Polarization, partisanship, and pandemic: The relationship between county-level support for Donald Trump and the spread of Covid-19 during the spring and summer of 2020

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Abstract
Objective: Republicans and Democrats have displayed widely divergent beliefs and behaviors related to COVID-19, creating the possibility that geographic areas with more Donald Trump supporters may be more likely to suffer from the disease.

Methods: I use 2016 election data, COVID-19 case and mortality data, and multilevel linear growth models with state fixed effects to estimate the relationship between county-level support for Donald Trump and the trajectory of cumulative COVID-19 cases and deaths per 100,000 county residents between March 17, 2020 and August 31, 2020.

Results: Counties more supportive of Trump had fewer COVID-19 cases and deaths in the early months of the pandemic. However, as the summer moved into July and August, counties less supportive of Trump stopped growth rates of COVID-19 cases and deaths, while counties more supportive of Trump saw a trajectory of increased cases and deaths in July and August. This is likely due to the widely divergent beliefs and behaviors displayed by Republicans and Democrats toward COVID-19.

Conclusion: This study underscores the power of polarization and partisanship in the public sphere, even when it comes to a public health issue.

The detection in fall 2019 of a novel coronavirus, subsequently designated COVID-19 by the World Health Organization, and its rapid spread has significantly impacted life across the globe. In the United States a variety of factors have been associated with increased exposure and vulnerability to the disease. Initially, geography was an obvious factor, although geography may play less of a role as the disease proliferates. The further away a locale is from an initial COVID-19 hotspot, like New York City, the less likely it is that that locale will face an outbreak since it is harder for the virus to reach people there. Places further from the first reported U.S. cases in Washington state and New York City were viewed as less likely to see proliferation of the disease (Bursztyn et al., 2020). In the same vein, rural counties in the United States
were viewed as less likely to experience the impact of COVID-19 as they were more insulated from global travel and major population centers, in addition to their reduced population density (Healy et al., 2020).

Beyond geography, the most obvious factors discovered to be closely linked to the effects of COVID-19 are age and underlying health conditions. As age increases, so does the chance of becoming symptomatic and dying from COVID-19 (Wu et al., 2020), with people over the age of 60 being especially vulnerable. Common underlying conditions, like diabetes and obesity, have been closely linked with vulnerability to COVID-19, regardless of age (Patel et al., 2020; Wu et al., 2020).

As COVID-19 began to spread and proliferate in the United States, socioeconomic and racial/ethnic factors were found to be associated with exposure and vulnerability to the disease. Although whites make up the majority of the total number of COVID-19 cases and deaths because they make up over 60 percent of the U.S. population (Elflein, 2021), Black, Latinx, and indigenous individuals have been disproportionately impacted by the pandemic and are more likely to become infected and die from COVID-19 than their white counterparts (Chowkwanyun and Reed, 2020; Denice et al., 2020; Elflein, 2021). This is largely attributed to the increased likelihood of these non-white individuals working in service jobs where they are in close contact with others, inequities in access to quality healthcare, living and working in unhealthy environmental conditions, the probability of having an underlying medical condition, and sustained systemic discrimination both in society-at-large and within the healthcare establishment (Chowkwanyun and Reed, 2020). People living in overcrowded homes are also more likely to become infected and spread the disease since an important element in its spread is close and sustained contact with an infected person (Patel et al., 2020).

**POLARIZATION AND PARTISANSHIP DURING A PANDEMIC**

Although these geographic, racial/ethnic, socioeconomic, and health factors are often discussed as primary correlates for exposure to and spread of COVID-19, another factor has received media and scholarly attention: political attitudes and polarization. Republicans and Democrats have reported and displayed widely divergent beliefs and behaviors related to COVID-19, with Republicans reporting less concern about the disease and taking fewer precautionary measures recommended by public health experts to combat its spread. This creates the possibility that geographic areas with a higher percentage of Republicans—and therefore Donald Trump supporters (Gallup, 2020)—may be more likely to suffer from the disease.

Although a crisis like COVID-19 might seem to be above politicization in the United States—as it is inherently a public health issue and not necessarily a political issue—viewing the pandemic through the lens of political and cultural polarization provides reason to believe that partisanship could impact perspectives on even a pandemic. Although it appears that most Americans were generally in the middle of the political spectrum even as recently as the early part of the 21st Century (Fiorina and Abrams, 2008; Prior, 2013), Abramowitz (2010, 2018) argues that the United States has become increasingly politically and culturally polarized over the last two decades. Abramowitz demonstrates how Americans have aligned themselves within clearly and increasingly divergent political ideologies represented by the Republican and Democratic parties.

Modern-day Republican ideologies prioritize individual rights, small government, and state and local control over most matters. Alternatively, modern-day Democratic ideologies prioritize social responsibility, large government, and federal government intervention in state and local matters (Abramowitz, 2018). Another important distinction between Republicans and Democrats that has arisen recently is perspectives on science and professional expertise (Blank and Shaw, 2015). Compared to Democrats, Republicans tend to be less deferential to scientific findings and expert opinions, even during the COVID-19 pandemic (Evans and Hargittai, 2020). These diverging perspectives on science and experts during the pandemic can be seen in a public opinion poll conducted from June 26–28, 2020 where 24 percent of Republicans (compared to 1 percent of Democrats) blamed the recent increases in COVID-19 hospitalizations on scientists and medical researchers (Change Research/CNBC 2020).

As the concept of polarization has become more critical to understanding Americans’ political and cultural paradigms, the concept of polarization has been separated into several dimensions. One key contrast
is the division between elite polarization and polarization among the public. Initially, claims were made that only political elites were polarized, while the American public remained in the middle (Fiorina and Abrams, 2008). Abramowitz (2010, 2018), however, argues that this is no longer the case and that there is now no difference between polarization among elites and the public. From this vantage point, there is a feedback loop between political elites and the American people, and we see elite polarization because the American people are polarized, and the American people are better able to polarize because of the clear partisan cleavages maintained by political elites and the parties who represent them.

A second key contrast is between ideological polarization and affective polarization. Ideological polarization refers to key political policy differences between Republicans and Democrats—the proper role of government, for example. Alternatively, affective polarization speaks to the cultural component of polarization and is grounded in social identity theory. Affective polarization sees partisan social identity as the foundation for cultural polarization as it refers to the emotional connections one has for the in-group (one's own party) and its set of norms and ideals. Concurrently, emotional connection to the in-group results in animus for the out-group (the other party) and its set of norms and ideals (Iyengar et al., 2019). Where ideological polarization describes different perspectives on policy, affective polarization describes attitudinal and behavioral differences that allow for the social construction of a belief system and set of norms—a culture—unique to a particular political party. Indeed, emerging evidence demonstrates that partisan identity impacts who people are willing to befriend, marry, hire for a job, and their perceptions of the health of the economy (Iyengar et al., 2019). The question this engenders for the COVID-19 pandemic is whether a polarized America created differing sets of norms and ideals around a public health issue that then impacted the number of cases and deaths in an area based on level of support for the two major political parties.

**DIFFERENCES IN COVID-19 BELIEFS AND BEHAVIORS BETWEEN REPUBLICANS AND DEMOCRATS**

Initially, when the first cases of coronavirus in the United States were being detected at the beginning of 2020 and the impending impact of the pandemic on the nation was still unclear, differences in viewpoints on COVID-19 among Republicans and Democrats were essentially insignificant. In a national CNN/PBS/Marist poll of registered voters conducted from January 31-February 1, 2020, 57 percent of Republicans compared to 63 percent of Democrats reported they were concerned or very concerned about the spread of coronavirus in the United States, a difference within the margin of error (PBS NewsHour/NPR, 2020a). However, as the pandemic began unfolding in the United States in February of 2020, divisions based on political party affiliation about beliefs and behaviors related to COVID-19 became apparent. By March, when the disease was beginning to spread in pockets of the United States, Republicans and Democrats began to show differing views on the pandemic. In the next iteration of the CNN/PBS/Marist poll conducted from March 13–14, 58 percent of Republicans reported they were concerned or very concerned about the spread of coronavirus in the United States, while 84 percent of Democrats compared to 63 percent of Democrats reported they were concerned or very concerned (PBS NewsHour/NPR, 2020b). Similarly, in a Quinnipiac poll conducted from March 5–8, 35 percent of Republicans were somewhat or very concerned that they or someone they know would be infected by the coronavirus compared to 68 percent of Democrats who reported they were somewhat or very concerned (Quinnipiac University Poll, 2020). In the same poll, 38 percent of Republicans were somewhat or very concerned that the coronavirus would disrupt their daily lives compared to 78 percent of Democrats.

Although these divergent perspectives on the disease could be attributed to the fundamentally different worldviews of Republicans and Democrats on an unfolding crisis, other contributing factors could be the way that influential conservative media outlets and President Donald Trump discussed the virus at the beginning of the pandemic. Trump repeatedly emphasized throughout February, 2020 that COVID-19 was under control and on the decline in the United States and that it would disappear “like a miracle” (Rieder, 2020). Popular and influential conservative talk show host Rush Limbaugh on February 24 stated
on his radio program, “Now, I want to tell you the truth about the coronavirus. I’m dead right on this. The coronavirus is the common cold, folks.” Fox News, another extremely influential media outlet for Republicans, also generally downplayed the threat of the virus in the early days of the pandemic, although this varied considerably among the different television programs airing on the conservative media outlet (Bursztyn et al., 2020). One Fox News program, *Trish Regan Primetime*, referred to the pandemic as the “coronavirus impeachment scam” which resulted in the host’s dismissal from the network (Mullin, 2020).

A significant partisan watershed moment came on the morning of April 17, 2020 when President Donald Trump, who had for several weeks publicly supported stay-at-home guidelines, broke with his own administration’s and most state governors’ guidelines on stay-at-home directives. Early on April 17, Trump sent three consecutive tweets with a call to “LIBERATE” Minnesota, Michigan, and Virginia in support of anti-lockdown protests in those states (Epstein, 2020). Moreover, Trump’s call for liberation of Minnesota, Michigan, and Virginia came on the heels of images of Trump forgoing wearing a face mask in public after the U.S. Centers for Disease Control and Prevention recommended face coverings to mitigate spread of COVID-19 at the beginning of April.

It is not surprising, then, that differences in beliefs and behaviors related to COVID-19 between Republicans and Democrats solidified as the summer moved into June, July, and August as the disease continued to spread in the United States (1Point3Acres, 2020). Republicans and Democrats held dramatically different perspectives on the threat of the pandemic, as well as on facial coverings and social distancing measures—essential strategies recommended by the U.S. Centers for Disease Control and Prevention in limiting the spread of COVID-19 (CDC, 2020). A Pew Research Center study of nearly 5000 U.S. adults conducted at the end of June showed remarkable cleavages between Republicans and Democrats on COVID-19 beliefs and behaviors (Pew Research Center, 2020). When asked about health concerns over COVID-19, 35 percent of Republicans said they were very or somewhat concerned that they would get COVID-19 and require hospitalization, while 64 percent of Democrats reported they were very or somewhat concerned. When asked about acting as a vector for the virus, 45 percent of Republicans said they were very or somewhat concerned that they might unknowingly spread COVID-19, while 77 percent of Democrats said they were very or somewhat concerned. When asked how personal actions impact the spread of COVID-19 in the United States, 44 percent of Republicans said the actions of ordinary Americans affect the spread of the disease “a great deal” compared to 73 percent of Democrats.

The same June Pew poll inquired about specific personal behaviors undertaken during the COVID-19 pandemic, and found that partisanship was the biggest factor in predicting comfort with behaviors that could make maintaining social distancing difficult or impossible. Specifically, 65 percent of Republicans compared to 28 percent of Democrats reported feeling comfortable eating at a restaurant, 40 percent of Republicans compared to 11 percent of Democrats reported feeling comfortable attending an indoor sporting event, and 31 percent of Republicans compared to 8 percent of Democrats reported feeling comfortable attending a crowded party. When asked about the importance of wearing face coverings in public places, 52 percent of Republicans said people should wear a face mask always or most of the time, compared to 86 percent of Democrats.

These differences in reported behaviors during the summer of 2020 are consistent with studies that have tracked movement of people during the COVID-19 pandemic. Barrios and Hochberg (2020) find a positive relationship between the percentage of a county voting for Donald Trump in the 2016 presidential election and both daily distance traveled and visits to non-essential businesses during the early months of the COVID-19 pandemic, even after controlling for population density and other potential confounding factors. The study also found that Trump supporting counties were much less likely to search for information on COVID-19.

The dramatic partisan differences concerning beliefs and behaviors related to COVID-19 are important because differing beliefs and behaviors will have an impact on the spread of COVID-19 and, subsequently, the number COVID-19 deaths. The U.S. Centers for Disease Control and Prevention emphasized three key social behaviors as essential tools in mitigating the spread of COVID-19 during the late-spring and summer of 2020: avoidance of large gatherings indoors where maintaining social distancing is difficult, social distancing of at least six feet when interacting with others, and the use of face masks in public (CDC,
If in the spring and summer of 2020 Republicans were less likely to view the pandemic as a threat and more likely to congregate indoors with others, attend large gatherings, disregard social distancing guidelines, and go out in public without face masks, it stands to reason that as support for Donald Trump increases in an area (as over 90 percent of Republicans support Trump (Gallup, 2020)), spread of COVID-19 would also increase in that area. Further exacerbating this situation is the fact that people of the same political party tend to socialize together and live in close proximity to each other (Bishop, 2009; Iyengar et al., 2019), expediting potential exposure to and spread of the virus in geographic areas—such as U.S. counties—with a greater percentage of Republicans.

Having said this, though, it is important to emphasize that the analysis of this study is at the county-level and ecological in nature. It is important to refrain from making the ecological fallacy wherein group-level inferences are applied to individuals. In the case of the current study this means that inferences can only be made at the group-level which estimate the association between county-level support for Donald Trump and trendlines of cases and deaths from COVID-19 for all people in the county, regardless of political party or other key individual-level factors, such as race/ethnicity and social class standing. Based on the analyses done here, no associations can be drawn about the relationship between a person’s support for Trump and the probability that the individual will contract COVID-19 and die from the disease.

THE CURRENT STUDY

When it comes to COVID-19, government offices and public health officials across the globe, including in the United States, have documented the lethality of the disease and provided clear and evidence-based recommendations for behaviors that mitigate the spread of the disease. However, political and cultural polarization has created a set of partisan norms for COVID-19, where Republican beliefs and behaviors differ dramatically from Democratic beliefs and behaviors. Consequently, I theorize that if Republicans see COVID-19 as less of a threat and act in ways that run counter to the recommendations of public health experts—specifically, attending large indoor gatherings, failing to adequately socially distance, and refusing to wear facial coverings in public—then the disease will spread more prolifically in places with a greater number of Donald Trump supporters. Based on this premise, two hypotheses guide the current study:

Hypothesis 1 (H1): As support for Donald Trump increases in a county, so too will the growth of COVID-19 case counts in the county between March 17 and August 31, 2020.

Hypothesis 2 (H2): As support for Donald Trump increases in a county, so too will the growth of the number of COVID-19 deaths in the county between March 17 and August 31, 2020.

DATA SOURCES AND VARIABLES

All data are county-level data and are in county-day form. The two dependent variables in the analysis are cumulative COVID-19 cases per 100,000 residents in the county (i.e., county cases per capita) and cumulative COVID-19 deaths per 100,000 residents in the county (i.e., county deaths per capita). Cumulative number of COVID-19 cases per capita and deaths per capita are recorded for each day in each county starting with March 17, 2020 and ending on August 31, 2020 and come from New York Times COVID-19 Data (New York Times, 2020). March 17, 2020, was selected as the start date for the analysis since it was the first day that every U.S. state had reported at least one case of COVID-19, signifying that the disease had spread to all parts of the United States. An end date also had to be chosen so that analysis of the longitudinal data could begin. August 31, 2020, was selected as the last day of the study since the onset of the U.S. school year is typically at the end of August and cooler temperatures begin for much of the continental United States in September, and both factors could alter the relationship between political party identification and the spread of COVID-19 that is beyond the scope of this study.
Both cases per capita and deaths per capita were skewed. Consequently, both dependent variables were transformed using the natural logarithm of one plus cases/deaths per 100,000 county residents since it is not possible to transform zero-values using the natural logarithm. As a sensitivity check, all models were also run using an inverse hyperbolic sine (IHS) transformation of cases and deaths per capita with no discernible differences in the results. The log (plus 1) transformation was selected for the analysis due to the challenge of interpreting IHS transformed values.

New York Times COVID-19 data were selected because it includes county-level COVID-19 data, relies on a combination of CDC data, government announcements, and local agency reports, and it includes confirmed and probable cases and deaths. And, unlike data collected by the Center for Systems Science and Engineering at Johns Hopkins University, the data are gathered by reporters rather than scraped from official reports only (New York Times, 2020). Ultimately, however, there appears to be little difference between New York Times COVID-19 data and Johns Hopkins data overall (Wang, 2020; Fischer-Hwang and Mayo, 2020).

The two key independent variables are time (in the form of days) and a continuous measure of the percentage of the county who voted for Donald Trump in the 2016 presidential election, which comes from the MIT Election Data and Science Lab (MIT Election Data and Science Lab, 2020). Time is scaled to indicate the number of days since March 17 (coded as Day 1) up to August 31 (coded as Day 168).

It is important to recognize that how different U.S. states handled the initial months of the pandemic—like stay-at-home directives, re-opening schedules and procedures, and mask mandates—could have a significant impact on county-level case and death rates. To account for how different states approached handling the outbreak of COVID-19, the study uses a state fixed effects approach by entering each U.S. state into the model. This approach effectively controls for all state-level variables, such as the implementation and lifting of stay-at-home directives and mask requirements, and removes the possibility that the county-level results are biased by state-level policies.

The other measures included in the analysis are time-invariant county-level measures and attempt to account for obvious potential confounding factors—age, racial/ethnic, socioeconomic, population density, geographic, and health measures. These data were gathered from the United States Decennial Census, the American Community Survey, and the Robert Wood Johnson Foundation and the University of Wisconsin Population Health Institute 2020 County Health Rankings. Table 1 provides details for all variables included in the analysis.

COUNTRIES AND GEOGRAPHIC AREAS NOT INCLUDED IN THE ANALYSIS

Only the continental United States is included in the analysis, so data from Alaska, Hawaii, and Puerto Rico were excluded from the dataset. Additionally, data for Greater Kansas City and Greater New York, New York are problematic. Kansas City, Missouri and the four counties of Cass, Clay, Jackson and Platte in Missouri that house Kansas City are not included in the analysis since New York Times COVID-19 case and death data for Kansas City are reported separately from the four counties that the city overlaps. However, no election and health data are available for Kansas City, while those data from the four counties takes Kansas City residents into account which makes the COVID-19 and county-level data describing Kansas City and its counties incongruent. In New York, New York Times COVID-19 case and death data do not distinguish among the five New York counties (i.e., Bronx, King, New York, Queens, Richmond) that house the city and the data are simply labeled “New York City” making it impossible to know in which county the cases and deaths occurred. However, the various data sources used to gather demographic, election, health, and geographic data do distinguish among the five counties of the city. To address this issue, “New York City” case and death data were merged with New York County demographic, election, health, and geographic data, and the counties of Bronx, King, Queens, and Richmond were excluded from the dataset. Oglala Lakota County, South Dakota and Rio Arriba County, New Mexico are also not
TABLE 1  Descriptions for all variables included in the analysis

| Variables                        | Description                                                                 |
|----------------------------------|-----------------------------------------------------------------------------|
| **Dependent Variables**          |                                                                             |
| COVID-19 cases per capita        | Log plus 1 of cumulative number of COVID-19 cases per 100,000 county residents\(^a\) |
| COVID-19 deaths per capita       | Log plus 1 of cumulative number of COVID-19 deaths per 100,000 county residents\(^a\) |
| **Independent Variables**        |                                                                             |
| Day                              | Number of days from March 17 to August 31, 2020                             |
| Percentage voting for Trump      | Percentage of county residents who voted for Donald Trump in the 2016 U.S. presidential election\(^b\) |
| Age                              |                                                                             |
| Median age                       | Median age of county residents\(^c\)                                       |
| Percentage 65 and older          | The percentage of county residents who are 65 or older\(^c\)               |
| Race-ethnicity                   |                                                                             |
| Percentage Latinx                | Percentage of county residents who are Latinx\(^c\)                         |
| Percentage Black                 | Percentage of county residents who are Black\(^c\)                          |
| Socioeconomic status             |                                                                             |
| Median household income          | Median income of all hh in the county (in thousands)\(^c\)                |
| Percentage in poverty            | Percentage of county residents below the poverty line\(^c\)               |
| Percentage college educated      | Percentage of county residents who have 4-year degree\(^c\)               |
| Percentage crowded hh            | Percentage of households in the county with more than one person per room\(^c\) |
| Health indicators                |                                                                             |
| Percentage smokers               | Percentage of county residents who smoke\(^f\)                            |
| Percentage obese                 | Percentage of county residents who are obese\(^f\)                         |
| Percentage diabetic              | Percentage of county residents with diabetes\(^f\)                        |
| Percentage uninsured             | Percentage of county residents who are uninsured\(^f\)                    |
| Geography                        |                                                                             |
| Total population                 | Total population of the county\(^c\)                                       |
| Percentage rural housing units   | Percentage of households in the county in rural geographic area (< 2500 people)\(^d\) |
| Distance to 11 largest cities    | Miles to the City of New York, Los Angeles, Chicago, Dallas, Houston, Washington DC, Miami, Philadelphia Atlanta, Phoenix, Seattle (included since Seattle was an early hotspot)\(^e\) |
| State                            | All 48 continental U.S. states and Washington, DC                           |

\(^a\)New York Times COVID-19 Data.  
\(^b\)MIT Election Data and Science Lab.  
\(^c\)American Community Survey 2018 5-Year Estimates.  
\(^d\)U.S. 2010 Decennial Census.  
\(^e\)U.S. Census Bureau 2019 Gazetteer Files.  
\(^f\)Robert Wood Johnson Foundation and the University of Wisconsin Population Health Institute 2020 County Health Rankings.

included in the analysis due to missing election, public health, or demographic data. The final dataset includes 466,859 observations within 3052 counties in 48 states and Washington, DC.

**APPROACH TO THE ANALYSIS**

I used multilevel linear growth curve models with state fixed effects where time is nested within counties to estimate the trajectory of the cumulative number of cases of COVID-19 per 100,000 county residents
and the trajectory of the cumulative number of COVID-19 deaths per 100,000 county residents within each U.S. county between March 17 and August 31, 2020.

Multilevel linear growth curve models are one of the primary strategies for analyzing panel data within units of analysis—counties, in this case—to track rates of change over time (Bryk and Raudenbush, 2001; Rabe-Hesketh and Skrondal, 2012). Multilevel linear growth curve models are referred to as “multilevel” because time is considered a level-1 variable and is nested within a level-2 variable that is the unit of analysis. In the current study, the panel data are structured in such a way so that units of time (days) are observed for each day of the pandemic between March 17 and August 31 (168 total days) for each county in the United States. Structuring panel data in such a way allows analysts to model trajectories of units of analysis (in this case, counties) over time (in this case, every day for 168 days) and how these trajectories vary based on key subject-level observed variables (in this case, the percentage of the county voting for Trump) along with other potentially confounding covariates. Similar to how a cross-sectional linear model can estimate change in individual income related to an interaction between respondents’ years of education and their race/ethnicity, linear growth models can estimate change in an outcome variable (e.g., COVID-19 cases) related to an interaction between time (e.g., days) and a key covariate (e.g., county-level support for Trump). As Rabe-Hesketh and Skrondal (2012:343) artfully articulate, “A somewhat flamboyant expression for this kind of modeling is to study interindividual differences in intraindividual change.”

An additional consideration necessary for modeling change over time is the potential that growth trajectories shift as time passes, curving the trajectory and creating a non-linear arc over time. Fortunately, multilevel linear growth curve modeling easily accounts for such non-linearity by adding a quadratic term for time (e.g., day$^2$) which allows for the trajectory to bend over time (Rabe-Hesketh and Skrondal, 2012). Modeling the non-linear nature of the number of COVID-19 cases and deaths over time in the United States is essential since an examination of the rates of spread from March to August show a non-linear pattern where daily cases generally rose between March and July and then began to decrease at the end of July and through August (1Point3Acres, 2020). To account for the non-linearity of the trajectory of cases and deaths, a quadratic function was added to the models that captures curves in the growth line (i.e., a shift in the trendline of COVID-19 cases and deaths between March and August). This approach allows for the construction of the following multilevel linear growth model with a polynomial function:

$$y_{cd} = \beta_0 + \beta_1 v_c + \beta_2 t_{cd} + \beta_3 t_{cd}^2 + \beta_4 x_c + \zeta_c + \epsilon_{cd}$$  \hspace{1cm} (1)

where $y_{cd}$ is COVID-19 cases/deaths per 100,000 residents in county $c$ on day $d$, $v_c$ is the percentage of county $c$ who voted for Donald Trump in the 2016 U.S. presidential election, $t_{cd}$ is the time elapsed in county $c$ on day $d$, $t_{cd}^2$ is the quadratic term (i.e., the polynomial function) needed to capture potential changes in the trajectory of COVID-19 cases/deaths over time, $x_c$ is a set of county-level time-invariant covariates, $\zeta_c$ is a county-specific error term, and $\epsilon_{cd}$ is a day-specific error term.

RESULTS

Table 2 displays the means, standard deviations, minimums, and maximums for all the dependent and independent variables in the analysis. County cumulative COVID-19 cases and deaths per capita are in log (plus 1) form and range from roughly 1 to 10 for cases and 0 to 7 for deaths. Within the average U.S. county Donald Trump secured 62 percent of the vote for President of the United States in 2016 as the majority of counties voted for Trump, even though the counties Trump won were less populous than the counties carried by Hillary Clinton. There is a total of 168 days (Day 1 to Day 168) analyzed between March 17 and August 31, 2020.

Cumulative COVID-19 cases per capita

The relationship between support for Trump and cumulative COVID-19 cases per capita is examined first. The results are presented in Table 3. The basic model in Table 3 presents the relationship between time
in the form of days and the spread of COVID-19 cases, including the quadratic term for time (day²). The basic model also displays the relationship between county-level Trump support and the total number of cumulative COVID-19 cases in a county between March 17 and August 31, net of controls. On average the cumulative number of COVID-19 cases in counties initially increased starting on March 17, which is demonstrated by the statistically significant positive coefficient for day (B = 0.048, p < 0.001). However, this increase in cases is not linear and began to slow as time passed, demonstrated by the statistically significant negative coefficient for day² (B = -0.0001, p < 0.001). Figure 1 illustrates the waning of the curve by depicting the trend of predicted COVID-19 cases per county over time while holding all variables

### TABLE 2 Descriptive statistics

| Variables                          | Mean   | SD    | Min  | Max  |
|------------------------------------|--------|-------|------|------|
| **Dependent variables**            |        |       |      |      |
| COVID-19 cases per capita          | 5.267  | 1.631 | 0.107| 9.735|
| COVID-19 deaths per capita         | 1.581  | 1.574 | 0    | 7.281|
| **Key independent variables**      |        |       |      |      |
| Day                                | 90.766 | 46.012| 1    | 168  |
| Percentage voting for Trump        | 62.444 | 15.563| 4.087| 96.033|
| **Control variables**              |        |       |      |      |
| Percentage Latinx                  | 9.226  | 13.545| 0    | 99.100|
| Percentage Black                   | 9.510  | 14.795| 0    | 87.400|
| Median age                         | 41.059 | 5.268 | 21.700| 67.000|
| Percentage 65 and older            | 18.178 | 4.448 | 3.800| 55.600|
| Median household income            | 51.759 | 13.819| 20.188| 136.268|
| Percentage in poverty              | 15.672 | 6.374 | 2.300| 55.100|
| Percentage college educated        | 21.840 | 9.669 | 0    | 78.500|
| Percentage crowded households      | 2.327  | 1.756 | 0    | 21.200|
| Total population                   | 110.742| 341.747| 102 | 10,100,000|
| Percentage rural housing units     | 57.155 | 31.135| 0    | 100.000|
| Percentage smokers                 | 17.495 | 3.511 | 5.909| 41.491|
| Percentage obese                   | 32.940 | 5.453 | 12.400| 57.700|
| Percentage diabetic                | 12.183 | 4.041 | 1.800| 34.100|
| Percentage uninsured               | 11.260 | 5.030 | 2.263| 33.750|
| Distance to New York               | 1000.281| 564.941| 0.000| 2605.512|
| Distance to Seattle                | 1712.297| 550.847| 0.000| 2724.554|
| Distance to LA                     | 1609.263| 525.506| 0.002| 2756.348|
| Distance to Chicago                | 5940.691| 106.917| 0.000| 1891.007|
| Distance to Dallas                 | 788.503| 366.871| 0.000| 1770.206|
| Distance to Houston                | 876.505| 385.078| 0.000| 1964.821|
| Distance to DC                     | 861.083| 555.137| 0.000| 2474.934|
| Distance to Miami                  | 1183.822| 514.455| 0.000| 2807.815|
| Distance to Philadelphia           | 944.060| 563.026| 0.000| 2556.562|
| Distance to Atlanta                | 706.853| 480.210| 0.000| 2254.840|
| Distance to Phoenix                | 1357.189| 467.270| 0.002| 2504.710|

Note: Number of Observations = 466,859; number of Counties = 3052.
Table 3: Multilevel linear growth models with state fixed effects estimating the relationship between county-level support for Donald Trump and cumulative COVID-19 cases per 100,000 residents in the county between March 17 and August 31, 2020

| Key predictors                      | Basic model | Trump-by-day interactions |
|-------------------------------------|-------------|----------------------------|
|                                     | B          | SE            | B            | SE          |
| Day                                 | 0.048***   | (0.000)       | 0.077***     | (0.000)     |
| Day$^2$                             | -0.0001*** | (0.000)       | -0.0003***   | (0.000)     |
| Percentage voting for Trump         | -0.006***  | (0.002)       | 0.005*       | (0.002)     |
| Percentage voting for Trump*Day     | -           | -             | -0.0005***   | (0.000)     |
| Percentage voting for Trump*Day$^2$ | -           | -             | 0.000003***  | (0.000)     |
| Controls                            |             |               |              |             |
| Percentage Latinx                   | 0.016***   | (0.002)       | 0.015***     | (0.002)     |
| Percentage Black                    | 0.020***   | (0.002)       | 0.020***     | (0.002)     |
| Median age                          | -0.000     | (0.007)       | -0.001       | (0.007)     |
| Percentage 65 and older             | -0.015     | (0.009)       | -0.014       | (0.009)     |
| Median household income             | 0.000002***| (0.000)       | 0.000002***  | (0.000)     |
| Percentage in poverty               | -0.000     | (0.005)       | -0.000       | (0.005)     |
| Percentage college educated         | -0.006     | (0.003)       | -0.006*      | (0.003)     |
| Percentage crowded households       | 0.042***   | (0.011)       | 0.041***     | (0.011)     |
| Total population                    | 0.000      | (0.000)       | 0.000        | (0.000)     |
| Percentage rural housing units      | -0.004***  | (0.001)       | -0.004***    | (0.001)     |
| Percentage smokers                  | -0.014     | (0.010)       | -0.013       | (0.010)     |
| Percentage obese                    | 0.002      | (0.003)       | 0.002        | (0.003)     |
| Percentage diabetic                 | 0.006      | (0.004)       | 0.006        | (0.004)     |
| Percentage uninsured                | 0.052***   | (0.006)       | 0.052***     | (0.006)     |
| Distance to New York                | -0.004     | (0.002)       | -0.004       | (0.002)     |
| Distance to Seattle                 | -0.003***  | (0.000)       | -0.003***    | (0.000)     |
| Distance to LA                      | -0.006***  | (0.001)       | -0.006***    | (0.001)     |
| Distance to Chicago                 | 0.000      | (0.000)       | 0.000        | (0.000)     |
| Distance to Dallas                  | 0.002***   | (0.001)       | 0.002***     | (0.001)     |
| Distance to Houston                 | -0.003***  | (0.001)       | -0.003***    | (0.001)     |
| Distance to DC                      | 0.008***   | (0.001)       | 0.008***     | (0.001)     |
| Distance to Miami                   | -0.004***  | (0.000)       | -0.004***    | (0.000)     |
| Distance to Philadelphia            | -0.007*    | (0.003)       | -0.007*      | (0.003)     |
| Distance to Atlanta                 | 0.001      | (0.000)       | 0.001        | (0.000)     |
| Distance to Phoenix                 | 0.004***   | (0.001)       | 0.004***     | (0.001)     |
| Intercept                           | 18.828***  | (1.523)       | 18.253***    | (1.533)     |
| County—level variance               | 0.398***   | (0.010)       | 0.403***     | (0.010)     |

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$ (two-tailed); N Observations = 466,859, N Counties = 3052.
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FIGURE 1  County-level cumulative COVID-19 cases per 100,000 county residents between March 17 and August 31, 2020

in the model constant. Essentially, Figure 1 illustrates the trendline for cumulative COVID-19 cases in an average U.S. county.

The basic model also indicates that, overall, there is a statistically significant negative relationship between county-level support for Donald Trump and the cumulative number of COVID-19 cases in a county ($B = -0.006$, $p < 0.001$). This finding indicates that, on a day-to-day basis, counties more supportive of Trump averaged fewer total COVID-19 cases between March 17 and August 31, 2020. However, the basic model does not include a trajectory component to measure growth of COVID-19 cases over time between March 17 and August 31 based on support for Trump.

As discussed above, this study is primarily interested in examining the trajectory of COVID-19 cases over time since recommended behaviors to mitigate the spread of COVID-19, such as the importance of social distancing and the use of face coverings, were less clear in the early portion of the pandemic, and pandemic attitudes and behaviors had little time to solidify into partisan norms. To examine the relationship between county-level support for Trump and the spread of COVID-19 in counties over time between March 17 and August 31, 2020, support for Trump was interacted with day and day$^2$. The results of this Trump-by-Day Interaction Model are presented in Table 3. The main effects coefficient for percentage voting for Trump, which indicates the relationship between Trump support and cases per 100,000 county residents on Day 1, is statistically significant and positive ($B = 0.005$, $p < 0.05$), indicating that county-level support for Trump was positively related to differences in the cumulative COVID-19 case counts at the very beginning of the pandemic on March 17. The interaction terms between percentage voting for Trump and the measures for time provide insights into how county-level support for Trump is related to the spread of the disease between mid-March and the end of August. Initially, as the percentage voting for Trump in a county increased, the number of COVID-19 cases in the county were slower to increase ($B = -0.0005$, $p < 0.001$). However, as the curve of COVID-19 cases began to slow across the country (indicated by the statistically significant and negative coefficient for day$^2$), counties with greater support for Trump saw a more muted slowing of the spread of the disease ($B = 0.000003$, $p < 0.001$).

Due to the difficulty of discerning substantive meaning from small coefficients within a longitudinal model that includes interaction terms and a quadratic term, a modified version of the Trump-by-Day Interaction Model is put into graphic form. Figure 3 displays the predicted log (plus 1) of cumulative COVID-19 cases per 100,000 county residents based on level of support for Trump. In order to clearly
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graph the impact of county-level support for Trump, counties are placed into five categories of level of support: 0–34.9 percent, 35–44.9 percent, 45–54.9 percent, 55–64.9 percent, and 65–100 percent. All control variables are set to their mean.

Figure 3 visually displays what the coefficients from Table 3 statistically suggest: the counties more supportive of Trump show a slower initial trajectory of growth of COVID-19 cases but also have a trajectory that curves less—indicating less of an ability to slow the spread of COVID-19 cases—as the summer moves into July and August. Upon examining Figure 3, with the exception of counties most supportive of Trump, U.S. counties follow a similar pattern of growth in the number of cases of COVID-19 until the end of July. As the summer progressed, counties least supportive of Trump (< 35 percent) and moderately unsupportive of Trump (i.e., between 35 and 44.9 percent support) show a clear trend of fewer cumulative COVID-19 cases and appear to flatten the growth curve. This does not indicate that these counties no longer had any cases of COVID-19, rather that new cases were not presenting themselves within the county. However, counties moderately supportive of Trump (i.e., counties with 55–64.9 percent support) do not show the same rate of case reduction as those counties unsupportive of Trump and were unable to flatten the growth curve, indicating that the number of cases continued to increase in these counties day-over-day.

When it comes to the growth in the number of COVID-19 cases for counties highly supportive of Trump (i.e., counties with more than 65 percent support), a different pattern is apparent. In fact, the growth trajectory for COVID-19 cases in the counties most supportive of Trump is essentially linear where cases in such counties were higher than other counties at the outset of the pandemic and display an almost linear increase from March 17 to August 31 with little perceptible bend in the growth curve. Although counties most supportive of Trump see fewer cases from approximately day 40 to day 130 compared to other counties—which helps explain why, in the basic model, on a day-to-day basis counties more supportive of Trump averaged fewer total COVID-19 cases between March 17 and August 31—these lower case counts compared to other counties does not last. As the summer wears on they show a clear increase in the growth of the curve with no indication of flattening.

Table 3 and Figure 3 demonstrate the statistical impact of county-level support for Donald Trump on the trajectory of COVID-19 cases, but is there a substantive impact? Recall that the dependent variable of cumulative COVID-19 cases is in log (plus 1) form, making interpretation challenging while also slightly inflating the overall number of cases due to adding 1 to each county’s daily number of cumulative cases before taking the natural log. However, exponentiating the predicted number of the log of COVID-19 cases in Figure 3 can “un-log” the values and provide estimations about predicted COVID-19 cases to reveal differences in case counts among counties based on county-level support for Trump.

On August 31, 2020—the last day of the analysis—a county with less than 35 percent support for Trump is predicted to have 649 cases of COVID-19 per 100,000 county residents (log (COVID-19 cases + 1) = 6.475 = e^{6.475} = 649 cases [95 percent CI: 563 cases, 747 cases]), regardless of state and all other controls in the model. Alternatively, a county with 65 percent support for Trump or more is predicted to have 1188 cases of COVID-19 per 100,000 county residents (log (COVID-19 cases + 1) = 7.080 = e^{7.080} = 1188 cases [95 percent CI: 1132 cases, 1244 cases]), regardless of state and all other controls in the model. That is a difference of 539 cases per capita between the counties least supportive and most supportive of Trump. Comparison between a county moderately unsupportive of Trump (i.e., 35 to 44.9 percent support) and a county moderately supportive of Trump (i.e., 55–64.9 percent support) is also revealing. On August 31 a county moderately unsupportive of Trump is predicted to have 671 COVID-19 cases per 100,000 county residents (log (COVID-19 cases + 1) = 6.509 = e^{6.509} = 671 cases [95 percent CI: 604 cases, 745 cases]). Alternatively, a county identical to the moderately unsupportive county but moderately supportive of Trump is predicted to have 891 COVID-19 cases per 100,000 county residents (log (COVID-19 cases + 1) = 6.792 = e^{6.792} = 891 cases [95 percent CI: 845 cases, 939 cases]), a difference of 220 cases per capita.

The results presented in Table 3 and the predicted number of COVID-19 cases illustrated in Figure 3 provides partial support for H1 (as support for Donald Trump increases in a county, so too will the growth of COVID-19 case counts in the county between March 17 and August 31, 2020). Although COVID-19
cases are fewer within counties more supportive of Trump earlier in the pandemic, the trajectory for counties more supportive of Trump shows a more linear pattern with less abating of COVID-19 cases as the summer moved from June into July and August. So much so, that by the end of August the average county with high Trump support saw hundreds of more cases of COVID-19 than the average county with low Trump support, even after controlling for state-level restrictions and county-level factors related to health, geography, race/ethnicity, age, and population.

Cumulative COVID-19 deaths per capita

The second part of the analysis examines the relationship between county-level support for Donald Trump and cumulative COVID-19 deaths per 100,000 county residents. The basic model in Table 4 presents the relationship between time in the form of days and the cumulative number of COVID-19 deaths per 100,000 county residents and the relationship between county-level Trump support and the number of cumulative COVID-19 deaths, net of controls. Similar to the analysis of cases, on average the cumulative number of COVID-19 deaths in counties initially increased starting in March 17 which is demonstrated by the statistically significant positive coefficient for day ($B = 0.028, p < 0.001$) and then began to slow as time passed which is demonstrated by the statistically significant negative coefficient for day ($B = -0.00006, p < 0.001$). Figure 2 illustrates these shifts in the curve by depicting the trend of predicted COVID-19 deaths per county over time while holding all variables in the model constant.

Also, like the analysis of cases, the basic model shows that there is a statistically significant negative relationship between county-level support for Donald Trump and the number of COVID-19 deaths in a county between March 17 and August 31 ($B = -0.011, p < 0.001$). This indicates that, on a day-to-day basis, counties more supportive of Trump averaged fewer total COVID-19 deaths between March 17 and August 31, 2020. However, as discussed previously, this study is primarily interested in examining the trajectory of COVID-19 deaths by looking at the relationship between county-level support for Trump and number of COVID-19 deaths over time, and the basic model does not include a trajectory component to measure growth of COVID-19 deaths.
TABLE 4 Multilevel linear growth models with state fixed effects estimating the relationship between county-level support for Donald Trump and cumulative COVID-19 deaths per 100,000 residents in the county between March 17 and August 31, 2020

| Key predictors                                    | Basic model | Trump-by-day interactions |
|--------------------------------------------------|-------------|---------------------------|
| Day                                              | 0.028***    | 0.065***                  |
| Day<sup>2</sup>                                  | -0.00006*** | -0.0002***                |
| Percentage voting for Trump                      | -0.011***   | 0.015***                  |
| Percentage voting for Trump*Day                  | -           | -0.001***                 |
| Percentage voting for Trump*Day<sup>2</sup>      | -           | 0.00003***                |
| Controls                                         |             |                           |
| Percentage Latinx                                | 0.003 (0.003) | 0.002 (0.003)         |
| Percentage Black                                 | 0.015***    | 0.015***                  |
| Median age                                       | 0.000 (0.010) | 0.001 (0.010)         |
| Percentage 65 and older                         | 0.007 (0.013) | 0.005 (0.013)          |
| Median household income                          | 0.00002*** | 0.00002***                |
| Percentage in poverty                            | 0.012 (0.007) | 0.012 (0.007)         |
| Percentage college educated                      | -0.015***   | -0.014**                  |
| Percentage crowded households                    | 0.049**     | 0.048**                   |
| Total population                                 | 0.000 (0.000) | 0.0000001*           |
| Percentage rural housing units                   | -0.011***   | -0.011***                 |
| Percentage smokers                               | -0.010 (0.015) | -0.012 (0.014)         |
| Percentage obese                                 | 0.001 (0.004) | 0.000 (0.004)          |
| Percentage diabetic                              | 0.009 (0.006) | 0.009 (0.006)          |
| Percentage uninsured                              | 0.034***    | 0.036***                  |
| Distance to New York                             | -0.004 (0.003) | -0.004 (0.003)         |
| Distance to Seattle                               | -0.002***   | -0.002***                 |
| Distance to LA                                   | -0.004**    | -0.004**                  |
| Distance to Chicago                              | 0.001 (0.000) | 0.001 (0.000)          |
| Distance to Dallas                                | 0.002**     | 0.002**                   |
| Distance to Houston                              | -0.002**    | -0.002**                  |
| Distance to DC                                   | 0.009***    | 0.009***                  |
| Distance to Miami                                 | -0.003***   | -0.003***                 |
| Distance to Philadelphia                         | -0.007 (0.004) | -0.007 (0.004)         |
| Distance to Atlanta                              | -0.000 (0.001) | -0.000 (0.001)         |
| Distance to Phoenix                              | 0.002 (0.001) | 0.002 (0.001)          |
| Intercept                                        | 13.722***   | 12.249***                 |
| County-level variance                            | 0.839***    | 0.835***                  |

***p < 0.001; **p < 0.01; *p < 0.05 (two-tailed); N Observations = 466,859, N Counties = 3052.
To examine the relationship between county-level support for Trump and the number of COVID-19 deaths in counties over time, support for Trump was interacted with day to provide the initial trajectory of COVID-19 deaths based on the level of Trump support, and support for Trump was also interacted with day^2 to demonstrate the curve in the trajectory of COVID-19 deaths as time passed based on level of support for Trump. In this Trump-by-Day Interaction Model we see that county-level support for Trump is positively related to COVID-19 deaths on Day 1 (β = 0.015, p < 0.001). Like the models for COVID-19 cases, the interaction term between support for Trump and day is negative and statistically significant (β = −0.001, p < 0.001) indicating less growth in cumulative COVID-19 deaths in counties more supportive of Trump. However, the interaction between support for Trump and day^2 is positive and statistically significant (β = 0.000003, p < 0.001) indicating less curve in the trajectory of COVID-19 deaths as time passes in counties more supportive of Trump. Simply put, greater support for Trump in a county is associated with fewer COVID-19 deaths in those counties in the early months of the pandemic, but as the summer wore on counties less supportive of Trump saw a more pronounced slowing of COVID-19 deaths compared to counties more supportive of Trump.

To clarify the Trump-by-day interaction model, a modified version of the model is put into graphic form (Figure 4) showing predicted cumulative COVID-19 deaths between March 17 and August 31, 2020. As was done with the graphing of cases, to graph the impact of county-level support for Trump on number of deaths, counties are placed into five categories of level of support: 0–34.9 percent, 35–44.9 percent, 45–54.9 percent, 55–64.9 percent, and 65–100 percent. All control variables are set to their mean. Differences among counties with varying levels of Trump support early in the pandemic are hard to discern due to some of the predicted values being negative. This is not surprising, given that early on in the pandemic many counties reported very few deaths, making reliable and meaningful estimates of COVID-19 deaths at time 1 in a longitudinal model challenging. However, as time passed a pattern similar to what was seen in the graph of COVID-19 cases becomes apparent: the counties more supportive of Trump show a slower initial trajectory of growth of COVID-19 deaths but also have a trajectory that curves less—indicating less of an ability to curb the increase of COVID-19 deaths within the county—as the summer moves into July and August. Alternatively, counties less supportive of Trump were able to curve the trendline and nearly flatten the curve, indicating an ability to slow, and perhaps even stop, an increase in COVID-19 deaths within the county.

Unlike the graph of COVID-19 cases, though, we see convergence on August 31 where all counties, regardless of the level of support for Trump, have roughly the same number of cumulative COVID-19 deaths per 100,000 county residents. It is unclear how these trajectories would continue to unfold since data past August are beyond the scope of this analysis, but it is apparent that Figure 4 follows the same general pattern as Figure 3 if Figure 3 were clipped at day 140. It is possible, then, that the trajectory of COVID-19 deaths displayed in Figure 4 would eventually catch up to the trajectory of cases given that it can take several weeks or more for those diagnosed with COVID-19 to die from the disease. Still, the current study finds only partial evidence for H2 since counties more supportive of Trump actually saw fewer COVID-19 deaths early in the pandemic. But, unlike counties less supportive of Trump, counties more supportive of Trump were unable to slow the number of deaths as the summer moved into July and August leading to no difference among the counties in cumulative COVID-19 deaths per 100,000 county residents, on average, by the end of the analysis on August 31.

**DISCUSSION**

Based on a theoretical framework built upon the concepts of political and cultural polarization and extreme partisanship, this study hypothesized that the trajectory of COVID-19 cases and deaths between March 17 and August 31, 2020 would be higher in counties more supportive of Trump than in counties less supportive of him, leading to a greater number of COVID-19 cases and deaths in pro-Trump counties. Analysis of nearly six months of COVID-19 case and mortality data provides mixed support for these hypotheses. Counties more supportive of Trump had fewer COVID-19 cases and deaths in the early months of the
FIGURE 3  Predicted county-level cumulative COVID-19 cases per 100,000 county residents by county-level support for Trump. In the prediction models “percentage voting for Trump” was allowed to vary while all control variables were set to their mean.

FIGURE 4  Predicted county-level cumulative COVID-19 deaths per 100,000 county residents by county-level support for Trump. In the prediction models “percentage voting for Trump” was allowed to vary while all control variables were set to their mean.
pandemic. However, as spring moved into summer and COVID-19 mitigation strategies were established and pandemic behaviors were inculcated along partisan lines, counties less supportive of Trump slowed growth rates of COVID-19 cases and deaths, while counties more supportive of Trump continued to see a trajectory of increased cases and deaths. So much so, that by the end of the analysis on August 31 counties most supportive of Trump were predicted to have over 500 more cases per 100,000 county residents than counties least supportive of Trump. COVID-19 deaths, on the other hand, converged by the end of the study so that by August 31 no discernible difference in cumulative deaths was apparent based on county-level support for Trump.

Theoretically, these differences in growth trajectories were expected since, collectively, Republicans and Democrats differ widely in how they view COVID-19 and how they behave in the face of a deadly and communicable disease that is easily transmitted between people. Although these partisan differences were not always present, conservative media and political elites, including President Trump, voiced doubts about the seriousness of the pandemic and the necessity of mitigation efforts, which clearly impacted the attitudes and behaviors of Republicans compared to Democrats. Put simply, Republicans are less fearful of the disease and take fewer precautionary measures to combat its spread, such as avoiding large gatherings, social distancing, and donning facial coverings. This set of cultural norms appears to have impacted the trajectory of the spread of COVID-19 in places with a larger number of Republicans—that is, places more supportive of Donald Trump.

It is unclear why counties more supportive of Trump saw fewer COVID-19 cases and deaths in the first few months of the pandemic. Two potential explanations seem most plausible. First, counties more supportive of Trump tend to be more rural and less populated than counties less supportive of Trump, both of which strongly impacted the spread of COVID-19, especially early in the pandemic (1point3Acres, 2020; Healy et al., 2020). Although the current study controlled for rurality, proximity to major urban areas, and county population size, perhaps these controls did not fully account for the effects of rurality and population, which would bias the results. For example, the study does not control for intricate county-level factors—such as travel patterns, crowd sizes, social network size, or average number of social interactions—all of which may vary based on population density and level of support for Trump, and could therefore impact the study’s findings.

A second potential explanation lies in testing and seeking treatment for COVID-19. If counties more supportive of Trump are less concerned about the disease, it is possible that early in the pandemic—when testing was scarce and difficult to access—county residents would be less likely to get tested for COVID-19, seek medical assistance, and be admitted into a hospital as a COVID-19 patient. However, as case counts began to rise in all parts of the country and testing became more prevalent and easier to access, this could have changed. Not pursuing testing and medical treatment for COVID-19 symptoms would impact the official recording of the number of COVID-19 cases and deaths in a county, especially in the early months of the pandemic.

Caution should be taken, however, not to commit the ecological fallacy and infer that at the end of August, 2020 an individual Republican—and so a likely Trump supporter—is more likely to contract COVID-19 and potentially die from the disease. Rather, in August, 2020 places such as U.S. counties with a greater number of Trump supporters appear to have more COVID-19 cases, but the people testing positive and dying from COVID-19 in those locales could potentially identify with any political party and be of any race/ethnicity, social class, or gender.

This study offers several contributions to our understanding of the spread of COVID-19, as well as to the scholarly literature. First and foremost, it provides evidence that Republican counties saw a steeper trajectory of cumulative COVID-19 cases and deaths as the pandemic wore on into the summer months compared to Democratic counties. It is likely that this is due to locales with a greater share of Republicans developing a set of cultural norms that adhere less to behaviors that were found to mitigate the spread of the disease and promoted by the preponderance of scientific and medical experts, such as avoiding large crowds indoors and the use of face masks. Although the findings from this study cannot directly address this postulation since the relationship between county-level support for Donald Trump and a steeper trajectory of cumulative COVID-19 cases and deaths found here is only correlational and suggestive.
Second, this study underscores the power of polarization and partisanship in the public sphere. Along partisan lines the American public is polarized on policy perspectives regarding COVID-19—like the proper role of government in combating the pandemic—and polarized on cultural perspectives on COVID-19—like the necessity of wearing facial coverings and avoiding large social gatherings. Prior research has indicated that partisan divisions impact who we socialize with, marry, and hire for a job. It also impacts how we see the state of the world, like how we view the strength of the economy. It appears that partisanship also colors how we view obvious matters of life and death. If partisanship creates wide cleavages in how we think and act in a pandemic that kills about 3 percent of the people who test positive for the disease as of August 31, 2020 (1point3Acres, 2020), what issue is safe from extreme partisanship in modern America?

Although this study provides important insights, it also has limitations. Chiefly, as previously mentioned, the study is correlational and not causal. It relies on a set of control variables to reduce the possibility that some other factor (e.g., rurality, overall health measures, location) are driving the relationship between county-level support for Donald Trump and COVID-19 case and death rates, but the possibility of endogeneity looms. Future studies could apply instrumental variable models or counterfactual modeling, like propensity score matching. Matching counties adequately, however, could be a challenge given that counties highly unsupportive of Trump and counties highly supportive of Trump tend to differ widely on key metrics like rurality and race/ethnicity. Perhaps this issue could be circumvented by focusing on smaller geographic areas opposed to focusing on counties.

An additional limitation is that this study focuses on only a five-and-a-half-month snapshot of the pandemic in the United States. As of August 31, 2020 COVID-19 was still rapidly spreading throughout the United States infecting tens of thousands daily and killing nearly 1000 Americans each day. The factors related to the spread of the disease could have changed after August 31, 2020, such as the onset of cooler temperatures in many parts of the country, the beginning of the school year, and fatigue of COVID-19 mitigation efforts resulting in less adherence to such efforts regardless of political party affiliation.

Lastly, the current study is correlation and suggestive only and does not include an empirical analysis of what specific factors related to support for Donald Trump explain the relationship between Trump support and the increased trajectory of COVID-19 cases and deaths in the summer months. Is it how conservative media outlets cover the pandemic? Is it misinformation? Is it how silos of social media interactions reinforce perspectives on the pandemic? Is it Trump himself through his actions and words? This is unclear, and future research should continue to examine why areas more supportive of Donald Trump saw a greater increase in COVID-19 cases and deaths as the pandemic moved into the summer of 2020, even though clear public health guidelines had been established to effectively curb the spread of the disease.

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