates associated with state government mandates requiring face mask use in public. Health Affairs 2020;39:1419-25.

68. Rubin D, Huang J, Fisher BT, et al. Association of social distancing, population density, and temperature with the instantaneous reproduction number of SARS-CoV-2 in counties across the United States. JAMA Netw Open 2020;3:e2016099.

69. Forbes [Internet]. The Frustrating Coronavirus School Opening Debate 2020 [cited 2020 Dec. 7]. Available from: https://www.forbes.com/sites/mikemcshane/2020/12/07/the-frustrating-coronavirus-school-opening-debate/?sh=5b9ecfe42123

70. Esposito S, Cotugno N, Principi N. Comprehensive and safe school strategy during COVID-19 pandemic. Ital J Pediatr 2021;47:6.

71. Viner RM, Mytton OT, Bonell C, et al. Susceptibility to SARS-CoV-2 infection among children and adolescents compared with adults: a systematic review and meta-analysis. JAMA Pediatrics 2020;175:143-56.

72. Gudbjartsson DF, Helgason A, Jonsson H, et al. Spread of SARS-CoV-2 in the Icelandic population. N Engl J Med 2020;382:2302-15.

73. Di Domenico L, Pullano G, Pullano G, et al. Expected impact of school closure and telework to mitigate COVID-19 epidemic in France. EPIcx Lab 2020;15.

74. The Washington Post [Internet]. Europe's schools still open, still relatively safe, through covid-19 second wave 2020 [cited 2020 Dec. 1]. Available from: https://www.washingtonpost.com/world/europe/europe-schools-covid-open/2020/12/01/4480a5c8-2e61-11eb-9dd6-2d0179981719_story.html/

75. Esposito S, Principi N. School closure during the coronavirus disease 2019 (COVID-19) pandemic: an effective intervention at the global level? JAMA Pediatrics 2020;174:921-2.

76. Poletti M, Raballo A. COVID-19 and effects of school closure for children and their families: a deafening silence. JAMA Pediatr 2021;175:210.

77. Van Lancker W, Parolin Z. COVID-19, school closures, and child poverty: a social crisis in the making. Lancet Public Health 2020;5:e243-e4.

78. Armitage R, Nellums LB. Considering inequalities in the school closure response to COVID-19. Lancet Global Health

2020;8:e644.

79. Department of Health. Impact of school closures on an influenza pandemic. Scientific evidence base review. 2014. Available from: https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/316203/School_Closures_Evidence_review.pdf

80. Thu TPB, Ngoc PNH, Hai NM. Effect of the social distancing measures on the spread of COVID-19 in 10 highly infected countries. Sci Total Environ 2020;742:140430.

81. Medline A, Hayes L, Valdez K, et al. Evaluating the impact of stay-at-home orders on the time to reach the peak burden of Covid-19 cases and deaths: does timing matter? BMC Public Health 2020;20:1750.

82. Schneider EC. Failing the test - The tragic data gap undermining the US pandemic response. N Engl J Med 2020;383:299-302.

83. Dunford R, Su Q, Tamang E. The pareto principle. Plymouth Stud Sci. 2014;7:140-8.

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