**Partisan Differences in Physical Distancing are Linked to Health Outcomes
During the COVID-19 Pandemic**

Article Accepted for Publication at *Nature Human Behaviour*.

Please cite as: Gollwitzer, A., Martel, C., Brady, W.J., Pärnamets, P., Freedman, I.G., Knowles, E.D., & Van Bavel, J.J. (*in press*). Partisan differences in physical distancing are linked to health outcomes during the COVID-19 pandemic. *Nature Human Behaviour*.

Anton Gollwitzer^{1*} Cameron Martel² William J. Brady¹
Philip Pärnamets^{3,4} Isaac G. Freedman⁵ Eric D. Knowles³ Jay J. Van Bavel^{3, 6*}

¹Department of Psychology, Yale University, New Haven, CT, USA

²Sloan School of Management, Massachusetts Institute of Technology, Cambridge, MA, USA

³Department of Psychology, New York University, New York, NY, USA

⁴Department of Clinical Neuroscience, Karolinska Institutet, Stockholm, Sweden

⁵Yale School of Medicine, Yale University, New Haven, CT, USA

⁶Center for Neural Science, New York University, New York, NY, USA

**Corresponding Authors:*

Anton Gollwitzer, Yale University, Department of Psychology, 2 Hillhouse Avenue, New Haven, CT, 06511, anton.gollwitzer@yale.edu

Jay J. Van Bavel, New York University, Department of Psychology, 6 Washington Place, New York, NY, 10003, jay.vanbavel@nyu.edu

Abstract

Numerous polls suggest that COVID-19 is a profoundly partisan issue in the U.S. Using the geotracking data of 15 million smartphones per day, we found that U.S. counties that voted for Donald Trump (Republican) over Hillary Clinton (Democrat) in the 2016 presidential election exhibited 14% less physical distancing between March and May 2020. Partisanship was more strongly associated with physical distancing than numerous factors, including counties' median income, COVID-19 cases, population density, and racial and age demographics. Contrary to our predictions, the observed partisan gap strengthened over time and remained when stay-at-home orders were active. Additionally, county-level consumption of conservative media (Fox News) related to reduced physical distancing. Finally, the observed partisan differences in distancing were associated with subsequently higher COVID-19 infection and fatality growth rates in pro-Trump counties. Taken together, these data suggest that U.S. citizens' responses to COVID-19 are subject to a deep—and consequential—partisan divide.

Introduction

Political partisanship has been on the rise in the United States and across the world. People in the political minority are afraid to reveal their political identity¹, people view the opposing party more unfavorably than ever before², and partisan echo chambers abound both in person and online³⁻⁵. Partisanship also significantly impacts behavior^{6,7}. For instance, people's choices of where to work, live, and shop are driven by political identity as much as they are by religion⁸, partisan attachments distort memory for political events⁹, and political homophily is as influential as educational homophily in online dating¹⁰. Further, an estimated 81 million Americans reported arguing about politics with close friends and family after the 2016 election¹¹, and 34 million hours of Thanksgiving dinner conversation may have been lost in 2016 due to partisan differences between hosts and guests¹². Exacerbating these partisan differences, social media discourse has the potential to increase political polarization^{13,14}, and slanted news outlets tangibly impact voting decisions¹⁵. In the current era of polarization, then, differences in partisan identity appear to influence a wide variety of social judgments and behaviors¹⁶.

The coronavirus pandemic provides a unique test of the limits of political partisanship and identity. Does an international crisis threatening substantial loss of life and prolonged economic hardship bring people together in a bipartisan manner? Or, does even a public health crisis of such great magnitude become subject to partisanship? This is a particularly important issue because partisan polarization during a pandemic could lead people to engage in varying health behaviors¹⁷. For instance, tuning in to right wing news (such as Fox News) might communicate very different information about the risks of the pandemic—and how to prevent its spread—than more left-leaning sources (such as MSNBC). Similarly, political leaders from different parties might communicate different levels of risk or fail to model prudent health behaviors (e.g., wearing a mask). These factors could then lead partisans to behave differently during a pandemic, which could in turn have important downstream consequences in terms of infection and mortality.

Numerous polls have found a partisan gap in perceptions of risk and support for preventative health behaviors during the COVID-19 pandemic. For instance, an NBC News/Wall Street Journal poll conducted from March 11 to 13, 2020 found that 68 percent of Democrats reported worrying that someone in their family could catch the virus, compared with 40 percent of Republicans¹⁸. Further, nationally-representative Gallup polls documented that Republicans were

less likely to report practicing physical distancing in the last 24 hours than Democrats (March 7-23, 2020: ~78% vs. ~90%), and this gap strengthened with time through mid June (June 8-14: ~48% vs. ~89%)¹⁹. Finally, studies surveying Americans using online data collection platforms found self-identified conservatives to be less likely to endorse a variety of physical distancing measures (e.g., staying 6 feet away from others, wearing masks)²⁰⁻²². These polls reflect a clear partisan gap in beliefs about the pandemic, but do they translate into real behavior?

It remains unclear whether these polls reflect genuine partisan differences. Polls have significant limitations. For instance, self-reported partisan differences may be driven by liberals responding in what they think is a socially appropriate manner or conservatives responding more honestly^{23,24}. Additionally, partisan differences may reflect participants responding in ways they believe align with their political ingroup and party leaders—known as political “cheerleading”²⁵. And even when people do express genuine attitudes, these attitudes often do not align with their actual behavior²⁶. To overcome these limitations, we tested whether the documented partisan differences in responding extend to real-world behavior.

In the current pandemic, epidemiologists and public health officials have strongly encouraged people to physically distance from one another. Numerous studies have shown that physical distancing effectively stopped the exponential spread of COVID-19 at its onset, preventing the inundation of healthcare providers and saving numerous lives²⁷⁻³⁰. To see if physical distancing differs as a function of partisanship, we examined whether the political lean of over 3,000 counties in the United States is linked to the extent to which residents of those counties practiced physical-distancing behaviors during the first few months of the pandemic (March through May 2020). Specifically, we analyzed the aggregated GPS coordinates of approximately 15 million people in the U.S. per day (tracked via smartphone location coordinates) and quantified the degree of physical distancing in each U.S. county. Physical distancing was measured in terms of reduction in general movement and reduction in visiting nonessential services (e.g., restaurants). Furthermore, to examine the association between party identity and public health, we tested whether partisan differences in physical distancing mediated the relationship between partisanship and COVID-19 infection and fatality growth rate.

Critically, in testing these questions, we anticipated that what could appear to be partisan differences in physical distancing may actually reflect social or economic third-variables. For

instance, liberal areas in the U.S. experienced greater COVID-19 infections and fatalities at the start of the pandemic (early March 2020) and thus may have perceived COVID-19 as more dangerous and engaged in greater preventative measures³¹. To account for this and other possible explanations, we included numerous covariates in our models when testing partisan differences in physical distancing and health outcomes.

Results

Validation

We examined people's physical distancing behaviors in 3,025 U.S. counties between March 9 and May 29, 2020. Physical distancing was assessed via counties' percent reduction in general movement and percent reduction in visiting nonessential services (e.g., barbers, restaurants, clothing stores) relative to before COVID-19 struck the United States with force (before March 9). The two physical distancing variables—general movement and visiting nonessential services—were calculated using approximately 15 million daily smartphone GPS coordinates across the U.S. (see Method and Supplements for details).

We first validated the two physical distancing measures by examining whether distancing increased as COVID-19 began to spread across the United States (March through early April, 2020) but then decreased as states began to reopen (late April through May 2020). All models reported below are three-level mixed-effects models where observations are nested within counties and counties within states. For the validation analyses, we report models with random intercepts of county and state and random slopes of linear and quadratic time (fitted using linear and quadratic orthogonal terms) at the state-level (see Supplements). The outcome variables were counties' percent reduction in general movement and reduction in visiting nonessential services compared to pre-COVID-19 (before March 9; see Supplemental Note 1). Two-tailed statistical tests were used in all analyses.

As expected, general movement and visiting nonessential services reduced as COVID-19 first spread in the U.S. (early March into early April), and this reduction dissipated as states began to reopen (end of April through May). As seen in Figure 1, changes in physical distancing over time were characterized by a negative quadratic effect (a convex distribution; $B_{movement} = -0.858$, 95% CI[-0.863, -0.854] and $B_{visitation} = -1.317$, 95% CI[-1.325, -1.309], $ps < .001$) and an additional negative linear trend ($B_{movement} = -0.336$, 95% CI[-0.341, -0.331] and $B_{visitation} = -0.734$, 95% CI[-

0.741, -0.726], $ps < .001$. See Supplements for additional details of these and all following analyses).

Figure 1. Physical distancing (percent reduction in general movement and visiting nonessential services relative to before COVID) as a function of time (March 9 to May 29, 2020). In line with physical distancing restrictions being rapidly implemented during mid-March and then weakening as U.S. States began to reopen, physical distancing increased up until early/mid April and then began to decline. Each point represents one county. 3,025 counties were included for general movement and 2,073 for nonessential visitation across 82 days. The number of total data points was 248,050 and 169,890, respectively. The dashed line is the daily average across counties. The blue line represents the average prediction from a multi-level model including effects of orthogonal linear and quadratic time terms, weekends, state stay-at-home policy, and county median income. Error bands are bootstrapped 95% prediction intervals (see Supplemental Note 2).

We conducted additional analyses to further substantiate the validity of our physical distancing measures. As expected, distancing was greater when stay-at-home policies had been implemented ($B_{\text{movement}} = 0.055$, 95% CI[0.053, 0.057] and $B_{\text{visitation}} = 0.062$, 95% CI[0.059, 0.065], $ps < .001$), on weekends, when fewer people travel for work ($B_{\text{movement}} = 0.088$, 95% CI[0.087, 0.090] and $B_{\text{visitation}} = 0.026$, 95% CI[0.025, 0.028], $ps < .001$), and in higher-income counties, where people are able to work from home ($B_{\text{movement}} = 0.030$, 95% CI[0.027, 0.032] and $B_{\text{visitation}} = 0.041$, 95% CI[0.036, 0.046], $ps < .001$; see Supplementary Tables 19 and 20). The final model—

including effects of orthogonal linear and quadratic time, weekends, state stay-at-home policy, and county median income—provided a good fit to the average trend in the data (see Figure 1). Model marginal R^2 was .35 for the movement model and .37 for the visitation model (Supplementary Tables 19 and 20; Supplemental Note 3). Together, these results suggest that the utilized geotracking data provide valid indices of physical distancing and allow us to test for differences as a function of political partisanship.

Linking Partisanship to Physical Distancing

We examined whether county-level partisanship is linked to physical distancing. Partisanship was measured in terms of county-level voting gap in the 2016 election—the proportion of total votes for Donald Trump (Republican) minus the proportion of total votes for Hillary Clinton (Democrat). We tested three-level mixed-effects models with random intercepts of state and county (county nested within state), random slope of partisanship at the county and state levels, random slopes of linear and quadratic time at the state level, and the random slope of the interaction between partisanship and linear time at the state level (when possible, Supplemental Note 4). Fixed effects included the orthogonal time terms (linear and quadratic), partisanship (vote gap), the interactions between partisanship and the two time terms, the weekend indicator, and key covariates likely to be associated with physical distancing, including counties' COVID-19 infections per capita (cumulative; assessed daily), whether a stay-at-home policy was in effect on a specific day, party affiliation of state governor, population density, median income, income inequality, median age, age composition (proportion of population 0-17, over 65, over 85; Supplemental Note 5), race/ethnicity (proportion of population Black, Hispanic, and Asian), low access to grocery stores (e.g., because of distance or income), number of grocery stores, travel time to work, religiosity, change in life expectancy from 1985 to 2010, and percent employment (see Method and Supplements for details, descriptives, and information on variable coding). Indicating that our findings are robust to different models, our results were also consistent when running models without these control variables (see Supplementary Tables 22 and 23).

We found that the more a county favored Donald Trump over Hillary Clinton in the 2016 election, the less it exhibited physical distancing between March 9 and May 29, 2020. Specifically, for every 1% point increase in vote share for Donald Trump over Hillary Clinton, counties exhibited 0.11 percentage points less physical distancing in terms of general movement and 0.13

percentage points less physical distancing in terms of visiting nonessential services ($B_{\text{movement}} = -0.114$, 95% CI[-0.140, -0.087] and $B_{\text{visitation}} = -0.125$, 95% CI[-0.162, -0.088], $ps < .001$; Table 1; for a visualization of physical distancing by specific location and partisanship see Figures 2 and 3). Model marginal R^2 was .46 for the movement model and .54 for the visitation model (Supplemental Note 6).

Figure 2. Map of predicted reduction in general movement as a function of county location and leaning pro-Trump vs. pro-Clinton. Predictions derived from multilevel models described in Table 1 and main text. Each circle represents a county, its size proportional to its population. Lighter colors indicate less physical distancing; darker colors indicate greater physical distancing. Blue indicates Clinton-leaning county, red indicates Trump-leaning county.

Figure 3. Map of predicted reduction in visiting nonessential services as a function of county location and leaning pro-Trump vs. pro-Clinton. Predictions derived from multilevel models described in Table 1 and main text. Each circle represents a county, its size proportional to its population. Lighter colors indicate less physical distancing; darker colors indicate greater physical distancing. Blue indicates Clinton-leaning county, red indicates Trump-leaning county.

Table 1. Results of the main multilevel mixed-effects models in terms of reduction in general movement and visiting nonessential services.

<i>Variables (range of fitted variable)</i>	Reduction in General Movement			Reduction in Visiting Nonessential Services		
	<i>Estimates</i>	<i>CI</i>	<i>p</i>	<i>Estimates</i>	<i>CI</i>	<i>p</i>
Intercept	0.220	0.209 – 0.231	<0.001	0.346	0.332 – 0.360	<0.001
2016 Trump-Clinton vote gap, county (-.88,.84)	-0.114	-0.140 – -0.087	<0.001	-0.125	-0.162 – -0.088	<0.001
Time linear (-.19,.19)	-0.241	-0.248 – -0.234	<0.001	-0.503	-0.514 – -0.492	<0.001
Time quadratic (-.12,.24)	-0.814	-0.821 – -0.807	<0.001	-1.192	-1.203 – -1.181	<0.001
Weekend (0-1)	0.089	0.088 – 0.090	<0.001	0.026	0.024 – 0.028	<0.001
Median income (10k), county (-2.7, 8.2)	0.020	0.017 – 0.024	<0.001	0.022	0.016 – 0.028	<0.001
Log population density scaled, county (-2.8,4.5)	0.029	0.024 – 0.034	<0.001	0.048	0.041 – 0.055	<0.001
Cases/ 100 capita, county (-0.11,8.12)	0.013	0.011 – 0.016	<0.001	0.033	0.029 – 0.037	<0.001

Supermarkets per 1000, county (-.23, 1.4)	0.055	0.034 – 0.076	< 0.001	-0.097	-0.158 – -0.035	0.002
Low access store access, county (-.21,.79)	0.004	-0.015 – 0.022	0.691	0.151	0.103 – 0.199	< 0.001
Proportion religious, country (-.46,1.41)	-0.010	-0.031 – 0.010	0.323	-0.024	-0.064 – 0.016	0.233
Proportion employed, county (-.27, .25)	-0.080	-0.138 – -0.022	0.007	0.288	0.164 – 0.412	< 0.001
Median age 2018 (10y), county 2018 (-1.9, 2.6)	0.044	0.028 – 0.060	< 0.001	-0.139	-0.171 – -0.108	< 0.001
Proportion 85plus, county (-.018, .052)	0.170	-0.449 – 0.790	0.590	0.174	-1.248 – 1.596	0.810
Proportion 65to85, county (-.12, .36)	-0.344	-0.556 – -0.132	0.001	0.509	0.058 – 0.959	0.027
Proportion 0to17, county (-.15, .20)	0.029	-0.093 – 0.151	0.638	-1.319	-1.581 – -1.058	< 0.001
Stay at home policy, state (-.48, .51)	0.038	0.036 – 0.039	< 0.001	0.044	0.042 – 0.047	< 0.001
GOP governor, state (-.56, .43)	0.012	-0.007 – 0.032	0.222	-0.015	-0.039 – 0.010	0.244
Gini coefficient, county, (-.10, .22)	0.232	0.134 – 0.329	< 0.001	0.426	0.232 – 0.621	< 0.001
Proportion Hispanic/Latino, county (-.09, .89)	-0.078	-0.113 – -0.044	< 0.001	0.081	0.019 – 0.144	0.011
Proportion Asian, county (-.02, .59)	0.171	0.041 – 0.301	0.010	-0.034	-0.219 – 0.152	0.722
Proportion Black, county (-.10, .77)	-0.140	-0.181 – -0.099	< 0.001	-0.103	-0.172 – -0.035	0.003
2010-1985 life expectancy difference (-4.3, 8.0)	0.004	0.001 – 0.006	0.001	0.001	-0.003 – 0.005	0.588
Commute time hrs (-.25, .35)	-0.047	-0.086 – -0.007	0.021	-0.164	-0.245 – -0.084	< 0.001
2016 Trump-Clinton vote gap * Time linear	-0.382	-0.396 – -0.367	< 0.001	-1.030	-1.054 – -1.005	< 0.001
2016 Trump-Clinton vote gap * Time quadratic	0.229	0.215 – 0.243	< 0.001	-0.055	-0.079 – -0.031	< 0.001

Random Effects

σ^2	0.0138	0.0283
τ_{00}	0.0038 county_fips	0.0106 county_fips
	0.0010 state_name	0.0013 state_name
τ_{11}	0.0074 county_fips.gop_advantage_2016	0.0020 state_name.gop_advantage_2016
	0.0043 state_name.gop_advantage_2016	
ρ_{01}	-0.1172 county_fips	-0.0452 state_name
	-0.1336 state_name	
ICC	0.3163	0.3008
N	2987 county_fips	2057 county_fips
	50 state_name	50 state_name

Observations	244934	168586
Marginal R ² / Conditional R ²	0.462 / 0.632	0.536 / 0.676

Notes. Numbers in parentheses after the included variables indicates the actual range of each fitted variable.

Collapsing counties into pro-Trump vs. pro-Clinton bins, Trump-voting counties reduced their general movement 9.5% points less and reduced their visiting of nonessential services 19.4% points less than Clinton voting counties (average reduction: 14.5% points) across the study duration. Illustrating the relative power of the observed links, partisanship was more strongly associated with physical distancing in our main models (when *z*-scoring all the included variables) than any of the other included variables (aside from the time terms, the weekend factor, and median age in the case of visitation; see *z*-scored models in our analysis outputs hosted [here](#); see Supplemental Note 7). To put this into context, partisanship was more strongly associated with distancing than counties' income, number of COVID-19 cases per capita, percent employment, average travel time to work, governor political affiliation, and racial make-up, as well as the other variables noted above.

Additionally demonstrating the robustness of our findings, partisanship was associated with reduced physical distancing even after adjusting for the interactions between each of the included covariates and partisanship (Supplementary Tables 22 and 23), when adding counties' percent of employment in various types of professions to the analyses (e.g., agriculture, finance, manufacturing; Supplementary Table 24), when adding specific state-policies to the analyses (e.g., closing restaurants, closing childcare centers; Supplementary Tables 32 and 33), and when running generalized additive models (GAMs) with time as a smoothed variable (Supplementary Table 25; Supplemental Note 8).

We next examined how partisan differences in physical distancing changed over time (between March and May 2020). We predicted that the observed differences would decrease as the pandemic worsened and people became more aware of the dangers of COVID-19 (see preregistration of this hypothesis [here](#); Supplemental Notes 9, 10). We found the opposite pattern. As indicated by negative interaction terms between vote gap and linear time in the models noted above ($B_{\text{movement}} = -0.382$, 95% CI[-0.396, -0.367], and $B_{\text{visitation}} = -1.030$, 95% CI[-1.054, -1.005], $ps < .001$; see Table 1), the partisan gap in physical distancing actually increased rather than decreased between March 9 and May 29, 2020. And, this was especially true for visiting nonessential services (see model predictions in Figure 4; Supplemental Note 11).

Figure 4. U.S. counties' average physical distancing (percent reduction in general movement and visits to nonessential services) as a function of time and partisanship (Trump vs. Clinton vote gap in 2016). For graphing purposes, counties were binned as Trump Lean if a greater percentage of residents voted for Trump and as Clinton Lean if a greater percentage of residents voted for Clinton. Each point represents one county. 3,007 counties were included for general movement and 2,068 for nonessential visitation across 82 days. The number of total data points was 246,574 and 169,480, respectively. Dashed lines depict the daily average across counties, split by partisan lean. Bold blue and red lines represent the average predictions of vote gap from the multilevel models described in Table 1 and main text. Error bands are bootstrapped 95% prediction intervals.

We also examined the link between partisanship and physical distancing over time in a different manner. We conducted a series of mixed-effects models to extract the specific coefficients for the link between partisanship and physical distancing (general movement and nonessential visitations, multiplied by 100 to yield percentages) on each day from March 9 to May 29. All of the covariates noted above were included in these models. We then plotted the extracted coefficients over time (Figure 5). Linear models predicting these coefficients with orthogonal linear and quadratic time terms (z -scored) indicated that the negative association between pro-Trump voting and physical distancing (collapsed across the two measures) strengthened by approximately -0.047 percentage points per day (-3.85 percentage points across March 9 to May 29; linear time term: $B_{\text{movement}} = -0.96$, 95% CI[-1.15, -0.77] and $B_{\text{visitation}} = -1.30$, 95% CI[-1.60, -1.00], $ps < .001$). We also observed a quadratic pattern for general movement. Pro-Trump voting increasingly linked to decreased physical distancing as the pandemic progressed, finally peaking in early May and beginning to weaken slightly thereafter (quadratic time effect: $B_{\text{movement}} = 0.86$,

95% CI[0.67, 1.05], $p < .001$, and $B_{\text{visitation}} = 0.36$, 95% CI[0.06, 0.67], $p = .019$; Figure 5; Supplemental Note 12). These analyses further confirm that the observed partisan gap in distancing increased over time.

Figure 5. Percent reduction in general movement and visiting nonessential services (relative to pre-COVID; before March 9) as a function of Trump voting (z-scored) and as a function of time (between March 9 to May 29, 2020). For instance, -6 on the y-axis indicates 6 percentage points less physical distancing in Trump counties (+1 *SD* pro-Trump vote lean) on a specific day. Individual points represent regression coefficients; more negative coefficients represent a greater partisan gap. Given the date range of 82 days, 82 observations are included for each of the two physical distancing measures. Blue lines represent predictions from linear regression models with linear and quadratic time terms. For GAM models of these data see Supplements. Error bands: $\pm 2 SE$.

Partisanship, Physical Distancing, and State-Policies

Possibly, local stay-at-home policies attenuate the observed findings as such policies send clear signals about the dangers of COVID-19. In line with this reasoning, we predicted that state-level stay-at-home orders would potentially reduce the observed partisan differences (see our pre-registered hypotheses [here](#)). Our data did not support this prediction. The link between voting for Trump and reduced physical distancing was actually stronger when stay-at-home orders were in effect, as evidenced by negative interactions between vote gap (with higher values indicating greater pro-Trump lean) and state policy: $B_{\text{movement}} = -0.017$, 95% CI[-0.022, -0.013], $p < .001$, and

$B_{\text{visitation}} = -0.009$, 95% CI[-0.016, -0.001], $p = .030$ (for examinations of detailed state-policies, such as closing restaurants and closing schools, see Supplementary Tables 32 and 33; Supplemental Note 13). These results align with recent work finding that Democratic counties responded more quickly to stay-at-home orders than Republican counties at the start of the pandemic³².

We considered the possibility that variability in state stay-at-home policies explains our findings instead of county-level partisanship. For instance, stay-at-home orders may have been more stringent and remained in place longer in Democratic states or in states with Democratic governors, in turn resulting in Republican leaning counties (which are more common in Republican states) exhibiting less physical distancing. We accounted for this possibility in three ways. First, our results remained when adjusting for whether state policies were in effect on a given date, state governors' political affiliation, and interactions between these variables and partisanship (Table 1; see Supplementary Table 31). Second, we also found our results when adding specific state policies (including closing restaurants, closing childcare, closing K-12 schools, closing non-essential business more generally, and closing religious institutions/gatherings) and the interactions between these policies and governor political party and partisanship in our models (see Detailed State Policies section in the Supplements; Supplementary Tables 32 and 33). And third, as can be seen in Supplementary Figure 4, while there was some variation in our findings between states, most states were in line with the population average of the observed partisan differences (see also Supplementary Figures 5 and 6 and Supplemental Note 14). In sum, while differences in state-policies contribute to variation in county-level physical distancing, our results indicate that county-level partisanship explains unique variance in physical distancing (see Supplements for more details).

Partisan Media and Physical Distancing

One method through which partisan viewpoints are propagated is partisan media. Potentially, then, watching more Republican than Democratic-leaning media (e.g., Fox News versus MSNBC) is linked to lower levels of physical distancing. Indeed, recent research has found a causal effect of Fox News viewership on reducing stay-at-home behavior³³ and indicated that behavioral responses to COVID-19 change in line with the specific cable news show people watch (e.g., Tucker Carlson Tonight versus Hannity)³⁴. To examine whether viewing Republican- versus

Democratic-leaning media is associated with differences in physical distancing, we analyzed viewership data from SimplyAnalytics. We found that the degree to which people in different counties watched Fox News over CNN and MSNBC was associated with lower levels of physical distancing ($B_{\text{movement}} = -0.053$, 95% CI[-0.076, -0.030] and $B_{\text{visitation}} = -0.099$, 95% CI[-0.136, -0.062], $ps < .001$; Supplementary Figure 2; Supplemental Note 15). Importantly, these results were found while accounting for all covariates (Main Model in Supplementary Tables 27 and 28), and remained when additionally controlling for interactions between watching Fox News (over CNN and MSNBC) and these covariates, $ps < .001$ (Saturated Model in Supplementary Tables 27 and 28). And, as was the case for partisanship as assessed by 2016 vote-gap, the observed partisan media differences in physical distancing strengthened over time (see Supplementary Tables 27, 28, and 30 and Supplementary Figures 2 and 3).

We also tested whether consuming Republican-leaning media and 2016 pro-Trump vs. pro-Clinton voting account for independent variance in physical distancing. Supporting this possibility, we found that Fox News consumption (over MSNBC and CNN) still negatively related to physical distancing when including 2016 vote gap, the interactions between vote gap and linear and quadratic time, and the interaction between vote gap and Fox News lean in the models, $B_{\text{visitation}} = -0.038$, 95% CI[-0.063, -0.014], $p = .002$, and $B_{\text{visitation}} = -0.053$, 95% CI[-0.092, -0.013], $p = .009$ (Supplementary Table 29). Furthermore, in these analyses, the coefficients for partisan vote gap and Fox News lean both decreased (see Table 1 and Supplementary Tables 27 and 29), suggesting that Republican-leaning media consumption may in part account for the observed covariance between vote gap and physical distancing (and vice-versa).

Linking Physical Distancing to COVID-19 Infections and Fatalities

We next examined whether the observed partisan differences in distancing relate to COVID-19 infections and fatalities. Applying three-level mixed-effects models, with counties nested within states, we first tested whether counties' time-lagged physical distancing is associated with decreased COVID-19 infection and fatality growth rate. Growth rates were examined because the main goal of physical distancing is to "flatten the curve," or the spread of coronavirus disease (see Method for calculation)^{34,35}.

Given the time-lag between contracting COVID-19, experiencing symptoms, and receiving a positive test result, physical distancing should not have an immediate impact on infection or

fatality growth rate. In line with this reasoning, we considered the length of the delay between physical distancing and subsequent reductions in infections and fatalities. We treated the incubation period of COVID-19 as the time from exposure to symptom onset³⁶⁻³⁹. Although this period may include a period of asymptomatic viral shedding, we did not account for this in our analysis³⁹. Based on previous work, we estimated the incubation period of COVID-19 to be between 2 to 11 days (median 4-5 days)³⁶⁻³⁹. We then estimated that receiving positive test results typically takes at least one day (and often takes much longer). Given these estimates, physical distancing could begin to reduce counties' infection growth rate as early as 3 days thereafter, but more likely begins to have a measurable impact around 7-8 days later (~5 day incubation period plus ~3 days to seek and receive test results). Importantly, this estimate does not represent when the impact of physical distancing is strongest. That is, physical distancing should relate to decreased growth rate more and more strongly as delayed testing is completed, residual infections die out, and cases with long incubation periods pass, until eventually, this link peaks and then starts to decline (Supplementary Figures 12 through 15)⁴⁰.

We conducted a series of mixed-effects models to identify the lag time in which physical distancing most strongly relates to reduced infections. Specifically, we examined the predictive power of rolling 7-day averages of general movement and visiting nonessential services, $[(p_t + p_{t-1} + \dots + p_{t-6})/7; t = \{35, 34, \dots, 7\}]$, where t = lag day and p = physical distancing score) on infection growth rate. Both for general movement and visiting nonessential services, physical distancing between 17 and 23 days before a given date (z-scored; 7-day lagged average) most strongly related to lower infection growth rate on that date, $B_{\text{movement}} = -3.05$, 95% CI[-3.15, -2.94], and $B_{\text{visitation}} = -3.53$, 95% CI[-3.65, -3.41], $ps < .001$ (Table 2; Supplementary Figures 12 and 13; the first 7-day lag to negatively relate to infections was between 6 and 12 days for general movement and 7 and 13 days for visitation). In other words, a reduction in infection growth rate on a specific day was best accounted for by the degree to which people in a county were physically distancing between 17 and 23 days earlier (see Supplements for other 7-day lags).

Importantly, this link remained when including all covariates from our earlier analyses (e.g., population density, distance traveling to work, age), and when additionally including non-time-lagged physical distancing—physical distancing on the same day—in these models, $B_{\text{movement}} = -3.31$, 95% CI[-3.42, -3.21], and $B_{\text{visitation}} = -4.54$, 95% CI[-4.66, -4.41], $ps < .001$ (Table 2). Moreover, supporting the unique relationship between time-lagged physical distancing and

subsequent infections, counties' non-lagged physical distancing (i.e., same-day physical distancing) was associated with a higher rather than lower infection growth rate, $B_{\text{movement}} = 1.66$, 95% CI[1.55, 1.77], and $B_{\text{visitation}} = 2.94$, 95% CI[2.81, 3.08], $ps < .001$, $ps < .001$ (Table 2). These positive same-day relationships between distancing and growth rate reflect that counties hit hardest by the pandemic were also those that responded by engaging most in physical distancing (see Supplements for cross-lagged analyses substantiating this claim).

Turning to fatalities, estimates of the time lag from COVID-19 infection to death vary between 2 to 4 weeks (approximately 1 to 2 weeks after symptoms appear)^{41,42}. Using the same 7-day lagged approach as for infections, we found that counties' physical distancing 25-31 days before a given day most strongly related to lower fatality growth on that day, $B_{\text{movement}} = -0.67$, 95% CI[-0.74, -0.59], and $B_{\text{visitation}} = -0.69$, 95% CI[-0.79, -0.59], $ps < .001$ (Table 2; Supplementary Figures 14 and 15). As was true for infections, these results remained when including all covariates, and when including non-lagged physical distancing in the models, $B_{\text{movement}} = -0.70$, 95% CI[-0.78, -0.62], and $B_{\text{visitation}} = -0.81$, 95% CI[-0.91, -0.70], $ps < .001$ (Table 2). And, as was also true for infections, non-lagged distancing was associated with higher rather than lower fatalities, $B_{\text{movement}} = 0.45$, 95% CI[0.38, 0.51], and $B_{\text{visitation}} = 0.55$, 95% CI[0.46, 0.64], $ps < .001$ (Table 2). Collectively, these results suggest that counties' degree of physical distancing 17-23 days and 25-31 days earlier best accounts for reductions in infection and fatality growth rates, respectively.

Table 2. Results of multilevel mixed-effects models testing whether physical distancing is linked to infection and fatality growth rates. Physical distancing 17-23 days before a given date related to decreased infection growth rates on that date. Physical distancing 25-31 days before a given date related to decreased fatality growth rates on that date.

	Infection Growth Rate				
	Estimates	SE	z	CI	p
<i>General Movement</i>					
17-23 Days Lagged Physical Distancing (Absent Covariates)	-3.05	0.05	-56.29	-3.15 – -2.94	<0.001

17-23 Days Lagged Physical Distancing (All Covariates Included)	-3.24	0.05	-59.30	-3.34 – -3.13	<0.001
17-23 Days Lagged Physical Distancing (All Covariates and Non-Lagged Physical Distancing Included)	-3.31	0.05	-61.95	-3.42 – -3.21	<0.001
Non-Lagged Physical Distancing (All Covariates Included)	1.66	0.06	30.02	1.55 – 1.77	<0.001
<i>Visiting Nonessential Services</i>					
17-23 Days Lagged Physical Distancing (Absent Covariates)	-3.53	0.06	-57.41	-3.65 – -3.41	<0.001
17-23 Days Lagged Physical Distancing (All Covariates Included)	-4.24	0.06	-65.33	-4.37 – -4.11	<0.001
17-23 Days Lagged Physical Distancing (All Covariates and Non-Lagged Physical Distancing Included)	-4.54	0.06	-71.51	-4.66 – -4.41	<0.001
Non-Lagged Physical Distancing (All Covariates Included)	2.94	0.07	42.14	2.81 – 3.08	<0.001
<hr/>					
Fatality Growth Rate					
	<i>Estimates</i>	<i>SE</i>	<i>z</i>	<i>CI</i>	<i>p</i>
<hr/>					
<i>General Movement</i>					
25-31 Days Lagged Physical Distancing (Absent Covariates)	-0.67	0.04	-17.65	-0.74 – -0.59	<0.001
25-31 Days Lagged Physical Distancing (All Covariates Included)	-0.71	0.04	-17.84	-0.79 – -0.64	<0.001
25-31 Days Lagged Physical Distancing (All Covariates and Non-Lagged Physical Distancing Included)	-0.70	0.04	-17.59	-0.78 – -0.62	<0.001
Non-Lagged Physical Distancing (All Covariates Included)	0.45	0.03	13.73	0.38 – 0.51	<0.001
<i>Visiting Nonessential Services</i>					
25-31 Days Lagged Physical Distancing (Absent Covariates)	-0.69	0.05	-13.37	-0.79 – -0.59	<0.001
25-31 Days Lagged Physical Distancing (All Covariates Included)	-0.82	0.05	-15.12	-0.93 – -0.72	<0.001
25-31 Days Lagged Physical Distancing (All Covariates and Non-Lagged Physical Distancing Included)	-0.81	0.05	-14.80	-0.91 – -0.70	<0.001

Non-Lagged Physical Distancing (All Covariates Included)	0.55	0.05	12.15	0.46 – 0.64	<0.001
---	------	------	-------	-------------	--------

Notes. For a list of covariates see Method.

Linking Partisanship and Physical Distancing to COVID-19 Infections and Fatalities

Finally, we tested whether partisan-linked failures to physically distance during the pandemic related to higher infection and fatality growth rates. We approached this analysis by testing mediation models in Stata following multilevel mediation procedures⁴³. These mediation models included three-level mixed-effects models as in the analyses reported throughout this article (Supplemental Note 16). The models included counties' pro-Trump voting (z -scored) as the predictor variable, lagged physical distancing (general movement and visiting nonessential services lagged 17-23 days for infections and 25-31 days for fatalities; z -scored) as the mediators, infection growth rate or fatality growth rate as the outcome variables, and all covariates as control variables (see Supplements).

The mediation analyses revealed significant indirect links between counties' pro-Trump voting and infection growth rate via physical distancing (lagged 17 to 23 days), $B_{\text{movement}} = 0.855$, 95% CI[0.622, 1.088], and $B_{\text{visitation}} = 0.896$, 95% CI[0.679, 1.113], $ps < .001$ (Table 3). Regarding the total effects, Trump-leaning counties on average exhibited marginally higher infection growth rates than Clinton-leaning ones between March 26 and May 29, 2020, $B_{\text{movement}} = 0.272$, 95% CI[-0.020, 0.564], and $B_{\text{visitation}} = 0.313$, 95% CI[0.032, 0.594], $ps < .068$ (Total Effects in Table 3; Supplemental Note 17); however, this would not have been the case if Trump-leaning counties had physically distanced the same degree as more Clinton-leaning counties. If they had done so, Trump-leaning counties would actually have had lower infection growth rates than Clinton-leaning ones between March 26 and May 29, 2020, $B_{\text{movement}} = -0.583$, 95% CI[-0.915, -0.251], and $B_{\text{visitation}} = -0.582$, 95% CI[-0.912, -0.253], $ps < .002$ (Direct Effects in Table 3).

Similar indirect effects were also observed for fatality growth rate, $B_{\text{movement}} = 0.183$, 95% CI[0.090, 0.277], and $B_{\text{visitation}} = 0.176$, 95% CI[0.087, 0.264], $ps < .001$ (lagged 25 to 31 days earlier; Table 3). Regarding total effects, Trump-leaning counties exhibited smaller fatality growth rates than Clinton-leaning ones, $B_{\text{movement}} = -0.417$, 95% CI[-0.647, -0.188], and $B_{\text{visitation}} = -0.533$, 95% CI[-0.850, -0.216], $ps < .001$ (between April 3 and May 29, 2020; see Total Effects, Table 3); however, these counties would have exhibited even smaller fatality growth rates had they physically distanced to the same extent as more Clinton-leaning counties, $B_{\text{movement}} = -0.601$, 95%

CI[-0.858, -0.344], and $B_{\text{visitation}} = -0.709$, 95% CI[-1.050, -0.368], $ps < .001$ (see Direct Effects in Table 3; Supplemental Note 18).

Table 3. *Output of mediation models. The link between partisanship (vote-share for Trump over Clinton in 2016; z-scored) and COVID-19 infection and fatality growth rate was mediated by time-lagged physical distancing (reduction in general movement and visiting nonessential services 17-23 days and 25-31 days earlier, respectively; z-scored).*

Predictor Variable			Mediator		Outcome Variable
Mediation 1:	Partisanship		Lagged Reduction in General Movement (17-23 days prior)		Infection Growth Rate
Total Effect	$B = 0.272$	$SE = 0.149$	$z = 1.83$	$p = .067$	95% CI: [-0.020, 0.564]
Direct Effect	$B = -0.583$	$SE = 0.170$	$z = -3.44$	$p = .001$	95% CI: [-0.915, -0.251]
Indirect Effect	$B = 0.855$	$SE = 0.119$	$z = 7.19$	$p < .001$	95% CI: [0.622, 1.088]
Mediation 2:	Partisanship		Lagged Reduction in Visiting Nonessential Services (17-23 days prior)		Infection Growth Rate
Total Effect	$B = 0.313$	$SE = 0.143$	$z = 2.19$	$p = .029$	95% CI: [0.032, 0.594]
Direct Effect	$B = -0.582$	$SE = 0.168$	$z = -3.47$	$p = .001$	95% CI: [-0.912, -0.253]
Indirect Effect	$B = 0.896$	$SE = 0.111$	$z = 8.09$	$p < .001$	95% CI: [0.679, 1.113]
Mediation 3:	Partisanship		Lagged Reduction in General Movement (25-31 days prior)		Fatality Growth Rate
Total Effect	$B = -0.417$	$SE = 0.117$	$z = -3.56$	$p < .001$	95% CI: [-0.647, -0.188]
Direct Effect	$B = -0.601$	$SE = 0.131$	$z = -4.58$	$p < .001$	95% CI: [-0.858, -0.344]
Indirect Effect	$B = 0.183$	$SE = 0.048$	$z = 3.85$	$p < .001$	95% CI: [0.090, 0.277]
Mediation 4:	Partisanship		Lagged Reduction in Visiting Nonessential Services (25-31 days prior)		Fatality Growth Rate
Total Effect	$B = -0.533$	$SE = 0.162$	$z = -3.30$	$p = .001$	95% CI: [-0.850, -0.216]
Direct Effect	$B = -0.709$	$SE = 0.174$	$z = -4.07$	$p < .001$	95% CI: [-1.050, -0.368]
Indirect Effect	$B = 0.176$	$SE = 0.045$	$z = 3.89$	$p < .001$	95% CI: [0.087, 0.264]

This pattern of results was robust. The observed mediations remained consistent when including employment type as further control variables, $ps < .003$ (Supplementary Table 34), when testing earlier date ranges for the lagged mediators (e.g., March 26 to May 29 for infections), $ps < .005$ (Supplementary Table 35), when excluding all cases in which growth rate was 0 (to account for potential zero-inflation in the data), $ps < .001$ (Supplementary Table 36), when calculating infection and fatality growth rate using moving averages, $ps < .001$ (Supplementary Table 37), and when including specific state-policies (e.g., closing restaurants, closing schools) as additional control variables, $ps < .001$ (Supplementary Table 38).

To put our findings into context, our model indicated that extremely pro-Trump voting counties (+2 z -score in the vote gap variable) experienced a daily infection growth rate of .59 percentage points higher than average (between March 26 and May 29, 2020; the average daily infection growth rate across all counties in this date-range was 5.72 percentage points; Supplemental Note 19). Such pro-Trump counties would have experienced a daily infection growth rate of 1.17 percentage points less on average, however, if they had socially distanced to the same extent as the average county—a swing of 1.76 percentage points in infection growth rate. Our findings thus suggest that partisan differences in physical distancing were linked to higher growth rates of infections and fatalities in pro-Trump counties than necessary.

Finally, we reconducted our mediation analyses when calculating infection and fatality growth rate using an exponential model of disease spread (see Supplements; $r = \ln(I_{t+1}/I_t)$)³⁵. Applying an exponential growth rate is illuminating from an epidemiological perspective, as COVID-19 would initially spread exponentially in the scenario of a disease spreading within a closed, homogeneous population without interventions^{29,35,44,45}. Importantly, when doing so, we observed the same mediation results as above, $ps < .001$ (Supplementary Table 39).

It is possible that the estimated indirect effects are skewed by differences in reporting or tracking infections (e.g., certain areas testing more than others). To begin to account for this possibility, we examined and found that the observed indirect effects of county partisanship on infection growth rate remained when individually testing these mediations within states and then aggregating these results via a meta-analysis, $B = .417$, $z = 3.43$, $p < .001$ (see Supplements). These analyses help address reporting concerns because, although reporting differences may exist across states, it is less likely that they exist within states (the utilized mixed-effects modeling should also

help allay this concern; see Supplemental Note 20). Nonetheless, biased estimates in reporting and testing remain possible, if not probable, and thus are a limitation of our results.

Discussion

The present work examined whether partisan identity is linked to objective measures of physical distancing during the coronavirus pandemic using geotracking data of approximately 15 million people a day across the United States. We found that Republican-leaning counties exhibited lower physical distancing than Democratic-leaning counties both in terms of overall movement and visiting nonessential services. Counties that voted for Trump in the 2016 election exhibited a ~24% drop in general movement and visiting nonessential services between March 9 and May 29, 2020, while counties that voted for Clinton exhibited a ~38% drop (a 14% difference in physical distancing). Moreover, this partisan gap remained consistent after adjusting for numerous third variables, including counties' median income, wealth distribution, number of COVID-19 cases per capita, population density, travel time to work, and racial and age make-up, among other factors (see Method). These data suggest that partisan differences in self-reported attitudes toward COVID-19¹⁸⁻²² are mirrored by behavioral differences at the U.S. county level.

We also linked the observed partisan differences in physical distancing to COVID-19 infections and fatalities. Mediation analyses revealed that reduced physical distancing in counties was linked to an increase in COVID-19 infection and fatality growth rate roughly 17-23 days and 25-31 days later, respectively. These results imply that Trump-leaning counties could have curbed their infection and fatality growth rates if they had distanced to the same degree that Clinton-leaning counties did. Such findings provide evidence that partisanship in the U.S. during the COVID-19 pandemic may have had significant—and severe—health-related consequences. Partisanship may therefore be an important risk factor during a public health crisis, one that is likely especially relevant when the electorate is highly polarized and leaders fail to generate bipartisan support for public health measures.¹⁷

The observed partisan differences appear to be relatively strong and highly robust. Partisanship was more strongly associated with physical distancing than most of the covariates included in our models, including more traditionally examined health-related variables, such as economic and social indicators. The relationship between partisanship and distancing also held after statistically adjusting for numerous control variables and for interactions between partisanship and these controls variables. The robustness of these findings is consistent with

findings from independent research groups who have also observed links between partisanship and physical distancing using different data sources^{46,47}. Taken together, these findings provide a more complete picture of partisanship during a pandemic and establish it as an important risk factor for COVID-19 in the United States.

The observed partisan gap in physical distancing was not limited to the beginning of the COVID-19 pandemic. Though we had expected that this difference would attenuate as the pandemic worsened after March 23, 2020 (Supplemental Note 21), we instead found that the partisan gap actually increased over time (Figure 5). We also expected that local-government intervention would attenuate the observed partisan differences. Again, we instead found that stay-at-home orders actually exacerbated the observed partisan gap. That is, stay-at-home orders appeared to be more successful in encouraging Democratic counties to physically distance than Republican ones. This difference may be driven by more Republican-leaning counties ignoring local stay-at-home orders in light of national messaging from right-wing media and federal leaders. Or, Republicans may simply hold a greater distrust of government than Democrats⁴⁸. These issues require further investigation to determine how to intervene locally to ensure greater compliance with public health recommendations.

The observed partisan differences may be partially driven by Republican counties experiencing fewer COVID-19 infections and fatalities than Democratic ones at the start of the pandemic. Simply put, for Republicans, the threat of COVID-19 may have been less salient. Arguing against this possibility, our findings remained when adjusting for counties' infections per capita (Table 1); doing so should account for Republican counties being objectively less threatened during the examined time-frame (between March 9 and May 29, 2020). Moreover, desired political outcomes (e.g., wanting the pandemic to be less serious than it is for political reasons), and not one's actual experiences with COVID-19 (e.g., knowing someone who was infected), appear to drive self-reported partisan differences in concern about the pandemic⁴⁹. As such, it seems that objective risks of infection do not account for the observed partisan differences in physical distancing.

In our view, a more likely, albeit partial, explanation for the observed results is media polarization or a "broadcasting effect"^{15,50}. Republican-leaning media outlets appear to have downplayed the dangers of the coronavirus as compared to more Democratic outlets. For instance, in early March, Fox News repeatedly claimed the coronavirus was less dangerous than the flu and

even referred to other media reports as a hoax (though some commentators took it more seriously than others, and the organization took the pandemic more seriously by mid-March, 2020)⁵¹. Consistent with this messaging about COVID-19, we found that U.S. counties that consumed Fox News more so than Democratic-leaning outlets (MSNBC and CNN) exhibited less physical distancing. These findings also remained significant when controlling for counties' partisanship in terms of 2016 voting. These results, along with self-report data indicating similar findings²² and recent evidence demonstrating a link between Fox News viewership and decreased social distancing³³, suggest that Republican-leaning media downplaying the virus at the start of the pandemic may have signaled to Republicans that they should not take the virus very seriously, in turn potentially in part causing the observed partisan differences. This possibility underscores the importance of considering communication and mass media when designing public health messaging.

Of course, other factors may help account for the observed differences as well. For instance, political role-models may have signaled different actions as appropriate responses to the pandemic (e.g., not wearing versus wearing a mask). For example, President Donald Trump referred to criticisms about his administration's response to the pandemic as "their new hoax." Moreover, public events hosted by Donald Trump in Tulsa and Arizona (June 2020) revealed, accordingly, that at least some of his supporters are willing to attend high risk events, like large, indoor gatherings.

Finally, we consider that conservative versus liberal political ideologies may lead individuals to respond differently to threat or specifically to the threat of a viral pandemic^{52,53}. We find this conclusion unlikely, however, given that conservatives were actually more likely than liberals to report being worried about the potential spread of a different virus—Ebola—in the U.S. in 2014⁵⁴. As such, it seems that our findings are more likely to be driven by modeling the behavior of political role-models and political identity (i.e., political group loyalty) than political ideology (i.e., political values)^{7,16,55,56}. Indeed, Democrats are not only more likely than Republicans to say they prioritize stay-at-home orders, but this partisan difference is most pronounced among highly-identified group members⁵⁷.

Our findings draw from a very large sample of real behavior and are robust to several model specifications, but nevertheless have limitations. First, these data are correlational and cannot be used to draw causal conclusions. Second, the data are county-level aggregates and thus do not tell

us whether individual Republicans engage in less physical distancing than Democrats (though self-reported data indicate they are likely to)¹⁹. Likewise, though we accounted for numerous structural state-level factors (e.g., Governor's political party, types of state policy), it remains plausible that certain state-level factors explain a portion of the observed findings. Third, the current results are limited to the United States; it remains unclear whether partisanship or political polarization played a role in COVID-19 responses in other countries. Fourth, we did not consider the role of face-masks or other public health behaviors in the present findings. That is, our findings may or may not extend to other preventative COVID-19 practices, and additionally, these other practices may covary with distance and therefore help account for subsequent infections and mortality. Fifth, infection and fatality counts may be unreliable. For instance, certain areas may have failed to provide proper testing or failed to count deaths at home as COVID-19 fatalities. As such, our mediation results should be approached cautiously. Sixth, several of the variables we examined failed to capture nuanced variance; for instance, though we controlled for counties' average number of supermarkets, these values may vary substantially within a county (creating "food deserts" that we do not account for). And, though we control for counties' type of employment in our analyses, physical distancing may vary greatly within these employment types. Finally, people in pro-Trump counties may need to travel further to shop for essential goods or for work. However, we found consistent results when statistically adjusting for access to supermarkets and average time to travel to work. Nevertheless, future research should examine individual behavioral differences using causal tests to help determine if partisanship is causally related to public health behavior.

Though few things bind groups together like a common obstacle, the COVID-19 pandemic has had a deeply partisan flavor in the United States (and seemingly continues to do so). Here we found that partisanship is associated with differences in physical distancing behavior at the level of U.S. counties—and that this degree of physical distancing may have impacted counties' COVID-19 infection and fatality growth rates. This suggests that partisanship might be an important risk factor for the current pandemic and potentially other public health crises. We encourage researchers who study other health issues to consider the role that partisanship might play in health-related decision-making. Our work highlights the possibility that political partisanship in the U.S. is now far-reaching and pernicious enough to threaten the health of citizens during a pandemic.

Method

Our research complies with all relevant ethical regulations. As the data in question included aggregated county level data collected by an external source (Unacast), it categorizes as exempt according to the Yale University Institutional Review Board. We are unaware of whether participants were compensated. Participants completed opt-in consent. The sample included approximately 15 million smartphone users per day in the United States. Given the aggregated nature of this data, sex, age, and the exact number of participants are unknown. No statistical methods were used to pre-determine sample size (in terms of the number of included U.S. counties), but our sample was quite large (3,025 counties were included in our analyses). This sample size provides enough statistical power to observe relationships even of a very small size. Pre-registrations of hypotheses can be found [here](#). These pre-registrations specify two hypotheses—that the observed partisan differences would reduce with time and would reduce when stay-at-home orders were in effect. These pre-registrations do not speak to any other hypotheses and do not include clear analysis plans or model specifications and thus solely qualify as preregistrations of these two specific hypotheses (see Supplemental Notes 9 and 10).

Physical distancing. We examined people's physical distancing behaviors in 3,025 U.S. counties (those with a population of at least 2,000; Supplemental Note 22) between March 9 and May 29, 2020. Physical distancing was assessed via a county's percent reduction in general movement and visiting nonessential services (e.g., barbers, restaurants, clothing stores; Supplemental Note 23) relative to before COVID-19 struck the United States with force (before March, 9th; Supplemental Note 24). Physical distancing on a specific day was calculated as the change in a county's general movement and visiting nonessential services from the same day of the week during the four weeks leading up to March 9 (percent reduction in general movement: $M = 0.21$, $SD = 0.19$; percent reduction in general movement: $M = 0.31$, $SD = 0.30$). For example, a county's level of physical distancing on Monday, March 9 was calculated as the percent reduction in movement and nonessential visits from the average levels of movement and nonessential visits on the four pre-COVID Mondays (February 10, February 17, February 24, and March 2) in that county. In our main analyses, we included 3,007 counties across 82 days when examining general movement (18 counties were excluded for missing partisanship data; see below) and 2,068 counties across 82 days when examining nonessential visitation (957 counties were excluded [and some additional physical distancing data points] for missing partisanship or missing visitation

data). This resulted in the inclusion of 248,050 total physical distancing data points when examining general movement, and 169,480 total physical distancing data points when examining nonessential visitation.

The two assessed physical distancing variables—general movement and visiting nonessential services—were calculated by Unacast (a software company that provides location tracking and map services) using approximately 15 million smartphone GPS coordinates across the U.S per day. Unacast gathers GPS data from thousands of opt-in consent apps. This GPS data is then categorized in terms of stops (a device being stationary over a period of time) and travel events (a device moving). General movement is thus, for instance, calculated as the total time traveled for each device in a county, averaged across all the devices in that county (see Supplements for greater detail on how the physical distancing variables were constructed). The data were anonymized in that GPS coordinates were aggregated at the county level (the locations of specific individuals were not shared with the authors).

Partisanship: Vote-gap. A continuous index of partisanship was created using the county-level voting gap in the 2016 election—that is, the proportion of total votes for Donald Trump (Republican) minus proportion of total votes for Hillary Clinton (Democrat). Average vote share across the 3,007 counties for which we obtained data was 31% greater for Trump; $M = 0.31$, $SD = 0.30$, $\min = -0.89$, $\max = .85$. Binning counties according to Trump- vs. Clinton-lean produced 480 Clinton counties (average vote share favoring Clinton; $M = -0.23$, $SD = 0.19$) and 2,527 Trump counties (average vote share favoring Trump; $M = 0.41$, $SD = 0.19$). Greater detail of all the included measures can be found in the Supplements and on our OSF project page ([here](#)).

Fox News preference. We created a Fox News preference score by subtracting the proportion of people watching CNN and MSNBC (averaged) from the proportion of people watching Fox News per U.S. county. Across counties, Fox News was on average watched 7.6% more (in terms of proportion of population) than CNN and MSNBC, $M = 0.076$ (7.6%), $SD = 0.004$, $\min = 0.059$, $\max = 0.098$.

Control variables. All covariates were, insofar as possible, kept on their original scale to aid understanding of regression coefficients reported in the Supplemental Tables. The covariates included weekend (0 = Weekday, 1 = Weekend), COVID-19 infections per 100 capita (on each date for the included date range, mean-centered), state policy (0 = stay-at-home order not in effect

and 1 = stay-at-home order in effect on each day for the included date range, mean-centered), party affiliation of state governor (0 = Republican, 1 = Democrat, mean-centered), population density (log, standardized), median household income in 2018 (in units of \$10K, mean-centered), degree of income inequality (Gini coefficient; mean-centered), median age in 2018 (mean-centered), proportion of population aged 0-17 (mean-centered), proportion of population over 65 (mean-centered), proportion of population over 85 (mean-centered), race/ethnicity (proportion of population Black, Hispanic, and Asian; all mean-centered), low access to grocery stores (e.g., because of distance or income; mean-centered), number of grocery stores per 1,000 people (mean-centered), mean travel time to work (hours, mean-centered), religiosity (mean-centered), change in life expectancy from 1985 to 2010 (years, mean-centered), and proportion employed (mean-centered). We also controlled counties' percent of employment in various types of professions (e.g., agriculture, finance, manufacturing) in additional analyses (e.g., Supplementary Table 24). For more details regarding these control variables, descriptive statistics, and the strength of the links between these factors and physical distancing, see Supplements (Supplementary Tables 1-10, 22-24, 27-29).

Infection and fatality growth rates. Growth rate in infections was calculated as $(I_t - I_{t-1})/I_{t-1} \times 100$, where I is the cumulative number of infections and t is the time (day). Exponential growth rate was calculated as the growth rate tailored to an exponential model of disease spread (see Supplements; $r = \ln(I_{t+1}/I_t)$). Fatality growth rate simply substitutes cumulative fatalities for infections. Calculated as such, growth rate is identical to growth rate in cases per capita because counties' populations did not vary during the sample period (see Supplements for more details).

Data Availability Statement

We are unable to publicly share some of the data as it is proprietary. To access this data please contact Unacast (<https://www.unacast.com/covid19/social-distancing-scoreboard#get-started>).

The data is fully accessible upon agreeing to certain sharing restrictions and ethics guidelines.

For instance, the data cannot be used for commercial purposes and can only be used for academic/research purposes.

Code Availability Statement

Code for all analyses can be found [here](#)

(https://osf.io/u5pmw/?view_only=33f0691a7e694276bef606cb3e22d141).

References

- 1) Perez-Truglia, R. & Cruces, G. Partisan interactions: evidence from a field experiment in the United States. *J. Political Econ.* **125**, 1208-1243 (2017).
- 2) Motyl, M., Iyer, R., Oishi, S., Trawalter, S., & Nosek, B. A. How ideological migration geographically segregates groups. *J. Exp. Soc. Psychol.* **51**, 1-14 (2014).
- 3) Brady, W. J., Wills, J. A., Jost, J. T., Tucker, J. A., & Van Bavel, J. J. Emotion shapes the diffusion of moralized content in social networks. *Proc. Natl. Acad. Sci. USA.* **114**, 7313-7318 (2017).
- 4) Doherty, C., Kiley, J., & Jameson, B. Partisanship and political animosity in 2016. *Pew Research Center* <https://www.people-press.org/2016/06/22/partisanship-and-political-animosity-in-2016/> (2016).
- 5) Garrett, R. K. Echo chambers online?: politically motivated selective exposure among internet news users. *J. Comput.-Mediat. Commun.* **14**, 265-285 (2009).
- 6) Iyengar, S. & Krupenkin, M. Partisanship as social identity: implications for the study of party polarization. *The Forum* **16**, 23-45 (2019).
- 7) Mason, L. *Uncivil Agreement: How Politics Became Our Identity*. (U. of Chicago Press, 2018).
- 8) McConnell, C., Margalit, Y., Malhotra, N., & Levandusky, M. The economic consequences of partisanship in a polarized era. *Am. J. Political Sci.* **62**, 5-18 (2018).

- 9) Frenda, S. J., Knowles, E. D., Saletan, W., & Loftus, E. F. False memories of fabricated political events. *J. Exp. Soc. Psychol.* **49**, 280-286 (2013).
- 10) Huber, G. A., & Malhotra, N. Political homophily in social relationships: evidence from online dating behavior. *J. Politics* **79**, 269-283 (2017).
- 11) Data dive: the emotional cost of the 2016 election. *Reuters*
<https://www.reuters.com/article/us-datadive-election/data-dive-the-emotional-cost-of-the-2016-election-idUSKBN15M1YC> (2017).
- 12) Chen, M. K. & Rohla, R. The effect of partisanship and political advertising on close family ties. *Science* **360**, 1020-1024 (2018).
- 13) Bail, C. A. et al. Exposure to opposing views on social media can increase political polarization. *Proc. Natl. Acad. Sci. USA.* **115**, 9216-9221 (2018).
- 14) Brady, W. J., Crockett, M. J., & Van Bavel, J. J. The MAD model of moral contagion: the role of motivation, attention, and design in the spread of moralized content online. *Perspect. Psychol. Sci.* 1745691620917336 <https://doi.org/10.1177/1745691620917336> (2019).
- 15) Martin, G. J. & Yurukoglu, A. Bias in cable news: persuasion and polarization. *Am. Econ. Rev.* **107**, 2565-99 (2017).
- 16) Van Bavel, J. J. & Pereira, A. The partisan brain: an identity-based model of political belief. *Trends Cogn. Sci.* **22**, 213-224 (2018).
- 17) Van Bavel, J. J., et al. Using social and behavioral science to support COVID-19 pandemic response. *Nature Human Behavior* **4**, 460-471 (2020).

- 18) Hart Research Associates/Public Opinion Strategies, NBC News/Wall Street Journal Survey data sets. <https://www.documentcloud.org/documents/6810602-200149-NBCWSJ-March-Poll-Final-3-14-20-Release.html> (2020).
- 19) Gallup Editors. Is the media creating division on COVID-19 health practices? *Gallup* <https://news.gallup.com/poll/312749/media-creating-division-covid-health-practices.aspx> (2020).
- 20) Gadarian, S. K., Goodman, S. W., & Pepinsky, T. B. Partisanship, health behavior, and policy attitudes in the early stages of the covid-19 pandemic. Preprint at SSRN https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3562796 (2020).
- 21) Gollwitzer, A., Martel, C., Marshall, J., Höhs, J. M., & Bargh, J. A. Connecting self-reported physical distancing to real-world behavior at the individual and us state level. Preprint at PsyArXiv <https://psyarxiv.com/kvnwp/> (2020).
- 22) Rosenfeld, D. L., Rothgerber, H., & Wilson, T. Politicizing the COVID-19 pandemic: ideological differences in adherence to physical distancing. Preprint at PsyArXiv <https://psyarxiv.com/k23cv/> (2020).
- 23) Fisher, R. J. Social desirability bias and the validity of indirect questioning. *Journal of Consum. Res.* **20**, 303-315 (1993).
- 24) Maccoby, E. E. & Maccoby, N. in *Handbook of Social Psychology* 449-487 (Addison-Wesley, 1954).

- 25) Bullock, J. G., Gerber, A. S., Hill, S. J., & Huber, G. A. Partisan bias in factual beliefs about politics. *Q. J. Political Sci.* **10**, 519-578 (2015).
- 26) Ajzen, I. The theory of planned behavior. *Organ. Behav. Hum. Decis. Process.* **50**, 179-211 (1991).
- 27) Anderson, R. M., Heesterbeek, H., Klinkenberg, D., & Hollingsworth, T. D. How will country-based mitigation measures influence the course of the COVID-19 epidemic? *Lancet* **395**, 931-934 (2020).
- 28) Gao, S., et al. Mobile phone location data reveal the effect and geographic variation of physical distancing on the spread of the COVID-19 epidemic. Preprint at arXiv <https://arxiv.org/abs/2004.11430> (2020).
- 29) Hsiang, S., et al. The effect of large-scale anti-contagion policies on the COVID-19 pandemic. *Nature* <https://doi.org/10.1038/s41586-020-2404-8> (2020).
- 30) McGrail, D. J., Dai, J., McAndrews, K. M., & Kalluri, R. Enacting national physical distancing policies corresponds with dramatic reduction in covid19 infection rates. Preprint at medRxiv <https://www.medrxiv.org/content/10.1101/2020.04.23.20077271v1> (2020).
- 31) Chinni, D. Uneven coronavirus spread leads to uneven partisan response. *NBC News* <https://www.nbcnews.com/politics/meet-the-press/uneven-covid-spread-leads-uneven-partisan-response-n1171491> (2020).

- 32) Painter, M. & Qiu, T. Political beliefs affect compliance with COVID-19 physical distancing orders. Preprint at SSRN https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3569098 (2020).
- 33) Simonov, A., Sacher, S., Dubé, J. P., & Biswas, S. The persuasive effect of fox news: non-compliance with social distancing during the Covid-19 pandemic. Preprint at SSRN https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3600088 (2020).
- 34) Bursztyn L, Rao A, Roth C, & Yanagizawa-Drott D. Misinformation during a pandemic. Preprint at Becker Friedman Institute https://bfi.uchicago.edu/wp-content/uploads/BFI_WP_202044.pdf (2020).
- 35) Courtemanche, C., Garuccio J., Le A., Pinkston J., & Yelowitz A. Strong social distancing measures in the united states reduced the COVID-19 growth rate. *Health Affairs* **39**, 7 (2020).
- 36) Guan, et al. Clinical characteristics of coronavirus disease 2019 in China. *N. Engl. J. Med.* **382**, 1708-1720 (2020).
- 37) Lauer, et al. The incubation period of coronavirus disease 2019 (COVID-19) from publicly reported confirmed cases: estimation and application. *Ann. Intern. Med.* **172**, 577-582 (2020).
- 38) Linton, et al. Incubation period and other epidemiological characteristics of 2019 novel coronavirus infections with right truncation: a statistical analysis of publicly available case data. *J. Clin. Med.* **9**, 538 (2020).

- 39) Furukawa, N. W., Brooks, J. T., & Sobel, J.. Evidence supporting transmission of severe acute respiratory syndrome coronavirus 2 while presymptomatic or asymptomatic. *Emerg. Infect. Dis.* **26** (2020).
- 40) Johnson, D. B., & Thompson, A. S. How non-pharmaceutical interventions, politics, race, and economic conditions impacted the rate of new infections of COVID-19. Preprint at Open Science Framework <https://osf.io/yx7zs/> (2020).
- 41) Kim, D. D. & Goel, A. Estimating case fatality rates of COVID-19. *Lancet Infect. Dis.* **20**, 774-775 (2020).
- 42) Wilson, N., Kvalsvig, A., Barnard, L. T., & Baker, M. G. Case-fatality risk estimates for COVID-19 calculated by using a lag time for fatality. *Emerg. Infect. Dis.* **26**, 1339-1441 (2020).
- 43) Krull, J. L. & MacKinnon, D. P. Multilevel modeling of individual and group level mediated effects. *Multivariate Behav. Res.* **36**, 249-277 (2001).
- 44) Livadiotis, G. Statistical analysis of the impact of environmental temperature on the exponential growth rate of cases infected by COVID-19. *PLOS One* **15**, e0233875 (2020).
- 45) Yuan, J., Li, M., Lv, G., & Lu, K. Monitoring transmissibility and mortality of COVID-19 in Europe. *Int. J. Infect. Dis.* **95**, 311-315 (2020).
- 46) Allcott, H. *et al.* Polarization and public health: partisan differences in social distancing during the coronavirus pandemic. Preprint at SSRN https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3574415 (2020).

- 47) Andersen, M. Early evidence on physical distancing in response to COVID-19 in the United States. Preprint at SSRN https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3569368 (2020).
- 48) Dyck, J. J. Political distrust and conservative voting in ballot measure elections. *Political Res. Q.* **63**, 612-626 (2010).
- 49) Conway, L. Why conservatives and liberals are not experiencing the same pandemic. *Heterodox: The Blog* <https://heterodoxacademy.org/social-science-liberals-conservatives-covid-19/> (2020).
- 50) Smith, G. Fox News Nation. Preprint at SSRN https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1766884 (2020).
- 51) Haltiwanger, J. Video shows how fox news rapidly shifted from downplaying coronavirus to taking it seriously as cases rose across the US. *Business Insider* <https://www.businessinsider.com/coronavirus-video-shows-fox-news-shift-take-covid-19-seriously-2020-3> (2020).
- 52) Nail, P. R., McGregor, I., Drinkwater, A. E., Steele, G. M., & Thompson, A. W. Threat causes liberals to think like conservatives. *J. Exp. Soc. Psychol.* **45**, 901-907 (2009).
- 53) Janoff-Bulman, R. To Provide or Protect: Motivational bases of political liberalism and conservatism. *Psychol. Inq.* **20**, 120-128 (2009).
- 54) Doherty, C., Kiley, J., & Jameson. Ebola worries rise, but most are 'fairly' confident in government, hospitals to deal with disease. *Pew Research Center* <https://www.people->

press.org/2014/10/21/ebola-worries-rise-but-most-are-fairly-confident-in-government-hospitals-to-deal-with-disease/ (2014).

- 55) Cohen, G. L. Party Over Policy: The dominating impact of group influence on political beliefs. *J. Pers. Soc. Psychol.* **85**, 808-822 (2003).
- 56) Macy, M., Deri, S., Ruch, A., & Tong, N. Opinion cascades and the unpredictability of partisan polarization. *Science Advances* **5**, eaax0754 (2019).
- 57) Druckman, J. N., Klar, S., Krupnikov, Y., Levendusky, M., & Ryan, J. B. The political impact of affective polarization: how partisan animus shapes COVID-19 attitudes. Preprint at PsyArXiv <https://psyarxiv.com/ztgpn> (2020).
- 58) Te Grotenhuis et al. When size matters: advantages of weighted effect coding in observational studies. *Int. J. Public Health* **62**, 163-167 (2017).
- 59) Frey, W. H. COVID-19 continues spreading into counties with strong Trump support. *The Avenue - Brookings Institution* <https://www.brookings.edu/blog/the-avenue/2020/05/07/as-states-reopen-covid-19-is-spreading-into-even-more-trump-counties/> (2020).

Acknowledgments

The authors thank Julia Marshall, Aaron Deslatte, Clay Routledge, and the NYU Social Identity & Morality Lab for their helpful feedback. Philip Pärnamets was supported by the Swedish Research Council (2016-06793). The funder had no role in study design, data collection and analysis, decision to publish or preparation of the manuscript. The authors received no specific funding for this work.

Author Contributions

AG developed the study concept and study design. Data preparation and acquisition were performed by AG, CM, and WJB. PP, AG, WJB, IGF, CM, and EDK, completed the data analysis and interpretation. AG, CM, and PP drafted the manuscript and IGF, WJB, EDK, and JJVB provided critical revisions. All authors approved the final version of the manuscript for submission.

Competing Interests

The authors declare no competing interests.