

By Charles Courtemanche, Joseph Garuccio, Anh Le, Joshua Pinkston, and Aaron Yelowitz

# Strong Social Distancing Measures In The United States Reduced The COVID-19 Growth Rate

DOI: 10.1377/hlthaff.2020.00608  
HEALTH AFFAIRS 39, NO. 7 (2020): 1237-1246  
©2020 Project HOPE—The People-to-People Health Foundation, Inc.

**ABSTRACT** State and local governments imposed social distancing measures in March and April 2020 to contain the spread of the novel coronavirus disease (COVID-19). These measures included bans on large social gatherings; school closures; closures of entertainment venues, gyms, bars, and restaurant dining areas; and shelter-in-place orders. We evaluated the impact of these measures on the growth rate of confirmed COVID-19 cases across US counties between March 1, 2020, and April 27, 2020. An event study design allowed each policy's impact on COVID-19 case growth to evolve over time. Adoption of government-imposed social distancing measures reduced the daily growth rate of confirmed COVID-19 cases by 5.4 percentage points after one to five days, 6.8 percentage points after six to ten days, 8.2 percentage points after eleven to fifteen days, and 9.1 percentage points after sixteen to twenty days. Holding the amount of voluntary social distancing constant, these results imply that there would have been ten times greater spread of COVID-19 by April 27 without shelter-in-place orders (ten million cases) and more than thirty-five times greater spread without any of the four measures (thirty-five million cases). Our article illustrates the potential danger of exponential spread in the absence of interventions, providing information relevant to strategies for restarting economic activity.

**Charles Courtemanche** (courtemanche@uky.edu) is an associate professor of economics at the University of Kentucky, in Lexington, Kentucky.

**Joseph Garuccio** is a doctoral student in economics at Georgia State University, in Atlanta, Georgia.

**Anh Le** is a doctoral student in economics at the University of Kentucky.

**Joshua Pinkston** is an associate professor of economics at the University of Louisville, in Louisville, Kentucky.

**Aaron Yelowitz** is a professor of economics at the University of Kentucky.

A critical question during the novel coronavirus disease (COVID-19) pandemic is the effectiveness of the social distancing policies adopted by US states and localities in bending the curve. Although these policies take a variety of forms—such as imposing shelter-in-place orders; restricting dine-in at restaurants; closing nonessential business such as bars, entertainment venues, and gyms; banning large social gatherings; and closing public schools—their effectiveness depends critically on the cooperation of the public. For example, although California's first-in-the-nation shelter-in-place order carries threats of fines and incarceration, its effectiveness fundamentally relies on social

pressure.<sup>1</sup> Compliance with social distancing orders appears to be related to local income, partisanship, and political beliefs in the US, and compliance with self-quarantines is related to potential losses in income in Israel.<sup>2-4</sup>

Some epidemiological models forecast the eventual number of COVID-19 cases and fatalities based on untested assumptions about the impact of social distancing policies in contemporary society. The widely cited Imperial College London model assumes that contact outside the home, school, or workplace declines by 75 percent; school contact rates are unchanged; workplace contact rates fall by 25 percent; and household contact rates rise by 25 percent.<sup>5</sup> Another study assumes that social distancing measures

will reduce the average contact rate by 38 percent, based on evidence from the 1918 influenza pandemic.<sup>6</sup>

In the US, the literature on models of social distancing during the COVID-19 pandemic is evolving rapidly; at the time of writing, we were aware of several working papers that examined the consequences of social distancing policies. Recent work found statistically significant effects of stronger measures (such as shelter-in-place orders) on movement, using difference-in-differences methods and state-level data from Google.<sup>7</sup> Similar findings have been obtained in a study with SafeGraph mobility data,<sup>8</sup> although a different study using PlaceIQ and SafeGraph data found that strong measures were not important.<sup>9</sup> Another paper used synthetic control methods to show that California's shelter-in-place order markedly reduced COVID-19 cases.<sup>1</sup> A study of shelter-in-place orders across the US also found a reduction in cases, as well as higher rates of staying home full time.<sup>10</sup> Other authors used interrupted time-series methods and found that early statewide social distancing measures were associated with decreases in states' COVID-19 growth rates, but later shelter-in-place orders did not lead to further reductions.<sup>11</sup>

At issue is not whether isolation works to limit the spread of disease but, rather, whether the particular government restrictions designed to encourage social distancing in the US reduced spread relative to simply providing information and recommendations. Individuals may voluntarily engage in avoidance behavior, such as washing hands or wearing masks, once they fully perceive the risks of contagion.<sup>12,13</sup> Critics of more stringent government measures highlight Sweden's less intrusive response to COVID-19, although Sweden's strategy is increasingly being questioned.<sup>14</sup> Rigorous empirical research is needed to determine the impacts of the various aspects of governments' responses in the US.

Our work, which leveraged both state and county policy variation and used a flexible event study method that allowed for effects to vary across measures and over time, estimated the impacts of four types of social distancing measures on confirmed COVID-19 case growth rates through April 27, 2020. The reduced-form approach captures any potential pathways driven by these mandates, including complementary avoidance behaviors the public may engage in if these orders provide an informational shock in addition to increasing social distancing.

## Study Data And Methods

**STUDY DATA** The unit of observation was daily US counties or county equivalents. Although there

are 3,142 US counties, official COVID-19 records report New York City as a whole instead of dividing it into five counties, reducing this number to 3,138. Our data set tracked counties over the course of fifty-eight days from March 1, 2020, to April 27, 2020, leading to a sample size of 182,004. We chose March 1 as the start date because no new cases were reported in the entire US on most days in January and February. We chose the April 27 end date to coincide with the first removal of one of the four types of restrictions we analyzed (the reopening of restaurants and other entertainment facilities in Georgia).<sup>15</sup> Each county observation was weighted by population, using 2018 estimates from the Department of Agriculture's Economic Research Service.<sup>16</sup>

**OUTCOME OF INTEREST** We examined the daily growth rate in confirmed COVID-19 cases at the county level, which originated from the COVID-19 Dashboard provided by the Johns Hopkins Center for Systems Science and Engineering. This repository contains data on COVID-19 cases worldwide, collected from a range of sources including government and independent health institutions.<sup>17</sup>

The daily exponential growth rate was calculated as the natural log of cumulative daily COVID-19 cases minus the log of cumulative daily COVID-19 cases on the prior day. We chose this functional form because epidemiological models predict exponential growth in the absence of intervention. Percentage growth in cases is identical to percentage growth in cases per capita because reported county populations did not vary during the sample period. The growth rate was multiplied by 100 and can be read as percentage-point changes. In computing the growth rate, we followed a recent COVID-19 study and added 1 to the case counts to avoid dropping counties that started with zero cases.<sup>18</sup>

**COVARIATES** The data on the timing of state and local government social distancing interventions were gathered from a host of sources and made available by Johns Hopkins University.<sup>19</sup> Part A of the online appendix explains a few corrections we made to the dates and provides a list of state- and county-level policies used in the analysis.<sup>20</sup>

We focused on four government-imposed interventions: shelter-in-place orders, public school closures, bans on large social gatherings, and closures of entertainment-related businesses. For large gatherings we used the date of the first prohibition that was at least as restrictive as five hundred people. Most of the bans were much more restrictive: 95 percent of the time (in our population-weighted sample) the prohibition extended to fifty people. For enter-

tainment-related businesses, we used the date of the first closure of either restaurant dining areas (including bars) or gyms and entertainment centers. Ninety-six percent of the time, if one such prohibition was in place, the other was in place as well.

We included control variables related to the availability of COVID-19 tests. The same data repository that provides case counts also includes daily counts of positive, negative, and pending tests in each state on each day, which we added together.<sup>17</sup> To mirror our measure of cases, we converted this testing variable to the exponential daily growth rate of cumulative tests performed. Because COVID-19 test results are generally not available immediately, we also included the one-day lag of this growth rate. Further lags (out to ten days) were considered but were always statistically insignificant, so we did not include them. Most states did not report any pending tests, meaning that they did not officially record tests until the results were obtained. This likely explains the lack of a longer lag between testing growth and case growth.

**METHODS** We estimated the relationship between social distancing policies and the exponential growth rate of confirmed COVID-19 cases, using an event study regression with multiple policies. Statistical analysis was conducted using Stata MP, version 15. This approach is akin to difference-in-differences but is more flexible, as it interacts the policy variables with multiple indicators of time since implementation, thereby tracing out the evolution of the policy effects over time.<sup>21</sup>

For each of the four policies, we included seven variables: whether the policy was implemented one to five, six to ten, eleven to fifteen, sixteen to twenty, or more than twenty days before a given sample day and whether it will be implemented five to nine or ten or more days after that day. Implementation on the current day through four days later was, therefore, the reference group. If a county never adopted the policy, each of these variables was set to 0 throughout the sample period.

An event study model is particularly useful for studying the impact of social distancing policies on COVID-19 cases for two reasons. First, after accounting for the incubation period and time between the onset of first symptoms and a positive test result, such policies likely affect official cases after a considerable lag only.<sup>22</sup> In addition, the inclusion of variables reflecting future implementation allows for an analysis of prepolicy trends. As it is not plausible for policies that have not yet been implemented to causally affect current cases, finding such associations could suggest misspecification. For instance, one might

expect counties with rapidly growing case counts to be the most likely to enact these measures, leading to a reverse-causal relationship between current cases and future policies that would be detected by our model.

Each policy was implemented at least ten days after the start of the sample period and at least 20 twenty days before the end. Therefore, each policy contributes to the identifying variation for all coefficients except those for implementation more than twenty days before the specified sample day and ten or more days after the specified sample day. Because the estimated policy effects at those two catch-all periods could partially reflect compositional changes, they should therefore be interpreted with more caution than the estimates for the other time intervals.

In addition to the testing controls discussed here, the model also included fixed effects for geography and time. County fixed effects accounted for the likelihood that even aside from differences in policies, case growth rates may have varied because of a number of county characteristics. These characteristics include population density and residents' education, political orientation, and age.<sup>3,4</sup> Fixed effects for each day in each of the nine US census divisions (522 fixed effects in total) allowed for flexible underlying trends in growth rates that could vary in different parts of the country, helping account for the staggered nature of the outbreak across locations.<sup>23</sup> We report 95 percent confidence intervals, with standard errors robust to heteroskedasticity and clustered by state, which is the level of most of the policy variation. Part B of the appendix provides the formal notation for the event study model.<sup>20</sup>

**LIMITATIONS** There were several limitations to our analysis. Official COVID-19 case counts are known to understate the true prevalence of the disease, as they do not include asymptomatic carriers, those who are not ill enough to seek medical care, and those who are unable to obtain a test because of supply constraints.<sup>1</sup> Nonetheless, confirmed case counts are crucial to the Trump administration's "Opening Up America Again" plan, which proposes either a "downward trajectory of documented cases within a 14-day period" or a "downward trajectory of positive tests as a percent of total tests within a 14-day period (flat or increasing volume of tests)" as criteria for loosening social distancing measures.<sup>24</sup> Moreover, to the extent that testing shortages led to only the sickest individuals receiving tests, official case counts can loosely be interpreted as the prevalence of moderate-to-severe illness, a relevant metric for policy purposes.

A related caveat is that, ideally, we would like

to be able to control more precisely for access to testing. Available data allowed us to control for the number of tests performed at only the state, rather than county, level. However, most of our policy variation is at the state level, so controlling for state-level testing should go a long way toward alleviating bias. In addition, the number of tests performed is not an ideal measure of the ease of obtaining a test because it also reflects the level of illness in the community.

Also, we might ideally want to estimate a richer econometric model. It would be interesting to trace out the timing of impacts more exactly and study the policies' interactions with each other or with county characteristics. Future work should also examine the impacts of other social distancing policies such as closing public parks and beaches, the requirement to wear masks in public, restrictions on visitors in nursing homes, state announcements of first cases or fatalities, and federal government actions such as prohibiting international travel.<sup>9</sup> However, it is difficult to include numerous correlated policy variables without reducing precision to the point at which statistical inference is uninformative.

Finally, as is typical of observational data analyses, we could not rule out all possible threats to causal inference. Numerous possible confounders could vary across time and space, including the other policies mentioned here, informal encouragement by government officials to

wear masks or improve hygiene, changing business practices, and social norms regarding distancing. That said, including census division by day and county fixed effects in our model and examining prepolicy trends helped us push in the direction of causality.

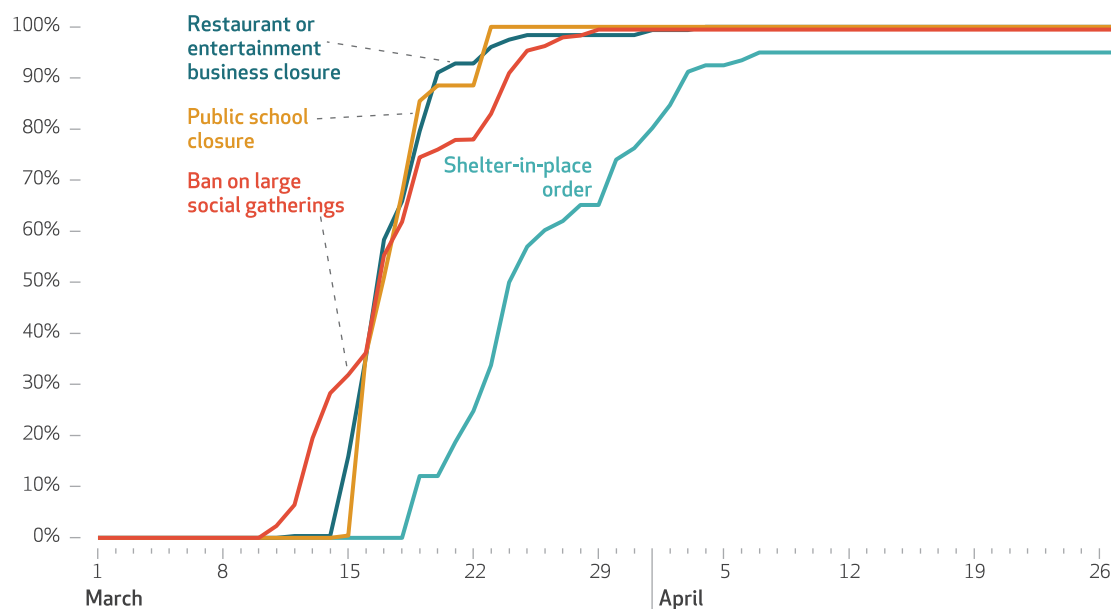
## Study Results

**DESCRIPTIVE INFORMATION** The number of confirmed COVID-19 cases in the US grew rapidly during the sample period, going from just 30 on March 1 to 978,047 on April 27. Part C of the appendix shows the number of counties with any COVID-19 cases on each day.<sup>20</sup> On March 1 the vast majority of counties had zero cases; across all days, 49 percent of unweighted county-by-day observations were zero. However, counties with zero cases tended to have low populations, so our population weights limited the influence of these counties on the results.

Exhibit 1 illustrates the coverage of the US population by social distancing policies over time. Shelter-in-place orders were generally the last policy to be implemented, and adoption of them was uniformly lower than for the other policies. On March 1 no jurisdiction had implemented all four measures. By March 22 nearly 25 percent of the US population was covered by all of the measures. This rose to approximately 65 percent by March 29 and 95 percent by

### EXHIBIT 1

**Percent of US population covered by four social distancing measures in response to the COVID-19 pandemic, March 1–April 27, 2020**



**SOURCE** Authors' calculations from COVID-19 data from the Johns Hopkins University Center for Systems Science and Engineering.

**NOTE** Estimates are weighted by county population.

April 7, when the last shelter-in-place order took effect.

**IMPACT OF SOCIAL DISTANCING POLICIES**  
Exhibit 2 illustrates the coefficients (and confidence intervals) for shelter-in-place orders and bans on large social gatherings derived from the event study model. Relative to the reference category of zero to four days before implementation, shelter-in-place orders led to statistically significant ( $p < 0.01$ ) reductions in the COVID-19 case growth rate of 3.0 percentage points after six to ten days, 4.5 percentage points after eleven to fifteen days, 5.9 percentage points after sixteen to twenty days, and 8.6 percentage points from twenty-one days onward. Because the model held constant the other types of policies, these estimates should be interpreted as the additional effect of shelter-in-place orders beyond the effects of shutting down schools, large social gatherings, and entertainment-related businesses. This additional effect may come either from the requirement or strong advisement to shelter in place aside from essential activities or from the accompanying closure of any nonessential businesses that remained open. We did not observe any statistically significant placebo effects of shelter-in-place orders in the periods before implementation, which gives credence to a causal interpretation of our main results. If anything, the pre trend appears to point upward, which would make our estimates in the postpolicy period conservative.

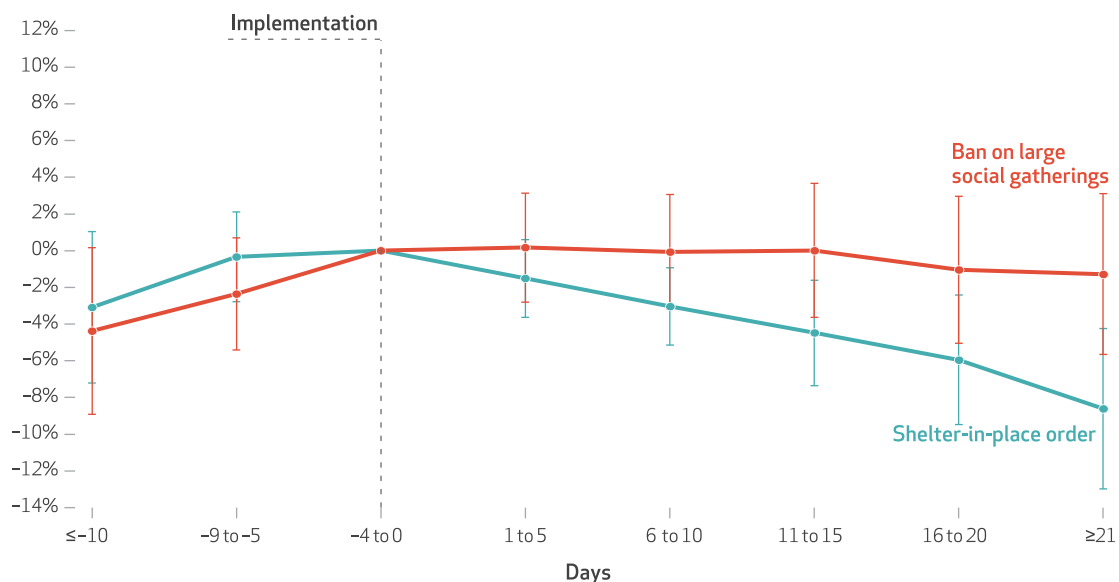
riod conservative.

We found no evidence that bans on large social gatherings influenced the growth rate of confirmed COVID-19 cases. The point estimates for banning gatherings were statistically insignificant ( $p > 0.56$  in all cases). However, the 95% confidence intervals included reductions of up to 3–6 percentage points, so the lack of evidence of an effect should not be misinterpreted as clear evidence of no effect. Also, the lack of a statistically significant reduction in the postintervention period could potentially be the result of an upward (although not statistically significant) prepolicy trend. However, results from the aforementioned event study with separate variables for each day showed that the pre trend disappeared four days before implementation.

Exhibit 3 shows similar estimates for the closure of restaurants, entertainment-related businesses, and schools. Closing restaurant dining rooms and bars or entertainment centers and gyms led to significant reductions in the growth rate of COVID-19 cases in all periods after implementation ( $p < 0.05$ ). The estimated effect was 4.4 percentage points after one to five days, 4.7 percentage points after six to ten days, 6.1 percentage points after eleven to fifteen days, 5.6 percentage points after sixteen to twenty days, and 5.2 percentage points after twenty-one days or longer. Before implementation, policies relat-

## EXHIBIT 2

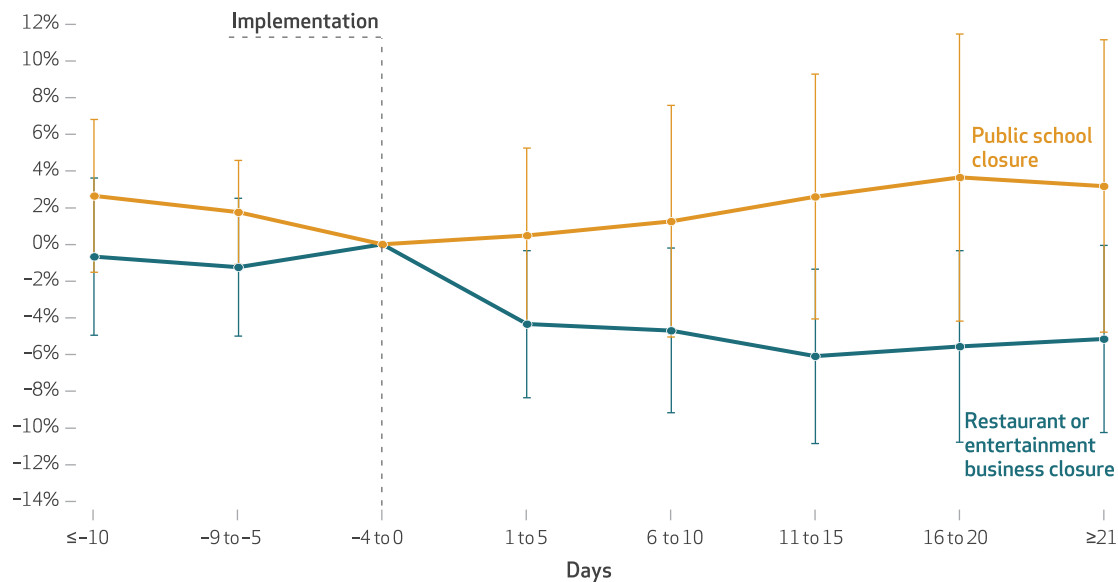
**Estimated effects of shelter-in-place orders and bans on large gatherings on the daily growth rate in confirmed COVID-19 cases in the US, 2020**



**SOURCE** Authors' analysis of county-level COVID-19 case data. **NOTES** The exhibit shows coefficient estimates from the event study model. Day, county, and census division by day fixed effects and testing growth controls were included in the data. Standard errors were heteroskedasticity robust and clustered by state. Bars are 95% confidence intervals.

## EXHIBIT 3

Estimated effects of public school closures and restaurant or entertainment center closures on the daily growth rate in confirmed COVID-19 cases in the US, 2020



**SOURCE** Authors' analysis of county-level COVID-19 case data. **NOTES** The exhibit shows coefficient estimates from the event study model. Day, county, and census division by day fixed effects and testing growth controls were included in the data. Standard errors were heteroskedasticity robust and clustered by state. Bars are 95% confidence intervals.

ed to businesses showed no effect on the growth rate, again passing the placebo test.

In contrast, we found no evidence that school closures influenced the growth rate in confirmed COVID-19 cases. The point estimates were never close to statistically significant ( $p > 0.37$  in all cases), but the 95% confidence intervals meant that we could not rule out reductions of up to 4–5 percentage points.

Adding the coefficient estimates for each policy gives the combined effect of implementing all four social distancing policies. In the first one to five days after implementation, the bundle of restrictions reduced the growth rate of COVID-19 cases by 5.4 percentage points. This reduction grew to 6.8 percentage points after six to ten days, 8.2 percentage points after eleven to fifteen days, 9.1 percentage points after sixteen to twenty days, and 12.0 percentage points after twenty-one days or more. As discussed previously, the estimate for twenty-one days or longer should be viewed with caution, as it did not use the same geographic balance of policies as did the estimates for the other time intervals. A conservative interpretation of these results would therefore be that the impact reached 9.1 percentage points after sixteen to twenty days and appeared to remain at least as high after that.

**ROBUSTNESS CHECKS** Part D of the appendix presents and discusses results from a number of robustness checks designed to address possible

concerns with our model.<sup>20</sup> These checks begin with regressions with just one variable per policy to help rule out the null results for gathering bans and school closures being a result of multicollinearity (appendix exhibit 4).<sup>20</sup> We then evaluated robustness to either using different functional forms for the testing controls or omitting them (appendix exhibit 5).<sup>20</sup> Next, appendix exhibit 6 varied the sample start date and the approach used to deal with counties with no cases.<sup>20</sup> Appendix exhibit 7 shows results from dropping the uniquely affected states of California, New York, and Washington.<sup>20</sup> Appendix exhibit 8 displays results from a more fine-grained event study model with separate variables for each day from ten days before the policy to twenty days after.<sup>20</sup> Finally, appendix exhibit 9 presents results from other checks related to data and measurement issues, as well as controlling for county-specific prepolicy implementation trends.<sup>20</sup> The general pattern of results was robust to these different specifications.

**COUNTERFACTUAL SIMULATIONS** Exhibit 4 uses the results from the baseline model to compare the observed growth rate of COVID-19 cases with two counterfactuals: first, none of the four social distancing measures ever being imposed, and second, no shelter-in-place order ever being imposed. The process for creating these counterfactuals is described in the appendix.<sup>20</sup> The mean exponential growth rate without any interven-

# EXHIBIT 4

Comparison of the observed COVID-19 growth rate and predicted daily growth rates either without shelter-in-place orders or without social distancing policies, March 1–April 27, 2020



**SOURCE** Authors' calculation based on observed data and coefficient estimates from the event study model. **NOTE** The counterfactual growth rates set the shelter-in-place order or all four social distancing policies to zero in the event study window for all US counties.

tions was 16.2 percent over the full period. The observed and both counterfactual growth rates peaked March 19, 2020, at 26–28 percent but started to diverge eight days after the earliest restriction. Without any social distancing policies, the model predicts that the case growth rate would have stayed similarly high for another week before gradually falling to 14 percent by April 27, 2020. Without shelter-in-place orders but keeping the other restrictions, the growth rate would have fallen to 11 percent. The actual growth rate, which reflects all implemented distancing policies including shelter-in-place orders, fell to 3 percent by that date.

Exhibit 5 compares the reported number of COVID-19 cases over time with the number of cases predicted by our event study regression under these same two counterfactual scenarios. Part E of the appendix describes the technical details of these simulations along with the required assumptions.<sup>20</sup> The graph in exhibit 5 uses the natural logarithm of nationwide cases (or predicted cases) for the y axis scale, but with corresponding numbers labeled on the y axis instead of logs.

In all three scenarios, cases increased roughly linearly on the log scale, as expected under exponential growth, until the last week of March, approximately two weeks after the first restrictions and one week after the first shelter-in-place order. The actual curve then began to flatten substantially, eventually leading to 978,047

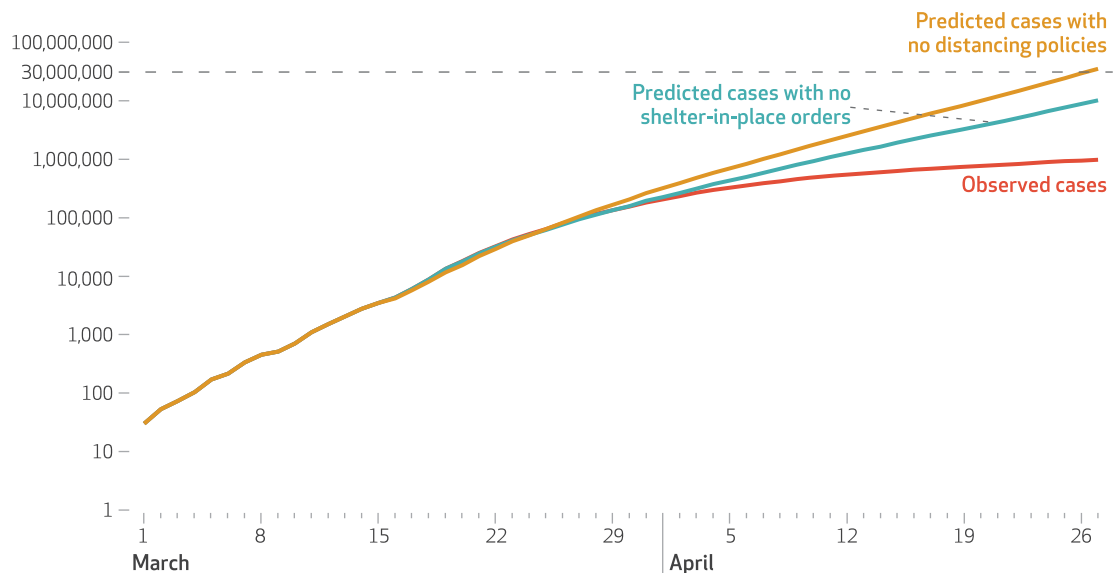
cases by April 27. In contrast, the two counterfactual curves flattened only slightly. By the end of the sample period, the model predicts that cases would have been ten times higher without shelter-in-place orders ( $n = 10,224,598$ ) and thirty-five times higher ( $n = 35,257,098$ ) without any social distancing restrictions. Interestingly, the closures of restaurants and entertainment facilities accounted for a larger share of the reduction in cases than shelter-in-place orders, despite the latter having larger coefficient estimates. This is because restaurant and entertainment facility closures were implemented earlier and in more places than shelter-in-place orders.

## Discussion

Nuance is required when interpreting the results presented in exhibit 5. We view the simulation as providing an illustration of the power of exponential growth and the effectiveness of social distancing restrictions at flattening the curve, even when their impacts are not immediately visible. As late as April 6, nearly a month after the earliest interventions, the number of cases would still have been under one million even without any restrictions—just 2.4 times the actual number of cases. The explosion in cases without social distancing measures happens later, and by the time it is happening, the lagged effects of these measures mean that it is too late to stop it.

## EXHIBIT 5

Reported numbers of confirmed COVID-19 cases (natural log scale) and predicted numbers of cases as a result of social distancing policies, March 1–April 27, 2020



**SOURCE** Estimates derived from authors' event study model.

At the same time, we urge caution about taking the specific numbers of cases averted too literally. Simulations that use estimated parameters to predict outside the range of observed policy variation are inherently subject to a high level of uncertainty that is difficult to quantify. Moreover, had policy makers not taken action and COVID-19 continued to spread throughout April in the manner depicted by our simulations, voluntary social distancing by individuals and businesses would have likely increased as panic over the rising death toll and hospital overcrowding across the country mounted. In technical terms, the census division by day fixed effects would have evolved differently than what we observed. This would have likely offset at least some of the additional predicted cases, although, because of the lag to impact, it is unclear how much of this offsetting could have occurred before the end of our sample period.

Relatedly, testing shortages would likely have prevented official case counts from reaching the numbers presented in our simulations. However, this is largely a semantic distinction, as these infections would still be severe enough to warrant testing in the absence of a shortage. If anything, a patient not being confirmed as a COVID-19 case could lead to their receiving inadequate treatment.

As striking as our counterfactual estimates are, they still are not worst-case scenarios because they account for at least some voluntary

social distancing. Even without any government restrictions, exhibit 4 illustrates a 14.3-percent-age-point drop from the peak growth rate to the end of the sample period. The most plausible explanation is the responses of individuals and businesses to information about the severity of the pandemic and federal guidelines.

Although our results suggest that both shelter-in-place orders and other measures can be effective at averting COVID-19 cases, the lack of evidence of effects of school closures or bans on large social gatherings is noteworthy. We cannot rule out the possibility that these null results are a result of statistical imprecision, but it is also possible that both policies may displace social interaction instead of reducing it. For example, school closures may have led families to continue social interactions outside the school setting, such as at day care centers or parks. Google mobility data through April 5, 2020, show increases of 10 percent or more in visits to parks in twenty-eight states.<sup>25</sup> A new study finds that schools are only slightly more dangerous than parks and playgrounds for COVID-19 transmission, supporting this explanation.<sup>26</sup> Alternatively, school closures primarily affect children, and the vast majority of children experience mild symptoms and therefore might not be included in confirmed cases.<sup>27</sup> Although asymptomatic children can pass the virus to adults who become more severely ill, our results imply that the extent to which this led to confirmed cases did not change

when schools were closed.

Similarly, official group events may have simply been replaced by informal gatherings. Alternatively, official prohibitions may have been largely redundant since the largest events (such as college and professional sports) were already being cancelled in response to Centers for Disease Control and Prevention guidance or other information.

Also note that school closures and large event bans occurred before the implementation of shelter-in-place orders, meaning that substitute types of social gatherings were still allowed. Our results, therefore, should not be interpreted as a forecast about what would happen if schools were reopened or certain large gatherings were allowed while other aspects of shelter-in-place orders remained in place.

## Conclusion

We estimated the separate and combined impacts of four widely adopted social distancing policies in response to the COVID-19 pandemic in the US. Both shelter-in-place orders and closures of restaurants, bars, and entertainment-related businesses substantially slowed the spread of COVID-19. We did not find evidence that bans on large social gatherings and closures of public schools also did, although the confidence intervals cannot rule out moderate-size effects. Interestingly, two recent papers on the effect of social distancing restrictions on mobility found the same pattern we did in terms of

which restrictions mattered and which ones did not;<sup>7,8</sup> this suggests that the null effects of gathering bans and school closures on case growth are at least plausible.

Our contribution was to provide credible empirical evidence on whether US social distancing measures worked as intended in flattening the COVID-19 curve. Estimating other important benefits and costs from social distancing, including total lives saved and economic harm, was beyond the scope of our study. Other work has attempted to estimate job losses, simulate effects on the overall economy and economic growth, or estimate distributional consequences from current and past pandemics.<sup>1,6,28–31</sup>

Nonetheless, we provide important information about the benefits of social distancing for policy makers to consider as they decide on strategies for restarting economic activity. For instance, our results argue against returning to partial measures such as school closures and restrictions on large gatherings while removing restrictions that prevent the redirection of social activity to other settings. At issue moving forward is whether cases averted simply turn into cases delayed, and a premature return to light measures would make this more likely. At the same time, our results are not informative about the effectiveness of intermediate measures, such as lifting a shelter-in-place order but requiring masks in public or opening restaurants at reduced capacity. Further research is needed as gradual, untested steps toward reopening are taken across the country. ■

The authors thank Don Metz and Sarah Dine of *Health Affairs*, as well as four anonymous referees, Felipe Benguria, Jim Fackler, Jose Fernandez, John Garen,

Steve Gohmann, Tim Harris, Carlos Lamarche, Lala Ma, David Wildasin, and Jim Ziliak for helpful feedback. An unedited version of this article was

published online May 14, 2020, as a Fast Track Ahead Of Print article. That version is available in the online appendix.

## NOTES

- 1 Friedson AI, McNichols D, Sabia JJ, Dave D. Did California's shelter in place order work? Early coronavirus-related public health effects [Internet]. Cambridge (MA): National Bureau of Economic Research; 2020 Apr [cited 2020 May 11]. (NBER Working Paper No. 26992). Available from: <https://www.nber.org/papers/w26992>
- 2 Bodas M, Peleg K. Self-isolation compliance in the COVID-19 era influenced by compensation: findings from a recent survey in Israel. *Health Aff (Millwood)*. 2020;39(6):936–41.
- 3 Painter M, Qiu T. Political beliefs affect compliance with COVID-19 social distancing orders [Internet]. St. Louis (MO): Saint Louis University; 2020 Apr 30 [cited 2020 May

- 11]. Available from: [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=3569098](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3569098)
- 4 Wright AL, Sonin K, Driscoll J, Wilson J. Poverty and economic dislocation reduce compliance with COVID-19 shelter-in-place protocols [Internet]. Chicago (IL): University of Chicago, Becker Friedman Institute for Economics; 2020 Apr 29 [cited 2020 May 11]. (Working Paper No. 2020-40). Available from: [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=3573637](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3573637)
- 5 Ferguson NM, Laydon D, Nedjati-Gilani G, Imai N, Ainslie K, Baguelin M, et al. Report 9: impact of non-pharmaceutical interventions (NPIs) to reduce COVID19 mortality and healthcare demand [Internet]. London: Imperial College London;

2020 Mar 16 [cited 2020 May 11]. Available from: <https://www.imperial.ac.uk/media/imperial-college/medicine/sph/ide/gida-fellowships/Imperial-College-COVID19-NPI-modelling-16-03-2020.pdf>

- 6 Thunstrom L, Newbold S, Finnoff D, Ashworth M, Shogren JF. The benefits and costs of using social distancing to flatten the curve for COVID-19 [Internet]. Laramie (WY): University of Wyoming; 2020 Mar 27 [last updated 2020 Apr 14; cited 2020 May 11]. Available from: [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=3561934](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3561934)
- 7 Abouk R, Heydari B. The immediate effect of COVID-19 policies on social distancing behavior in the United States [Internet]. Wayne (NJ):

- William Paterson University; 2020 Apr 8 [last updated 2020 Apr 27; cited 2020 May 11]. Available from: [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=3571421](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3571421)
- 8 Andersen M. Early evidence on social distancing in response to COVID-19 in the United States [Internet]. Greensboro (NC): University of North Carolina Greensboro; 2020 Apr 6 [cited 2020 May 11]. Available from: [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=3569368](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3569368)
  - 9 Gupta S, Nguyen TD, Rojas FL, Raman S, Lee B, Bento A, et al. Tracking public and private responses to the COVID-19 epidemic: evidence from state and local government actions [Internet]. Cambridge (MA): National Bureau of Economic Research; 2020 Apr [cited 2020 May 11]. (NBER Working Paper No. 27027). Available from: <https://www.nber.org/papers/w27027>
  - 10 Dave DM, Friedson AI, Matsuzawa K, Sabia JJ. When do shelter-in-place orders fight COVID-19 best? Policy heterogeneity across states and adoption time [Internet]. Cambridge (MA): National Bureau of Economic Research; 2020 May [cited 2020 May 11]. (NBER Working Paper No. 27091). Available from: <https://www.nber.org/papers/w27091>
  - 11 Siedner MJ, Harling G, Reynolds Z, Gilbert R, Venkataramani AS, Tsai AC. Social distancing to slow the U.S. COVID-19 epidemic: an interrupted time-series analysis [Internet]. Boston (MA): Massachusetts General Hospital; 2020 Apr [cited 2020 Jun 2]. Available from: [https://www.researchgate.net/publication/340518052\\_Social\\_distancing\\_to\\_slow\\_the\\_US\\_COVID-19\\_epidemic\\_an\\_interrupted\\_time-series\\_analysis](https://www.researchgate.net/publication/340518052_Social_distancing_to_slow_the_US_COVID-19_epidemic_an_interrupted_time-series_analysis)
  - 12 Abaluck J, Chevalier JA, Christakis NA, Forman HP, Kaplan EH, Ko A, et al. The case for universal cloth mask adoption and policies to increase supply of medical masks for health workers [Internet]. New Haven (CT): Yale University; 2020 Apr 1 [cited 2020 May 11]. Available from: [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=3567438](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3567438)
  - 13 Harris JE. The coronavirus epidemic curve is already flattening in New York City [Internet]. Cambridge (MA): National Bureau of Economic Research; 2020 Apr [cited 2020 May 11]. (NBER Working Paper No. 26917). Available from: <https://www.nber.org/papers/w26917>
  - 14 Ahlander J, O'Connor P. Sweden's liberal pandemic strategy questioned as Stockholm death toll mounts. Reuters [serial on the Internet]. 2020 Apr 3 [cited 2020 May 11]. Available from: <https://www.reuters.com/article/us-health-coronavirus-sweden/swedens-liberal-pandemic-strategy-questioned-as-stockholm-death-toll-mounts-idUSKBN21L23R>
  - 15 The State of Georgia. Providing guidance for reviving a healthy Georgia in response to COVID-19 [Internet]. Atlanta (GA): Governor's Office; 2020 Apr 23 [cited 2020 Jun 2]. Executive Order. Available for download from: <https://gov.georgia.gov/document/2020-executive-order/04232002/download>
  - 16 Department of Agriculture, Economic Research Service. Population [Internet]. Washington (DC): USDA; 2018 [last updated 2019; cited 2020 May 11]. Available from: <https://data.ers.usda.gov/reports.aspx?ID=17827>
  - 17 Johns Hopkins University and Medicine, Coronavirus Resource Center. COVID-19 Dashboard by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (JHU) [Internet]. Baltimore (MD): JHU; 2020 [cited 2020 May 11]. Available from: <https://coronavirus.jhu.edu/map.html>
  - 18 Bursztyn L, Rao A, Roth C, Yanagizawa-Drott D. Misinformation during a pandemic [Internet]. Chicago (IL): University of Chicago, Becker Friedman Institute for Economics; 2020 Apr 19 [cited 2020 May 11]. (Working Paper No. 2020-44). Available from: [https://bfi.uchicago.edu/wp-content/uploads/BFI\\_WP\\_202044.pdf](https://bfi.uchicago.edu/wp-content/uploads/BFI_WP_202044.pdf)
  - 19 Killeen BD, Wu JY, Shah K, Zapaishchykova A, Nikutta P, Tamhane A, et al. A county-level dataset for informing the United States' response to COVID-19 [Internet]. Baltimore (MD): Johns Hopkins University; 2020 [cited 2020 May 11]. Available from: <https://arxiv.org/pdf/2004.00756v1.pdf>
  - 20 To access the appendix, click on the Details tab of the article online.
  - 21 Saloner B, Maclean JC. Specialty substance use disorder treatment admissions steadily increased in the four years after Medicaid expansion. Health Aff (Millwood). 2020;39(3):453–61.
  - 22 Lauer SA, Grantz KH, Bi Q, Jones FK, Zheng Q, Meredith HR, et al. The incubation period of coronavirus disease 2019 (COVID-19) from publicly reported confirmed cases: estimation and application. Ann Intern Med. 2020;172(9):577–82.
  - 23 Census Bureau. Census regions and divisions of the United States [Internet]. Washington (DC): Census Bureau; [cited 2020 May 11]. Available from: [https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us\\_regdiv.pdf](https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf)
  - 24 White House. Opening up America again [Internet]. Washington (DC): White House; 2020 [cited 2020 May 26]. Available from: <https://www.whitehouse.gov/openingamerica/>
  - 25 Google. COVID-19 community mobility report: mobility changes [Internet]. Google [serial on the Internet]. 2020 Apr 5 [cited 2020 May 11]. Available from: [https://www.gstatic.com/covid19/mobility/2020-04-05\\_US\\_Mobility\\_Report\\_en.pdf](https://www.gstatic.com/covid19/mobility/2020-04-05_US_Mobility_Report_en.pdf)
  - 26 Benzell S, Collis A, Nicolaides C. Rationing social contact during the COVID-19 pandemic: transmission risk and social benefits of US locations [Internet]. Cambridge (MA): Massachusetts Institute of Technology; 2020 Apr 18 [last updated 27 Apr 2020; cited 2020 May 11]. Available from: [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=3579678](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3579678)
  - 27 Pandemic school closures: risks and opportunities [editorial]. Lancet Child Adolesc Health. 2020;4(5):341.
  - 28 Scherbina AD. Determining the optimal duration of the COVID-19 suppression policy: a cost-benefit analysis [Internet]. Boston (MA): Brandeis University; 2020 Mar 24 [cited 2020 May 11]. Available from: [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=3562053](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3562053)
  - 29 Hall RE, Jones CI, Klenow PJ. Trading off consumption and COVID-19 deaths [Internet]. Stanford (CA): Stanford University; 2020 Apr 24 [cited 2020 May 11]. (Working Paper). Available from: [https://web.stanford.edu/~chadj/Consumption\\_v\\_Covid.pdf](https://web.stanford.edu/~chadj/Consumption_v_Covid.pdf)
  - 30 Greenstone M, Nigam V. Does social distancing matter? [Internet]. Chicago (IL): University of Chicago, Becker Friedman Institute for Economics; 2020 Mar 30 [cited 2020 May 11]. (Working Paper No. 2020-26). Available from: [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=3561244](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3561244)
  - 31 Correia S, Luck S, Verner E. Pandemics depress the economy, public health interventions do not: evidence from the 1918 Flu [Internet]. Washington (DC): Board of Governors of the Federal Reserve System; 2020 Mar 26 [cited 2020 May 11]. Available from: [https://papers.ssrn.com/sol3/papers.cfm?abstract\\_id=3561560](https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3561560)