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# Policy Interventions, Social Distancing, and SARS-CoV-2 Transmission in the United States: A Retrospective State-level Analysis



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## ABSTRACT

**Background:** Various non-pharmaceutical interventions (NPIs) such as stay-at-home orders and school closures have been employed to limit the spread of Coronavirus disease (COVID-19). This study measures the impact of social distancing policies on COVID-19 transmission in US states during the early outbreak phase to assess which policies were most effective.

**Methods:** To measure transmissibility, we analyze the average effective reproductive number ( $R_t$ ) in each state the week following its 500th case and doubling time from 500 to 1000 cases. Linear and logistic regressions were performed to assess the impact of various NPIs while controlling for population density, GDP, and certain health metrics. This analysis was repeated for deaths with doubling time to 100 deaths with several healthcare infrastructure control variables.

**Results:** States with stay-at-home orders in place at the time of their 500th case were associated with lower average  $R_t$  the following week compared to states without them ( $p < 0.001$ ) and significantly less likely to have an  $R_t > 1$  (OR 0.07, 95% CI 0.01–0.37,  $p = 0.004$ ). These states also experienced longer doubling time from 500 to 1000 cases (HR 0.35, 95% CI 0.17–0.72,  $p = 0.004$ ). States in the highest quartile of average time spent at home were also slower to reach 1000 cases than those in the lowest quartile (HR 0.18, 95% CI 0.06–0.53,  $p = 0.002$ ).

**Conclusions:** Stay-at-home orders had the largest effect of any policy analyzed. Multivariate analyses with cellphone tracking data suggest social distancing adherence drives these effects. States that plan to scale back such measures should carefully monitor transmission metrics.

**Keywords:** COVID-19; SARS-CoV-2; Coronavirus; Novel coronavirus; Public policy; Social distancing; Non-pharmaceutical interventions; Stay-at-home order; School closure; Non-essential business closure; Limitations on mass gatherings. [Am J Med Sci 2021;361(5):575–584.]

## INTRODUCTION

Coronavirus disease 2019 (COVID-19), caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), was first reported in Wuhan, China in December 2019.<sup>1</sup> It quickly spread globally, and was characterized as a pandemic by the World Health Organization (WHO). Local and national governments worldwide have employed a variety of non-pharmaceutical interventions (NPIs) to mitigate the impact of this novel coronavirus. Mandated policies including limitations on mass gatherings, business closures, and stay-at-home orders aimed to encourage social distancing and “flatten the curve”.<sup>2–4</sup>

By April 30, 2020, over 3249,000 COVID-19 cases had already been confirmed worldwide, with more than

1067,000 cases and 62,000 resulting deaths in the United States.<sup>5</sup> In an effort to contain the virus, broad shutdowns resulted in severe economic impacts including 26 million Americans filing for unemployment within a 5 week period.<sup>6</sup> Simultaneously, there is concern that quarantine puts people at increased risk of domestic violence and severe psychological suffering, as well as physical inactivity, weight gain, behavioral addiction disorders, and insufficient sunlight exposure.<sup>7–12</sup> It is therefore important to quantify the effects of early, proactive social distancing measures on disease spread in order to guide future policy decisions which may continue to limit economic security and healthy lifestyles.

As state and local governments fiercely debate costs and benefits of reopening, it is important to look back at

how disease spread was modulated by differing social distancing policies in the early stages of the epidemic and which policies were most effective. Previous modeling studies have described the importance of social distancing in mitigating the spread of COVID-19,<sup>13–19</sup> and these findings have been supported by case data.<sup>2,20–22</sup> Mandated NPIs have also been associated with reduced transmission,<sup>23</sup> presumably due to subsequent reductions in community mobility.<sup>3</sup> However, little has been done to characterize the impact of NPIs in states with poor compliance. Furthermore, efforts to quantify the effects on transmission have not accounted for different stages of outbreak, discounting that the effectiveness of policy changes will likely differ if they are instituted in the context of 20 cases or 10,000. This study accounts for the stage of disease spread by selecting a normalized point on the epidemic curve, analyzing each state in the week following its 500th case and assessing how different NPIs influence the burgeoning case load early in outbreaks.

## METHODS

### Measures

In order to retrospectively analyze metrics of early disease spread and mortality, case and death data for all 50 states and the District of Columbia were compiled up to April 30th, 2020 from the Coronavirus Resource Center at Johns Hopkins University. Daily state-level estimates of the virus's effective reproduction number ( $R_t$ ) were collected from Rt.live, a widely-followed online resource that tracks COVID-19 spread and provides real-time estimates of  $R_t$ . Details on their methodology used to calculate  $R_t$  are publicly available online.

To standardize the stage of disease spread and minimize the confounding effect of increased caseload on disease transmission across states, these analyses were conducted in the weeks after each state's 500th case. The 500-case threshold was chosen to ensure that each state had a sustained epidemic.

The primary outcomes were average  $R_t$  in the weeks following 500 cases and doubling time from 500 to 1000 cases, both measures of disease transmission.  $R_t$  is a real-time measure of the average number of infections expected from one case in a susceptible population.

A secondary analysis investigated the effects of NPIs on doubling time from 50 to 100 deaths and case fatality rate. Again, the 50 deaths threshold was chosen to ensure that each state had faced enough COVID-19 spread to experience sustained morbidity. An estimate of case fatality rate was calculated by simply dividing deaths by total cases for each state.

In order to better understand effects of NPIs on social mobility, and the effects of social mobility on disease spread, social distancing metrics were collected from the COVID-19 community mobility reports made available by Google. These reports compare the average time spent in places of residence based on Google location

tracking data compared to the median value, for the corresponding day of the week, during the 5-week period Jan 3–Feb 6, 2020. Averages of these measures were calculated for the week after stay-at-home order to assess the impact of NPI on social distancing. Furthermore, average increase in time spent in residential areas was also calculated for the week before the 500th case to assess the impact of social distancing on disease transmission directly.

### Covariates

We tested the association between change in  $R_t$  and four unique policies: stay-at-home orders, school closures, closure of non-essential businesses, and bans on mass gatherings. Demographic data including population density, population size, and GDP were obtained from publicly available data for each state and territory and examined as covariates in multivariable models. State-wide health information, including the percentage of state residents with diabetes, chronic obstructive pulmonary disease (COPD), current and ever smokers, and cardiovascular disease, were included to control for potential confounding effect. Lastly, the number of hospital beds and physicians per 1000 people were used to control for state-specific health care capacity. These measures were assessed as covariates in the secondary analysis examining case fatality rate.

### Statistical analysis

All analyses were complete in R (Version 1.1.442) and Microsoft Excel. Descriptive statistics are reported using means (standard deviation [SD]) and median (interquartile range [IQR]) for normally and non-normally distributed continuous variables, respectively. The Kruskal Wallis test was used to determine differences for non-normally distributed variables. Policy changes were modeled as dichotomous variables distinguishing states that had implemented each order 1) prior to the 500th case in primary analyses and 2) prior to the 50th death in secondary analyses. Univariable linear regression was used to test the association between each policy change and the primary outcome, average  $R_t$  after a state's 500th case. Average  $R_t$  after the 500th case was then dichotomized into values above and below 1 and evaluated in logistic regression.

To assess the effectiveness of stay-at-home orders at different points in disease outbreak, we also compared changes in  $R_t$  before and after policy intervention by the number of confirmed COVID-19 cases at the time this policy went into effect. Multivariable models were then built to adjust for demographic, state-wide health, and health care capacity covariates. Kaplan Meier survival analysis and the log-rank sum test were used to identify differences in the time to reach the 1000th case. The average% time spent at home was separated into quartiles and the highest and lowest quartiles were compared. Cox proportional hazards regression was then used to test the association between covariates the risk

for reaching 1000 cases. Visual inspection and calculation of the scaled Schoenfeld residuals were used to confirm the proportional hazard assumption. All analyses were then repeated for case fatality rate and time to 100th death. Multivariable models were built by selecting covariates with  $p < 0.1$  in univariable analyses, backwards eliminating covariates with  $p > 0.1$ , and removing collinear variables identified by a variance inflation factor  $> 5$ .

## RESULTS

As of April 30th, 2020, 48 states and the District of Columbia had reached 500 cases and were included in the analysis. Alaska and Montana were excluded because they had not yet reached 500 confirmed COVID-19 cases. Of these states, 15 had stay-at-home orders enacted prior to the date of their 500th case (Table 1). These locations had a significantly smaller median population compared to states without this policy implemented before reaching 500 cases (1,826,156 vs. 5,967,435,  $p = 0.0071$ ). There were no statistically significant differences between states with or without a stay-at-home order in population density, hospital beds per 1000 people, physicians per 1000 people, percent current smokers, percent with COPD, percent with diabetes, or percent with cardiovascular disease.

### NPI effects on disease spread

Average  $R_t$  for all included territories the week prior to implementing stay-at-home orders ( $R_t=1.256$ ) compared to the week following ( $R_t=1.088$ ) was reduced  $-13.3\%$  (absolute change =  $-0.1673$ ,  $SD=0.070$ ). States with stay-at-home orders preceding the date of their 500th case

were negatively associated with average  $R_t$  ( $\beta=-0.15$ , 95% CI  $-0.23$  to  $-0.07$ ,  $p < 0.001$ , Table 2, Fig. 1). Educational facilities closure ( $\beta=-0.17$ , 95% CI  $-0.30$  to  $-0.05$ ,  $p = 0.0081$ ), non-essential business closure ( $\beta=-0.13$ , 95% CI  $-0.21$  to  $-0.05$ ,  $p = 0.0026$ ), and average% time spent at home the week before ( $\beta=-0.02$ , 95% CI  $-0.02$  to  $-0.01$ ,  $p < 0.001$ ) were also associated with a significant reduction in  $R_t$  compared to states without these policies the week following 500 cases. Analysis was repeated with an additional week delay (from days 8 to 14 after 500 cases), which yielded similar results (Table 2).

Policies were enacted in different orders and with varying degrees of overlap. For example, about half of states enacted school closures as the first step in disease prevention, while other states decided to lead with limitations on mass gatherings (Table 3). A few enacted both of these policies at the same time, while no states moved directly to stay-at-home orders or business closures. Overall, there was a spread of policy timing with a slight clustering of school closures and limitations on mass gatherings enacted earlier in pandemic and business closures and stay-at-home orders later (Table 3).

In multivariable analyses, average percent time spent at home during the week before remained a significant predictor of reduction in  $R_t$  ( $\beta=-0.01$ , 95% CI  $-0.02$  to  $-0.01$ ,  $p = 0.0012$ ) when adjusting for stay-at-home orders. However, when evaluating the  $R_t$  with a one-week delay after the 500th case, average percent time spent at home was no longer associated ( $\beta=-0.01$ , 95% CI  $-0.01$  to  $-0.00$ ,  $p = 0.068$ ). Other covariates, including school closures, limitations on mass gatherings, non-essential business closure, population density, and population size were not found to be associated with  $R_t$  when evaluated

**Table 1.** Summary of included states and territories ( $N = 49$ ).

Variable (Median [IQR])	All states and District of Columbia $N = 49$	States without stay-at-home order at 500 cases $N = 34$	States with stay-at-home order at 500 cases $N = 15$	$p$
Population	4,645,184 [1,952,570 to 7,797,095]	<b>5,967,435</b> <b>[3,149,705 to 9,767,915]</b>	<b>1,826,156</b> <b>[1,358,518 to 4,400,391]</b>	<b>&lt;0.0071*</b>
Population density	112.82 [56.93 to 228.02]	110.44 [57.11 to 225.63]	113.96 [56.48 to 253.72]	0.83
Hospital beds per 1000 people	2.50 [2.10 to 3.10]	2.55 [2.10 to 3.18]	2.10 [1.95 to 2.60]	0.088
Physicians per 1000 people	2.74 [2.41 to 3.14]	2.55 [2.10 to 3.18]	3.08 [2.62 to 3.29]	0.13
% Current smokers	17.00 [14.60 to 19.30]	17.15 [14.80 to 19.18]	16.10 [14.70 to 19.30]	0.91
% COPD	6.70 [5.60 to 8.30]	6.50 [5.38 to 8.28]	6.90 [5.95 to 8.30]	0.68
% Diabetes	11.00 [9.90 to 12.50]	10.90 [9.75 to 12.57]	11.00 [10.25 to 12.35]	0.77
% Cardiovascular Disease	4.30 [3.70 to 5.00]	4.30 [3.80 to 5.07]	3.90 [3.65 to 5.00]	0.75

Bolding represents significant demographic differences between state groupings.

Abbreviations: IQR = interquartile range, COPD = chronic obstructive pulmonary disease.

\* =  $p < 0.05$ .

**Table 2.** Linear and logistic regressions assessing the impact of non-pharmaceutical interventions on  $R_t$  following 500 cases.

Covariate	$\beta$ (95% CI)	p	OR (95% CI)	p
Week immediately following 500th Case (days +1 to +7)				
Stay-at-home order	<b>-0.15 (-0.23 to -0.07)</b>	<b>&lt;0.001*</b>	<b>0.07 (0.01 to 0.37)</b>	<b>0.0032*</b>
Limitation on mass gatherings	-0.08 (-0.20 to 0.04)	0.16	Limited sample size	
Educational facilities closure	<b>-0.17 (-0.30 to -0.05)</b>	<b>0.0081*</b>	Limited sample size	
Non-essential business closure	<b>-0.13 (-0.21 to -0.05)</b>	<b>0.0026*</b>	<b>0.09 (0.01 to 0.43)</b>	<b>0.0050*</b>
Average% time spent at home in the week before	<b>-0.02 (-0.02 to -0.01)</b>	<b>&lt;0.001*</b>	0.82 (0.64 to 0.99)	0.069
One-week delay from 500th case (days +8 to +14)				
Stay-at-home order	<b>-0.09 (-0.15 to -0.04)</b>	<b>0.0017*</b>	<b>0.16 (0.04 to 0.58)</b>	<b>0.011*</b>
Limitation on mass gatherings	-0.05 (-0.13 to 0.03)	0.27	0.18 (0.01 to 1.15)	0.11
Educational facilities closure	<b>-0.12 (-0.21 to -0.04)</b>	<b>0.0060*</b>	Limited sample size	
Non-essential business closure	<b>-0.05 (-0.13 to 0.03)</b>	<b>0.0042*</b>	<b>0.21 (0.05 to 0.72)</b>	<b>0.023*</b>
Average% time spent at home in the week before	<b>-0.01 (-0.01 to -0.00)</b>	<b>0.0051*</b>	<b>0.82 (0.67 to 0.95)</b>	<b>0.022*</b>

Bolding represents significant demographic differences between state groupings.  
\* =  $p < 0.05$ .

**Table 3.** Relative timing of non-pharmaceutical policy interventions.

	First policy implemented (# of states)	Average days after first order	Average days before stay-at-home order
Stay-at-home order	0	12.1	0
Limitation on mass gatherings	27	3.16	9.44
Educational facilities closure	28	2.18	10.4
Non-essential business closure	0	9.76	1.85

alongside average time spent at home and therefore were not included in the multivariable model.

We then dichotomized  $R_t$  into values above and below 1 and repeated the analysis with a univariable logistic regression model. In this analysis, implementing a stay-at-home order was associated with a 93% decrease in the odds of having a positive  $R_t$  in the week immediately following the 500th case (OR 0.07, 95% CI 0.01 to 0.37,  $p = 0.0032$ ). The following week also experienced an 84% decrease in the odds of having an average  $R_t$  greater than 1 (OR 0.16, 95% CI 0.04 to 0.58,  $p = 0.011$ ).

In Kaplan Meier analyses, implementation of a stay-at-home order prior to the date of 500 cases was associated with a decreased probability of reaching 1000 cases within 5 days (log rank sum,  $p = 0.02$ ). Similarly, in cox proportional hazards regression, stay-at-home orders correlated with an increase in time to reach 1000 cases (OR 0.32, CI 0.16 to 0.66,  $p = 0.0022$ , Table 4, Fig. 2). States in the highest quartile of average percent time spent at home were also slower to reach 1000 cases (log rank sum,  $p < 0.001$ , HR 0.15, 95% CI 0.05 to 0.47,  $p < 0.001$ ). Other distancing measures did not affect the time from 500 to 1000 cases.

**NPI effects on deaths**

In linear regression, this study found that none of the included policies (stay-at-home orders, school closures, bans on mass gatherings, or closure of non-essential

businesses) were associated with a decrease in case fatality rate (CFR). In Kaplan Meier event analysis, stay-at-home orders were non-significant in predicting time from 50 deaths to 100 deaths (Fig. 3).

**NPI interaction with social distancing**

After the implementation of state-wide stay-at-home orders, the average amount of time spent at home increased by 29.2% relative to the week prior to the order. This translates to an average absolute increase of 4.18% in time spent at home in the week following a stay-at-home order when compared to the previous

**Table 4.** Cox proportional hazards regression for time to event analysis.

Covariate	Time to 1000th Case	
	Hazard ratio (95% CI)	p
Stay-at-home order	<b>0.32 (0.16 to 0.66)</b>	<b>0.0022</b>
Educational facilities closure	0.62 (0.25 to 1.63)	0.33
Non-essential business closure	0.50 (0.25 to 1.10)	0.055
Limitation on mass gatherings	0.63 (0.28 to 1.42)	0.27
Average% time spent at home (Q4 vs. Q1)	<b>0.15 (0.05 to 0.47)</b>	<b>&lt;0.001*</b>

Bolding represents significant demographic differences between state groupings.  
Abbreviations: Q4 = fourth quartile, Q1 = first quartile.  
\* =  $p < 0.05$ .

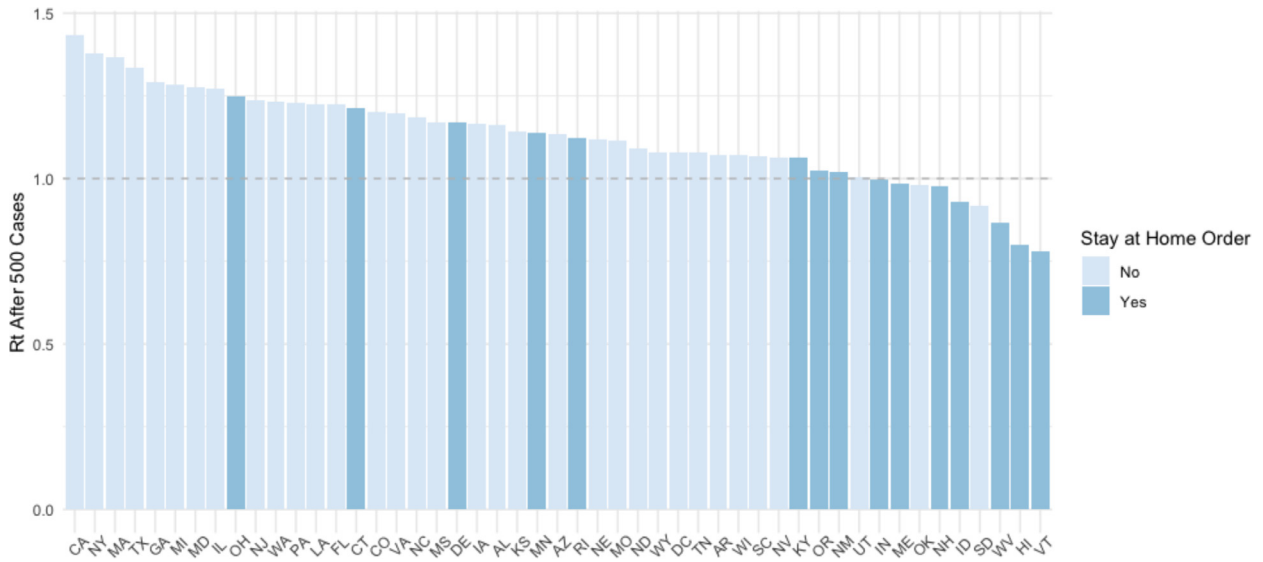


FIGURE 1. Average  $R_t$  during the week following the 500th case by each U.S. state.

week (Fig. 4). School closures, non-essential business closures, and limitations on mass gatherings led to absolute increases of 10.2%, 5.3%, and 8.1%, respectively.

Social distancing adherence varied from state to state even in the wake of similar policy interventions, and this difference in response was influenced by several factors. Of interest, in the week following stay-at-home orders there was less time spent at home in states that voted for the Republican ticket in the 2016 presidential election, 16.9% vs 20.1% ( $p < 0.001$ , Table 5). These represented absolute changes from the week prior to the order of +3.25% and +5.08% for Republican-voting (red) vs Democrat-voting (blue) states, respectively. This did not translate to a significant difference in the change in  $R_t$  from the week prior, but there was a disparity between the total  $R_t$  for red and blue states the week following the stay-at-home order of 1.04 vs 1.14, respectively ( $p = 0.0077$ ) (Table 5).

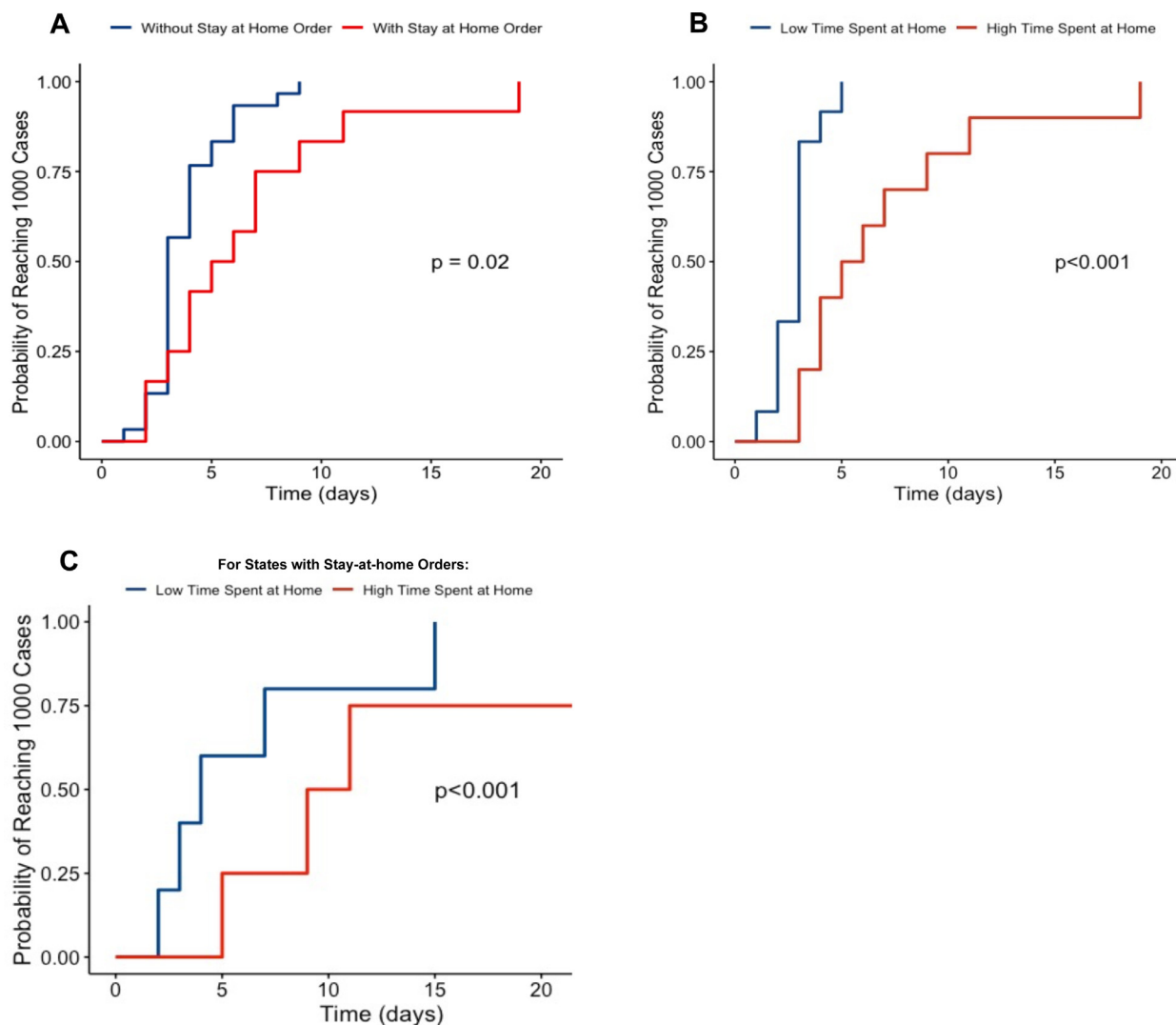
## DISCUSSION

This study analyzes state-level transmission rates of COVID-19 after each state's 500th case, grouping them according to policies implemented prior to their date of 500 cases, in order to determine the effectiveness of various social distancing measures in controlling disease spread in the early outbreak phase. In states that implemented a stay-at-home order prior to reaching 500 cases, we observe a significant decrease in the effective viral transmission rate and an increase in the time to reach 1000 cases. Subsequent multivariable analyses indicate that this effect may have been driven by a state-wide increase in the amount of time spent at home. We found no association between distancing efforts and case fatality rate or doubling time from 50 to 100 deaths.

## Context and contribution

As cases have accumulated around the world, it has become increasingly possible to retrospectively assess the impact of early-implemented NPIs on measured outcomes, comparing the effectiveness of different policies and confirming the scale of their impact. Many previous research studies and news sources characterizing disease burden have relied on the metrics of cumulative case and death counts; however, these metrics are unidirectional and do not account for bidirectional changes in the rate of viral transmission over time, a much more powerful metric for predicting an epidemic's trajectory. In this study, we examine effective reproduction number ( $R_t$ ) as the primary metric of disease burden, which describes the virus's transmission potential in real-time and can thus account for the impact of contextual changes in policy and behavior on disease spread. Further, this  $R_t$  metric has been used widely in popular media to report the rate of disease spread in different areas.<sup>28–36</sup> Developed and publicized by Instagram's co-founder Kevin Systrom, *Rt.live* has the potential to greatly impact public opinion and shape behaviors, such as willingness to adhere to social distancing guidelines. Understanding effective reproductive number is therefore critical both to guiding legislators and promoting buy-in to the policies implemented.

In one comparison of 20 countries, Banholzer et al. found public venue closures to be the most effective NPI in reducing new cases, followed by public gathering bans, non-essential business closures, and international travel restrictions, with school closures decreasing case count minimally. Interestingly, they found 'lockdowns' to be among the least effective policies in mitigating disease spread.<sup>2</sup> Analysis at the city level in China has also associated comprehensive social distancing measures with preventing disease spread.<sup>23,24</sup> In Wuhan, a reduction in  $R_t$  was shown to chronologically follow implementation of

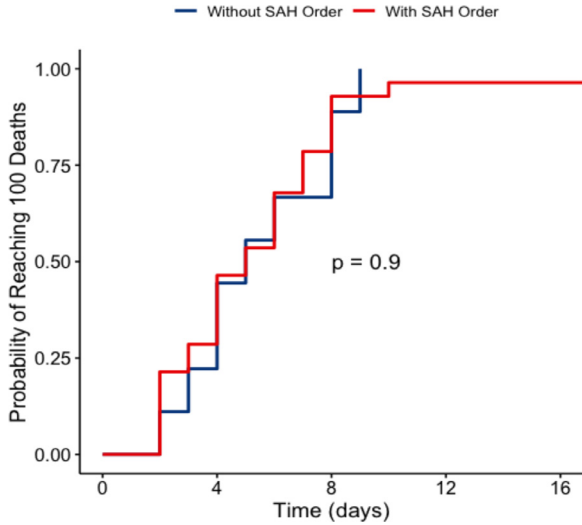


**FIGURE 2.** Hazards curve demonstrating the probability of reaching 1000 cases separated by (A) states with and without a stay-at-home order prior to the 500th case, (B) the highest vs. lowest quartile of percent time spent at home based on Google mobility data for all states, and (C) the highest vs. lowest quartile of percent time spent at home amongst states that had a stay-at-home order prior to the 500th case.

traffic restrictions, home confinement, centralized quarantine, and other social distancing measures.<sup>23</sup> Such retrospective analyses of NPI impact on disease spread, to date, have primarily compared disease metrics before and after policy implementation,<sup>2,20,21,23–27</sup> but these analyses may not fully account for the confounding effects of disease prevalence and public response. This study controls for the stage of disease spread by selecting a normalized point on the epidemic curve, 500 cases, and assesses how different NPIs influence the swelling case load while also controlling for population density.

The United States presents unique challenges in epidemiological management due to its governmental emphasis on state and local autonomy. As such, an analysis of the pandemic’s impact in the U.S. should account for potentially different trajectories across states and at

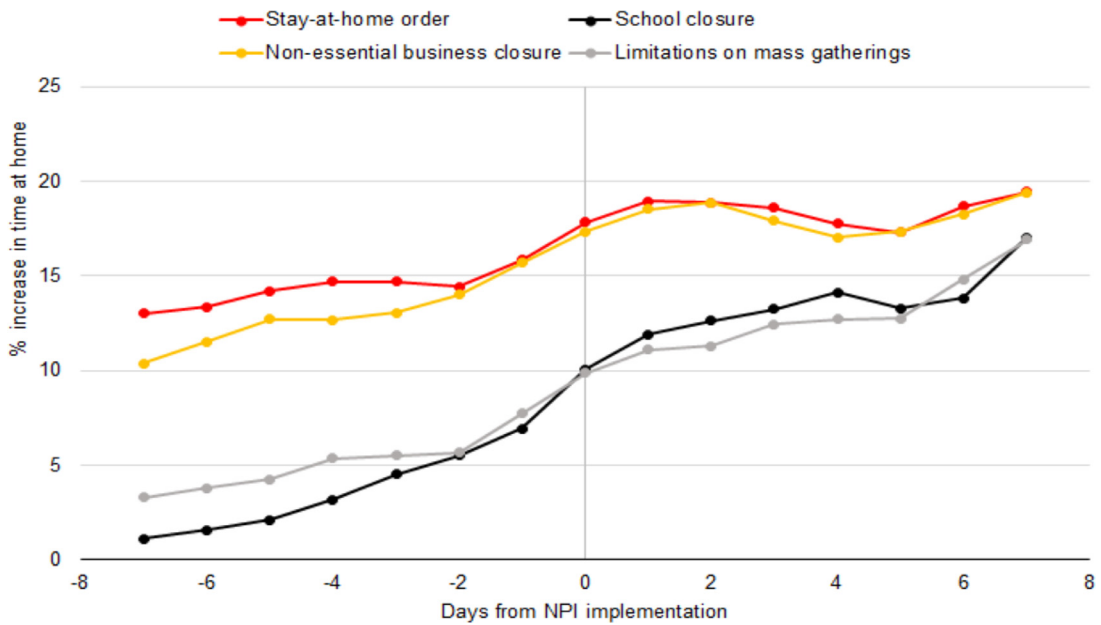
the local level. Ebell & Bagwell-Adams compared differences in social distancing measures employed by counties in the state of Georgia. They demonstrated that Clarke County, which implemented a shelter-in-place policy two weeks before it was adopted at the state level, had increased case doubling time compared to surrounding counties and the state as a whole.<sup>22</sup> Siedner et al. performed a time-series analysis to compare disease spread before and after statewide social distancing policies were put in place, and found that decreases in epidemic growth occurred four days after implementation of each state’s first social distancing policy.<sup>37</sup> However, in this section of their analysis the authors did not differentiate between alternate social distancing measures. Additionally, once an initial policy was in place, they found no significant effect of further enacting



**FIGURE 3.** Hazard curve showing the probability of reaching 100 deaths separated by states with and without a stay-at-home (SAH) order prior to the 50th death.

statewide lockdowns.<sup>37</sup> In this study, we compare the effects of different policies, finding stay-at-home orders to be most effective in reducing transmission.

Lasry et al. used cell phone data from SafeGraph to assess the relationship between various social distancing policies and percentage of mobile devices leaving home in four major U.S. cities.<sup>3</sup> They found that combinations of multiple social distancing policies, including limits on gatherings and school closures, significantly reduced mobility. Stay-at-home orders further reduced movement in their study as well.<sup>3</sup> By including cell phone tracking data made publicly available by Google, this study directly assesses the connection between mobility and virus transmission at the state level. In agreement with Lasry et al., we demonstrate that stay-at-home orders significantly increase the amount of time people spend at home.<sup>3</sup> Further, our multivariable linear regression analysis, which demonstrates that relative percent time spent at home was the most significant modulator of  $R_t$ , indicates that the primary driving factor in reducing viral transmission was limiting mobility. In conjunction, these results provide evidence that NPIs can be useful in



**FIGURE 4.** Time spent in residential areas before and after stay-at-home order.

**Table 5.** Social distancing and  $R_t$  the week following stay-at-home order compared to the week before the order in Republican-voting vs. Democrat-voting states.

	Voted Republican in 2016	Voted Democrat in 2016	P
Portion of time spent at home	16.9%	20.1%	<0.001*
$\Delta$ Portion of time spent at home (% change)	+3.25% (23.8%)	+5.08% (33.8%)	<b>0.032*</b>
$R_t$	1.04	1.14	<b>0.0077*</b>
$\Delta R_t$ (% change)	-0.17 (14.0%)	-0.17 (12.6%)	0.804

\* =  $p < 0.05$ .



controlling early COVID-19 outbreaks by effectively reducing social mobility.

### Differing effects of NPIs

Our analysis demonstrates that stay-at-home order, the strictest policy included in our models, had the most significant effect on disease spread. This measure both reduced transmission rate and increased doubling time from 500 to 1000 cases within states. Comparatively, mass gathering restrictions had the least effect on reducing  $R_t$ . As states across the U.S. continue to disagree on policy approaches to containing the virus and, in particular, opening schools in the fall, our results suggest that mass gathering restrictions or school closure alone may have a weaker effect in maintaining  $R_t < 1$ . Careful monitoring of  $R_t$  values in these states may be necessary to proactively identify and control recurrent outbreaks.

To assess the effectiveness of stay-at-home orders at different points in disease outbreak, we also compared states by number of confirmed COVID-19 cases at the time this policy went into effect. We found that reduction in average  $R_t$  the week following stay-at-home order was consistent across variation in number of cases at the time of policy implementation. States benefited from similar reduction in  $R_t$  regardless of how many confirmed cases they had before their orders went into effect. However, this finding does not imply that timing of stay-at-home order is unimportant, since high  $R_t$  in the weeks prior will contribute to greater overall caseload. Furthermore, when looking at  $R_t$  averages for the week of April 23rd to April 30th, states that had yet to implement a state-wide stay-at-home order had amongst the highest values in the country, accounting for four of the eight states with an average  $R_t > 1$ , suggesting that they had not yet successfully contained the virus.

Interestingly, in the week following enactment of stay-at-home orders, states that voted blue in the 2016 U.S. presidential election demonstrated a greater increase in social distancing relative to red states, possibly reflecting greater adherence to government policies. This difference in social distancing was not associated with a difference in  $R_t$  reduction between red and blue states, and in fact the overall  $R_t$  was higher in blue states despite better adherence to social distancing policies. This adjunct analysis it is not intended to establish voting patterns as a definitive driver of these differences, rather, it illuminates the common notion that there are underlying factors that modulate the effectiveness of NPIs. These results may be confounded by a number of other variables including the relative timing of outbreaks, geographic distributions, and various cultural factors, which should be explored further.

Our analysis finds no significant correlation between mobility or social distancing policy and time from 50 to 100 deaths. This lack of association may be a result of studying outcomes early on in each state's disease outbreak. Future studies that look at death rates later on may find that social

distancing measures help prevent overflow of healthcare systems, and therefore reduce fatality.

### Limitations

Our study has several important limitations to consider. First, our state-level analysis may miss variation at the county level. Certain counties may have benefited from more localized control due to social distancing measures implemented before state-wide mandates. Similarly, county-level variation in COVID-19 cases, resulting deaths, population density, and other demographic factors were not accounted for. Future analyses should consider county-level data to account for these local variations.

Our mobility results are further limited by potential flaws in Google's publicly available phone data, which this study relies on for mobility analyses. As noted by Lasry et al., data that tracks phones, not people, are subject to distortion by individuals with multiple devices and people leaving home without their phones.<sup>3</sup> Further, these data do not differentiate between individuals who leave home but remain distanced from others and people who ignore social distancing guidelines altogether while in public. Finally, our analysis focused exclusively on social distancing policies, and did not account for other transmission-preventing NPIs that states may have employed such as requiring masks.

Different NPIs were sometimes enacted simultaneously or soon after one another. The effects of less extreme measures may be masked due to interdependence with other policies, or artificially enhanced due to chronological association with more extreme initiatives. This is particularly true for business closures, which generally occurred nearest in time to stay-at-home orders. Also, we found that educational facility closures and limitations on mass gatherings often preceded business closures and stay-at-home orders, making the latter policies more difficult to assess in isolation. While our multivariate analysis controls for the effect of co-existing policies, these nuances in chronology complicate the findings.

Though rates of testing have been noted to vary widely between states and serve as a potentially confounding variable, the model used to calculate  $R_t$  values analyzed here corrects for state-wide differences in testing. The  $R_t$  model also accounts for variation in serial interval and delay between symptom onset and a positive test result; however, it does not account for any period in which individuals are infectious but asymptomatic, which mounting evidence suggests is an important factor in SARS-CoV-2 dynamics. As such, future analyses of  $R_t$  should be calibrated with this in mind.

Our results suggest that statewide social distancing policies, and in particular stay-at-home orders, reduced disease spread in the early stage of the COVID-19 outbreak, but the present data does not indicate whether or not these measures are effective long term. Recent studies have demonstrated that stay-at-home mandates

limited social mobility and COVID-19 transmission in the U.S. beyond the timeframe of this study, through May and June.<sup>38–41</sup> However, it remains unclear whether or not adherence to stay-at-home mandates is sustainable long term, or at what point beyond the initial outbreak the costs of these policies begin to outweigh the benefits.<sup>40</sup>

## Implications

Reducing COVID-19 spread and alleviating overburdened healthcare systems has become an international priority, and, in the absence of available pharmaceutical options, understanding the efficacy of policy interventions is paramount. Disease modeling has indicated that social distancing is a critical measure to achieve this goal, but studies validating these findings with case data can increase buy-in from policy makers and the public. This study indicates that stay-at-home orders, limitations on mass gatherings, educational facility closures, and non-essential businesses closures are all effective measures at reducing transmission rates, thereby “flattening the curve,” with stay-at-home orders having the largest effect. Of note, adherence to social distancing appears to be the driving force behind the effectiveness of these policies, as states with stay-at-home orders but relatively poor adherence experienced doubling times more similar to those without such policies. By more rigorously characterizing the state-level strategies that have proved most effective at reducing disease burden, this study aims to provide stakeholders with a more standardized, data-driven framework to guide future policy decisions.

## AUTHORS CONTRIBUTIONS

N.D., Z.S., F.M.M., L.K., J.R.D., A.G., J.T.K., and T.F.C. conceived and designed the analysis; N.D., Z.S., F.M.M., J.R.D., N.F.M., M.A., A.Y.L., and T.C.H. collected the data; N.D. and L.K. performed the analysis; N.D., Z.S., F.M.M., and L.K. wrote the paper. All authors contributed to editing and revising the manuscript.

## DECLARATION OF COMPETING INTEREST

The authors of this manuscript have no conflicts of interest to disclose.

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