Political partisanship influences behavioral responses to governors' recommendations for COVID-19 prevention in the United States

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Abstract

Voluntary physical distancing is essential for preventing the spread of COVID-19. Political partisanship may influence individuals' responsiveness to recommendations from political leaders. Daily mobility during March 2020 was measured using location information from a sample of mobile phones in 3,100 US counties across 49 states. Governors' Twitter communications were used to determine the timing of messaging about COVID-19 prevention. Regression analyses examined how political preferences influenced the association between governors' COVID-19 communications and residents' mobility patterns. Governors' recommendations for residents to stay at home preceded stay-at-home orders, and led to a significant reduction in mobility that was comparable to the effect of the orders themselves. Effects were larger in Democratic than Republican-leaning counties, a pattern more pronounced under Republican governors. Democratic-leaning counties also responded more to recommendations from Republican than Democratic governors. Political partisanship influences citizens' decisions to voluntarily engage in physical distancing in response to communications by their governor.

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1 Background

The outbreak of COVID-19 in the USA has prompted unprecedented efforts to prevent disease spread. In the absence of a vaccine, effective treatments, or widespread testing, individuals' preventive measures—from hand-washing to physical distancing—are essential for reducing the speed and extent of the virus's spread (1). Some measures, such as staying home, are particularly subject to non-compliance, with possible dire consequences for attempts to "flatten the curve" of new infections.

Political leaders play an important role in persuading the public to voluntarily comply with costly preventive measures during pandemics. In addition to issuing orders that serve to reduce contact between individuals, politicians' communications about the severity with which individuals should treat COVID-19 and the preventive measures they should take are likely to be particularly influential when there is limited information about a novel disease. A better understanding of the link between politicians' communications and individuals' voluntarily adoption of preventive measures is crucial for ongoing efforts to limit the spread of COVID-19 and for improving public health more generally.

This study is motivated by three stylized facts that have emerged since the COVID-19 outbreak in the US. First, both risk perceptions (2; 3; 4) and engagement in preventive behaviors (3; 5) have differed substantially by individuals' political party affiliation, with Republicans generally being slower or less likely to adopt preventive behaviors than Democrats. Second, there have been partisan differences in the COVID-19 response at the state level, with Democratic governors leading, on average, more aggressive responses than Republican governors (6). Third, there has been notable within-party variation in governors' responses, with some Republican governors taking decisive steps early on (e.g., in Ohio and Maryland) and other Republican governors being more ambivalent in their message or reluctant to issue stay-at-home orders. Based on these facts, this Research Note examines how US governors' communications influenced individuals' mobility patterns and engagement in physical distancing.

Theoretically, we build on past work that connects public opinion and actions to elites' cues (7). Here, constituents use both news outlets and social media to gauge the positions of political elites whom they trust in order to form their opinions based on these signals (8). Elite cues have been shown to steer uninformed citizens toward effective policy judgment (9; 10), but they can also cause citizens to reject valid scientific information (11; 12). While elite cues clearly matter in 'normal times' and when the stakes to individuals from following cues is relatively small, it is an open question of whether and how elite cues might matter during a pandemic in which individuals' actions can directly impact their own health.

On the one hand, as the US has become increasingly polarized (13), cues from elites who share citizens' partisan attachments could have greater effect. On the other hand, research on political endorsement has shown that elite cues are especially effective when the signal they emit does not conform with their own party position (14). It is thus possible, for example, that Republican governors who communicated the seriousness of COVID-19 in early-March, a period during which the right-leaning media and US President Donald Trump were skeptical of the risk posted by COVID-19, would have a stronger effect on Democrats' behavior than on the behavior of Republicans. Our study is designed to explore such dynamics.

Using geocoded county-level data on citizen mobility, past electoral returns that serve as proxy for partisan preferences, and Twitter-based communications about COVID-19 by governors of all 50 states in the US, this study examines how partisanship mediates the relationship between governors' COVID-19 communications of governors and residents' engagement in physical distancing. Specifically, we test the extent to which predominantly Democratic vs. Republican counties respond to COVID-19 prevention related messaging by their governors. Unlike other recent studies, our focus is on the effect of governors' communications encouraging COVID-19 prevention on *voluntary behavior* as these often preceded official stay-at-home mandates.

This paper explores three central questions about the ways in which governors' messages may have affected individuals' engagement in critical COVID-19 prevention behaviors. Rather than focus on the effect of stay-at-home orders (2; 15), we examine instead the effect of governors' messages encouraging physical distancing and limited mobility because these preceded the issuance of orders by a meaningful number of days or even weeks. We first assess whether governors' messages affect individuals' mobility patterns. Second, we examine whether messages from governors differentially influence Republican- vs. Democratic-leaning counties. And finally, we assess whether the party affiliation of governors affects the responsiveness of citizens with differing partisan preferences.

We find that governors' messages—as proxied by their Twitter feed—preceded the issuance of 'stay home' orders by a meaningful period and had a significant effect on residents' mobility. These effects were comparable in magnitude to the effects of 'stay home' orders. Second, governors' communications had, on average, a larger effect on mobility in Democratic counties. Finally, while both Democratic and Republican counties are equally responsive to Democratic governors, Democratic counties were more responsive to Republican governors than Republican counties. These results are consistent with the idea that elites cues that are not aligned with party lines serve as a strong signal for other-party voters but have more muted effects among own-party voters. Our study contributes to a better understanding of the nexus of elite cues and citizens' (voluntary) behavior.

2 Methods and Data

We use the following data to answer the study's research questions:

Mobility (physical distancing): Mobility of individuals in US counties is our main outcome of interest. We use publicly released mobility statistics from *Safegraph*, derived from geolocated devices.[1] The *Safegraph* data comprises a sample of 545 million unique device-days covering 3,140 US counties, measured continuously throughout the day and reported daily over the period of March 1-March 31, 2020. Using these data, our primary outcome was calculated at the county-day level and defined as the median time devices from a county spent at home on each day. Using the same data we also defined secondary outcomes as the share of devices in each county-day pair that stayed at home for the entire day and the number of miles travelled from home released by *Descartes Labs*.[2] Percentage of devices that remained at home during the entire day is a better proxy for physical distancing than distance travelled, particularly in sparsely populated areas where long-travel distances do not indicate a lack of physical distancing.

Risk perceptions: To assess risk perception of individuals, we used data from Google Trends on searches for the following terms: "Coronavirus," "social distancing," "stay at home," and "shelter in place." The higher the search share in a particular location and time period, the higher the perceived risk among that population (2). Here, we take the daily relative search interest for 202 metro areas for the period March 1 - March 31 2020. This provides a daily time series for each individual metro area, yielding 6,262 metro-days. We use these data to show within-metro trends in search interest overtime. However, these data are not appropriate for cross-sectional comparisons. For cross-sectional comparisons, we follow Stephens-Davidowitz and normalize search interest for each of the 202 metro-areas relative to the metro-day with the greatest search interest over the period of study (16).

Twitter data: Our main interest lies in explaining health behavior as a function of governors' messaging (cues) about the necessity of staying home and physical distancing more generally. To measure such cues, we download all tweets sent from both the personal and official Twitter accounts of the governors of all 50 US states between February 15th and March 31, 2020.[3] We then manually code each tweet using three binary indicators: (a) whether the tweet is relevant to Coronavirus, and if so, (b) whether the tweet encourages physical distancing and (c) whether the tweet encourages staying home ("sheltering-in-place"). Stay home messages necessarily entail physical distancing but

[1] `https://www.safegraph.com/dashboard/covid19-commerce-patterns`

[2] `https://github.com/descarteslabs/DL-COVID-19`

[3] For most governors, these tweets are duplicated on their personal and official Facebook page, and the information the tweets conveyed was repeated in press conferences they held. We thus view governors' tweets as a proxy for their messaging efforts more broadly.

not vice-versa (See SI, Section A for additional details). Our key input variable is *Post stay-home tweet*; an indicator that has a value of one for *all days* after the first time a governor explicitly encouraged staying home. We also check for robustness to using *Cumulative stay home tweets*, which is the number of cumulative tweets encouraging staying at home at any given day. Figure 1 shows that, in general, Democratic governors began encouraging social distancing at earlier date. For example, by March 21, sixteen Democratic governors, but only four Republican governors, have used social media to encourage state residents to stay home (bottom panel). Figure SI-1 shows that while the median democratic governor began encouraging staying home 6-7 days before the statutory order, the median GOP governor began encouraging staying home only a day before the policy came into effect. Figure SI-2 shows that not merely timing, but also the intensity of Democratic governors' messaging about COVID-19 was higher than their Republican counterpart.

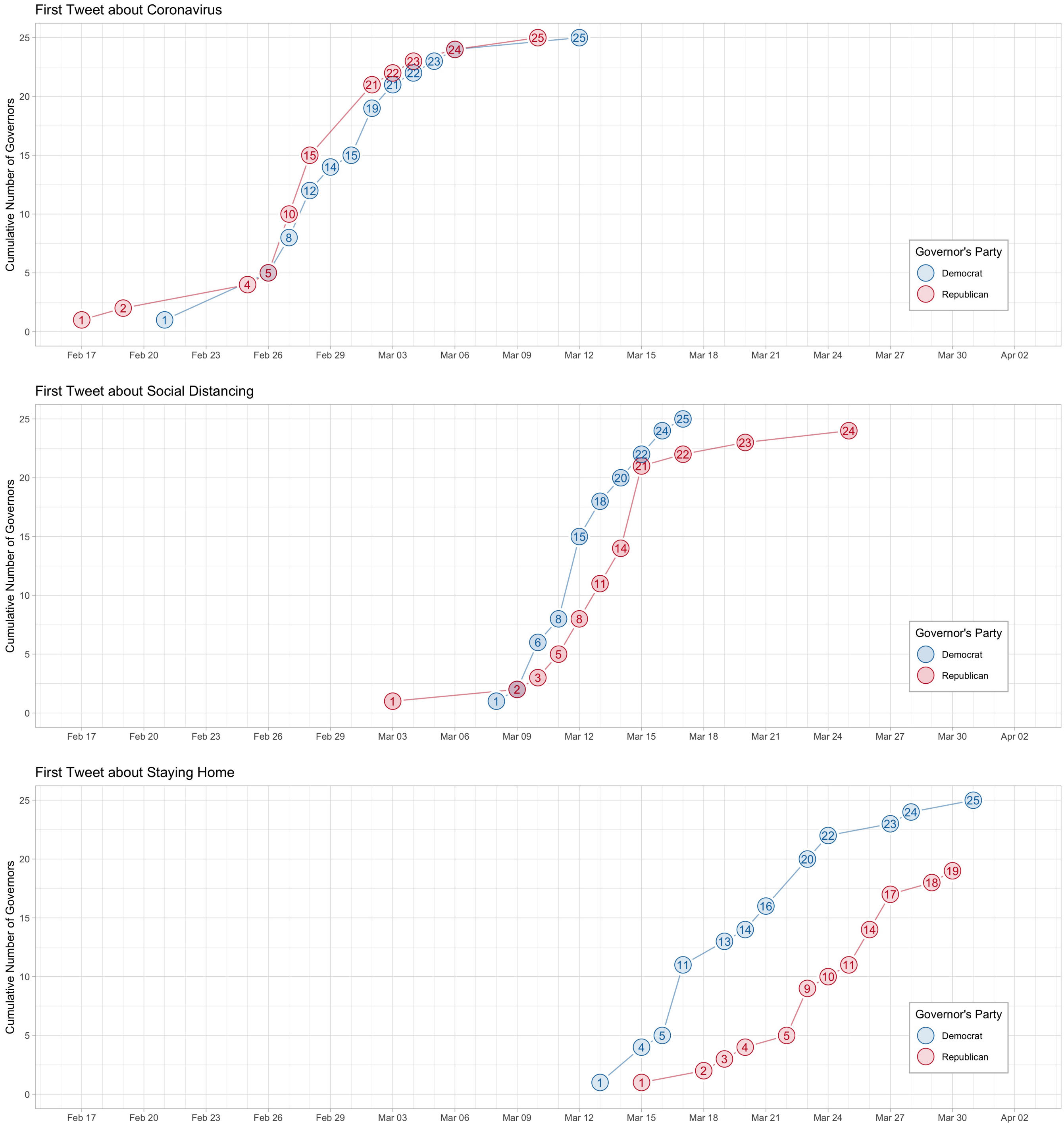
Moderators: We test whether the effect of governors' cues on mobility is moderated by the partisan affiliation of governors and counties. *GOP governor* is an indicator that has the value of one for Republican governors and zero for Democratic governors. In our main analysis, we measure counties' partisanship using Trump vote margin (in units of 10%) in the 2016 presidential elections. In some analysis, we split the sample by a county's partisan affiliation. Here, Republican counties are those in which Trump's vote margin is larger than zero. We obtain county and state-level electoral data from the CQ Press Voting and Elections Collection.[4]

Controls: We control for the number of daily county-level coronavirus positive cases and state-level deaths using data from the New York Times[5] and USAFacts,[6] a non-profit civic data clearinghouse, and for official physical distancing policies at the state level from Adolph et al. (2020).[7] Additional (fixed county-level) control variables are derived from the 5-year American Community Survey (2014-2018). These include: median household income, median age, population size, educational attainment by age category, population share over age 65, and the county's racial composition.

Since the state of Alaska does not report electoral returns at the county-level, we omitted observations from this state. The analysis sample therefore consisted of 3,100 counties from 49 states and yielded 94,690 county-day observations. Table 1 report the summary statistics of all variables used in the empirical analysis.

[4] `https://library.cqpress.com/elections/`
[5] `https://github.com/nytimes/covid-19-data`
[6] `https://usafacts.org/issues/coronavirus/`
[7] `https://github.com/COVID19StatePolicy/SocialDistancing`

Figure 1: Governors' tweets by topic



Note: Figure shows the cumulative number of governors tweeting about Coronavirus (top panel), Social distancing (middle panel), and staying home (bottom panel) by date and governor partisan affiliation. The governors of Alaska (R), Florida (R), Georgia (R), Iowa (R), South Carolina (R), South Dakota (R) did not tweet about staying home (shelter-in-place) during this time period.

Table 1: Summary statistics

Variable	Dem counties	Republican counties	All counties
Outcomes			
Median time at home (minutes)	638.41	641.14	640.72
	(229.07)	(185.42)	(192.86)
Log median time at home	6.34	6.38	6.37
	(0.64)	(0.54)	(0.56)
Share of devices home all day	28.40	25.52	25.97
	(9.21)	(7.91)	(8.19)
Log distance traveled	8.87	9.04	9.01
	(0.54)	(0.61)	(0.60)
Independent variables			
Tweets about COVID-19	5.05	5.20	5.17
	(6.86)	(7.85)	(7.68)
Tweets about social distancing	1.16	1.15	1.15
	(2.27)	(2.52)	(2.48)
Tweets about staying home	0.45	0.39	0.40
	(1.38)	(1.42)	(1.42)
Post social distancing tweet	0.62	0.61	0.61
	(0.49)	(0.49)	(0.49)
Post stay home tweet	0.30	0.28	0.28
	(0.46)	(0.45)	(0.45)
Trump vote margin	-0.19	0.43	0.32
	(0.19)	(0.19)	(0.30)
Covariates			
Post-emergency order	0.70	0.68	0.68
	(0.46)	(0.47)	(0.47)
Post-large gatherings ban	0.47	0.41	0.42
	(0.50)	(0.49)	(0.49)
Post-school closure	0.49	0.44	0.45
	(0.50)	(0.50)	(0.50)
Post-restaurant closure	0.44	0.40	0.41
	(0.50)	(0.49)	(0.49)
Post-non-essential business closure	0.17	0.13	0.14
	(0.37)	(0.34)	(0.34)
Post-stay home order	0.19	0.16	0.16
	(0.40)	(0.36)	(0.37)
Confirmed COVID-19 cases	49.48	2.48	11.08
	(405.59)	(51.52)	(180.58)
Median age	38.61	41.90	41.30
	(5.28)	(5.09)	(5.28)
Log household income	10.87	10.80	10.82
	(0.35)	(0.22)	(0.25)
Log population	11.47	10.05	10.31
	(1.73)	(1.25)	(1.46)
Share over 65	0.16	0.19	0.18
	(0.04)	(0.04)	(0.04)
Share black	0.21	0.07	0.09
	(0.23)	(0.10)	(0.15)
Share hispanic	0.15	0.08	0.09
	(0.20)	(0.11)	(0.14)
Share male	0.49	0.50	0.50
	(0.02)	(0.02)	(0.02)
Observations	14708	79982	94690
Counties	484	2616	3100

Table displays means and standard deviations of key variables of interest, as well as the number of observations and the number of cluster. Sample is 94,690 county-days from March 1-March 31 2020 for which all data are non-missing. GOP counties are those in which Donald Trump's margin of victory in the 2016 presidential election was greater than 5%. Democratic counties are all others.

Estimation Strategy

We use difference-in-differences regressions to estimate the effect of governors' messaging (as captured by tweets' content) on mobility. Our main estimation uses an event study design (before/after): focusing on the first tweet in which a governor encourages her state residents to stay home. Our identification assumption is that given parallel trends, once we flexibly control for a county's fixed characteristics, and account for both date and county fixed effects, the daily number of deaths and confirmed COVID-19 cases, the type of state-wide orders issued at any given day, changes to the number of minutes at home from before to after a governor's message has a causal interpretation. See SI Section B for additional details.

3 Results

We present the study's main results in Table 2. We find that governors' messages encouraging residents to stay at home had a positive and significant effect on time spent at home, above and beyond the effect of state orders encouraging residents to stay home. Averaging across all US counties (Table 2, Panel A, column 1), a tweet encouraging residents to stay at home increased median time spent at home by 9.4 minutes per day (or 2.6%) compared to the immediate period before the tweet was sent. The finding is robust to using minutes at home in levels or in logs, to using alternative mobility measures (Table SI-4), to using cumulative number of tweets rather than the first tweet (Table SI-2), and to looking at tweets encouraging physical distancing (Table SI-6).

The effect of governors' messages on residents' mobility change were comparable to the effects of stay-at-home orders (Table 3 and SI Table SI-2). Among all residents, the effects of the tweets were generally larger than the effects of orders, although the difference between the two effects was not statistically significant.

We also find suggestive evidence that the effect of governors' messages encouraging residents to stay at home were more effective in Democratic-leaning counties than Republican-leaning counties (Table 2, Panel A, column 2). While the moderating effect of the vote margin for President Trump in the 2016 general election fell slightly below conventional significance level, the estimates indicate that a 10% increase in Trump's vote margin reduced the effect of tweets on mobility by 9 percent. Nonetheless, the overall effect of governors' cues on mobility remained significant in both Democratic- and Republican-leaning counties (Figure SI-8, left panel).

Table 2: Governors' tweets, partisanship, and mobility

Panel A: Full sample

Outcome	Median time at home		Log time at home	
Post stay home tweet	9.382**	12.989**	0.026***	0.023*
	(4.009)	(4.950)	(0.009)	(0.012)
Post stay home tweet × Trump vote margin		-1.127		0.001
		(0.702)		(0.002)
Observations	94690	94690	94690	94690
R^2	0.984	0.984	0.998	0.998
County FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Demographics × Day FE	Yes	Yes	Yes	Yes
Trump margin × Day FE	Yes	Yes	Yes	Yes
COVID controls	Yes	Yes	Yes	Yes
Orders	Yes	Yes	Yes	Yes

Panel B: By county party

Outcome	Median time at home		Log time at home	
County party	Dem	GOP	Dem	GOP
Post stay home tweet	14.768	8.935**	0.035	0.025**
	(9.280)	(3.780)	(0.022)	(0.009)
Observations	14708	79982	14708	79982
R^2	0.985	0.984	0.997	0.998
County FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Demographics × Day FE	Yes	Yes	Yes	Yes
Trump margin × Day FE	Yes	Yes	Yes	Yes
COVID controls	Yes	Yes	Yes	Yes
Orders	Yes	Yes	Yes	Yes

Panel C: Triple interactions

Outcome	Median time at home		Log time at home	
Interaction	Cont. vote margin	Binary	Cont. vote margin	Binary
Post stay home tweet	7.421	4.222	0.004	-0.011
	(4.732)	(7.006)	(0.014)	(0.027)
Post stay home tweet × GOP governor	12.084	26.960**	0.051**	0.102***
	(7.626)	(12.779)	(0.019)	(0.033)
Post stay home tweet × Trump vote margin	0.787		0.006	
	(1.308)		(0.004)	
Post stay home tweet × GOP governor × Trump vote margin	-3.920**		-0.012**	
	(1.540)		(0.005)	
Post stay home tweet × GOP county		5.700		0.034
		(6.738)		(0.027)
Post stay home tweet × GOP governor × GOP county		-35.127***		-0.115***
		(11.839)		(0.034)
GOP county × Day FE	No	Yes	No	Yes
Trump margin × Day FE	Yes	No	Yes	No
GOP gov × Day FE	Yes	Yes	Yes	Yes
GOP county × GOP gov × Day FE	No	Yes	No	Yes
Trump margin × GOP gov × Day FE	Yes	No	Yes	No
COVID controls	Yes	Yes	Yes	Yes
Orders	Yes	Yes	Yes	Yes
Observations	94690	94690	94690	94690
R^2	0.984	0.984	0.998	0.997

Standard errors in parentheses clustered at the state level. Sample is 96,690 county-days over the period March 1-March 31 2020. Treatment indicator equals one for all days after the governor of state s issues a tweet encouraging citizens to stay home. "Trump vote margin" is county i's vote margin for President Trump in the 2016 election. GOP counties are those in which the Republican vote margin in the 2016 presidential election was greater than zero. County-level demographic controls are median age, log family income, log population, share of population over 65, share black, share Hispanic, and share male. COVID controls includes controls for county-level COVID cases and state-level COVID deaths. "Orders" includes controls for whether the state has issued the following types of orders: emergency declarations, banning large gatherings, school closures, restaurant/bar closures, non-essential business closures, and stay-at-home orders.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

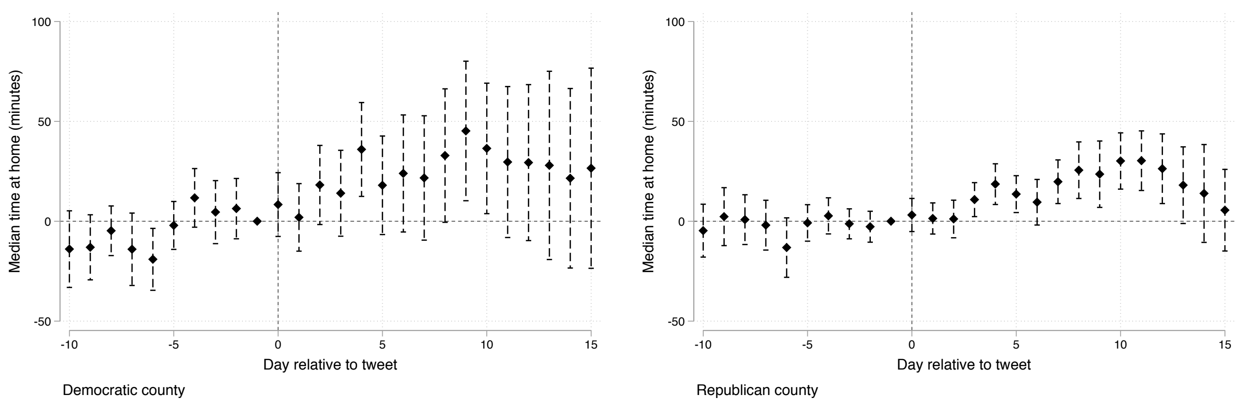
Table 3: Governors' tweets and stay at home orders

Outcome	Median time at home			Log time at home		
County party	All	Dem	GOP	All	Dem	GOP
	(1)	(2)	(3)	(4)	(5)	(6)
Post stay home tweet	9.382**	14.768	8.935**	0.026***	0.035	0.025**
	(4.009)	(9.280)	(3.780)	(0.009)	(0.022)	(0.009)
Post-stay home order	7.895	4.623	8.722*	0.004	-0.011	0.008
	(5.215)	(10.148)	(4.995)	(0.012)	(0.023)	(0.012)
$\beta_1 - \beta_2$	1.487	10.144	0.213	0.022	0.046	0.017
	(6.054)	(16.127)	(5.521)	(0.014)	(0.031)	(0.014)
Observations	94690	14708	79982	94690	14708	79982
R^2	0.984	0.985	0.984	0.998	0.997	0.998
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Demographics × Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Trump margin × Day FE	Yes	Yes	Yes	Yes	Yes	Yes
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes

Sample is 94,690 county-days between March 1 and March 31, 2020. Treatment indicator equals one for all days after the governor of state s issues a tweet about staying home. "Trump vote margin" is county i's vote margin for Donald Trump in the 2016 presidential election. GOP counties are those in which the Republican vote margin in the 2016 presidential election was greater than zero. County-level demographic controls are median age, log family income, log population, share of population over 65, share black, share Hispanic, and share male. COVID controls account for county-level COVID confirmed cases and state-level COVID deaths. "Orders" includes indicators for whether the state has issued the following orders: emergency declaration, banning large gatherings, school closures, restaurants closures, non-essential business closures, and stay-at-home orders. Standard errors clustered at the state level. $\frac{\beta_1}{\beta_2}$ is the ratio of tweet to stay at home coefficients.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Panel B of Table 2 shows that the effect of governors' first stay-at-home tweet on mobility was 1.6 times larger in counties that voted for Hilary Clinton (15 minutes, or 3.5 percent) than in counties that voted for President Trump (9 minutes, or 2.5 percent). This finding was further reinforced in the event-study plot of the estimated daily mobility change before and after the first tweet encouraging residents to stay at home (Figure 2). While there was always a discernible effect on mobility within 2-3 days after the first message from a governor, the effect was substantively more pronounced in Democratic-leaning counties (left panel).

Figure 2: Event study: governor tweets "stay home," by subsamples



Note: Figure shows coefficients from a county-level event-study regression of median time at home on indicators for leads and lags of the treatment (an indicator equaling 1 for all days after a governor issues her first tweet encouraging citizens to stay at home). Models include county and date fixed effects. Sample is split by Democratic counties (left panel) and Republican counties (right panel).

In models that tested whether county residents' partisan preference and governors' party affiliation moderated the effect of governors' messaging on mobility patterns (Table 2, Panel C), we found that Republican governors in particular have differing effects on Democratic- vs. Republican-leaning areas. To ease the interpretation of the triple-interaction models in Panel C, we divided the sample by governors' party affiliation and estimated the effect of governors' tweets on mobility conditional on President Trump's vote margin (SI Table SI-3).

In states with a Democratic governor, there was no significant difference between the responses of Democratic and Republican voters: the interaction of tweet and President Trump's vote margin is not significant (SI Table SI-3, Panel A, column 2). However, in states with a Republican governor, Democratic-leaning counties responded more strongly than Republican-leaning counties. In such states, a higher vote margin for President Trump was significantly associated with a smaller effect of communications on mobility (SI Table SI-3, Panel B, column 2).

These dynamics are further explored in Figure 3, which plots the marginal effect of the first tweet by a governor on mobility reported in SI Table SI-3. Panel A shows that the response to tweets from Republican governors encouraging residents to stay at home was strongly decreasing in President Trump's vote margin, while under Democratic governors (Panel B), it was weakly (but not significantly) increasing. The most responsive counties are Democratic-leaning areas in Republican states, while the least-responsive are deeply conservative areas in Republican states.[8] Since the latter comprise most of the data in Republican states, this leads to a smaller effect size (7.92 minutes increase post-tweet) in Republican states when averaging across the political spectrum (Table SI-3, Panel B, column 1). In contrast, both Democratic- and Republican-leaning counties in Democratic states respond similarly to their governor's messaging, yielding a somewhat larger average effect of 10 minutes (Table SI-3, Panel A, column 1).

Finally, with the exception of deeply conservative areas whose response diverges under different governors, Republican-leaning counties in general respond similarly to messaging from Republican and Democratic governors. For example, in states with a Democratic governor, the median county with respect to President Trump vote margin is Trump +29.5%. Using the coefficients of SI Table SI-3, Panel A, column 2 the first 'stay home' tweet increase time at home by 10.84 minutes.[9] Similarly, in states led by a Republican governor, the effects of governor's tweet in a Trump +29.5% county is estimated to be 11.28 minutes.[10]

4 Discussion

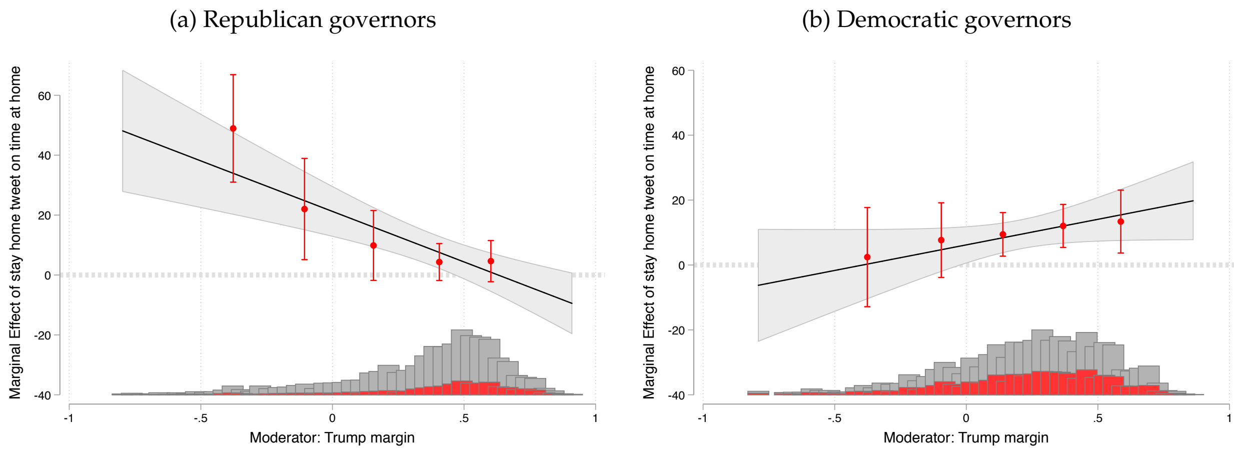
Governments play a central role in combating pandemics by financial the development and testing of vaccines and treatments, scaling-up testing and contact tracing, and coordinating the response of various agencies and institutions. Yet the success of efforts to prevent the spread of infectious diseases depends crucially on the actions taken by individuals who are asked to voluntarily comply with costly measures to prevent transmission. This study shows the importance of state governors' messaging efforts, but also that political party preferences influenced individuals' responses to communications from governors about the need to engage in social distancing and stay at home during the outbreak of the novel coronavirus in the US. We report three key findings.

[8] In Republican states, in the median *Democratic* county (Trump -22%), Democrats responded to a 'stay home' tweet by their GOP governor by increasing time at home by 29.8 minutes. By contrast, in those states, governors' messages were associated with 6 minutes increase in time spent at home in the median *Republican* county (here, President Trump's vote margin is +45%).

[9] The estimate is $6.197 + 1.576 \times 2.95 = 10.84$.

[10] The estimate is $21.233 - (3.373 \times 2.95) = 11.28$ using the coefficients of SI Table SI-3, Panel B, column 2.

Figure 3: Predictive margins: effect of "stay home" tweet by Trump vote share and governor party



Note: Figure shows predicted values and 95% confidence intervals from a county-level regression of median time at home on the treatment indicator, its interaction with Donald Trump's county-level vote share in the 2016 presidential election, county and day fixed effects, as well as day fixed effects interacted with control variables and Trump's 2016 margin, see Table SI-3 Panels A and B. The treatment is an indicator variable equaling 1 for all days after a governor issues their first tweet encouraging citizens to stay at home. We estimate the model separately for states with Democratic (Panel A) and Republican (Panel B) governors. The fitted line shows the linear marginal effect of the treatment at different levels of Trump vote share for each state type. The points with 95% confidence intervals show semi-parametric estimates of the marginal effect of the treatment at five different bins of Trump vote share. Bins are (-1,-0.25), (0.25, 0), (0, 0.25), and (0.25, 0.5). The histogram below the predicted margins displays the density of the county-level Trump vote margin by treatment status (red is treated, grey is untreated).

First, Democratic and Republican governors' messaging on COVID-19, which preceded the day in which stay-at-home orders were issued, was associated with a significant reduction in mobility in both Democratic-leaning and Republican-leaning counties.[11] This finding is consistent with the idea that political leaders can strongly influence the behavior of their constituents and achieve higher compliance with prevention measures during a public health crisis. Importantly, governors' messaging affected the behavior of citizens with congruent preferences (i.e., same party as the governor), but also of citizens with incongruent preferences. One reason governors' messaging can be consequential is by explaining why individuals are asked to take costly actions. Google Trends searches, which are an indicator of interest in an issue (2; 16)), show that governors' cues increased the frequency of search terms related to social distancing and staying home and these increases occurred days before stay-at-home orders were issued (Table SI-1).

Second, Republican-leaning counties responded less strongly than Democratic-leaning counties to messages from governors encouraging residents to stay at home. This finding persisted even after controlling for state fixed effects and county-level socio-economic characteristics, and it is consistent with a growing literature that finds both differential levels of social distancing by partisan affiliation (4), as well as differential responses to stay-at-home orders (3; 2; 15).

Third, and most notably, Democratic counties were especially responsive to cues from Republican governors. The reduction in mobility induced by a Republic governor was estimated to be about 25 minutes in counties where President Trump lost by 10% in the 2016 general election (Table SI-3, Panels B). In contrast, the effect of Democratic governors on mobility in similarly Democratic-leaning counties was 5 times lower, with only a 5 minute reduction in mobility (Table SI-3, Panels A). This finding is consistent with the literature on partisanship and the effects of political leaders' endorsements. Republican governors who sounded the alarm on COVID-19 sent a strong and consequential signal to citizens aligned with the opposite political party since those governors' messages were in contrast to the general views held by Republican leaders about COVID-19. In short, elite cues were stronger when they did not conform with the party affiliation of the elites. Republican governors who broke with national party members sent a strong signal to their Democratic constituents. However, Democratic governors were largely expected to encourage social distancing, blunting the force of the signal and therefore the overall effects of their messages.

Indeed, the fact the GOP leaders were sending mixed messages about COVID-19 helps explain why the effect of Republican governors' messaging on mobility was stronger in Democratic coun-

[11] We note that when weighting by population (Figure SI-8), the effect of governors' messaging on mobility is no different than zero in deeply conservative Republican counties where Trump's vote margin is over 40%.

ties and moderate Republic counties than conservative strongholds. This result is consistent with a "backlash" effect, whereby conservative Republican areas react to signals from their local Republican leaders that contradict national-level party messaging with either indifference or outright hostility. Under Democratic governors, this backlash effect is absent as Democratic governors' calls for isolation did not conflict with national-level party messaging.

This study has several limitations. Messages from governors' encouraging social distancing and staying at home were obtained from their Twitter accounts, which may not have been the primary mode of communication to constituents. However, these messages were likely to be closely accompanied with other forms of communication to constituents, such as radio and television. Another limitation is the Twitter messages encouraging residents to stay at home may have been correlated with the voluntary closure of workplaces, which may have been the reason why individuals tended to spend more time at home. While this can affect the magnitude of the association between messages and mobility, our analyses do control for the issuance of various orders for schools and other institutions to close. Moreover this should not have as strong an effect the associations found with political preferences of county residents.

This study demonstrates how and why political partisanship has influenced citizens' decisions to voluntarily engage in social distancing and reduce their mobility in response to communications by their state governor during the COVID-19 outbreak in the US. The results support several theories of how elite cues influence public opinion and actions, and they provide valuable insights on how governors' communications can influence behavior in the ongoing response to COVID-19.

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SUPPLEMENTARY INFORMATION

— For Online Publication —

A Twitter data

We use governors' tweets to capture their public messages (cues). In this section we describe how this measure was devised. First, we identified both the official and the personal Twitter accounts of all USA governors. We then collected tweets published by these accounts between February 15th and March 31st . For this purpose, we wrote a simple script to download tweets via Twitter API (Application Programming Interface) using R (version 3.5.1). We removed quoted tweets (tweets directly citing other tweets) and retweets from the downloaded dataset. Replying tweets (tweets directly replying to other tweets) were also excluded, except for the cases where a replying tweet and an original one were written by the same account (threads).

We downloaded a total of 11,266 tweets from the official and personal accounts of the governors of 50 USA states and the President. The tweets were aggregated into a single CSV file, and then coded using research assistants that were trained based on the following codebook:

A.1 Instructions to code governors' Twitter feed

For each tweet, we follow the following steps:

1. Identify if the tweet is about the COVID-19/Coronavirus crisis. If yes, mark 1 in the column titled "covid_related." If no, mark 0 and move to the next tweet.
2. If yes, then identify whether the tweet is related to social distancing. If it is, mark 1 in the social_distance column. If not, mark 0.
3. Then identify whether the tweet is related to shelter in place. If it is, mark 1 in the shelter_in_place column. If not, mark 0.

1. Coronavirus related: This includes all tweets that relate to the current COVID-19 crisis, whether or not they explicitly mention the words "coronavirus" or "Covid-19." For example, consider the following tweet. While it does not explicitly mention the name of the virus, it clearly refers to the coronavirus crisis.

> *"Have supplies on hand, but don't hoard. Contact your healthcare provider about obtaining extra necessary medications to have on hand."*

2. Social distancing: This includes all tweets that encourage, explain, or otherwise refer to the concepts of social distancing. Some key words and phrases to look out for in these tweets will be "avoid gatherings / crowded places / large events," "physical distancing," "keep 6 feet apart," and "flatten the curve". These key words are simply examples; they are NOT exhaustive. Please note that calls to "avoid sick people/people with symptoms" are NOT calls to social distancing. There is a distinction between tweets about avoiding your own infection (e.g., wash your hands, avoid sick people, etc), and those that focus more on not spreading the disease as a transmission vector. We care about the latter. For example:

> *"There are steps every Arizonan can take to prevent the spread: Wash your hands for at least 20 seconds; Avoid touching your eyes, nose and mouth; Avoid close contact with people who are sick; Cover your cough or sneeze.*

Is not about social distancing, since it only mentions how to prevent your own infection. In contrast, the tweet below is about social distancing, because it mentions "stay away from crowds"

> *"Don't fear covid19 virus, just be smart. Wash your hands. Don't shake hands, stay home if not feeling well,* **stay away from crowds.** *These simple steps will keep most of us away from the hospitals. It isn't the end of the world. Just focus on good hygiene and change a few habits."*

3. Shelter in place: This refers to tweets that explicitly call on citizens to stay at home and avoid going out for non-essential business. Some key words to look out for are "stay home," "work from home" "shelter in place," "safer at home." These key words are simply examples; they are NOT exhaustive. For example, the tweet below explicitly calls on people to stay home and should be coded as 1. However, the tweet below it does not call for staying at home, just social distancing.

> *"Reminder to our young people: you are not immune to #COVID19 or invincible. You can get coronavirus and you can spread it to loved ones. Don't be selfish. Take this seriously. Stay safe, stay home."*

> *"Social distancing is a primary protective measure to flatten the curve of this virus. I cannot underscore the seriousness of following these measures to help our neighbors, friends, and families."*

Finally, note that staying home is a form of extreme social distancing. Therefore all stay home tweets should also be social distancing tweets. However, the reverse is not true. There may be weaker forms of social distancing that are not fully stay home.

B Estimation strategy

To estimate the baseline effect of messaging, we estimate a simple differences-in-differences regression using a two-way fixed effects specification for county i in state s day t

$$y_{ist} = \alpha + \theta TWEET_{st} + \delta_t + \xi_i + X'_{ist}\beta + \epsilon_{ist}$$

Where $TWEET_{st}$ is a treatment indicator that equals one in all periods after the governor of state s issues a tweet encouraging citizens to stay home and δ_t are day fixed effects and ξ_i are county fixed effects. X_{ist} is a vector of county and state-level control variables, which are either time-varying or, if fixed, then interacted with day fixed effects δ_t. Controls are current and lagged confirmed COVID-19 cases, county-level demographics including median age, log family income, log population, share over 65, share black, Hispanic, white, and male, as measured in the most recent American Community Survey (ACS), and dummies for state-days in which various stay home orders are in effect. We include the following state-level orders: emergency declaration, banning large gatherings, school closures, closures of non-essential businesses, closure of bars/restaurants, and stay home/shelter in place orders.

We consider several different specifications, including measuring the independent variable $TWEET_{st}$ as the cumulative number of "stay home" tweets issued in the past 3 or 5 days, or one-day lagged number of stay home tweets. We also consider similar specifications where the tweets of interest are those encouraging social distancing. For these regressions, we cluster our standard errors at the level of the state, since all counties within a state are perfectly correlated in their treatment exposure. We estimate this difference-in-differences regression on the entire sample, and on GOP and Democratic counties separately.

To estimate the dynamic effects of messaging, as well as test pre-trends in the outcome variable before a tweet was issued, we estimate the following event-study regression using a two-way fixed effects specification for county i in state s day t

$$y_{ist} = \alpha + \sum_{\tau=-10}^{15} \theta_\tau TWEET_{s\tau} + \delta_t + \xi_i + X'_{ist}\beta + \epsilon_{ist}$$

Where τ indicates leads and lags of the treatment period, $TWEET_{s\tau}$ are dummies for these leads and lags, and θ_τ, $\tau > 0$ give the dynamic treatment effects while θ_τ, $\tau < 0$ test pre-treatment trends. The omitted reference period is $\tau = -1$. We estimate this event-study regression on the entire sample, and on GOP and Democratic counties separately.

To estimate the effect of messaging by county-level political affiliation, we estimate several triple-difference models using two-way fixed effects for county i in state s day t. In the first set of these models, we interact the exposure to state-level messaging with county-level variation in political affiliation.

$$y_{ist} = \alpha + \varphi_1 TWEET_{st} + \varphi_2 TWEET_{st} \times MARGIN_i + \delta_t + \delta_t \times MARGIN_i + X'_{ist}\beta + \xi_i + \epsilon_{ist}$$

In this case, $MARGIN_i$ is county i's Republican vote share – measured as Donald Trump's 2016 margin of victory. In these specifications, we also cluster standard errors conservatively at the county level, even though the variation of interest –the interaction term – is at the county-year level.

Finally, to test whether the county-level partisans response to political messaging varies by the governor's party, we consider the quadruple-difference estimation strategy:

$$\begin{aligned} y_{ist} = \alpha &+ \phi_1 TWEET_{st} + \phi_2 TWEET_{st} \times MARGIN_i + \phi_3 TWEET_{st} \times GOPGOV_s \\ &+ \phi_4 TWEET_{st} \times GOPGOV_s \times MARGIN_i + \delta_t + \delta_t \times MARGIN_i \\ &+ \delta_t \times GOPGOV_s + \delta_t \times GOPGOV_s \times MARGIN_i + \xi_i + X'_{ist}\beta + \epsilon_{ist} \end{aligned}$$

We consider specifications where $MARGIN_i$ is measured as a continuous measure of Trump's 2016 vote margin, or an indicator variable equaling one if Trump won the county in 2016. In the binary case, ϕ_1 gives the effect of the governor's tweet in Democratic states in centrist counties, $\phi_1 + \phi_2$ is the effect in Trump-supporting counties of Democratic states, $\phi_1 + \phi_3$ is Democratic counties under Republican governors, and $\phi_1 + \phi_2 + \phi_3 + \phi_4$ the effect of the tweet in the Republican counties of Republican states. The quadruple-difference model is completed by the relevant two- and three-way interactions with the day fixed effects.

C Supplementary figures

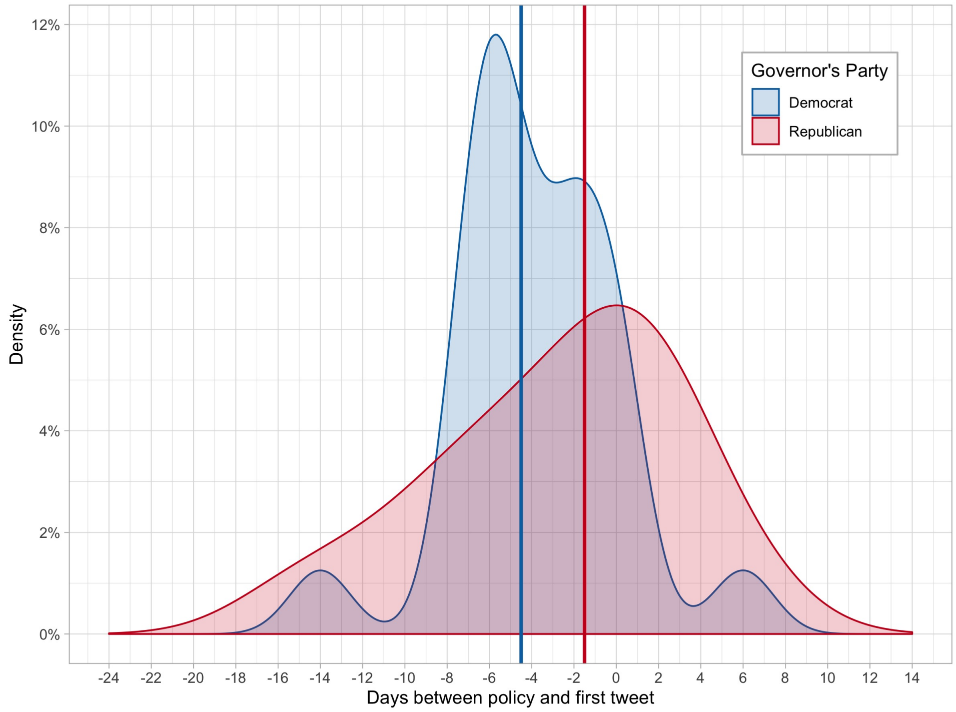
C.1 Descriptive information on Governors' tweets

In this section, we present basic descriptive information on the dataset of governors' tweets described in Appendix A.

In Figure SI-1, we calculate the state-level difference between the date of the first stay-at-home order and the date of the first tweet encouraging citizens to stay home/shelter-in-place. Negative numbers indicate that the tweet was issued before the policy, and positive numbers indicate the opposite. We then plot the distribution of these differences separately for Republican and Democratic governors, with vertical lines to indicate the group-specific median number of days between order and tweet. While the earliest tweeters appear to be Republican governors, the peak of the Democratic distribution is well to the left of zero, with a median of -6. In contrast, the Republican distribution is clustered near zero, with a median of -1.5. On average, Democratic governors tweet about staying home far before implementing orders, while Republican governors typically only tweet about staying home in the days leading up to and after an order is issued.

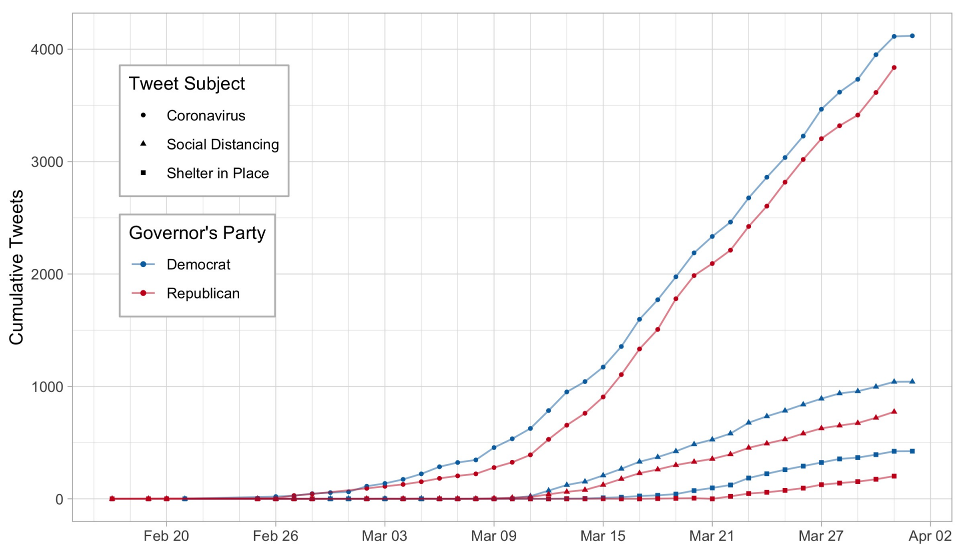
In Figure SI-2, we plot the cumulative number of tweets over time, separately by tweet subject and governor party. Comparing across tweet subjects, we find that governors tweet substantially more about COVID-19/coronavirus in general than they do about specific recommendations for either social distancing or staying at home. Democratic governors tweet more and earlier about all three topics.

Figure SI-1: Days between date of stay at home order and date of first tweet



Note: Figure shows the distribution of the difference in days between the governors' first tweet explicitly encouraging sheltering-in-place and the state's first official stay-at-home order. Vertical lines indicate median difference in days for each party.

Figure SI-2: Intensity of Governors' COVID-19 tweets over time



Note: Figure shows the cumulative number of governors' tweets about a topic, by topic, date, and governor party. Tweet topic is indicated in legend.

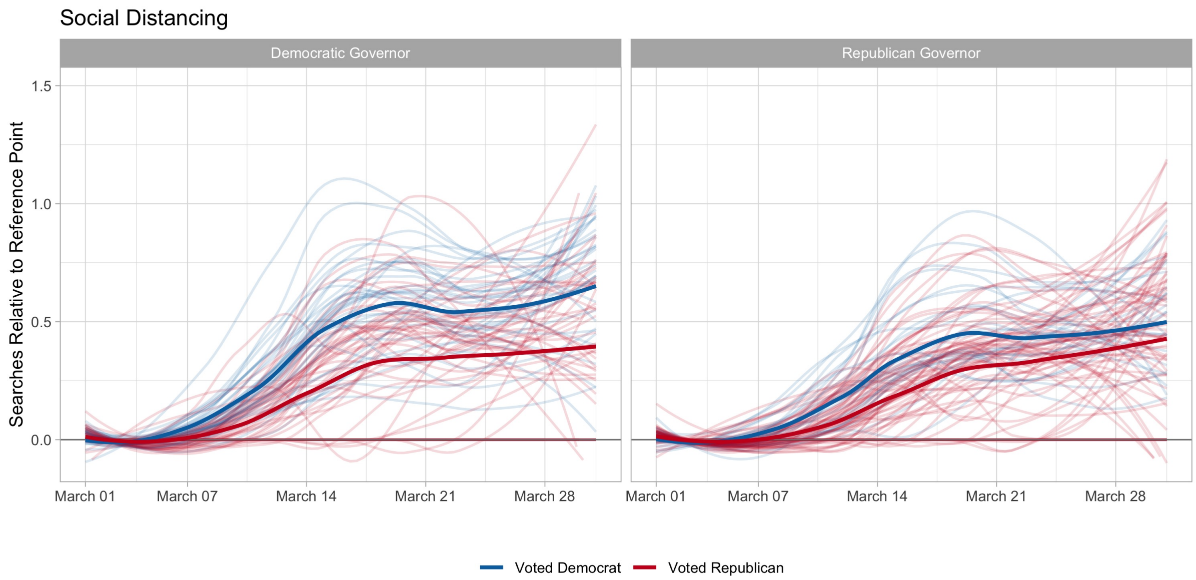
C.2 Google Trends

In this section, we consider trends in Google search interest for various search terms as a proxy for citizens' beliefs about coronavirus-related topics. First, we de-normalize the raw Google trends data such that all metro-day units are normalized relative to a single reference point. In Figure SI-3 we plot search interest over time for "social distancing" in Panel A and "coronavirus" in Panel B, for each metro area. We split these plots by metro areas under Democratic governors (left panel) vs. Republican governors, (right panel) and then overlay the mean search interest trend separately for metro areas that voted Republican vs. Democratic in the 2016 presidential election. All trends are estimated with a lowess smoother.

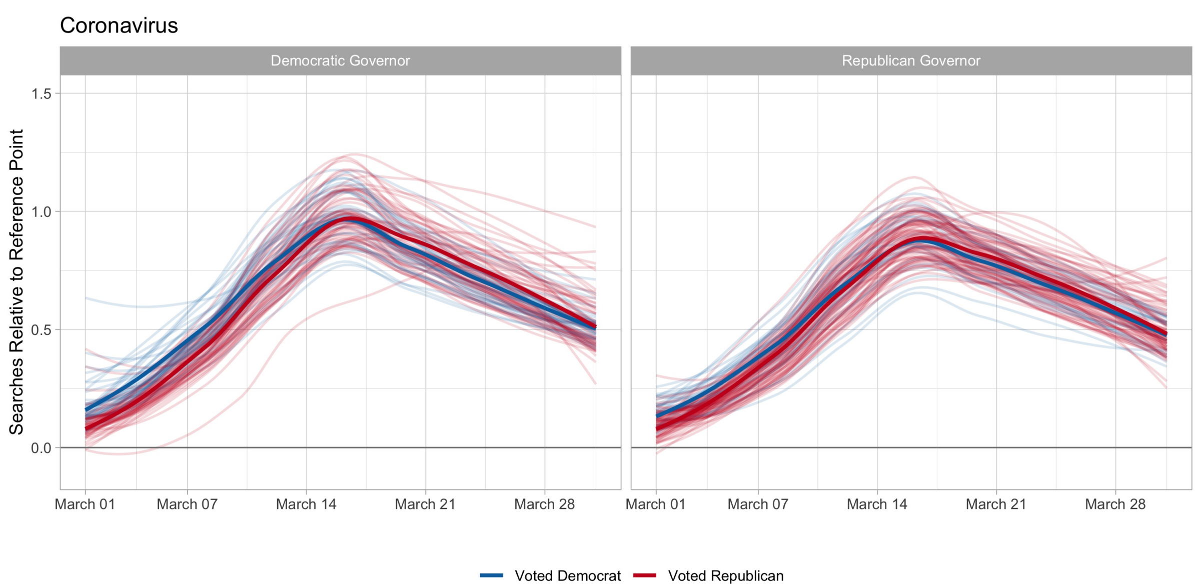
In Panel A, we see that mean search interest in social distancing among voters of both parties begins earlier and is greater under Democratic governors, likely because, as Figure SI-2 makes clear, Democratic governors are tweeting about social distancing earlier and more frequently than Republicans. In addition, across states of different parties, mean search interest in social distancing is always greater in Democratic-leaning metro areas. However, these partisan gaps differ depending on the identity of the governor. The partisan difference in search interest between voters is greater than among Democratic than Republican governors. Importantly, we see no such partisan differences – either across or within states – in search interest for "coronavirus." Therefore, while all citizens, regardless of political beliefs or governor identity, exhibit equal mean search interest for coronavirus, there are substantial differences in interest for social distancing. These patterns suggest a potentially interesting interaction between citizen and governor identity in forming beliefs about the merit of voluntary social distancing interventions.

Figure SI-3: Google search interest by partisan alignment and governor's party over time

(a) Social distancing



(b) Coronavirus



Note: Figure shows the daily relative Google search interest for the term "social distancing" in Panel A and "Coronavirus" for 205 metro-areas in the United States from March 1-March 31. All search numbers are normalized relative to a reference group. Trends are adjusted using a lowess smoother. Metro-areas are defined as "Republican" if Donald Trump's margin of victory in the 2016 presidential election is greater than 5%. Thick lines indicate mean search interest across metros for republican and democratic states.

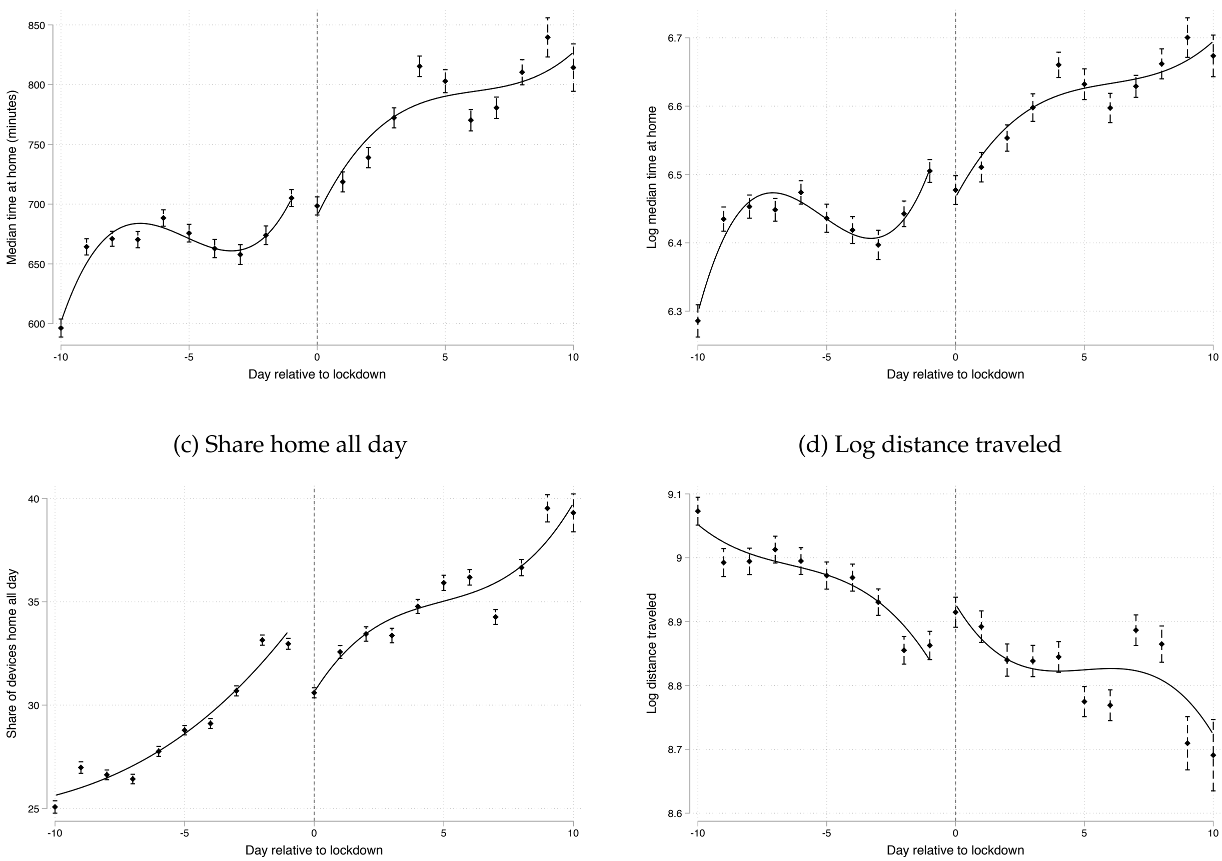
C.3 Mobility before and after stay-at-home orders

In this section, we analyze trends in mobility before and after state-level shelter-in-place/stay-at-home orders are issued for each of the four mobility outcomes. We estimate trends separately before and after the issuing of stay-at-home orders using a third-order polynomial. Across each outcome in Figure SI-4, we find that mobility reduces substantially before the stay-home order was issued. In fact, reductions in mobility are approximately equal in magnitude before and after the order, and the slope of the trend function does not meaningfully differ. This indicates that the pre-order period in which behavior change is broadly voluntary is critical for understanding behavioral responses to coronavirus.

Figure SI-4: Mobility relative to stay at home orders

(a) Median time at home

(b) Log time at home



(c) Share home all day

(d) Log distance traveled

Note: Figure shows trends in mobility, as measured by median home dwelling time (Panel A), log of median home time (Panel B), the share of location-enabled devices home all day (Panel C), and the log of median distance traveled (Panel D) relative to the governors' issuance of a statewide stay-home order. Points indicate means in the outcome variable across counties for a given day relative to the stay-home order, with 95% confidence intervals. Trends are estimated parametrically with a third-order polynomial separately before and after the stay-home order.

C.4 Event study plots

In this section, we assess the plausibility of the key assumption of our empirical strategy – that counties governed by governors that issued stay-home-related Twitter communications exhibit parallel trends in mobility relative to those in states that do not. To provide evidence for this assumption, we analyze the pre-treatment trends of the key mobility outcomes in treatment relative to control counties. We estimate pre-trends using the standard event-study regression model described in Appendix B, in which the outcome is regressed on dummy variables for leads and lags of the treatment, as well as controls and fixed effects.[12] The event-study model also allows us to estimate the dynamic path of effects in order to determine the "onset" time of the treatment, as well as whether the effects fade or grow over time.

Figure SI-5 plots the coefficients from the event-study regression for the four major outcomes – median home time, log median home time, share of devices home all day, and log distance travelled – in the full sample. In general, we see that parallel trends appear to hold; across all four outcomes, only one of the pre-period coefficients out of 40 are significantly different from zero at the 5% level. In contrast, the post-period coefficients are generally positive and significant, with the effects most pronounced for median time at home (Panel A) and share home all day (Panel C). In general, a stay-home tweet does not produce an immediate response, but rather takes 2-3 days to generate change in behavior. This makes sense if the first tweet marks a change in messaging that is followed by more tweets on the subject. The coefficients then rise monotonically (or fall, in Panel D) before plateauing 10-11 days after the initial tweet. For median time home – our main outcome of interest – the maximum daily impact of a tweet on behavior occurs on day 11 and corresponds to 29.4 minute increase in daily time at home, on average, or a 4.5% increase, as we can see from Panel B.

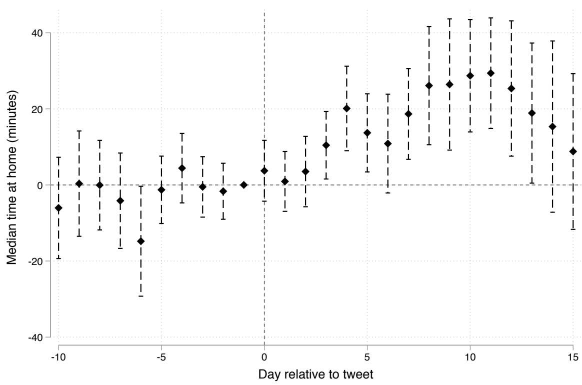
Figure SI-6 then splits the sample by county-level partisan alignment to test whether the assumption of parallel trends is likely to hold in these subsamples, as well as to compare the dynamic effect sizes by party. Again the parallel trends assumption seems likely to be satisfied, as pre-period coefficients are clustered around zero and are rarely significant. In general, the effect sizes do appear larger among the sample of Democratic counties. However, due to a much larger sample, the Republican coefficients are more precisely estimated. This provides at least suggestive evidence that Democrats respond more actively to their governors' stay home messaging with voluntary behavior change, though the differences in the event-study coefficients by party are unlikely to be statistically significant given the wide confidence intervals in the Democratic sample.

[12] Recall that the treatment date is defined as the date when the governor first issued a tweet encouraging individuals to stay home.

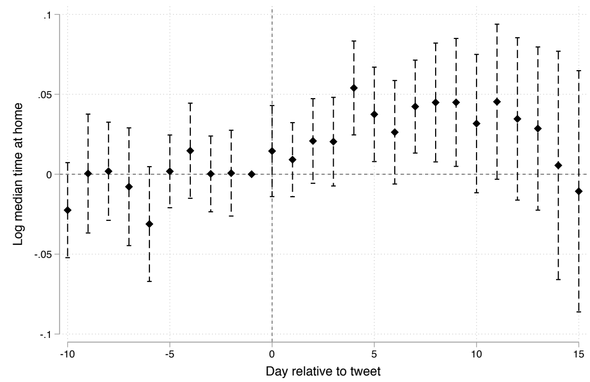
Lastly, in Figure SI-7 we estimate the event-study regression for the full sample on the metro-area-level Google trends data, with search interest for the term "stay at home" as the dependent variable. Again the pre-trend coefficients are not significantly different from zero and display no discernible trend. However, search interest for "stay at home" relative to the control group spikes on the exact day that the tweet is issued, and remains elevated for 3 days after, before dropping off. The fact that this spike in interest occurs in exactly the period before behavior change has begun suggests that individuals first respond to the tweet by updating their beliefs about the importance of staying home – as reflected in search interest – before moving to actively changing behavior.

Figure SI-5: Event study: governor tweets "stay home," baseline effects

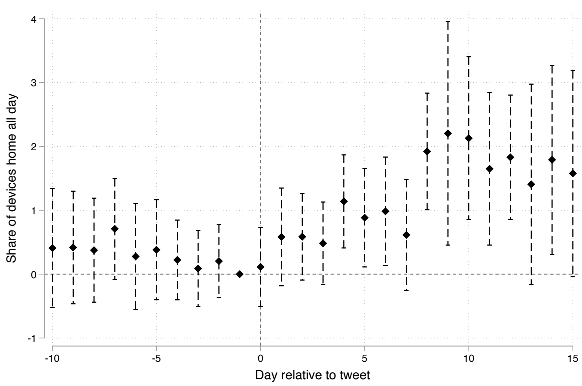
(a) Median time at home



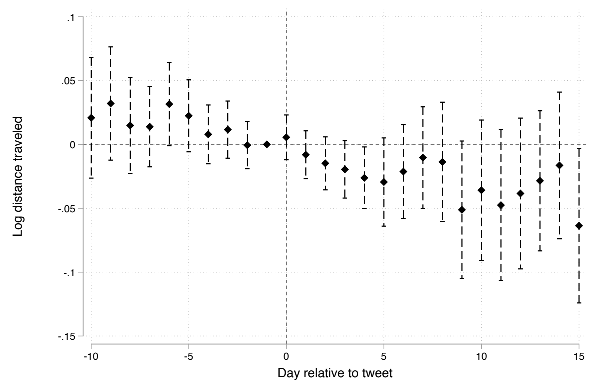
(b) Log time at home



(c) Share home all day



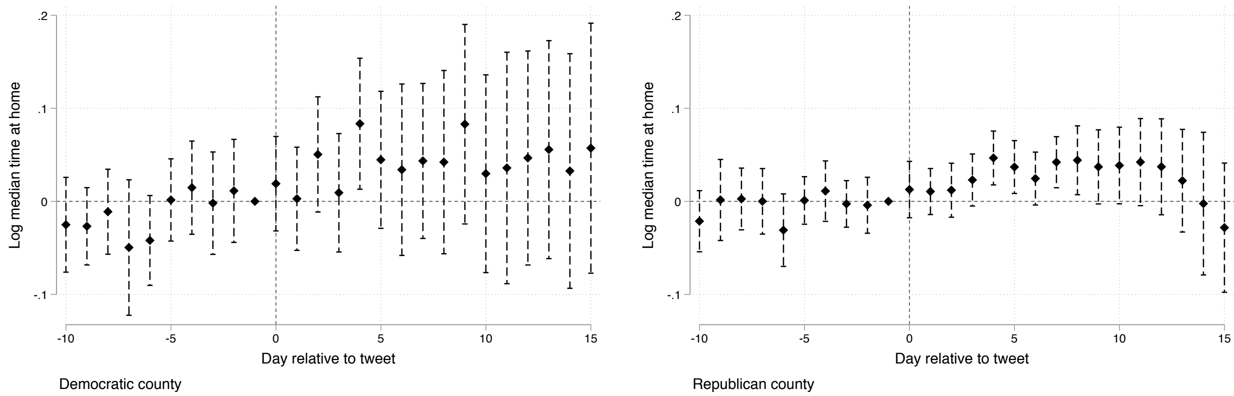
(d) Log distance



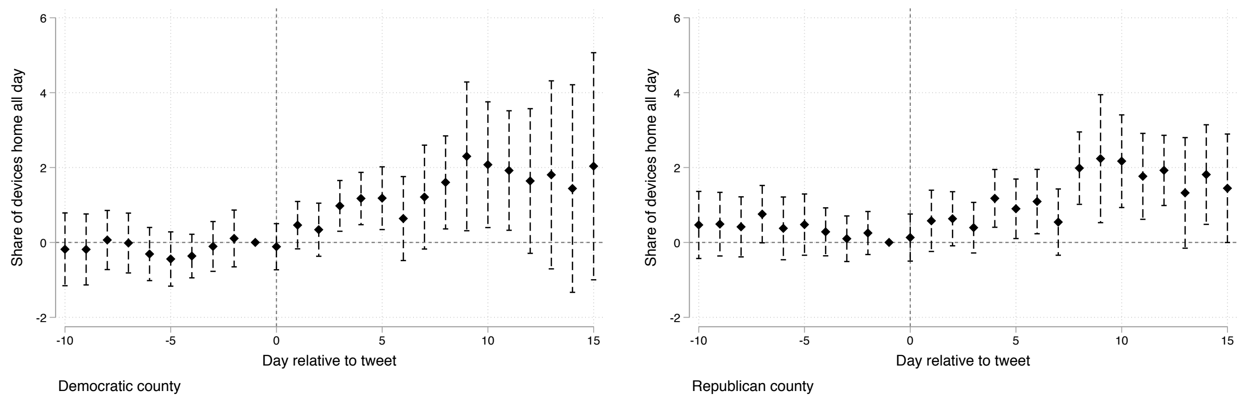
Note: Figure shows coefficients from a county-level event-study regression of median time at home (Panel A), log of median home time (Panel B), share home all day (Panel C), and log distance travelled (Panel D) on indicators for leads and lags of the treatment, county and day fixed effects, and controls for COVID cases, deaths, and other orders, as well as demographics and Trump margin interacted with day fixed effects. The treatment is a dummy variable equaling 1 for all days after a governor issues their first tweet mentioning the phrase "stay home." Standard errors are clustered at the state-level.

Figure SI-6: Event study: governor tweets "stay home," by partisan lean

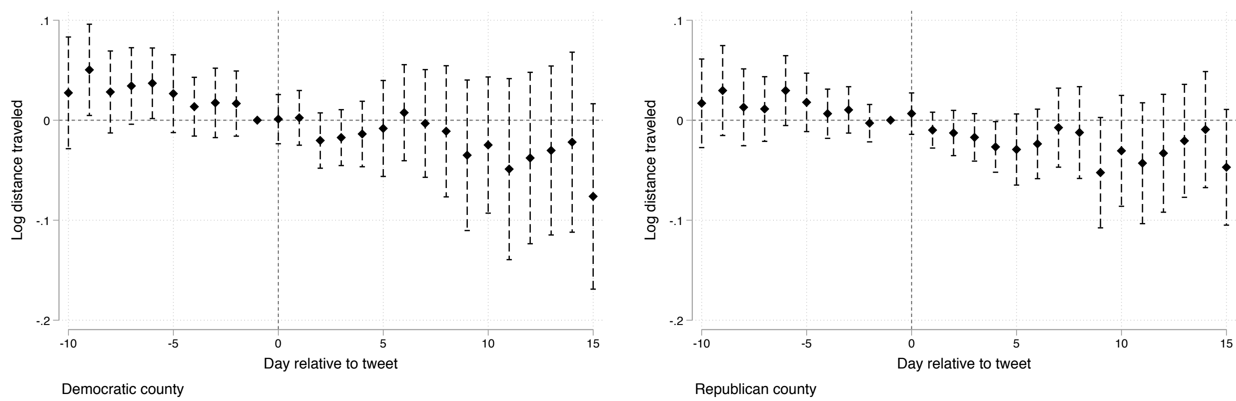
(a) Log time at home



(b) Share home all day

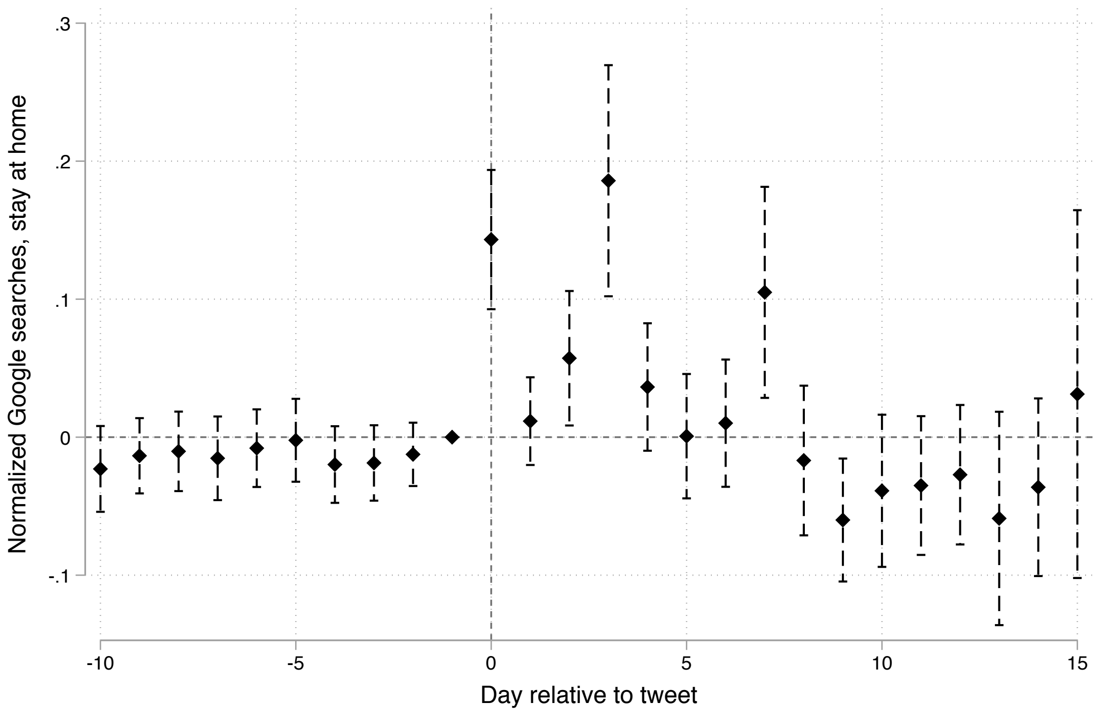


(c) Log distance traveled



Note: Figure shows coefficients from a county-level event-study regression of the outcome variable indicated in subfigure caption on indicators for leads and lags of the treatment, county and day fixed effects, and controls for COVID cases, deaths, and other orders, as well as demographics and Trump margin interacted with day fixed effects. The treatment is a dummy variable equaling 1 for all days after a governor issues their first tweet encouraging citizens to stay at home. Sample is split by Democratic counties and Republican counties. Republican counties are those where Donald Trump's margin of victory in the 2016 presidential election was greater than 5%. Standard errors are clustered at the state-level.

Figure SI-7: Event study: governor tweets “stay home,” Google searches



Note: Figure shows coefficients from a metro-area-level event-study regression of the outcome on indicators for leads and lags of the treatment, as well as county and day fixed effects. The treatment is a dummy variable equaling 1 for all days after a governor issues their first tweet encouraging citizens to stay home. Outcome variable is the daily search interest for the phrase “stay at home,” relative to reference point.

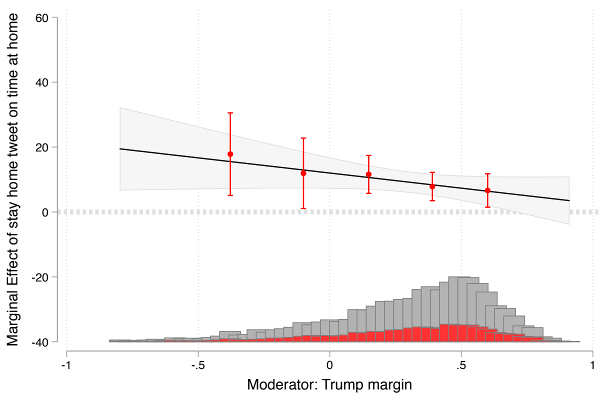
C.5 Predictive margins

Figure 3 estimates and plot predictive margins illustrating the effect of a tweet on behavior at different points across the political spectrum, along with a linear interaction fit, separately for Republican and Democratic states. In this section, we consider several extensions to this analysis. Firstly, in Figure SI-8 we plot the predictive margins for the full sample, either unweighted (Panel A) or weighted by county-level population (Panel B). We also overlay histograms of the density of Trump margin, as well as binned plots that provide a semi-parametric visualization of county-specific political heterogeneity that allows us to relax to the linearity assumption. In Panel A, consistent with the mildly negative interaction term in Table 2 Panel A, column (2), there is a slightly negative slope in the linear fit–areas with greater Trump share do experience lower marginal effects of the tweet. This is consistent with the binned estimates, which lie relatively close to the linear estimate. In Panel B, we re-weight by county-level population and find that the slope of the linear fit is now mildly positive. However, the binned estimates are still decreasing in Trump vote margin. This suggests that re-weighting has introduced substantial nonlinearities which make interpretation of the linear results more problematic. For a more extensive discussion on the role of reweighting, see Appendix D.5.

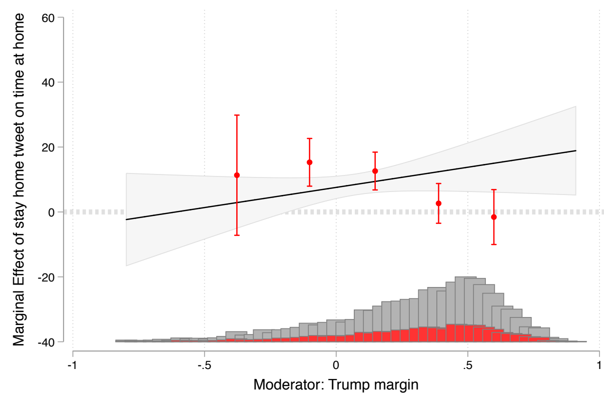
In Figure SI-9, we relax the linearity assumption entirely and re-estimate the predictive margins on the unweighted sample with a nonparametric kernel regression. Because the kernel regression is highly sensitive to sparse data at the boundaries, we exclude counties below a Trump margin of -0.5 and above 0.75, or 5% of the data. Firstly, we find evidence of substantial nonlinearities. In Democratic counties, the largest effects obtain in areas that overwhelmingly supported Clinton–where there is very little data – and in swing counties approaching a margin of zero. In contrast, the effects are smaller in solidly Democratic areas that are nonetheless not extremely to the left. On the Republican side, we find that the effects are largest in swing counties, and after which they are essentially monotonic in Trump share. Overall, despite the obvious nonlinearities, the nonparametric curve generally slopes downward, suggesting that the overall the linearity assumption is reasonable.

Figure SI-8: Predictive margins: effect of “stay home” tweet by Trump vote share, full sample

(a) Unweighted

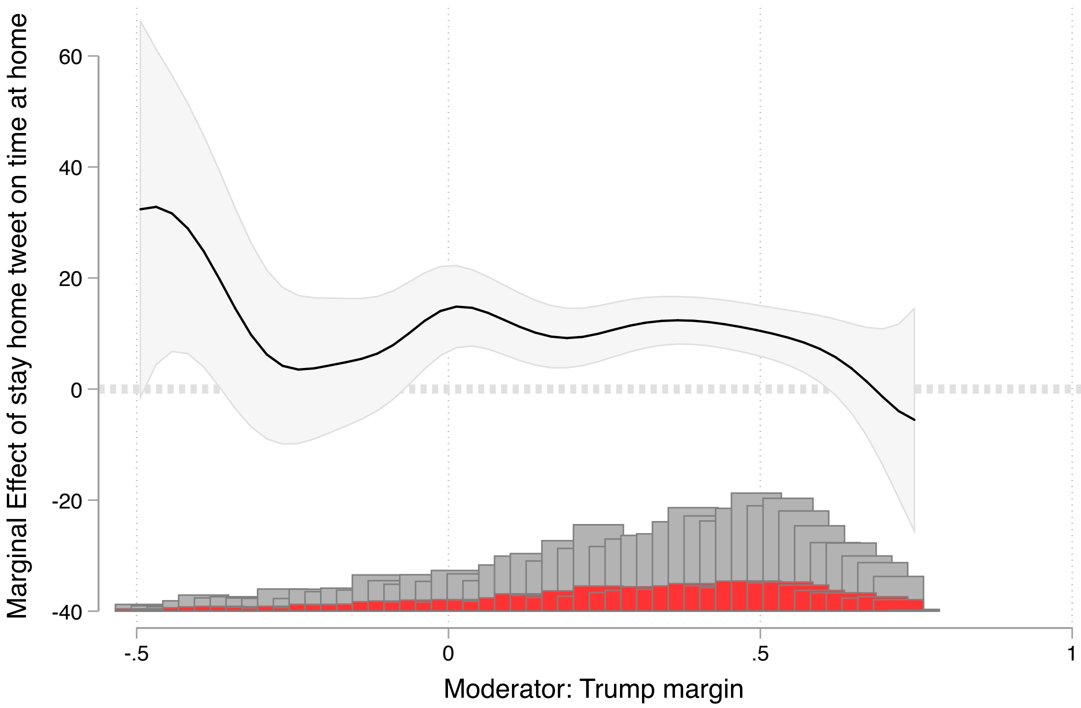


(b) Population weighted



Note: Figure shows predicted values and 95% confidence intervals from a county-level regression of median time at home on the treatment indicator, its interaction with Donald Trump’s county-level vote share in the 2016 presidential election, county and day fixed effects, as well as day fixed effects interacted with control variables and Trump’s 2016 margin, see Table 2 Panel A. Estimates are unweighted (Panel A) or weighted by county population (Panel B). The treatment is a dummy variable equaling 1 for all days after a governor issues their first tweet encouraging citizens to stay at home. We estimate the model separately for states with Democratic (Panel A) and Republican (Panel B) governors. The fitted line shows the linear marginal effect of the treatment at different levels of Trump vote share. The points with 95% confidence intervals show semi-parametric estimates of the marginal effect of the treatment at five different bins of Trump vote share. Bins are (-1,-0.25), (0.25, 0), (0, 0.25), and (0.25, 0.5). The histogram below the predicted margins displays the density of the county-level Trump vote margin by treatment status (red is treated, grey is untreated).

Figure SI-9: Predictive margins: effect of "stay home" tweet by Trump vote share, full sample, non-parametric estimation



Note: Figure shows predicted values and 95% confidence intervals from a county-level, population-weighted regression of median time at home on the treatment indicator, its interaction with Donald Trump's county-level vote share in the 2016 presidential election, county and day fixed effects, as well as day fixed effects interacted with control variables and Trump's 2016 margin. The treatment is a dummy variable equaling 1 for all days after a governor issues their first tweet encouraging citizens to stay at home. We estimate the model separately for states with Democratic (Panel A) and Republican (Panel B) governors. The fitted trend shows the non-parametric kernel estimate of the marginal effect of the treatment at different levels of Trump vote share. The histogram below the predicted margins displays the density of the county-level Trump vote margin by treatment status (red is treated, grey is untreated). Sample is trimmed to Trump margin between -0.5 and 0.75, or 95% of the data.

D Supplementary tables

D.1 Additional results

In this section, we consider two additional results that support the conclusions of Section 3. Firstly, in Table SI-1 we estimate the primary differences-in-differences regression using Google search interest for the terms “stay at home” (Panel A) and “shelter in place” (Panel B) as the outcome variables. The results in column (1) indicate that tweets about staying home do significantly increase search interest for both of these terms in the full sample of metro-areas. Columns (2)-(4) test whether these effects differ by partisan affiliation. Consistent with the main results on mobility, we do not find the interaction between the treatment and Trump’s 2016 metro-area-level vote margin to be significant, although in Panel B it is of the correct sign. Splitting the sample by local partisan affiliation reveals that Democratic and Republican metro-areas are essentially equally likely to search for “stay at home” following a stay home tweet by the governor. However, Panel B reveals that for “shelter in place” search interest, the coefficient in the Democratic sub-sample is over twice as large, providing more suggestive evidence that Democrats respond more to calls for voluntary social distancing than Republicans. Columns (5) and (6) do not find significant differences in reaction to tweet by governor party for either Democratic or Republican areas.

Table SI-2 tests the hypothesis that the response to governors’ tweets should vary over time, in particular that behavior should respond more the voluntary period before an official stay at home order is issued. We split the sample by periods before a state-level stay home order (columns 1-4) and after (columns 5-8), and re-estimate the main difference-in-differences regression that uses time at home as the outcome variable. We also consider whether these effects differ by how the treatment is defined; we consider our main post-treatment indicator, as well as cumulative tweets in the past 1, 3, or 5 days. In general – and consistent with the event-study results – we find that effects materialize both before and after a stay home order. However, the effects of recent tweets – as measured by cumulative tweets in the past 1, 3, or 5 days – are measurably larger in magnitude in the pre-order voluntary period, as expected. In contrast, the treatment indicator results are greater in the post-period, consistent with the dynamic event study results of Appendix C.4 that the response to the first tweet peaks 10-11 days after it is issued.

Lastly, in Table SI-3 we re-estimate the main results of Table 2, splitting the sample not by county-level partisanship but instead at the state-level by the governor’s partisan identity. Panel A estimates the main regression (columns 1, 3), and interaction with Trump’s county-level margin (columns 2, 4) for Democratic governors, while Panel B does so for Republican. Across both outcome variables, the main effect is similar in magnitude among Democratic and Republican governors. However, the interaction effects differ starkly. In Panel A, the interaction term is not significant or mildly positive, suggesting minimal partisan differentiation in response when a tweet is issued by a Democratic governor. In contrast, there is large and significant partisan differentiation in responses under Republican governors: Republicans are far less likely to respond than Democrats. The level coefficients in Panel B columns 2 and 4 imply that by far the most responsive groups are Democrats in Republican states.

Table SI-1: Governors' tweets and Google searches

Metro-area Party	All		Dem	GOP	Dem	GOP
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Search interest for "stay at home"						
Post stay home tweet	0.082***	0.076***	0.073***	0.092***	0.092***	0.114***
	(0.026)	(0.024)	(0.022)	(0.030)	(0.028)	(0.024)
Post stay home tweet × Trump vote share		0.004				
		(0.004)				
Post stay home tweet × GOP governor					-0.047	-0.049
					(0.043)	(0.053)
DMA FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Trump margin × Day FE	Yes	Yes	Yes	Yes	Yes	Yes
GOP gov × Day FE	No	No	No	No	Yes	Yes
Observations	6262	6262	1643	4619	1643	4619
R^2	0.406	0.406	0.413	0.416	0.423	0.427
Panel B: Search interest for "shelter in place"						
Post stay home tweet	0.155**	0.223**	0.263*	0.121**	0.313*	0.136
	(0.068)	(0.102)	(0.154)	(0.058)	(0.176)	(0.100)
Post stay home tweet × Trump vote share		-0.042				
		(0.031)				
Post stay home tweet × GOP governor					-0.265	-0.043
					(0.199)	(0.126)
DMA FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Trump margin × Day FE	Yes	Yes	Yes	Yes	Yes	Yes
GOP gov × Day FE	No	No	No	No	Yes	Yes
Observations	6262	6262	1643	4619	1643	4619
R^2	0.404	0.407	0.485	0.383	0.515	0.394

Standard errors clustered at the state level. Sample is 6,262 metro-area-days over the period March 1-March 31 2020. Outcome variable is Google search interest in the term "stay at home" or "shelter in place" relative to reference point, as indicated in the panel header. Treatment indicator equals one in all periods after the governor of state s issues a tweet encouraging citizens to stay home. All specifications include interactions between the 2016 Trump margin and day fixed effects. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table SI-2: Governors' tweets before and after stay home orders

Outcome	Median time at home							
Period	Pre-stay home order				Post stay-home order			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cumulative stay home tweets, 3 days	2.248**				0.831*			
	(0.935)				(0.449)			
Cumulative stay home tweets, 5 days		1.857**				1.306***		
		(0.747)				(0.403)		
Post stay home tweet			9.641**				24.311**	
			(4.064)				(11.612)	
Stay home tweets, $t-1$				2.712				1.704***
				(1.864)				(0.585)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographics $\times$ Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trump margin $\times$ Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	79329	79329	79329	76232	15361	15361	15361	15361
R^2	0.982	0.982	0.982	0.982	0.993	0.993	0.993	0.993

Standard errors clustered at the state level. Sample is 94,690 county-days over the period March 1-March 31 2020. Treatment indicator equals one for all days after the governor of state s issues a tweet about staying home, or is the cumulative number of tweets in a given period, as indicated in the Table. County-level demographic controls are median age, log family income, log population, share of population over 65, share black, share Hispanic, and share male. COVID controls includes controls for county-level COVID cases and state-level COVID deaths. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table SI-3: Governors' stay home tweets and mobility, by governor's party

Outcome	Median time at home		Log time at home	
	(1)	(2)	(3)	(4)
Panel A: Democratic governors				
Post stay home tweet	10.024**	6.197	0.024**	0.008
	(4.152)	(4.772)	(0.011)	(0.014)
Post stay home tweet × Trump vote margin		1.576		0.007*
		(1.157)		(0.004)
Observations	42750	42750	42750	42750
R^2	0.983	0.983	0.997	0.997
Panel B: Republican governors				
Post stay home tweet	7.920	21.233***	0.035***	0.064***
	(4.870)	(6.587)	(0.012)	(0.018)
Post stay home tweet × Trump vote margin		-3.373***		-0.007**
		(0.874)		(0.003)
Observations	51940	51940	51940	51940
R^2	0.985	0.985	0.998	0.998
County FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Demographics × Day FE	Yes	Yes	Yes	Yes
Trump margin × Day FE	Yes	Yes	Yes	Yes
COVID controls	Yes	Yes	Yes	Yes
Orders	Yes	Yes	Yes	Yes

Standard errors clustered at the state level. Sample is 94,690 county-days over the period March 1-March 31 2020. Treatment indicator equals one for all days after the governor of state s issues a tweet about social distancing. "Trump vote margin" is county i's vote margin for Donald Trump in the 2016 presidential election. GOP counties are those in which the Republican vote margin in the 2016 presidential election was greater than 5%. County-level demographic controls are median age, log family income, log population, share of population over 65, share black, share Hispanic, and share male. COVID controls includes controls for county-level COVID cases and state-level COVID deaths. "Orders" includes controls for whether the state has issued the following types of orders: emergency declarations, banning large gatherings, school closures, restaurant/bar closures, non-essential business closures, and stay-at-home orders. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

D.2 Other outcome variables

Recall that time spent at home is likely to be the best proxy of stay home behavior, since distance traveled may be biased by population density while share home all day is unlikely to fall below some minimum floor since individuals must continue to conduct essential business. However, in Table SI-4, we consider the robustness of the main results to different outcome variables, including the share of devices geolocated at home for the entire day (columns 1-2) and log of distance traveled (columns 3-4).

In Panel A, we find that governors' tweets about staying home increase the share of devices at home by 0.34 percentage points per day, and reduce distance traveled by 2.2%, however, neither effect is significant at the 5% level. Interestingly, however, column 2 shows a significant negative interaction between Trump's 2016 margin and the treatment, supporting the result that Republicans are less likely to respond to governors' communications. This interpretation is also supported by the results of Panel B, where the coefficients for stay home are now significant in the Democratic sample (column 1) and twice the magnitude of the insignificant coefficient for Republicans. However, in Panel C, we do not find any evidence that the triple-interaction effects observed in Table 2 carry over to these other outcome variables. Overall, the finding that tweets matter, and differentially so by county partisan lean, appears robust. However, the final finding that these effects vary depending on identity of the governor holds only for the median time at home outcomes.

Table SI-4: Governors' tweets, partisanship, and mobility, robustness to different outcome variables

Outcome	Share home all day		Log distance traveled	
	(1)	(2)	(3)	(4)
Panel A: Full sample				
Post stay home tweet	0.341	0.692**	-0.022*	-0.012
	(0.290)	(0.316)	(0.013)	(0.016)
Post stay home tweet × Trump vote margin		-0.110**		-0.003
		(0.047)		(0.003)
Observations	94690	94690	94690	94690
R^2	0.990	0.990	0.999	0.999
Panel B: By county party				
County party	Dem	GOP	Dem	GOP
Post stay home tweet	0.639**	0.313	-0.024	-0.020*
	(0.297)	(0.294)	(0.017)	(0.011)
Observations	14708	79982	14708	79982
R^2	0.993	0.990	0.999	0.999
County FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Demographics × Day FE	Yes	Yes	Yes	Yes
Trump margin × Day FE	Yes	Yes	Yes	Yes
COVID controls	Yes	Yes	Yes	Yes
Orders	Yes	Yes	Yes	Yes
Panel C: Triple interactions				
Post stay home tweet	0.908**	1.111**	-0.019*	-0.021
	(0.407)	(0.475)	(0.011)	(0.017)
Post stay home tweet × GOP governor	-0.285	0.033	0.005	0.010
	(0.556)	(0.899)	(0.025)	(0.035)
Post stay home tweet × Trump vote margin	-0.140**		-0.002	
	(0.065)		(0.003)	
Post stay home tweet × GOP governor × Trump vote margin	0.031		-0.002	
	(0.093)		(0.005)	
Post stay home tweet × GOP county		-0.726*		-0.003
		(0.399)		(0.017)
Post stay home tweet × GOP governor × GOP county		-0.391		-0.016
		(0.854)		(0.035)
GOP county × Day FE	No	Yes	No	Yes
Trump margin × Day FE	Yes	No	Yes	No
GOP gov × Day FE	Yes	Yes	Yes	Yes
GOP county × GOP gov × Day FE	No	Yes	No	Yes
Trump margin × GOP gov × Day FE	Yes	No	Yes	No
Observations	94690	94690	94690	94690
R^2	0.990	0.990	0.999	0.999

Standard errors in parentheses clustered at the state level. Sample is 93,030 county-days over the period March 1-March 31 2020 for which electoral data is available. Treatment indicator equals one for all days after the governor of state s issues a tweet encouraging citizens to stay home. "Trump vote margin" is county i's vote margin for Donald Trump in the 2016 presidential election. GOP counties are those in which the Republican vote margin in the 2016 presidential election was greater than 5%. County-level demographic controls are median age, log family income, log population, share of population over 65, share black, share Hispanic, and share male. COVID controls includes controls for county-level COVID cases and state-level COVID deaths. "Orders" includes controls for whether the state has issued the following types of orders: emergency declarations, banning large gatherings, school closures, restaurant/bar closures, non-essential business closures, and stay-at-home orders. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

D.3 Definition of treatment variable

Throughout the paper, we exploit a "staggered adoption" differences-in-differences design where the treatment indicator if interest equals one in all periods after the governor initial issues a stay at home tweet. In this section we consider the robustness of the main results to different definitions of the treatment variable. We begin in Table SI-5 by investigating whether the main effects differ when we consider tweets that recommend social distancing, but fall short of calling on citizens to stay home. As Figure 1 makes clear, these communications typically precede those about staying at home, and thus are of interest in understanding changes in voluntary social distancing behavior in the earliest phase of the pandemic.

In Table SI-5 we compare the magnitude of the behavior change induced by a social distancing tweet to that of the stay home tweet across our 4 outcome variables. First, we find that social distancing tweets also substantially reduce mobility (columns 2, 5, 8, 11), an effect that is significant for all outcomes except the share of devices home all day. In magnitudes, the first tweet about social distancing increases median time at home by 15.6 minutes per day. Furthermore, in columns 3,6,9,12 we include both treatment variables in the model. This does not materially affect either coefficient estimate, suggesting that the two types of tweets are largely orthogonal and implying that the social distancing effect occurs over and above the effect of stay home tweets. Lastly, social distancing tweets induce a larger reduction in mobility by about 6.2 minutes per day, though this difference is not statistically significant. This greater effect is likely due to the fact that governors social distancing tweets predominantly occurred during the earlier phase of the pandemic – prior to prohibitions of large gatherings and closures of schools and business – in which the scope for voluntary reduction of mobility was greater.

Having established that social distancing tweets also reduce mobility, we next consider whether these effects vary by political alignment and governors' identity. Table SI-6 replicates the main results of Table 2, using social distancing tweets instead of stay at home as the treatment of interest. In general, the differential effects by partisan identity and governor identity that we observe in the main results do not obtain when considering social distancing tweets. In particular, the responses does not differ by Trump's 2016 margin (Panel A), and is similar in magnitude for Democratic vs. Republican counties (Panel B). None of the two or three-way interaction terms in Panel C are significant.

Table SI-5: Governors' tweets, by content of tweet

Outcome	Median time at home			Log time at home			Share home all day			Log distance		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Post stay home tweet	9.382**		9.759**	0.026***		0.027***	0.341		0.350	-0.022*		-0.023*
	(4.009)		(3.739)	(0.009)		(0.009)	(0.290)		(0.287)	(0.013)		(0.012)
Post social distancing tweet		15.613***	15.926***		0.037***	0.038***		0.376	0.387		-0.033**	-0.034**
		(4.490)	(4.190)		(0.011)	(0.010)		(0.288)	(0.280)		(0.015)	(0.015)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographics × Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trump margin × Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
COVID cases	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Orders	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	94690	94690	94690	94690	94690	94690	94690	94690	94690	94690	94690	94690
R^2	0.984	0.984	0.984	0.998	0.998	0.998	0.990	0.990	0.990	0.999	0.999	0.999

Standard errors clustered at the state level. Sample is 94,690 county-days over the period March 1-March 31 2020. Treatment indicator equals one for all days after the governor of state s issues a tweet about staying home or social distancing, as indicated in the table. County-level demographic controls are median age, log family income, log population, share of population over 65, share black, share Hispanic, and share male. COVID controls includes controls for county-level COVID cases and state-level COVID deaths. "Orders" includes controls for whether the state has issued the following types of orders: emergency declarations, banning large gatherings, school closures, restaurant/bar closures, non-essential business closures, and stay-at-home orders. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table SI-6: Governors' social distancing tweets, partisanship and mobility

Outcome	Median time at home		Log time at home	
	(1)	(2)	(3)	(4)
Panel A: Full sample				
Post social distancing tweet	15.613***	17.318***	0.037***	0.027**
	(4.490)	(5.502)	(0.011)	(0.013)
Post social distancing tweet × Trump vote margin		-0.518		0.003
		(0.868)		(0.003)
Observations	94690	94690	94690	94690
R^2	0.984	0.984	0.998	0.998
County FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Demographics × Day FE	Yes	Yes	Yes	Yes
Trump margin × Day FE	Yes	Yes	Yes	Yes
COVID controls	Yes	Yes	Yes	Yes
Orders	Yes	Yes	Yes	Yes
Panel B: By county party				
County party	Dem	GOP	Dem	GOP
Post social distancing tweet	17.519***	15.388***	0.011	0.040***
	(6.009)	(4.535)	(0.018)	(0.011)
Observations	14708	79982	14708	79982
R^2	0.985	0.984	0.997	0.998
County FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Demographics × Day FE	Yes	Yes	Yes	Yes
Trump margin × Day FE	Yes	Yes	Yes	Yes
COVID controls	Yes	Yes	Yes	Yes
Orders	Yes	Yes	Yes	Yes
Panel C: Triple interaction				
Post social distancing tweet	14.525*	15.955*	0.033**	0.040*
	(7.305)	(8.512)	(0.016)	(0.024)
Post social distancing tweet × GOP governor	3.737	9.195	-0.010	0.003
	(11.279)	(13.289)	(0.026)	(0.036)
Post social distancing tweet × Trump vote margin	-0.922		0.003	
	(1.352)		(0.004)	
Post social distancing tweet × GOP governor × Trump vote margin	0.618		0.002	
	(1.697)		(0.005)	
Post social distancing tweet × GOP county		-3.915		0.003
		(7.906)		(0.022)
Post social distancing tweet × GOP governor × GOP county		-6.636		-0.012
		(12.366)		(0.036)
GOP county × Day FE	No	Yes	No	Yes
Trump margin × Day FE	Yes	No	Yes	No
GOP gov × Day FE	Yes	Yes	Yes	Yes
GOP county × GOP gov × Day FE	No	Yes	No	Yes
Trump margin × GOP gov × Day FE	Yes	No	Yes	No
COVID controls	Yes	Yes	Yes	Yes
Orders	Yes	Yes	Yes	Yes
Observations	94690	94690	94690	94690
R^2	0.984	0.984	0.998	0.997

Standard errors clustered at the state level. Sample is 94,690 county-days over the period March 1-March 31 2020. Treatment indicator equals one for all days after the governor of state s issues a tweet about social distancing. "Trump vote margin" is county i's vote margin for Donald Trump in the 2016 presidential election. GOP counties are those in which the Republican vote margin in the 2016 presidential election was greater than 5%. County-level demographic controls are median age, log family income, log population, share of population over 65, share black, share Hispanic, and share male. COVID controls includes controls for county-level COVID cases and state-level COVID deaths. "Orders" includes controls for whether the state has issued the following types of orders: emergency declarations, banning large gatherings, school closures, restaurant/bar closures, non-essential business closures, and stay-at-home orders. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

D.4 Robustness: random effects

Throughout the paper, we use a two-way fixed effects approach to estimate the coefficients of the difference-in-differences and event-study models. In this section, we consider the robustness of the main results to different estimation approach, namely, allowing for random intercepts at the county-level. Table SI-7 re-estimates the main results of Table 2 using a random-effects estimator, with day fixed effects and controls for county-level demographics, Trump margin, and COVID cases, as well as state-level COVID deaths and orders.

We find that the results are generally very similar to those in Table SI-7, even up to magnitudes. In Panel A column 1, the effect of the governor's stay home tweet is an increase in time home of 9.95 minutes per day, compared with 9.38 under fixed effects. This corresponds to a 3.2% increase, compared to a 2.6% daily change under fixed effects, though both are significant at the 1% level. In column 2, the interaction with Trump vote share is larger and now statistically significant; a 10 percentage-point increase in Trump's vote share reduces compliance by about 2.9 minutes per day. In contrast, this interaction coefficient is roughly half the magnitude, and insignificant under fixed effects.

In Panel B, columns 1 and 2 reveal very similar partisanship patterns – Trump-voting counties respond less half as much to stay at home tweets, similar in magnitude to the fixed effects result of Table 2. Lastly, in Panel C, we find similar triple-interaction effects – Trump-voting counties respond significantly less than Democratic ones under Republican governors, but not significantly differently under Democrats. Overall, Democrats under Republican governors respond the most, while Republicans under own-party governors respond the least, mirroring the fixed effects results exactly. Overall, the similarity of the results between the two estimation strategies – both qualitatively and quantitatively – suggest that assumptions over the structure of county-specific heterogeneity are not particularly important. This suggests that time-invariant county-level heterogeneity is not substantially correlated with governors' messaging.

Table SI-7: Governors' tweets, partisanship and mobility, random effects

Outcome	Median time at home		Log time at home	
	(1)	(2)	(3)	(4)
Panel A: Full sample				
Post stay home tweet	9.951**	18.943***	0.032***	0.041***
	(4.242)	(5.578)	(0.011)	(0.013)
Post stay home tweet × Trump vote margin		-2.885***		-0.003
		(0.962)		(0.002)
Observations	94690	94690	94690	94690
R^2	0.442	0.443	0.250	0.250
Day FE	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes
Trump margin × Day FE	Yes	Yes	Yes	Yes
COVID controls	Yes	Yes	Yes	Yes
Orders	Yes	Yes	Yes	Yes
Panel B: By county party				
County party	Dem	GOP	Dem	GOP
Post stay home tweet	19.134***	8.698**	0.039*	0.031***
	(7.133)	(4.167)	(0.021)	(0.011)
Observations	14708	79982	14708	79982
R^2	0.571	0.429	0.359	0.239
Day FE	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes
Trump margin × Day FE	Yes	Yes	Yes	Yes
COVID controls	Yes	Yes	Yes	Yes
Orders	Yes	Yes	Yes	Yes
Panel C: Triple interaction				
Post stay home tweet	7.929	8.206	0.010	-0.000
	(6.451)	(8.409)	(0.019)	(0.030)
Post stay home tweet × GOP governor	14.912	29.019**	0.056**	0.113***
	(9.171)	(13.526)	(0.023)	(0.035)
Post stay home tweet × Trump vote margin	-0.379		0.004	
	(1.658)		(0.005)	
Post stay home tweet × GOP governor × Trump vote margin	-3.663*		-0.012**	
	(2.008)		(0.005)	
Post stay home tweet × GOP county		-1.392		0.023
		(8.123)		(0.029)
Post stay home tweet × GOP governor × GOP county		-34.252**		-0.116***
		(13.491)		(0.036)
Day FE	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes
Trump margin × Day FE	Yes	No	Yes	No
GOP county × Day FE	No	Yes	No	Yes
GOP gov × Day FE	Yes	Yes	Yes	Yes
Trump margin × GOP gov × Day FE	Yes	No	Yes	No
GOP county × GOP gov × Day FE	No	Yes	No	Yes
COVID cases	Yes	Yes	Yes	Yes
Orders	Yes	Yes	Yes	Yes
Observations	94690	94690	94690	94690
R^2	0.446	0.433	0.252	0.241

Standard errors clustered at the state level. Sample is 94,690 county-days over the period March 1-March 31 2020. All specifications use a random effects estimator that allows intercepts to vary at the county-level. Treatment indicator equals one for all days after the governor of state s issues a tweet about staying home. "Trump vote margin" is county i's vote margin for Donald Trump in the 2016 presidential election. GOP counties are those in which the Republican vote margin in the 2016 presidential election was greater than 5%. County-level demographic controls are median age, log family income, log population, share of population over 65, share black, share Hispanic, and share male. COVID controls includes controls for county-level COVID cases and state-level COVID deaths. "Orders" includes controls for whether the state has issued the following types of orders: emergency declarations, banning large gatherings, school closures, restaurant/bar closures, non-essential business closures, and stay-at-home orders. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

D.5 Robustness: population weights

Throughout the paper, we estimate regressions on a daily panel of counties, unweighted by population. Consistent with the literature, we choose this strategy in order to estimate the average county-level effect. Under population weighting, it is likely that results will be driven primarily by larger, typically Democratic-leaning urban areas, whereas unweighted regressions allow us to uncover effects across the political spectrum. In this section, we consider how weighting by population affects the main estimates.

Table SI-8 re-estimates the results from from 2 with county-level population weights. The interpretation of these results is now at the level of individuals rather than counties. Panel A reveals that the main result remains large and statistically significant – governors' tweets reduce mobility, reflected in 7.6 more minutes at home per day, on average. However, in column (2) we find that the mildly negative interaction term with Trump's 2016 vote margin has now switched signs. This is likely because small, heavily pro-Trump counties that were previously driving this interaction effect have been down-weighted. This is clear in Panel B, where the effect is now positive and significant for Republicans but not for Democrats. Looking at the nonlinear pattern of effects in Figure SI-9, we can see that this is likely driven by the fact that population weighting up-weights Republican counties closer to the center – likely to be larger than those further to the right – which have large effect sizes. On the Democratic side, it up-weights larger cities, which are likely to to be further left and actually have smaller effects than more centrist Democratic areas. Panel C of Table SI-8 reveals that the triple-interaction effect is still of the correct sign, but much smaller in magnitude and no longer significant.

Table SI-9 re-estimates the results from Table SI-3 with county-level population weights. Column (1) flips the baseline result of the unweighted regression, indicating that effects are now greater in Republican rather than Democratic states. However, the interaction terms remain of the same sign, though the size and significance in Panel B is greatly diminished. The negative marginal effect slope in Republican states has flattened, whereas the mildly positive marginal effect slope in Republican states has strengthened.

Table SI-8: Governors' tweets, partisanship, and mobility, robustness to population weights

Panel A: Full sample

Outcome	Median time at home		Log time at home	
Post stay home tweet	7.623**	7.563**	0.015**	0.014**
	(3.653)	(3.686)	(0.006)	(0.006)
Post stay home tweet × Trump vote margin		1.243		0.004**
		(0.815)		(0.002)
Observations	94690	94690	94690	94690
R^2	1.000	1.000	1.000	1.000
County FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Demographics × Day FE	Yes	Yes	Yes	Yes
Trump margin × Day FE	Yes	Yes	Yes	Yes
COVID controls	Yes	Yes	Yes	Yes
Orders	Yes	Yes	Yes	Yes

Panel B: By county party

Outcome	Median time at home		Log time at home	
County party	Dem	GOP	Dem	GOP
Post stay home tweet	5.490	12.095***	0.007	0.024***
	(4.230)	(4.008)	(0.007)	(0.007)
Observations	14708	79982	14708	79982
R^2	1.000	1.000	1.000	1.000
County FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Demographics × Day FE	Yes	Yes	Yes	Yes
Trump margin × Day FE	Yes	Yes	Yes	Yes
COVID controls	Yes	Yes	Yes	Yes
Orders	Yes	Yes	Yes	Yes

Panel C: Triple interactions

Outcome	Median time at home		Log time at home	
Interaction	Cont. vote margin	Binary	Cont. vote margin	Binary
Post stay home tweet	7.621	4.470	0.013	0.001
	(5.254)	(5.874)	(0.010)	(0.011)
Post stay home tweet × GOP governor	-2.063	-0.209	0.006	0.021
	(7.117)	(9.405)	(0.012)	(0.015)
Post stay home tweet × Trump vote margin	1.949**		0.005***	
	(0.829)		(0.002)	
Post stay home tweet × GOP governor × Trump vote margin	-2.013		-0.005**	
	(1.603)		(0.003)	
Post stay home tweet × GOP county		4.191		0.018*
		(5.220)		(0.010)
Post stay home tweet × GOP governor × GOP county		-1.613		-0.019
		(9.255)		(0.014)
GOP county × Day FE	No	Yes	No	Yes
Trump margin × Day FE	Yes	No	Yes	No
GOP gov × Day FE	Yes	Yes	Yes	Yes
GOP county × GOP gov × Day FE	No	Yes	No	Yes
Trump margin × GOP gov × Day FE	Yes	No	Yes	No
COVID controls	Yes	Yes	Yes	Yes
Orders	Yes	Yes	Yes	Yes
Observations	94690	94690	94690	94690
R^2	1.000	1.000	1.000	1.000

Standard errors in parentheses clustered at the state level. All estimates weighted by county-level population. Sample is 96,690 county-days over the period March 1-March 31 2020. Treatment indicator equals one for all days after the governor of state s issues a tweet encouraging citizens to stay home. "Trump vote margin" is county i's vote margin for Donald Trump in the 2016 presidential election. GOP counties are those in which the Republican vote margin in the 2016 presidential election was greater than 5%. County-level demographic controls are median age, log family income, log population, share of population over 65, share black, share Hispanic, and share male. COVID controls includes controls for county-level COVID cases and state-level COVID deaths. "Orders" includes controls for whether the state has issued the following types of orders: emergency declarations, banning large gatherings, school closures, restaurant/bar closures, non-essential business closures, and stay-at-home orders.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table SI-9: Governors' stay home tweets and mobility by governor's party, robustness to population weights

Outcome	Median time at home		Log time at home	
	(1)	(2)	(3)	(4)
Panel A: Democratic governors				
Post stay home tweet	5.174	6.289	0.010	0.013
	(5.237)	(5.311)	(0.011)	(0.011)
Post stay home tweet × Trump vote margin		2.174**		0.006***
		(0.891)		(0.002)
Observations	42750	42750	42750	42750
R^2	1.000	1.000	1.000	1.000
Panel B: Republican governors				
Post stay home tweet	8.665*	8.959*	0.024***	0.025***
	(4.332)	(4.704)	(0.007)	(0.007)
Post stay home tweet × Trump vote margin		-0.244		-0.000
		(1.060)		(0.001)
Observations	51940	51940	51940	51940
R^2	1.000	1.000	1.000	1.000
County FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Demographics × Day FE	Yes	Yes	Yes	Yes
Trump margin × Day FE	Yes	Yes	Yes	Yes
COVID controls	Yes	Yes	Yes	Yes
Orders	Yes	Yes	Yes	Yes

Standard errors clustered at the state level. All estimates weighted by county-level population. Sample is 94,690 county-days over the period March 1-March 31 2020. Treatment indicator equals one for all days after the governor of state s issues a tweet about social distancing. "Trump vote margin" is county i's vote margin for Donald Trump in the 2016 presidential election. GOP counties are those in which the Republican vote margin in the 2016 presidential election was greater than 5%. County-level demographic controls are median age, log family income, log population, share of population over 65, share black, share Hispanic, and share male. COVID controls includes controls for county-level COVID cases and state-level COVID deaths. "Orders" includes controls for whether the state has issued the following types of orders: emergency declarations, banning large gatherings, school closures, restaurant/bar closures, non-essential business closures, and stay-at-home orders. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.