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ORIGINAL ARTICLE

Death by political party: The relationship between COVID-19 deaths and political party affiliation in the United States

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Abstract

This study explored social factors that are associated with the US deaths caused by COVID-19 after the declaration of economic reopening on May 1, 2020 by President Donald Trump. We seek to understand how county-level support for Trump interacted with social distancing policies to impact COVID-19 death rates. Overall, controlling for several potential confounders, counties with higher levels of Trump support do not necessarily experience greater mortality rates due to COVID-19. The predicted weekly death counts per county tended to increase over time with the implementation of several key health policies. However, the difference in COVID-19 outcomes between counties with low and high levels of Trump support grew after several weeks of the policy implementation as counties with higher levels of Trump support suffered relatively higher death rates. Counties with higher levels of Trump support exhibited lower percentages of mobile staying at home and higher percentages of people working part time or full time than otherwise comparable counties with lower levels of Trump support. The relative negative performance of Trump-supporting counties is robust after controlling for these measures of policy compliance. Counties with high percentages of older (aged 65 and above) persons tended to have greater death rates, as did more populous counties in general. This study indicates that policymakers should consider the risks inherent in controlling public health crises due to divisions in political ideology and confirms that vulnerable communities are at particularly high risk in public health crises.

Key Points

- Counties with higher levels of Trump support did not necessarily experience greater mortality rates due to COVID-19.
- The predicted weekly death counts per county tend to increase over time with the implementation of several key health policies.
- The difference in COVID-19 outcomes between counties with low and high levels of Trump support grew after several weeks of the policy implementation as counties with higher levels of Trump support suffered relatively higher death rates.
- Counties with higher levels of Trump support exhibited lower percentages of devices staying at home and higher percentages of people working part time or full time than otherwise comparable counties with lower levels of Trump support.

KEYWORDS

COVID-19, health policies, political affiliation, social distancing activities

INTRODUCTION

The 2019 coronavirus (severe acute respiratory syndrome coronavirus 2 or SARS-CoV-2) is a contagious virus associated with respiratory illness and severe pneumonia and is commonly called COVID-19. According to data from the World Health Organization, as of January 18, 2021, the COVID-19 pandemic had resulted in 93,611,355 confirmed cases and 2,022,405 confirmed deaths globally.[1] The virus first emerged in China before spreading to South Korea, Italy, and some European countries that experienced outbreaks in early 2020. On January 19, 2020, the first known COVID-19 case in the United States was that of a 35-year-old man who went to an urgent care clinic in Snohomish County, Washington, with cough and fever (Holshue et al., 2020). By March 29th, 2021, the United States had recorded 29,921,599 confirmed cases and 543,870 confirmed deaths due to COVID-19. Scholars proposed using social and behavioral science to support the pandemic response (Van Bavel et al., 2020). For instance, Mayer (2020) criticizes President Trump's strategies for managing the health crisis, including his downplaying of the seriousness of the disease early in the pandemic. Mayer considers this mismanagement to be among the worst crisis responses in American history. This study responds by analyzing the roles of several social factors, including political polarization, in mitigating this pandemic in the United States.

Combating the coronavirus pandemic has burdened US economy. On March 27, 2020, President Trump signed an economic relief package of over $2 trillion, the Coronavirus Aid, Relief, and Economic Security (CARES) ACT.[2] Furthermore, starting in April 2020, several political leaders proposed relaxing previously imposed public health measures to relieve the burden on the economy,[3] while health professionals continued to warn against “reopening” the economy.[4] This sent a mixed signal to state and local governments, as well as to the public, about how they should react to the pandemic.

We hypothesize that the mixed messages contributed, in varying degrees, to the public's adherence to public health measures and that this resulted in differential COVID-19 casualty rates. Specifically, we seek to understand how social factors, including the distribution of political affiliations, social distancing activities,[5] and the duration of implemented public health policies influenced the number of deaths associated with COVID-19 at the county level in the United States. We find evidence that political ideology interacts with public health policies in such a way that counties with higher levels of Trump support suffer worse COVID-19 outcomes than comparable counties with lower levels of Trump support. In other words, public health policies appear to be less effective in certain counties than others as a result of locally dominant political ideologies. Furthermore, we present evidence that this may be due to poor compliance with public health policies in those particular counties.

BACKGROUND

COVID-19 patients generally present with fever and cough (Carlos et al., 2020; N. Chen, Zhou, et al., 2020; Chung et al., 2020; Shi et al., 2020; Song et al., 2020; D. Wang, Hu, et al., 2020; W. Wang, Tang, et al., 2020) and, in the early stages of the pandemic, were often diagnosed by computerized tomography (CT) scan and by analysis of their travel histories (Chung et al., 2020; Fang et al., 2020; Kim et al., 2020; Wilson & Chen, 2020). Specialized tests for detecting the virus were developed within several months. The estimated incubation period for COVID-19 ranges from 2.1 to 11.1 days with a mean of 6.4 days. On January 23, 2020, the World Health Organization (WHO) reported 581 confirmed cases and only 10 cases outside of China (World Health Organization, 2020). However, COVID-19 has high transmissibility and was, therefore, able to quickly spread globally despite travel precautions (Riou & Althaus, 2020).

With respect to the treatment of COVID-19, there are some drug treatment options and suggestions from doctors (Z.-M. Chen, Fu, et al., 2020; Jin et al., 2020; Lin & Li, 2020; Lu, 2020). However, these treatments exhibit limited efficacy among high-risk groups. Therefore, prior to the development and widespread distribution of vaccines in 2021, policymakers and healthcare practitioners emphasized policies aimed at slowing the spread of COVID-19 due to the limited treatment options, the seriousness of symptoms, and the high transmissibility rate. Quarantine is a common method that governments have adopted worldwide (Carlos et al., 2020). Scholars suggest that cultural tightness and government efficiency play significant roles in controlling health crises (Gelfand et al., 2020). For instance, China adopted the most extensive quarantine in recent history to combat COVID-19. In some communities (Yiyang county, Luoyang City, Henan Province), only one person from a family was allowed to go out every day, with their temperature being taken before doing so. Additionally, grocery stores would test patrons' temperatures before admittance. Temperatures of all family members were reported to their local communities daily at the peak of the pandemic. However, some countries adopted quite different policies with respect to controlling the pandemic. In the United States, a policy of social distancing depended heavily on each individual's self-precautions and was largely unenforced by the government. The reliance on self-enforcement of preventative measures common in the United States means political ideology could play a role in the adoption of public health policies and recommendations.

Political affiliation

Political ideology plays an important role in how individuals form attitudes (Van Holm et al., 2020; Zaller, 1992) and process information (Lodge & Taber, 2013). Political ideology may even influence individuals' health behaviors. For example, Republicans have been found to be less likely to get the H1N1 vaccine in comparison with Democrats (Mesch &

Schwirian, 2015). Survey research also finds that Democrats are more likely to adopt several health-protective behaviors, more likely to worry, and more likely to support social distancing policies (Kushner Gadarian et al., 2021). Republicans appear to be less concerned about COVID-19, practice social distancing less, follow the social distancing orders after the state-wide policy enactment less and are less likely to shift their consumption toward e-commerce (Allcott et al., 2020; Gadarian et al., 2020; Gollwitzer et al., 2020; Painter & Qiu, 2020). Democrats, on the other hand, are more likely to exercise protective actions against COVID-19 like taking fewer trips, staying home more, maintaining safe distances, and touching their own faces less frequently (Van Holm et al., 2020). Governors' recommendations for residents to stay home did significantly more to reduce mobility in Democratic-leaning counties (Grossman et al., 2020).

As a polarizing Republican president, Donald Trump provides a benchmark for policy preference among Republicans but not Democrats, which may lead to differences in responding to policies and consequently may influence the spread of the COVID-19. The president publicly disagreed with health experts about what policies should be applied to manage COVID-19.[6] On March 23, Trump claimed that America would reopen the economy against the warnings of health experts.[7] By April 16, President Trump issued guidelines to enable states to reopen; governors could open their economies at either the state level or county-by-county.[8] Republican governors and governors from states with more Trump supporters were slower to adopt social distancing policies (Adolph et al., 2020). Political affiliation may have played a role in people's pandemic behaviors and consequently influenced subsequent death rates. In September 2020, President Trump even publicly admitted that he downplayed COVID-19 at the initial stages to reduce the panic.[9]

Relatedly, Painter and Qiu (2020) found that Republicans were more likely to assign credibility to the advice of Trump in comparison to other state officials. Trump voters search less for information on COVID-19 and engage in less social distancing behavior (SDB) (Barrios & Hochberg, 2020). Counties that voted for Trump in the 2016 election exhibited 16% less physical distancing than counties that voted for Hillary Clinton and pro-Trump voting has been found to be indirectly associated with a higher growth rate in COVID-19 infections and fatalities (Gollwitzer et al., 2020). Due to the expected differential adherence to public health protocols, we hypothesize that the dominant political affiliation in a county will predict higher or lower COVID-19 death rates:

Hypothesis H_1 *(Political Affiliation): Counties with higher levels of Trump support will experience greater weekly COVID-19 death rates.*

Policy duration

In the United States, a variety of policies were implemented at the state level or the county level including shelter-in-place orders (SIPOs),[10] closures of restaurants/bars/entertainment-related businesses, bans on large events, and closures of public schools. The effectiveness of these policies varied widely; SIPOs and closures of nonessential businesses worked toward curtailing COVID-19 while the prohibition of large events and closure of public schools did not show signs of slowing down COVID-19 (C. Courtemanche et al., 2020; C. J. Courtemanche et al., 2020; Dave et al., 2020, 2021). Statewide SIPOs had the strongest effect, accounting for a 37% decrease in confirmed cases 15 days after implementation (Abouk & Heydari, 2020). Additionally, the impact of a social distancing policy has a significant cumulative effect (Dave et al., 2021). For instance, the daily growth rates were reduced by 5.4 percentage points after 1–5 days of government-imposed social distancing measures and 9.1 percentage points after 16–20 days (C. Courtemanche et al., 2020). We therefore expect that counties with long-lasting social distancing policies will experience relatively lower coronavirus death rates.

Hypothesis H_2 *(Policy Duration): The longer certain COVID-19 policies were in effect in a county, the fewer COVID-19 deaths the county will experience per week*.

Hypothesis H_{2a} *The longer the implementation of a SIPO, the fewer deaths per week a county will experience*.

Hypothesis H_{2b} *The longer the implementation of a public-school closure, the fewer deaths per week a county will experience*.

Hypothesis H_{2c} *The longer the implementation of a dine-in restaurant closure, the fewer deaths per week a county will experience*.

Hypothesis H_{2d} *The longer the implementation of an entertainment facility and gym closure, the fewer deaths per week a county will experience*.

Additionally, political ideology may moderate the effect of policy duration on death count per county. Therefore, we hypothesize that there is an interaction effect between political ideology and policy duration on the deaths caused by COVID-19:

Hypothesis H_{2e} *The proportion of Trump supporters per county will mitigate the effect of policy duration on suppressing COVID-19 deaths*.

Put another way, as the duration of a health policy in a county increases, the number of deaths per county will increase more rapidly in the counties with higher levels of Trump support than in counties with lower levels of Trump support.

SDB: Working mode

Tang et al. (2020) found that the best method to stop the spread of the COVID-19 is persistent and strict self-isolation. However, not all individuals are able to fully self-isolate, particularly for those in certain jobs. To account for this, we measured three working types during the pandemic: staying at home completely, working outside the home part time, and working outside the home full time. Working from home corresponds to strict adherence to self-isolation while working outside the home part time corresponds to a moderate level of self-isolation and working outside the home full time corresponds to nonadherence to social distancing.

Hypothesis H_{3a} *(Working modes): Counties with more people working from home tend to have fewer weekly COVID-19 deaths*.

Hypothesis H_{3b} *(Working modes): Counties with more people working part-time from home tend to have fewer weekly COVID-19 deaths*.

Hypothesis H_{3c} *(Working modes): Counties with more people working full time tend to have more weekly COVID-19 deaths*.

Control variables

Population density has been shown to play an important role in understanding influenza mortality. In denser areas, the mortality rate has been found to be significantly higher in comparison to less dense areas (Chandra et al., 2013). Related to COVID-19, rural counties with low population density appear to have gained very little from social distancing policies, especially statewide orders, which suggests that more nuanced policies that account for the heterogeneity of counties are needed to defeat the pandemic (Dave et al., 2020).

The risk of death among COVID-19 infected individuals is between 0.3% and 0.6% (Nishiura et al., 2020). According to scientists (D. Wang, Hu, et al., 2020; W. Wang, Tang, et al., 2020), older individuals with COVID-19 have a higher mortality rate than do other age groups. We therefore control for the size of the population 65 years of age or older within a county. We use 65 as a cutoff because people aged 65 and above qualify for Medicare; other age groups do not. Low income exacerbates the risk of death due to higher proportions of certain health issues, such as smoking (Krueger & Chang, 2008), heart disease (Lotufo et al., 2013; Redmond et al., 2013), and cancer (Najem et al., 1985; Singh & Jemal, 2017; Tolkkinen et al., 2018) among low-income populations. Furthermore, poverty may exacerbate negative pandemic outcomes as low-income individuals have diminished access to high-quality health care.[11] Additionally, scholars suggest that people of color in America potentially suffer more from this pandemic because of their pre-existing disadvantages in health, social, and economic status (Cooper & Williams, 2020).[12] Because population size, age, income, and race are likely correlated with local pandemic outcomes, and these variables are likely correlated with the levels of Trump support per county, we control for all four.

METHODS

Data

There are a variety of data sources available for COVID-19 including those provided by WHO, CDC, and Johns Hopkins University. Here, the count of COVID-19 deaths per county is provided by Johns Hopkins University's CSSE COVID-19 Tracking Project[13] and Dashboard.[14] As for the county political affiliation information, this paper uses data on the 2016 US Presidential Election from the MIT Election Data Science Lab (Data & Lab, 2018).[15] Population, race, and income data are obtained from the U.S. Census.[16] To measure SDB, we use the Social Distancing Metrics[17] data provided by SAFEGRAPH, which includes information about people's working modes based on mobile device telemetry.

Measures

To measure aggregate political preferences at county level, we compute the level of Trump support per county from the 2016 presidential campaign as the number of total votes for Trump divided by the total number of votes per county. We base this calculation on the assumption that the vast majority of the votes in any given county were for candidates in the two major parties; we essentially ignore the influence of all third party candidates. We also assume that Trump support did not change substantially between 2016 and 2020. In measuring the duration of health policies, we count the length in days since a policy's first implementation; policies of interests include the closing of public schools, the closing of restaurants, the closing of entertainment facilities and gyms, and SIPOs.[18]

In terms of the social distancing activities, we measure the proportion of people who stayed at home completely, the proportion of people who worked part time, and the proportion of people who worked full time relative to the overall county population. These represent the three types of working routines. In SAFEGRAPH, home is defined as the "common nighttime location for the device over a 6-week period where nighttime is 6 pm–7 am," and the device count is measured by the "number of devices seen in our panel during the date range whose home is in this census block group." The data do not include "any census block groups where the count <5."[19] Descriptive statistics are provided in Table 1.

Data analysis

This study uses a zero-inflated negative binomial model. The time frame of this study is from April 6 to May 25. We also present supplementary pooled ordinary least square, random effects, and fixed effects models in Table A1.[20] The dependent variable is the death count per week per county. Since May 1 was the day that many states chose to reopen their economies, we focus on SDBs from April 6 to May 11 as key independent variable. For instance, the SDB in the first week will be represented by the aggregate device movement (i.e., working type) on April 6. The lengths of policies are also calculated from April 6. The dependent variable is the count of virus-related deaths lagged by 2 weeks. The first model mainly examines the relationships between SDBs, aggregate political preference, and the number of deaths 2 weeks later. The model formula for the zero-inflation component (omitting the log link function) is given by

$$\begin{aligned} \text{No deaths} = {} & \beta_0 + \beta_1 \ln(\text{total population}) + \beta_2 \ln(\text{population density}) \\ & + \beta_3 \ln(\text{per capita income}) + \epsilon. \end{aligned}$$

The formula for the negative binomial count component of our model, again omitting the link function, is given by

$$\begin{aligned} \text{Death count} = {} & \beta_0 + \beta_1(\text{race}) + \beta_2(\text{Asian}) + \beta_3(\text{pop 65 proportion}) \\ & + \beta_4 \ln(\text{total population}) + \beta_5 \ln(\text{population density}) \\ & + \beta_6 \ln(\text{per capita income}) + \beta_7(\text{public school closure days}) \\ & + \beta_8(\text{restaurant dine in closure days}) \\ & + \beta_9(\text{entertainment and gym closure days}) \\ & + \beta_{10}(\text{stay at home policy days}) \\ & + \beta_{11}(\text{completely home devices per capita}) \\ & + \beta_{12}(\text{part} - \text{time devices per capita}) + \beta_{13}(\text{full} - \text{time devices per capita}) \\ & + \beta_{14}(\text{Trump supporter proportion}) + \beta_{15}(\text{Trump supporter proportion} \\ & \times \text{stay at home policy days}) + \epsilon. \end{aligned}$$

We run the above-specified model four times, once each for all possible interactions between Trump support rate and the four selected policies. We focus primarily on the above model (shown in Table 2 as Model 3) and provide the others in Appendix A.

RESULTS

Figure 1 shows that the total number of devices detected by SAFEGRAPH from counties with low Trump supporter levels (≤0.25) is about 0.9 million more than the total number of devices from high Trump supporter level (≥0.75) counties. This gap narrows at the beginning of April. Figure 2 shows that the total number of devices staying at home from the low Trump support level counties is about 0.3 million more than the high Trump support level counties.

TABLE 1 Within and between variations[a] for COVID-19 panel data

Variable		Mean	*SD*	Min	Max	Observations
FIPS (Federal Information Processing Standers)	Overall			1001	78,030	*N* = 19,410
	Between			1001	78,030	*n* = 3235
	Within					*T* = 6
Time	Overall			406	511	*N* = 19,410
	Between					*n* = 3235
	Within			406	511	*T* = 6
Death number	Overall	3.77	41.51	0.00	3780.00	*N* = 18,760
	Between		35.47	0.00	1710.17	*n* = 3140
	Within		21.46	−1210.39	2073.61	*T* = 5.97452
Total population	Overall	99,714.99	320,957.10	0.00	10,100,000	*N* = 19,356
	Between		320,998.60	0.00	10,100,000	*n* = 3226
	Within		0	99,714.99	99,714.99	*T* = 6
Percentage of population aged 65 and above	Overall	0.19	0.05	0.06	1.66	*N* = 19,302
	Between		0.05	0.06	1.66	*n* = 3217
	Within		0	0.19	0.19	*T* = 6
Total income	Overall	2,960,000,000	10,200,000,000	0	295,000,000,000	*N* = 19,356
	Between		10,200,000,000	0	295,000,000,000	*n* = 3226
	Within		0	2,960,000,000	2,960,000,000	*T* = 6
Per capita income	Overall	24,693.09	6356.11	5662.83	66,518.36	*N* = 19302
	Between		6356.93	5662.83	66,518.36	*n* = 3217
	Within		0.00	24,693.09	24,693.09	*T* = 6

(Continues)

TABLE 1 (Continued)

Variable		Mean	*SD*	Min	Max	Observations
Trump support rate	Overall	0.63	0.16	0.04	0.96	$N = 18{,}684$
	Between		0.16	0.04	0.96	$n = 3114$
	Within		0.00	0.63	0.63	$T = 6$
Days after closing public schools	Overall	31.46	10.01	4.00	50.00	$N = 19{,}308$
	Between		3.42	16.83	34.83	$n = 3218$
	Within		9.41	18.63	46.63	$T = 6$
Days after closing restaurant dine-in	Overall	34.82	12.69	2.00	60.00	$N = 19{,}308$
	Between		4.25	19.50	42.50	$n = 3218$
	Within		11.96	17.32	52.32	$T = 6$
Days after closing entertainment facilities and gym	Overall	33.71	13.20	0.00	60.00	$N = 18{,}918$
	Between		5.59	17.50	42.50	$n = 3153$
	Within		11.96	16.21	51.21	$T = 6$
Days of SIPO	Overall	26.02	12.95	0.00	55.00	$N = 15{,}906$
	Between		4.99	16.67	37.50	$n = 2651$
	Within		11.95	8.52	43.52	$T = 6$
Total device number	Overall	5707.01	15,194.00	8.00	356,315.00	$N = 19{,}335$
	Between		15,183.43	8.00	345,984.30	$n = 3225$
	Within		476.24	−9328.32	18,563.85	$T = 5.99535$
Completely home device number	Overall	2300.43	6845.23	1.00	185,938.00	$N = 19{,}335$
	Between		6822.47	3.33	164,263.20	$n = 3225$
	Within		539.51	−9205.74	23,975.26	$T = 5.99535$

TABLE 1 (Continued)

Variable		Mean	*SD*	Min	Max	Observations
Part-time working device number	Overall	331.31	806.91	1.00	28,482.00	$N = 19,335$
	Between		798.85	1.00	19,973.33	$n = 3225$
	Within		112.63	−3635.03	8839.97	$T = 5.99535$
Full-time working device number	Overall	204.12	546.14	1.00	22,867.00	$N = 19,335$
	Between		539.75	1.00	15,293.17	$n = 3225$
	Within		82.56	−2848.05	7777.95	$T = 5.99535$

[a]Time-invariant variables (*total_population*, *pop65percentage*-ratio of population aged 65 and above, *total_ income*, *per_capita_income*, *rate*) have positive between variation and zero within variation. Death caused by COVID-19 has relatively higher between variation (35.47) than within variation (21.46).

TABLE 2 Deaths due to COVID-19 political ideology, social distancing behavior (2 weeks lag)

Variables (DV = Death number per county per week)	(1) ZINB_mode1	(1a) ZINB_model1 inflate	(2) ZINB_model2	(2a) ZINB_model2 inflate	(3) ZINB_model3	(3a) ZINB_model3 inflate
Percentage of people of color without Asian	2.962***		3.898***		4.560***	
	(0.169)		(0.213)		(0.221)	
Percentage of Asian population	3.124*		−1.964*		−2.094*	
	(1.221)		(0.995)		(0.895)	
Percentage of population aged 65 and above			5.989***		6.594***	
			(0.834)		(0.860)	
Total population (log)	1.189***	−0.220	0.973***	−0.619***	0.894***	−0.717**
	(0.0307)	(0.135)	(0.0413)	(0.172)	(0.0489)	(0.225)
Population density (log)		−0.998***	0.0928*	−0.750***	0.0731	−0.655*
		(0.151)	(0.0429)	(0.195)	(0.0542)	(0.265)
Per-capita-income (log)		2.089***	1.337***	3.224***	0.956***	2.985***
		(0.553)	(0.157)	(0.453)	(0.180)	(0.518)
Days after closing public schools			−0.0682***		−0.0665***	
			(0.00894)		(0.00941)	
Days after closing restaurant dine-in			−0.0198*		−0.00241	
			(0.00983)		(0.0102)	
Days after closing entertainment facilities and gyms			0.0392***		0.0336***	
			(0.00649)		(0.00652)	
Days of SIPO			0.0253**		0.0145	
			(0.00946)		(0.00930)	

TABLE 2 (Continued)

Variables (DV = Death number per county per week)	(1) ZINB_mode1	(1a) ZINB_model1 inflate	(2) ZINB_model2	(2a) ZINB_model2 inflate	(3) ZINB_model3	(3a) ZINB_model3 inflate
Completely home device percentage					4.156***	
					(0.843)	
Part-time working device percentage					–3.054	
					(3.069)	
Full-time working device percentage					–10.49*	
					(4.262)	
Trump support rate			0.0813		0.702	
			(0.344)		(0.383)	
Days of SIPO × Trump support rate	0.0104***		0.0174		0.0281*	
	(0.00297)		(0.0107)		(0.0109)	
Constant	–13.56***	–16.53**	–25.57***	–24.19***	–22.57***	–21.05***
	(0.377)	(5.562)	(1.654)	(4.796)	(1.900)	(5.804)
Observations	10,012	10,012	10,012	10,012	10,012	10,012

Note: Robust standard errors are given in parentheses.

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

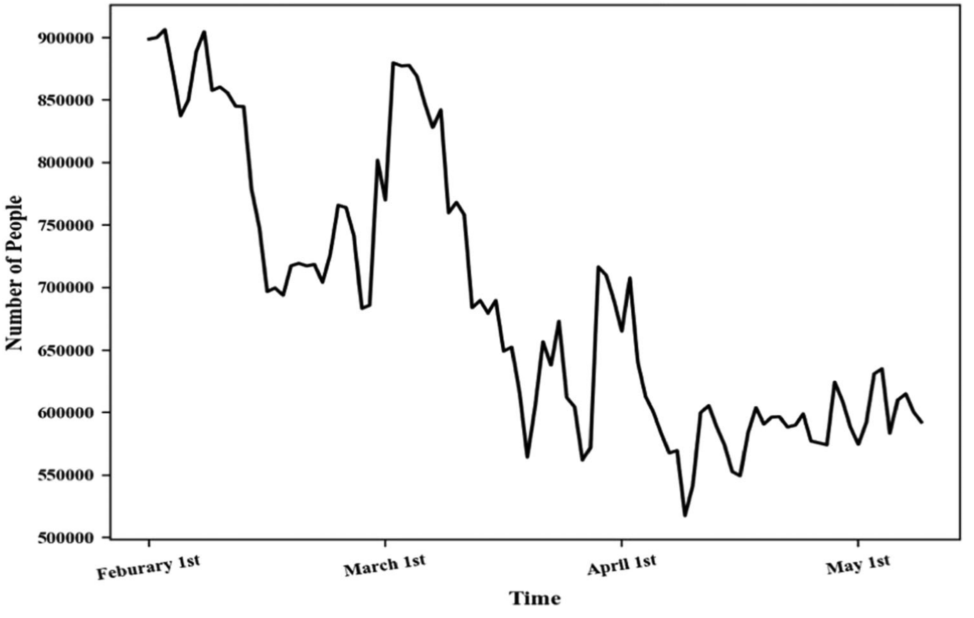

FIGURE 1 The difference of total devices between Democratic and Republican counties. This graph represents the total number of devices from counties with a low Trump support levels (≤0.25) minus the total number of devices from counties with high Trump support levels (≥0.75)

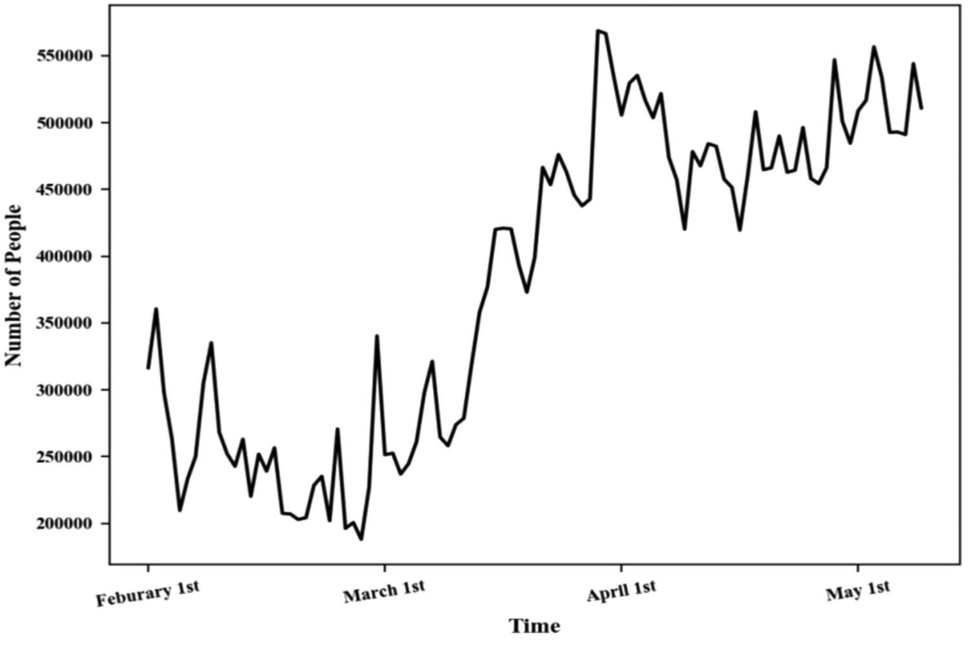

FIGURE 2 The difference of people completely staying at home between Democratic counties and Republican counties. This graph represents the total number of devices staying at home completely from counties with a low Trump support levels (≤0.25) counties minus the total number of devices staying at home completely from counties with high Trump support levels (≥0.75)

However, this gap increases until April 1st by which point the low Trump support level counties have 0.55 million more devices staying at home than the high Trump support level counties. This trend suggests that social distancing policies are adhered to more effectively in Democratic counties than in Republican counties.

Figures 3 and 4 show that the total number of devices out of the home part time and full time on February 1 from low Trump support level counties is 80,000 more than from high Trump support level counties. However, these gaps decrease until mid-April. By mid-March, the number of devices belonging to persons working outside the home part time is greater in high Trump support level counties and the gap for full-time work outside the home work has narrowed to just 10,000 devices.

Figures 1 through 4 suggest aggregate differences in how individuals in high Trump support level counties and low Trump support level counties responded to the pandemic between February and May. In particular, they point to decreases in the number of devices associated with outside-the-home working styles in low Trump support level counties relative to high Trump support level counties. With this in mind, we turn now to the results of our regression analysis that will allow us to isolate the relationship between political ideology and county-level COVID-19 outcomes.

We focus our attention on the fully specified Model 3 in Table 2. While the coefficient for the level of Trump support is positive, it is not significant; we find no evidence for a relationship between supporter rate and county-level COVID-19 death rates (H_1) after controlling for demographics, policy implementation, and working mode. However, the interaction effect between the level of Trump support per county and the duration of implementation of a SIPO is positive and statistically significant. Figure 5 depicts the average predicted deaths per county for three levels of Trump support (0.0, 0.5, and 1.0) at given days of implementation of a SIPO. The line representing a county with a Trump supporter

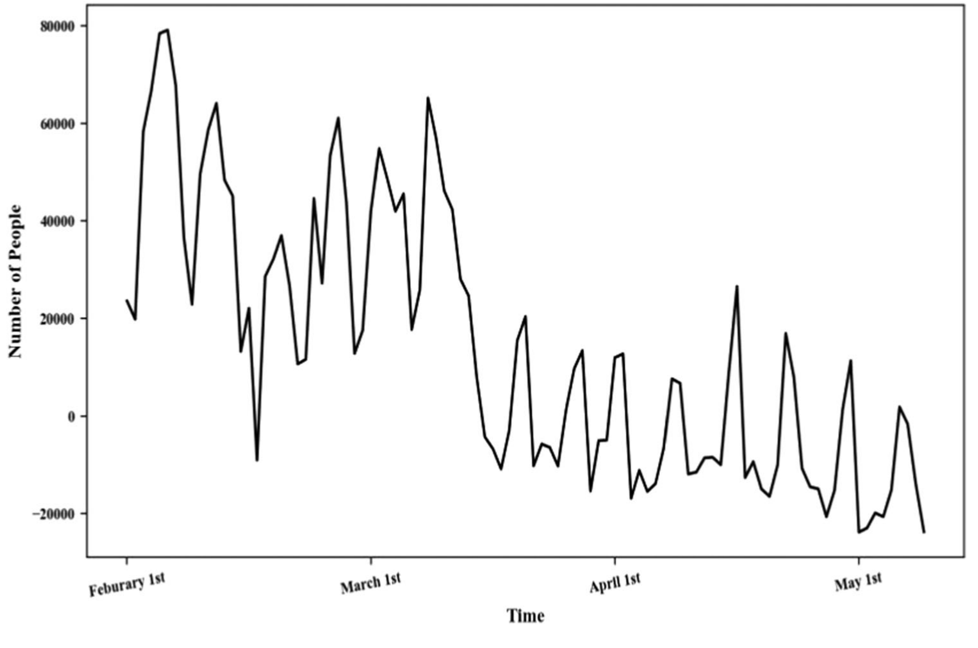

FIGURE 3 The difference of people working part time between Democratic counties and Republican counties. This graph represents the total number of devices working part time from counties with a low Trump support level (≤0.25) minus the total number of devices working part time from counties with high Trump support levels (≥0.75)

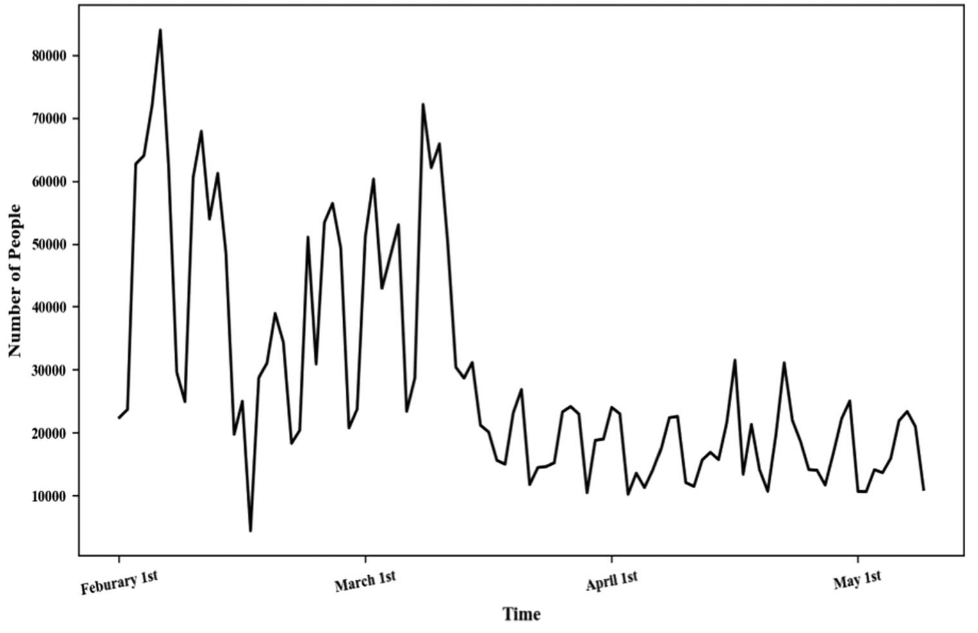

FIGURE 4 The difference of people working full time between Democratic counties and Republican counties. This graph represents the total number of devices working full time from counties with a low Trump support levels (≤0.25) minus the total number of devices working full time from counties with high Trump support levels (≥0.75)

rate of 0.0 is nearly flat; this reflects the insignificant and near-zero coefficient associated with the duration of a SIPO. However, the line representing a hypothetical county with a Trump supporter rate of 1.0 curves steeply upward over the duration of the SIPO, reflecting the positive coefficient found for that interaction. At the beginning of the implementation of a SIPO, the high Trump support counties have similar predicted death counts as the medium

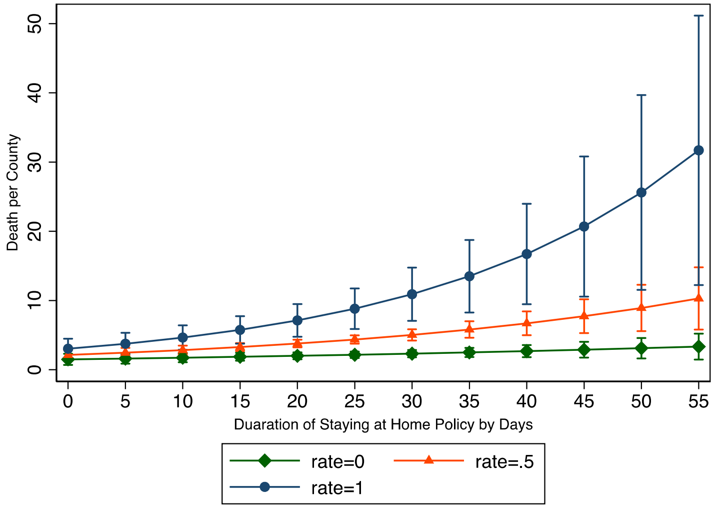

FIGURE 5 Interaction effect of Trump supporter level and the duration of SIPO. Based on Table 2 (zero-inflated negative binomial). Testing Hypothesis $H_1$and H_2. Shaded region = 95% confidence interval

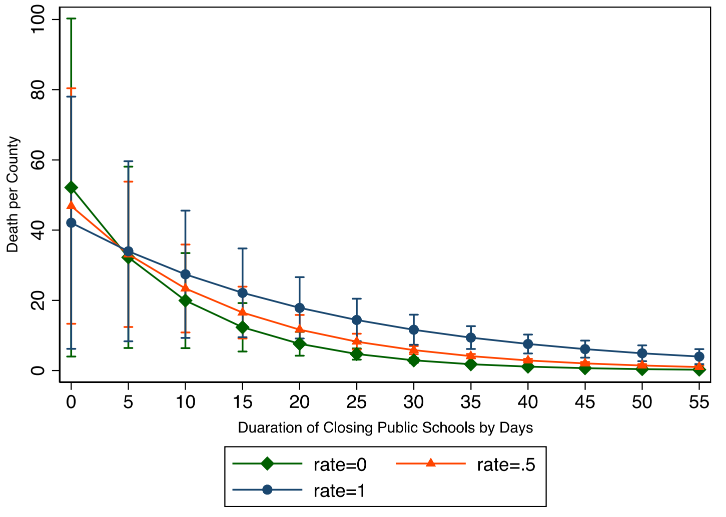

FIGURE 6 Interaction effect of Trump support level and the duration of public schools closure policy

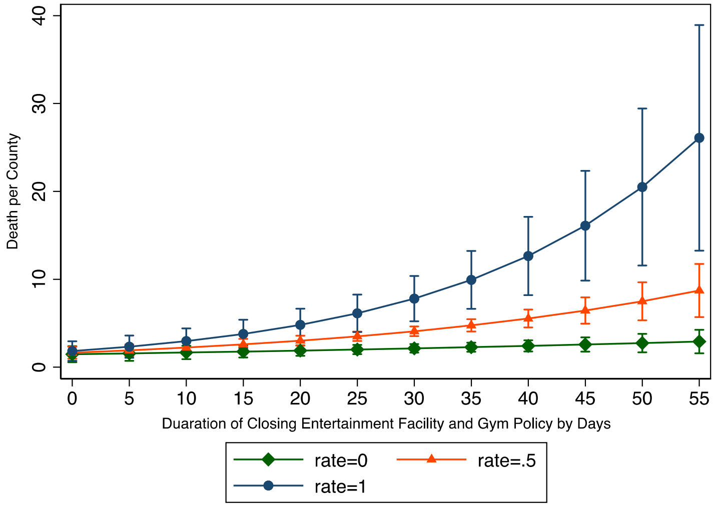

FIGURE 7 Interaction effect of Trump support level and the duration of entertainment facility and gym closure policy

and low Trump support counties. As the durations of SIPOs increase, the predicted COVID-19 death counts in all hypothetical counties also increase; however, the differences between these three groups become very pronounced after 3 weeks of a SIPO. In other words, even controlling for observed compliance via SDB data, we find that SIPOs are nonetheless apparently less effective in counties with high levels of Trump support. In particular, for a hypothetical county with zero Trump supporters, the coefficient associated with SIPOs is very near zero (0.015), controlling for compliance. For a hypothetical county that is 100% Trump supporters, the coefficient for SIPOs is just above 0.04. Additionally, the interaction effects between the level of Trump support and two other policies (the prohibition on restaurant dine-in and the closing of entertainment facilities and gyms) exhibit similar trends, as shown in Figures 7 and 8.[21] Figure 8 illustrates the differential relationship

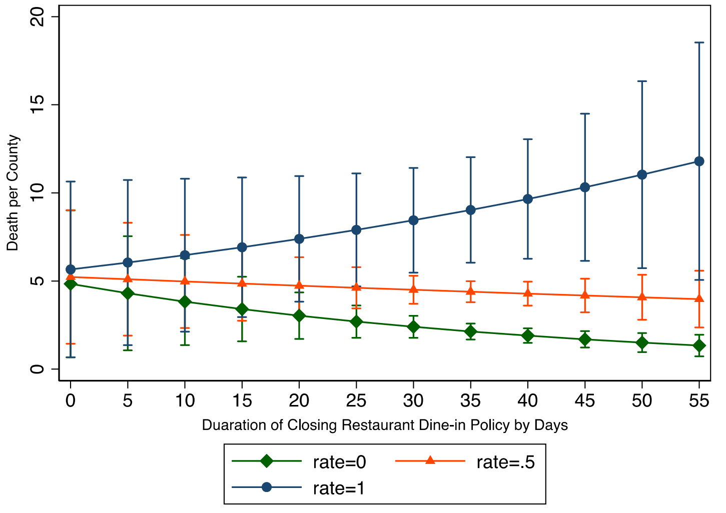

FIGURE 8 Interaction effect of Trump support level and the duration of restaurant dine-in closure policy

between restaurant dine-in prohibitions and predicted COVID-19 deaths for counties of differing aggregate political ideologies. For counties with very low levels of Trump support, restaurant policies resulted in decreases in the average death count over time while the opposite is true for counties with high levels of Trump support.

The only policy that does not follow the patterns as described above is public school closures (Figure 6). This is also the only policy for which the associated model coefficient is negative and significant. We suspect that the insignificant interaction effect here may be due to mandatory enforcement of this policy by state and local governments; while the other policies require individuals or small business owners to comply to assure efficacy, it is difficult to imagine how individuals would fail to comply with public school closures. These findings are generally in agreement with our expectations as outlined in H_{2e}: Trump supporter level mitigates the effectiveness of public health policies. Why these policies generally appear to be less effective in Trump-supporting counties is worth closer attention.

The inclusion of SAFEGRAPH data on working modes (home, part time, and fully outside the home) should at least partially control for noncompliance with these policies. Nonetheless, we find that Trump-supporting counties fare worse than their non-Trump-supporting counterparts over the course of public health policy implementation. We suspect this is due to forms of noncompliance that are not fully captured by the working mode covariates; these may include improper mask usage or failure to social distance in nonprofessional settings (e.g., parties or social gatherings).

We find little support for H_{2a} through H_{2d}: duration of school closure is the only policy that is associated with a statistically significant decrease in COVID-19 deaths. However, we caution against interpreting this finding directly: policy implementation is likely a function of both the current coronavirus case count in a county as well as a county's overall risk. Therefore, positive coefficients on policies (such as that associated with the closure of gyms and entertainment venues) may be due to the late implementation of those policies after increases in coronavirus cases had already become near-unavoidable. Furthermore, the counterfactual number of cases in counties without those policies is not clear.

Similarly, we fail to reject the null hypotheses for H_{3a} through H_{3c}, our working mode hypotheses. In fact, Model 3 indicates that the proportion of devices (relative to population) staying completely at home is associated with an increase in the predicted number of COVID-19 deaths and that the reverse is true for the proportion of devices working outside the home full time. As with the findings for H_2, we suspect this may be due to reverse causality: compliance is higher in areas with greater coronavirus risk (Figures 5–8).

Table 3 shows that high Trump support counties have, on average, significantly more people working full time or part time outside-the-home and fewer people staying at home than comparable low Trump support counties. We demonstrate this in a series of four linear models of working mode (represented as a proportion of the total population) regressed on predictors of working mode including the level of Trump support. Models 2 through 4 in Table 3 show that level of Trump support correlates with working mode behaviors that are contrary to public health guidance, even when controlling for the duration for which that guidance has been in place. This indicates that individuals in counties with high levels of Trump support show less compliance with these health policies. This finding reinforces our suspicion that the positive interaction effects found between policy implementation duration and level of Trump support are likely the result of poor compliance with public health guidance.

TABLE 3 Social distancing behaviors, political ideology, and health policies

Variables	(1) Percentage of devices stay at home	(2) Percentage of devices stay at home	(3) Percentage of devices working part time	(4) Percentage of devices working full time
Trump support rate	−0.175***	−0.136***	0.0373***	0.00557***
	(0.00403)	(0.00305)	(0.000905)	(0.000548)
Death number per county per week	0.000153*	4.13e−05	−8.78e−06	−3.71e−06
	(7.06e-05)	(3.67e−05)	(6.44e−06)	(2.28e−06)
Per-capita-income (log)		0.139***	−0.0180***	−0.00413***
		(0.00224)	(0.000643)	(0.000372)
Days after closing public schools		0.000546***	0.000293***	0.000490***
		(0.000118)	(4.24e−05)	(2.52e−05)
Days after closing restaurant dine-in		−0.00347***	0.000584***	−0.000222***
		(0.000122)	(4.35e−05)	(2.59e−05)
Days after closing entertainment facilities and gyms		−0.000385***	0.000170***	−0.000131***
		(8.37e−05)	(2.78e−05)	(1.66e−05)
Days of SIPO		0.00212***	−0.000629***	0.000122***
		(0.000103)	(3.48e−05)	(1.90e−05)
Constant	0.449***	−0.916***	0.207***	0.0699***
	(0.00279)	(0.0233)	(0.00674)	(0.00392)
Observations	18,604	15,675	15,675	15,675
R^2	0.189	0.494	0.268	0.086

Note: Robust standard errors are given in parentheses.

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

Finally, we note that the percentage of people of color (not including Asian persons) per county is positively associated with the number of COVID-19 deaths per county. This provides evidence that communities of color suffer more from COVID-19 than do communities with fewer people of color.

DISCUSSION AND POLICY IMPLICATIONS

We find that political ideology plays a role in health outcomes during major public health crises. By interacting ideology with measures of public health policy, we demonstrate that disparate public health outcomes during the coronavirus pandemic are likely due in part to differences across ideological lines in the practical implementation of public health policies. After controlling for a number of determinants of COVID-19 death counts, we find that ideology, operationalized as county-level Trump support, is not predictive of increased COVID-19 mortality on its own. However, predicted rates of COVID-19-related deaths in counties with high levels Trump support increase along with the duration of implementation of several COVID-19 policies (restaurant closures, gym and entertainment facility closures, and SIPOs). We hope these findings encourage policymakers and opinion leaders to consider the risks associated with mixed messaging during future health crises. Encouraging noncompliance with public health directives along ideological lines leads to suboptimal public health outcomes and, in the case of the coronavirus pandemic, unnecessarily high death rates. Policymakers should balance the cost of sacrificing individual freedoms against the grave health outcomes suffered disproportionately by vulnerable groups.

However, we also urge caution when interpreting our findings in the context of policy recommendations. Our study covered only a small time period (April 6 through May 25, 2020) and our conclusions may not generalize well beyond this period. As researchers learned more about the virus and the public increasingly saw its effects first-hand, both public health guidance and compliance may have adjusted accordingly.

Concerning SDB, we find that the number of people who work part time or full time outside the home is positively associated with the level of Trump support at the county level. Additionally, the number of people who work from home is negatively associated with the level of Trump support. This suggests that mixed health signals from experts and politicians may influence individuals' compliance with public health directives, even during major crises. Mixed signals from politicians may potentially cause people to underestimate the seriousness of a health crisis.

CONFLICTS OF INTEREST

The authors declare that there are no conflicts of interest. This research was not supported by any grants or outside sources. No patient data or personally identifiable information were used in this study.

ETHICS STATEMENT

All data and code needed to reproduce the study will be made publicly available on the author's website at the time of publication.

ENDNOTES

[1] https://www.who.int/emergencies/diseases/novel-coronavirus-2019

[2] https://home.treasury.gov/policy-issues/cares

[3] As Covid-19 continues to spread across the United States, President Donald Trump has given governors guidance on reopening state economies in the coming months (April 17, 2020). https://www.bbc.com/news/world-us-canada-52314866

[4]Tennessee doctors say it is not safe to reopen the economy without rapid testing, proper PPE (April 24, 2020). https://fox17.com/news/local/tennessee-doctors-say-its-not-safe-to-reopen-economy-with-rapid-testing-proper-ppe

[5]This paper uses working modes, full time, part time, or never at home, to represent social distancing activities.

[6]https://www.nytimes.com/2020/03/23/business/trump-coronavirus-economy.html

[7]https://www.nytimes.com/2020/03/23/business/trump-coronavirus-economy.html

[8]https://www.whitehouse.gov/briefings-statements/president-donald-j-trump-beginning-next-phase-fight-coronavirus-guidelines-opening-america/

[9]https://www.washingtonpost.com/politics/trump-reaction-woodward-interview-coronavirus/2020/09/09/fc21e67e-f2ca-11ea-b796-2dd09962649c_story.html

[10]Also known as a stay-at-home order.

[11]For instance, CNN documented one COVID-19 patient was worried about treatment costs even despite his serious health condition: https://www.cnn.com/2020/04/11/health/nurse-last-words-coronavirus-patient-trnd/index.html.

[12]We thank a helpful reviewer for the suggestion to distinguish the Asian population from other racial minorities in our analyses. The opposite signs on the coefficients associated with these covariates justify this decision. Therefore, the race variable represents the proportion of the population that is neither white nor of Asian descent.

[13]https://github.com/CSSEGISandData/COVID-19

[14]https://coronavirus.jhu.edu/map.html

[15] MIT Election Data and Science Lab, 2018, “County Presidential Election Returns 2000-2016,” https://doi.org/10.7910/DVN/VOQCHQ, Harvard Dataverse, V6, UNF:6:ZZe1xuZ5H2l4NUiSRcRf8Q==[fileUNF].

[16]https://data.census.gov/cedsci/

[17]https://docs.safegraph.com/docs/social-distancing-metrics

[18]https://github.com/JieYingWu/COVID-19_US_County-level_Summaries/blob/master/raw_data/national/public_implementations_fips.csv

[19]We use the SAFEGRAPH variable *completely_home_device_count* to represent persons who work entirely from home. This variable is described as “out of the device count, the number of devices that did not leave the geohash-7 in which their home is located during the period.” The variable *part_time_work_behavior_devices* represents “the number of devices that spent one period of between 3 and 6 hours at one location other than their geohash-7 home during the period of 8 am - 6pm in local time. This does not include any device that spent 6 or more hours at a location other than home.” Lastly, the variable *full_time_work_behavior_devices* represents “the number of devices that spent greater than 6 hours at a location other than their home geohash-7 during the period of 8 am - 6pm in local time.”

[20]While we include all four model specifications for completeness, we contend that the zero-inflated negative binomial model best reflects our understanding of the data generating process: one process governs the existence of COVID-19 in a county while another process, represented by a negative binomial distribute, models the number of cases conditional on the existence of at least one case.

[21]The full models that include these interaction effects are included in Appendix A.

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APPENDIX A

TABLE A1 Time series analysis of political ideology and deaths of COVID-19 with 2 weeks lag

Variables (DV = death per county per week)	(1) Pooled OLS regression	(2) Random effects	(3) County fixed effects
Total population (log)	2.136***	0.633	
	(0.613)	(1.302)	
Population density (log)	2.179***	3.889***	
	(0.492)	(1.048)	
Percentage of population aged 65 and above	41.80***	51.23*	
	(9.636)	(20.03)	
Per capita income (log)	13.60***	23.26***	
	(2.397)	(4.791)	
Days after closing public schools	–0.361*	–0.165	–0.0271
	(0.140)	(0.145)	(0.162)
Days after closing restaurant dine-in	0.0758	0.00151	3.428
	(0.155)	(0.279)	(4.956)
Days after closing entertainment facilities and gym	–0.0977	–0.135	
	(0.108)	(0.234)	
Completely home device percentage	11.21	5.684	3.262
	(10.41)	(9.708)	(10.71)
Part-time working device percentage	9.162	10.60	5.049
	(32.41)	(27.89)	(29.68)
Full-time working device percentage	–66.89	–33.75	–26.92
	(51.36)	(42.78)	(45.04)
Trump support rate	–22.35***	–38.54***	
	(5.682)	(7.373)	
Days of SIPO	0.134	–0.210	–3.929
	(0.174)	(0.267)	(4.965)

TABLE A1 (Continued)

Variables (DV = death per county per week)	(1) Pooled OLS regression	(2) Random effects	(3) County fixed effects
Trump support rate × Days of SIPO	0.192	0.685***	0.762***
	(0.201)	(0.130)	(0.132)
Constant	−154.6***	−235.5***	−27.18
	(23.28)	(48.08)	(47.08)
Observations	10,017		
R^2	0.0534		
Number of counties with FIPS (Federal Information Processing Standers)		2,625	2,625
R^2—within		0.0052	0.0054
R^2—between		0.0640	0.0075
R^2—overall		0.0525	0.00068
$Sigma_u$ (α)		45.90	53.61
$Sigma_e$		24.98	24.97
Rho		0.77	0.82

Note: Robust standard errors are given in parentheses.

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

[a]The Hausman test shows a significant difference ($p < 0.001$) between the coefficient for the fixed effects and the random effects model, so this study uses fixed effects for time-variant variables. However, the random effects model has multiple advantages, such as incorporating time-invariant variables (Bell & Jones, 2015), so we add a random effects model as a reference for explaining time-invariant variables' effects on death.

TABLE A2 Interaction effects for Figures 6–8

Variables (DV = Death number per county per week)	(1) ZINB_ Figure 6	(1a) ZINB_ Figure 6 inflate	(2) ZINB_ Figure 7	(2a) ZINB_ Figure 7 inflate	(3) ZINB_ Figure 8	(3a) ZINB_ Figure 8 inflate
Percentage of people of color without Asian	4.616***		4.548***		4.581***	
	−0.222		−0.222		−0.22	
Percentage of Asian	−2.291**		−2.133*		−2.203*	
	−0.885		−0.89		−0.886	
Percentage of population aged 65 and above	6.517***		6.535***		6.599***	
	−0.853		−0.858		−0.858	
Total population (log)	0.893***	−0.709***	0.893***	−0.705***	0.895***	−0.708***
	−0.047	−0.21	−0.0468	−0.208	−0.0478	−0.215
Population density (log)	0.0646	−0.663**	0.0688	−0.666**	0.0652	−0.663**
	−0.0515	−0.249	−0.0518	−0.245	−0.0524	−0.255
Per-capita-income (log)	0.959***	2.980***	0.952***	2.995***	0.954***	2.981***
	−0.177	−0.507	−0.177	−0.503	−0.178	−0.51
Days after closing public schools	−0.0962***		−0.0652***		−0.0658***	
	−0.0129		−0.00931		−0.00937	
Days after closing restaurant dine-in	−0.00182		−0.003		−0.0233*	
	−0.0102		−0.0102		−0.0116	
Days after closing entertainment facilities and gym	0.0334***		0.0124		0.0330***	
	−0.00649		−0.00903		−0.0065	
Days of SIPO	0.0301***		0.0311***		0.0309***	
	−0.00663		−0.00663		−0.00663	
Completely home device percentage	4.237***		4.207***		4.205***	
	−0.83		−0.837		−0.837	
Part-time working device percentage	−3.46		−3.217		−3.377	
	−3.052		−3.055		−3.06	
Full-time working device percentage	−10.88*		−10.48*		−10.50*	
	−4.235		−4.252		−4.249	
Trump support rate	−0.214		0.218		0.157	
	−0.537		−0.461		−0.493	
Days after closing public schools × Trump support rate	0.0533***					
	−0.0148					

TABLE A2 (Continued)

Variables (DV = Death number per county per week)	(1) ZINB_ Figure 6	(1a) ZINB_ Figure 6 inflate	(2) ZINB_ Figure 7	(2a) ZINB_ Figure 7 inflate	(3) ZINB_ Figure 8	(3a) ZINB_ Figure 8 inflate
Days after closing entertainment facilities and gym × Trump support rate			0.0359**			
			–0.011			
Days after closing restaurant dine-in × Trump support rate					0.0367**	
					–0.0117	
Constant	–22.04***	–21.05***	–22.23***	–21.22***	–22.23***	–21.06***
	–1.867	–5.612	–1.873	–5.54	–1.883	–5.667
Observations	10,012	10,012	10,012	10,012	10,012	10,012

Note: Robust standard errors are given in parentheses.
***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.