SUPPLEMENTARY INFORMATION

— For Online Publication —

A Social media data

We use governors' tweets as a proxy to capture their public messages (cues). In this section, we describe how this measure was devised. First, we identified all USA governors' official and personal Twitter accounts. 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 (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 10,688 tweets from the official and personal accounts of the governors of 50 US states, of which 7,958 contained information relevant to COVID-19. The tweets were aggregated into a single CSV file and then coded using research assistants who 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, 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 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 keywords 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 keywords 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 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.

It is not about social distancing since it only mentions how to prevent your 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 keywords are simply examples; they are NOT exhaustive. For example, the tweet below explicitly calls 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 entirely 'staying at home.'

A.2 Facebook data

We also consider a proxy for governors' messaging based on data from their Facebook posts. We identified both the official and the personal Facebook public pages of all the governors of all 50 states. We then collected Facebook posts published on these pages between February 15th and March 31st. For this purpose, we wrote a script to retrieve Facebook posts using the Python programming language (version 3.7.3). The downloaded posts were then coded using research assistants trained based on the exact instructions used to code the governors' tweets. We also collected information about the number of Facebook users following each page as of June 6th. We downloaded 6,771 Facebook posts, of which 4,461 contained information relevant to COVID-19.

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

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

Where $STAYHOME_{st}$ is a treatment indicator that equals one in all periods after the governor of state s first issues a public message 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 daily county-level confirmed COVID-19 cases and state-level confirmed COVID-19 deaths, county-level demographics including median age, log household income, population density, share over 65, share black, Hispanic, white, and male, as measured in the most recent American Community Survey (ACS), indicators for COVID-19 messaging that does not explicitly encourage staying at home, and dummies for state-days in which various stay home orders are in effect. We include state-level orders: emergency declarations, 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 $STAYHOME_{st}$

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 communications of interest encourage only physical distancing rather than staying at home. 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 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

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

Where τ indicates leads and lags of the treatment period, $STAYHOME_{s\tau}$ 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.

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

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 state level, even though the variation of interest –the interaction term – is at the county-year level.

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

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

We consider specifications where $MARGIN_i$ is 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

This section presents basic descriptive information on the dataset of governors' tweets described in Appendix A.

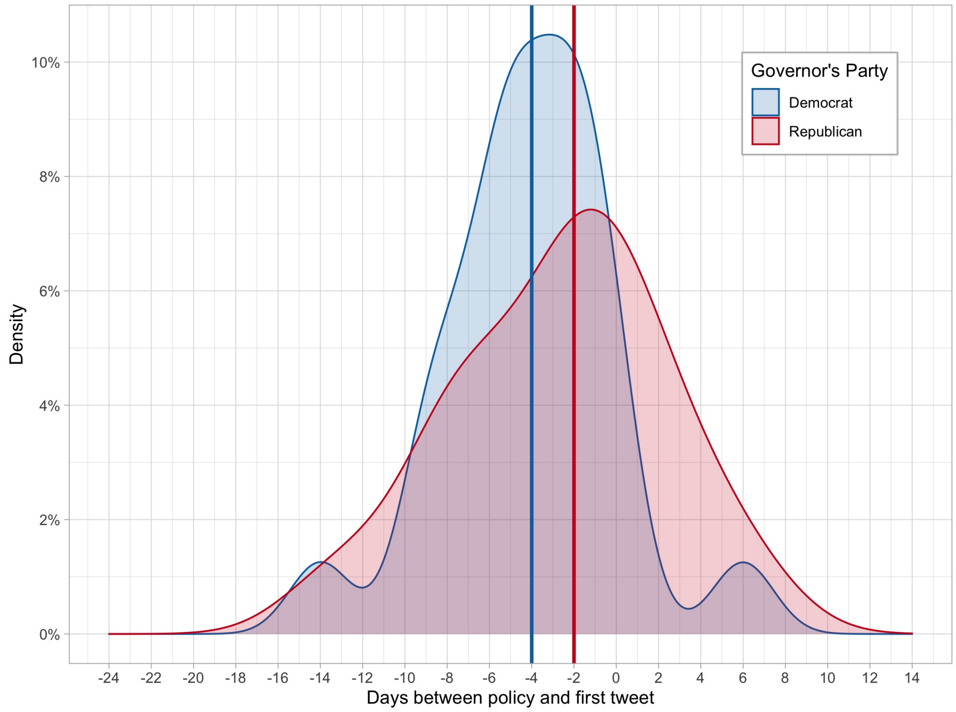
In Figure SI-1, we calculate the state-level difference between the date of the first stay-at-home order and the date of the first tweet encouraging citizens to stay home. Negative numbers indicate the tweet was issued before the policy, and positive numbers indicate the opposite. We then plot the distribution 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 -4. In contrast, the Republican distribution's median is -2.

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

Figure SI-3 visualizes the correlation between the timing of governors' communications around COVID-19 on different social media platforms. The x-axis indicates the date the governor first tweeted messages to stay at home, while the y-axis measures the same timing variable for Facebook communications. The dashed line indicates the 45-degree line – all governors above this line issued tweets before Facebook posts, while the reverse is true for all those below the line. The plot shows a strong positive correlation in timing between Facebook and Twitter stay-at-home messaging. The bivariate R^2 between the two is 0.858, and 32 governors issued these initial communications on both platforms on the same day. We take this as evidence that the timing of Twitter communications is a good proxy for communication across multiple media sources.

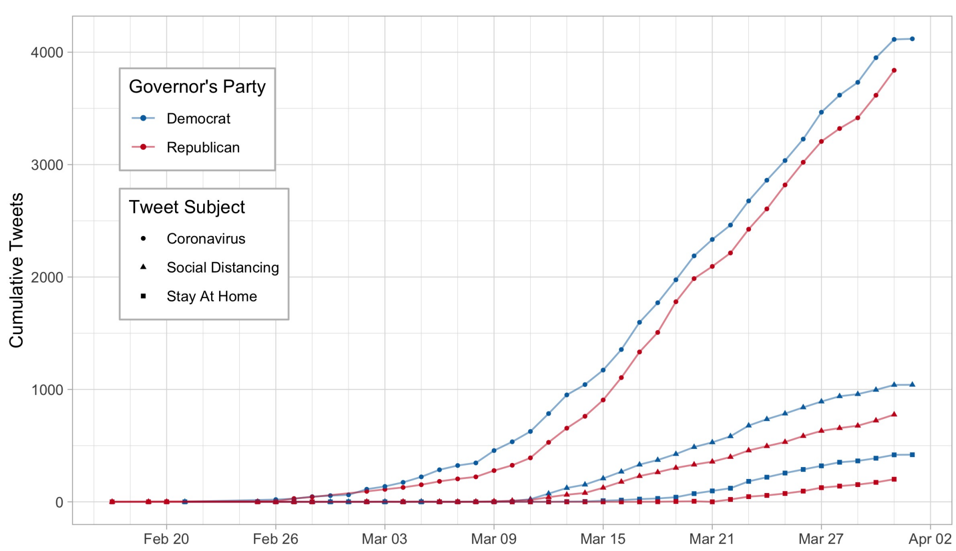
Figure SI-4 plots the correlation between the log number of followers on Facebook and Twitter for governors' official and private social media accounts. While Facebook accounts are typically larger, there is a strong positive correlation between followers across platforms. Again, this supports the assumption that Twitter exposure proxies well for exposure to governors' communications from other forms of media.

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



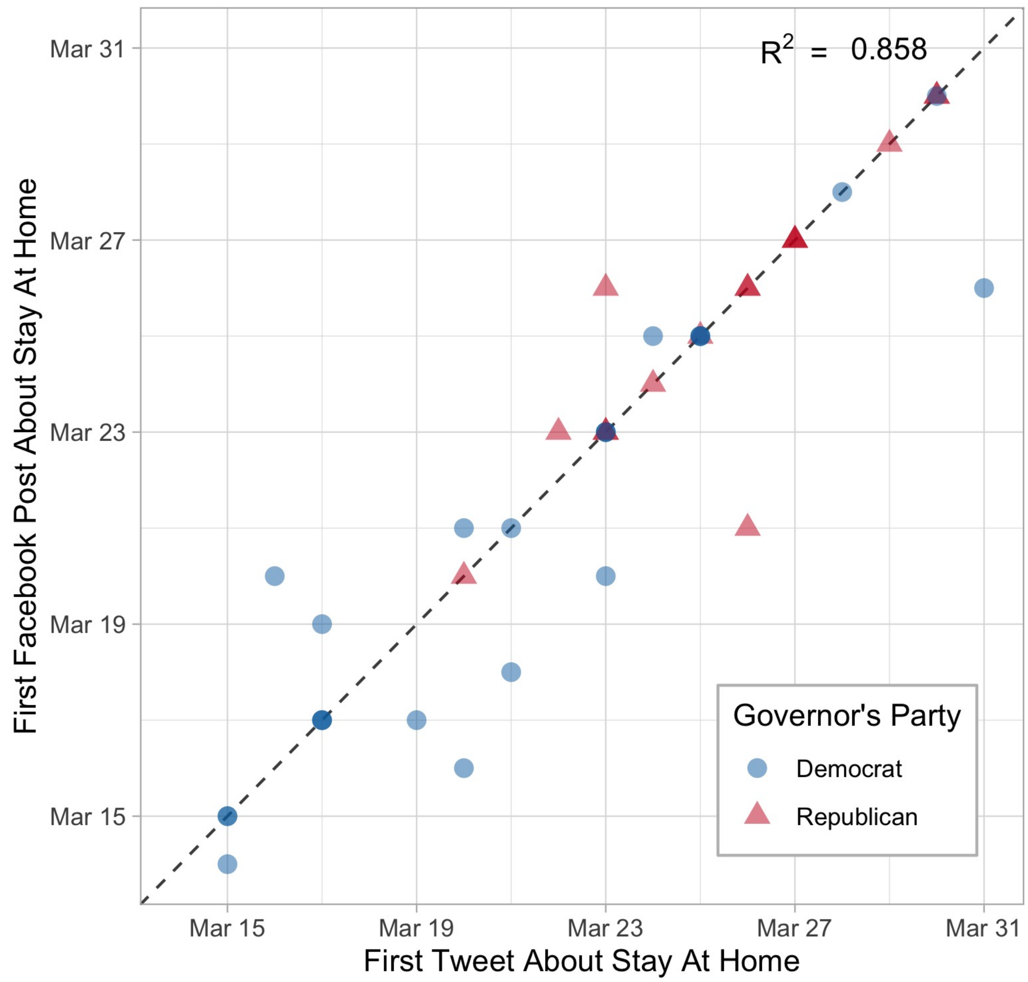
Note: Figure shows the distribution of the difference in days between the governors' first tweet explicitly encouraging staying at home and the state's first official stay-at-home order. Vertical lines indicate the median difference in days for each party.

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



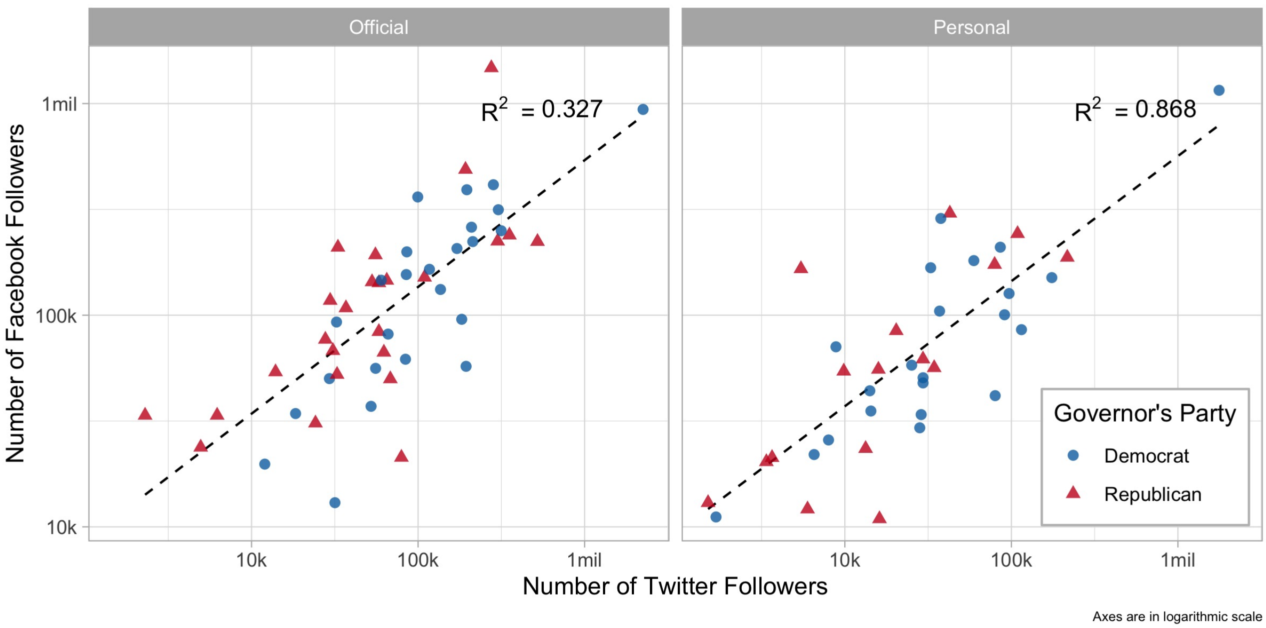
Note: Figure shows the cumulative number of governors' tweets about a topic by topic, date, and governor party. Tweet topic is indicated in legend.

Figure SI-3: Date of governors' first tweets and Facebook posts



Note: Figure plots the date of a governor's first Facebook post explicitly encouraging staying at home against the date of that governor's first tweet explicitly encouraging staying at home. The dashed line is the 45-degree line, with bivariate R^2 indicated in the plot.

Figure SI-4: Governors' followers on Facebook and Twitter



Note: Figure plots the log number of Facebook followers against the log number of Twitter followers for governors' official (left panel) and personal (right panel) social media accounts. The dashed line gives the linear OLS fit, with bivariate R^2 indicated in the plot.

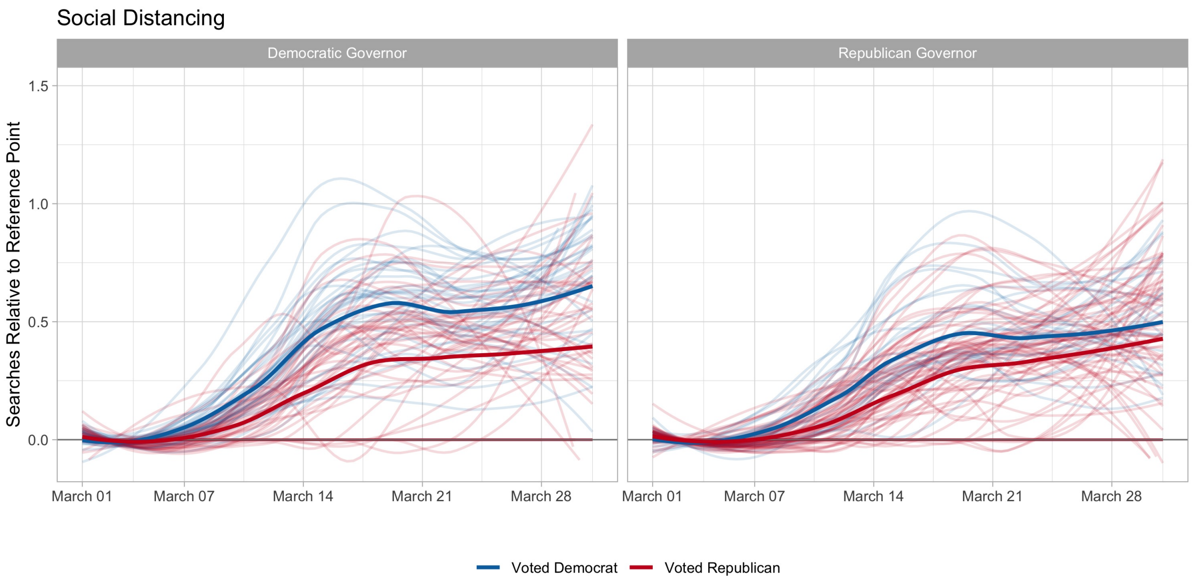
C.2 Google Trends

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 so that all metro-day units are normalized relative to a single reference point. In Figure SI-5, 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). Then, we overlay the mean search interest trend separately for metro areas that voted Republican vs. Democratic in the 2016 presidential election. All trends are estimated using a lowess smoother.

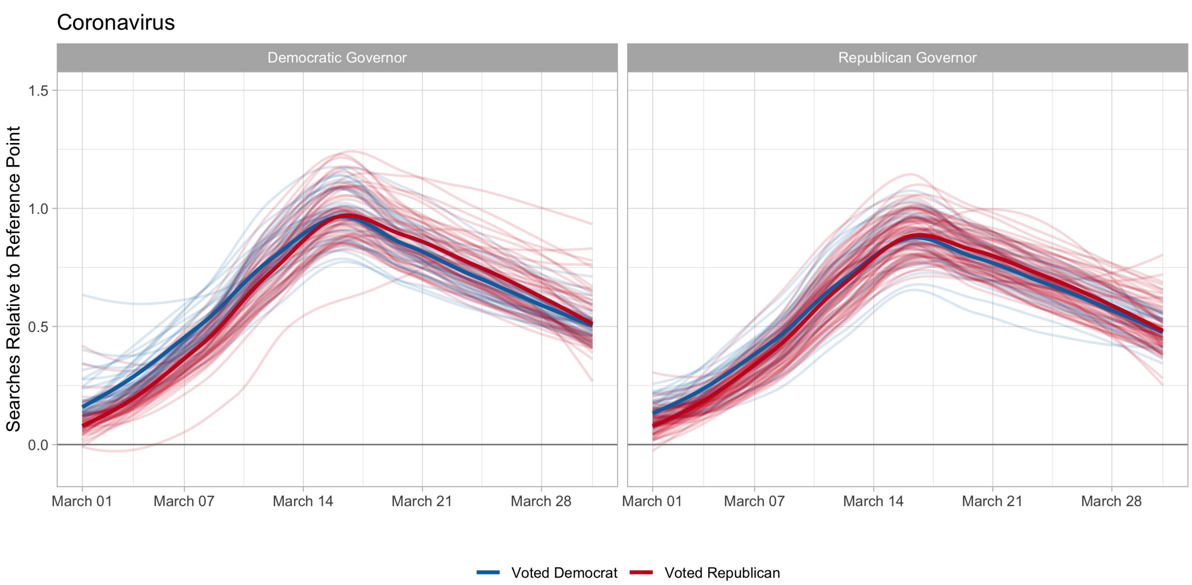
In Panel A, we see that mean search interest in social distancing among voters of both parties begins earlier and is greater under Democratic governors, likely because, as Figure SI-2 makes clear, Democratic governors are tweeting about social distancing earlier and more frequently than Republicans. 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-5: Google search interest by partisan alignment and governor's party over time

(a) Social distancing



(b) Coronavirus



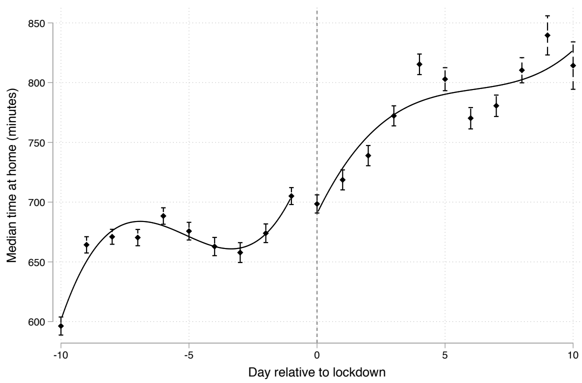
Note: Figure shows the daily relative Google search interest for the term "social distancing" in Panel A and "Coronavirus" for 205 metro areas in the United States from March 1-March 31. All search numbers are normalized relative to a reference group. Trends are adjusted using a lowess smoother. Metro-areas 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

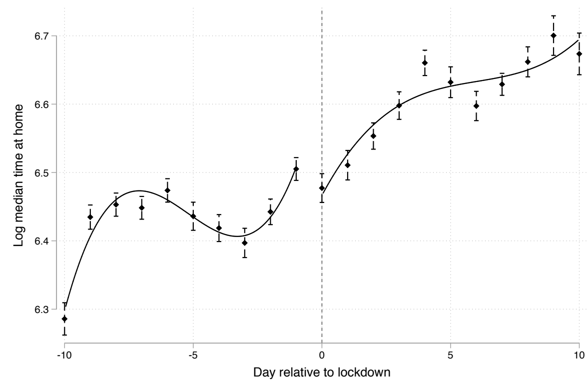
In this section, we analyze trends in mobility before and after state-level shelter-in-place/stay-at-home orders are issued for each of the four mobility outcomes. Using a third-order polynomial, we estimate trends separately before and after issuing stay-at-home orders. Across each outcome in Figure SI-6, we find that mobility reduced substantially before the stay-home order was enacted. 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-6: Mobility relative to stay-at-home orders

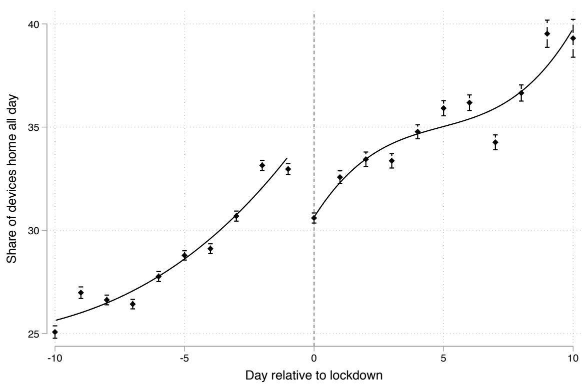
(a) Median time at home



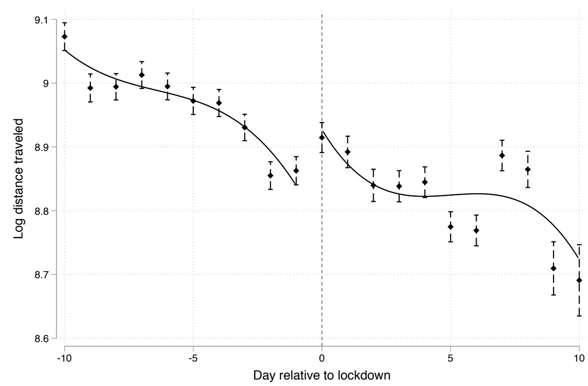
(b) Log time at home



(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.[1] The event-study model also allows us to estimate the dynamic path of effects to determine the "onset" time of the treatment and whether the effects fade or grow over time.

Figure SI-7 plots the coefficients from the event-study regression for the four primary outcomes – median home time, log median home time, the share of devices home all day, and log distance traveled – in the full sample. In general, parallel trends appear to hold; across all four outcomes, only one of the pre-period coefficients out of 36 significantly differs 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 message does not produce an immediate response but rather takes 2-3 days to generate behavior change. This makes sense if the first tweet marks a shift in messaging followed by more communications on the subject. The coefficients then rise (or fall in Panel D) before plateauing 10-11 days after the initial tweet. For the median time at home in minutes — our primary outcome of interest – the maximum daily impact of governors' messaging on behavior occurs 11 days after the initial communication. It corresponds to a 31.7-minute increase in daily time at home, on average, or a 6% increase, as we can see from Panel B.

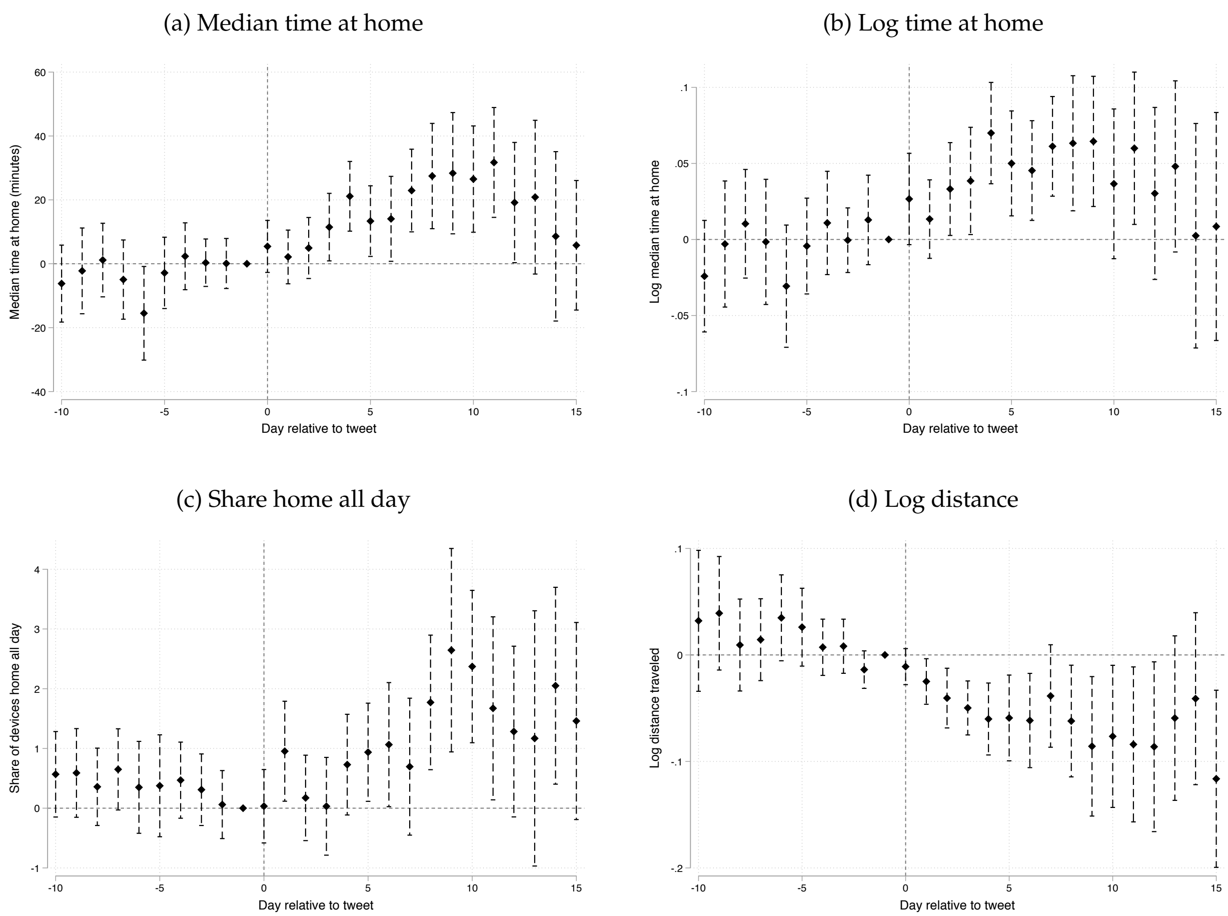
Figure SI-8 then splits the sample by county-level partisan alignment to test whether the assumption of parallel trends is likely to hold in these subsamples and to compare the dynamic effect sizes by party. Again, the assumption of parallel trends seems likely to be satisfied, as pre-period coefficients are clustered around zero and are rarely significant. In general, the effect sizes appear larger among the sample of Democratic counties. However, due to a much larger sample, the Republican coefficients are more precisely estimated. This suggests that Democrats respond more actively to their governors' stay-home messaging with voluntary behavior change. However, the differences in the event-study coefficients by party are unlikely to be statistically significant, given the wide confidence

[1] Recall that the treatment date is defined as the date when the governor first tweeted encouraging individuals to stay home.

intervals in the Democratic sample.

Lastly, in Figure SI-9, 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 the tweet is issued and remains elevated for four days before dropping off to zero. The fact that this spike in interest occurs before behavior change is observed in the data suggests that individuals 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.

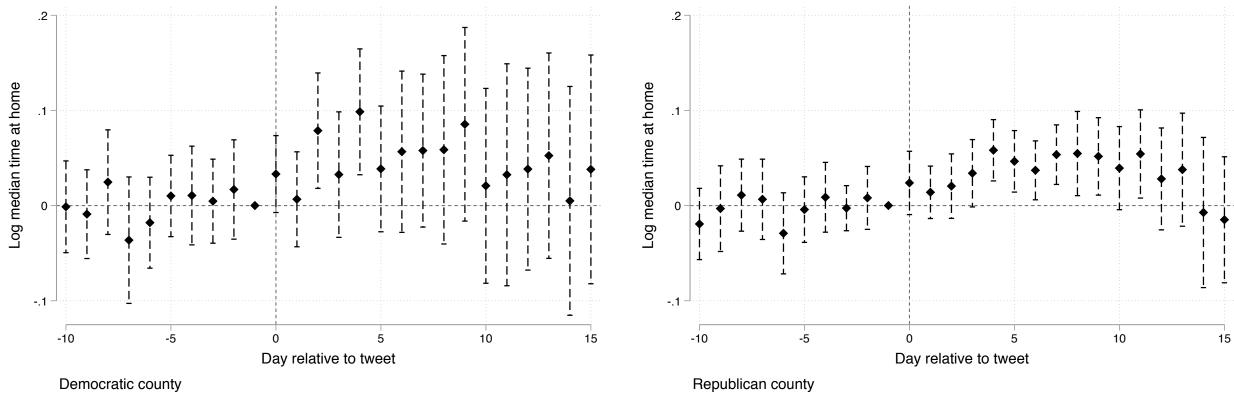
Figure SI-7: Event study: governor tweets "stay home," baseline effects



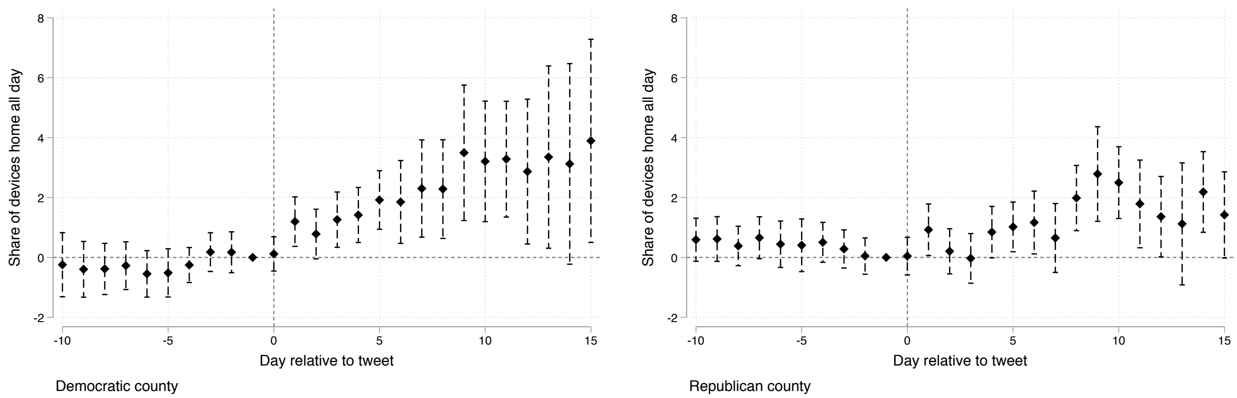
Note: Figure shows coefficients from a county-level event-study regression of median time at home (Panel A), log of median home time (Panel B), share home all day (Panel C), and log distance traveled (Panel D) on indicators for leads and lags of the treatment, county and day fixed effects, and controls 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-8: Event study: governor tweets "stay home," by partisan lean

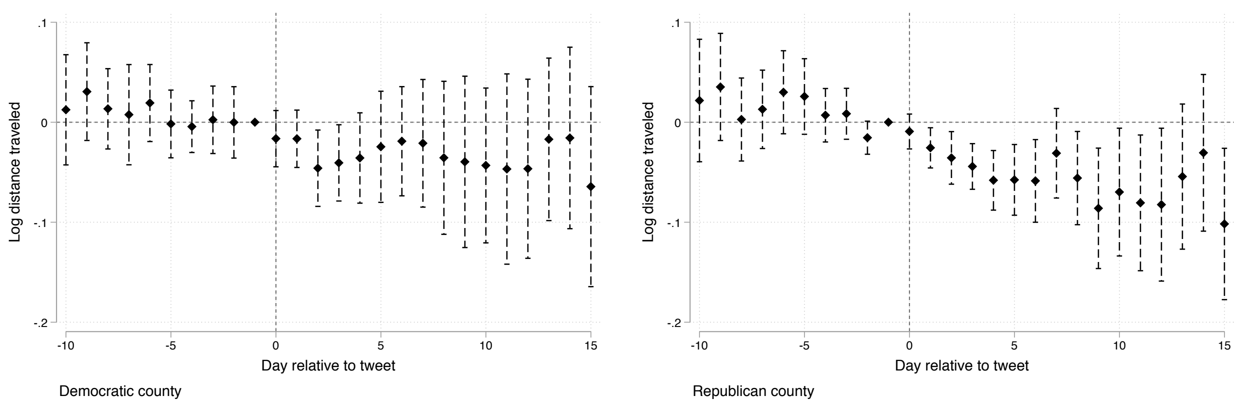
(a) Log time at home



(b) Share home all day

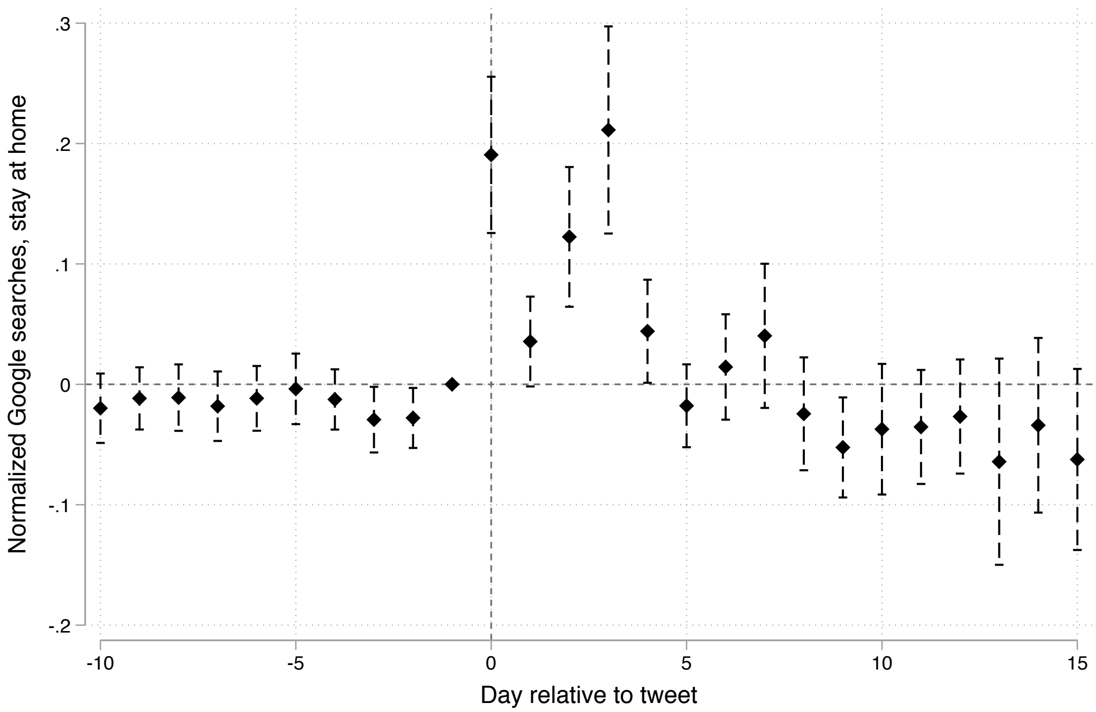


(c) Log distance traveled



Note: Figure shows coefficients from a county-level event-study regression of the outcome variable indicated in sub-figure 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. The sample is split into 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-9: 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. The outcome variable is the daily search interest for the phrase “stay at home” relative to a reference point.

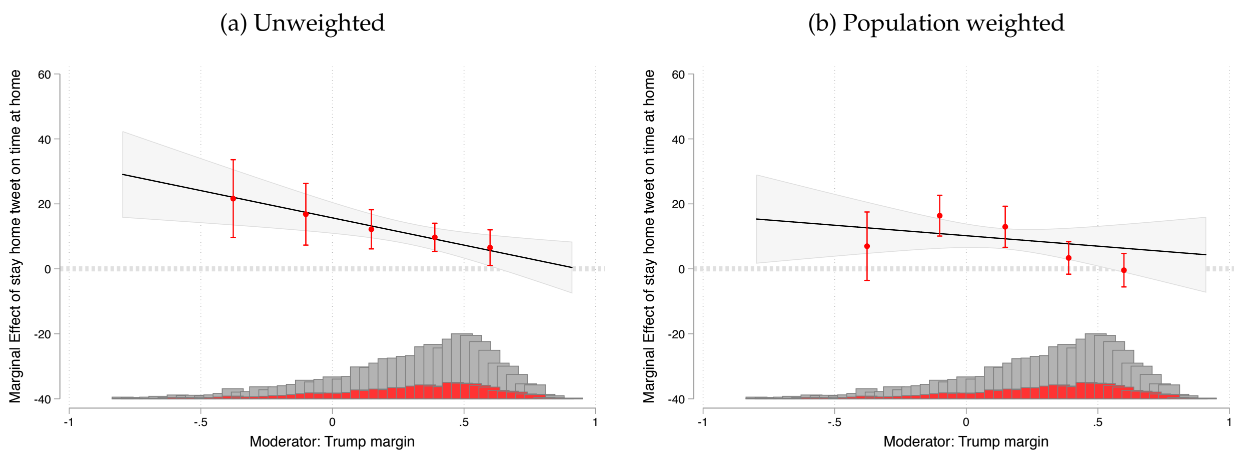
C.5 Predictive margins

Figure 3 in the main text estimates and plots 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-10, 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 the 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 negative and significant interaction term in Table 2 Panel A, column 2 (main text), there is a 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 remains negative, though it is flatter. This is because the binned estimates suggest that the effects on Trump's vote margin are nonlinear. 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.6.

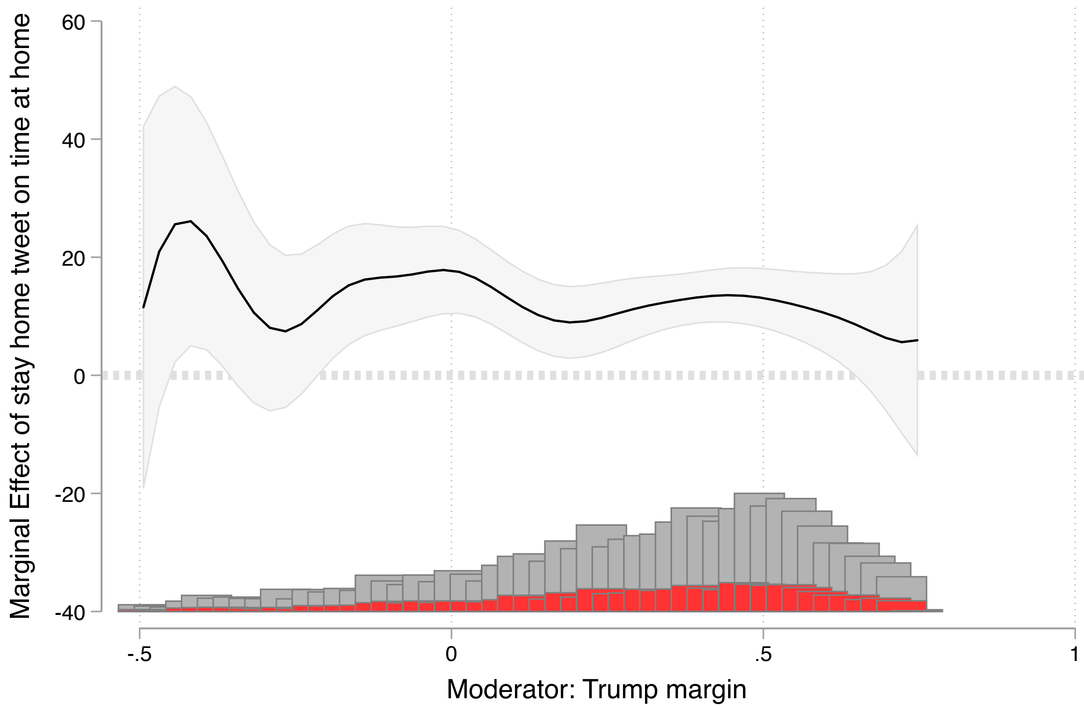
In Figure SI-11, we relax the linearity assumption entirely and re-estimate the predictive margins on the unweighted sample with a nonparametric kernel regression. Because the kernel regression is highly sensitive to sparse data at the boundaries, we exclude counties below a Trump margin of -0.5 and above 0.75, or 5% of the data. Firstly, we find evidence of substantial nonlinearities. In Democratic counties, the largest effects obtained were in areas that overwhelmingly supported Clinton–where the data is relatively sparse – 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, after which they are essentially monotonic in Trump share. Despite the apparent nonlinearities, the nonparametric curve generally slopes downward, suggesting that the overall linearity assumption is reasonable.

Figure SI-10: Predictive margins: effect of "stay home" tweet by Trump vote share, full sample



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 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 county-level Trump vote margin density by treatment status (red is treated, grey is untreated). Figure uses the INTERFLEX package from Hainmueller, Mummolo and Xu [3].

Figure SI-11: Predictive margins: effect of "stay home" tweet by Trump vote share, full sample, nonparametric 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 nonparametric kernel estimate of the marginal effect of the treatment at different levels of Trump vote share. The histogram below the predicted margins displays the county-level Trump vote margin density by treatment status (red is treated, grey is untreated). The sample is trimmed to a Trump vote margin between -0.5 and 0.75, or 95% of the data. Figure uses the INTERFLEX package from Hainmueller et al. [3].

D Supplementary results and robustness tests

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 significantly increase search interest for both terms in the full sample of metro areas. Columns (2)-(4) test whether these effects differ by partisan affiliation. We do not find the interaction between the treatment and Trump's 2016 metro-area-level vote margin significant, although, in both panels, it is of the correct sign. Splitting the sample by local partisan affiliation reveals that Democratic and Republican metro areas are 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. The interaction estimates in columns (5) and (6) do indicate smaller effects under Republican governors, a pattern more pronounced in Democratic metro areas. However, these estimates are not significant.

Table SI-2 tests the hypothesis that the response to governors' tweets should vary over time, particularly that behavior should respond more during 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 primary 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 and cumulative tweets in the past 1, 3, or 5 days. In general – and consistent with the event study results – we find that effects materialize 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 governors. Across both outcome variables, the main effect is similar among Democratic and Republican governors. However, the interaction effects differ starkly. In Panel A, the interaction term is mildly positive but insignificant, suggesting minimal partisan differentiation in response when a Democratic governor issues a tweet. 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 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 message	0.108**	0.115**	0.127**	0.109**	0.164***	0.141***
	(0.032)	(0.035)	(0.038)	(0.034)	(0.043)	(0.036)
Post stay home message × Trump vote share		-0.004				
		(0.006)				
Post stay home message × GOP governor					-0.086	-0.068
					(0.063)	(0.060)
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	0.413	0.413	0.430	0.421	0.442	0.432
Panel B: Search interest for "shelter in place"						
Post stay home message	0.197**	0.271**	0.328*	0.151*	0.375*	0.212*
	(0.069)	(0.095)	(0.141)	(0.058)	(0.146)	(0.090)
Post stay home message × Trump vote share		-0.049				
		(0.028)				
Post stay home message × GOP governor					-0.290	-0.110
					(0.182)	(0.120)
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	0.409	0.413	0.493	0.385	0.521	0.398

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 messages, 3 days	2.713***				0.423			
	(0.828)				(0.394)			
Cumulative stay home messages, 5 days		2.300***				1.141***		
		(0.689)				(0.316)		
Post stay home message			11.739***				11.023**	
			(3.418)				(5.407)	
Stay home messages, $t-1$				3.658**				1.381***
				(1.759)				(0.461)
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
Other tweets	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	79329	79329	79329	76230	15361	15361	15361	15360
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. The sample is 94,690 county days from 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 household income, population density, share of population over 65, share black, share Hispanic, and share male. "COVID controls" include controls for county-level confirmed cases and state-level COVID-19 deaths. "Other tweets" includes controls for post-COVID and social distancing-related tweets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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 message	12.768***	10.222**	0.024**	0.007
	(3.111)	(4.348)	(0.009)	(0.012)
Post stay home message × Trump vote margin		1.039		0.007**
		(0.871)		(0.003)
Observations	42750	42750	42750	42750
R^2	0.983	0.983	0.997	0.997
Panel B: Republican governors				
Post stay home message	5.609	20.413***	0.040***	0.068***
	(4.905)	(7.117)	(0.013)	(0.021)
Post stay home message × Trump vote margin		-3.703***		-0.007*
		(0.902)		(0.004)
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
Other tweets	Yes	Yes	Yes	Yes
Orders	Yes	Yes	Yes	Yes

Standard errors clustered at the state level. The sample is 94,690 county days from 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. Republican counties are those in which Trump's 2016 vote margin was greater than zero. County-level demographic controls are median age, log household income, population density, share of population over 65, share black, share Hispanic, and share male. "COVID controls" include controls for county-level confirmed cases and state-level COVID-19 deaths. "Other tweets" includes controls for post-COVID and social distancing-related tweets. "Orders" includes controls for whether the state has issued the following 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 Robustness to occupational, income, density, and media controls

We find in Tables 2 and SI-3 that Trump-supporting counties are less likely to respond to governors' stay-at-home messaging and that this relationship is more pronounced under Republican governors. However, political conservatism may be correlated with omitted variables that influence the responsiveness to messaging. In particular, these counties may be poorer, less dense, or have different occupational compositions, which may affect how individuals can adjust their mobility behavior in response to messaging. In this case, we must include these variables interacted with the treatment variable itself.

In Table SI-4, we consider the robustness of the main results to controlling for the interaction between the treatment variable and several covariates, including the share of the working-age population employed in retail, service, and manufacturing occupations, the log of household income, and population density. In Panel A we consider the full sample, while Panels B and C consider the sample of states with Democratic and Republican governors, respectively. Columns 1 and 2 compare the main estimates with and without occupational controls, column 3 re-prints the main interaction specification with Trump margin, while columns 4-8 include the interaction of each of these covariates with the treatment. We re-center these covariates around their sample median so that the level effect of the treatment variable can be interpreted as the daily effect of the stay-home tweet in a county where Trump's margin is zero and the covariate is set to its median value.

Panel A shows that for each specification, Trump-supporting counties remain significantly less likely to comply with stay-home messaging, and these interaction coefficients are remarkably stable. The pattern of results holds in Panels B and C as well: the interaction with Trump margin remains positive and insignificant under Democratic governors but negative and significant under Republican governors. None of the interactions are significant at conventional levels. Neither the main nor differential effects are driven by income, density, or employment composition.

In Table SI-5, we estimate robustness of the main results to controlling for the interaction between the treatment and covariates measuring TV and social media exposure from the 2018 Cooperative Congressional Election Study, including the share of the population getting news from TV, cable news, and social media, as well as the share of the population getting political news from social media. The sample for which these data are available is only 81,947 county-days. The main interaction effects are smaller in magnitude and no longer significant (Panel A). However, the comparison between columns 3 and 4-7 reveals that this is driven by the restricted sample rather than endogeneity of partisanship. The differential effects by governors' party remain significant (Panels B and C).

Table SI-4: Governors' stay home tweets and mobility, robustness to covariates

Outcome	Median time at home							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Full sample								
Post stay home message	10.409***	10.489***	15.694***	15.465***	15.433***	15.619***	15.897***	15.175***
	(3.542)	(3.587)	(4.697)	(4.743)	(4.736)	(4.671)	(4.809)	(4.731)
Post stay home message × Trump vote margin			-1.679**	-1.596**	-1.584**	-1.777**	-1.687**	-1.536**
			(0.707)	(0.706)	(0.720)	(0.686)	(0.706)	(0.721)
Post stay home message × Share retail				1.016				
				(0.730)				
Post stay home message × Share service					0.074			
					(0.530)			
Post stay home message × Share manufacturing						0.541		
						(0.327)		
Post stay home message × Log household income							-6.877	
							(8.425)	
Post stay home message × Population density								0.002
								(0.003)
Observations	94690	94690	94690	94690	94690	94690	94690	94690
R^2	0.984	0.984	0.984	0.984	0.984	0.984	0.984	0.984
Panel B: Democratic governors								
Post stay home message	12.768***	12.395***	10.222**	9.910**	8.834*	9.999**	8.742*	7.925*
	(3.111)	(3.086)	(4.348)	(4.356)	(4.697)	(4.329)	(4.335)	(4.328)
Post stay home message × Trump vote margin			1.039	1.021	1.170	0.972	1.281	1.503
			(0.871)	(0.856)	(0.884)	(0.870)	(0.876)	(0.881)
Post stay home message × Share retail				-0.123				
				(0.849)				
Post stay home message × Share service					0.885			
					(0.706)			
Post stay home message × Share manufacturing						0.112		
						(0.397)		
Post stay home message × Log household income							8.764	
							(8.378)	
Post stay home message × Population density								0.007**
								(0.003)
Observations	42750	42750	42750	42750	42750	42750	42750	42750
R^2	0.983	0.983	0.983	0.983	0.983	0.983	0.983	0.983
Panel C: Republican governors								
Post stay home message	5.609	5.233	20.413***	19.496**	19.903**	19.048**	18.981***	21.088***
	(4.905)	(4.968)	(7.117)	(7.218)	(7.382)	(7.235)	(6.642)	(7.215)
Post stay home message × Trump vote margin			-3.703***	-3.624***	-3.709***	-3.701***	-3.509***	-3.889***
			(0.902)	(0.923)	(0.965)	(0.885)	(0.849)	(0.882)
Post stay home message × Share retail				1.689*				
				(0.876)				
Post stay home message × Share service					-0.160			
					(0.851)			
Post stay home message × Share manufacturing						0.517*		
						(0.300)		
Post stay home message × Log household income							-19.837	
							(12.242)	
Post stay home message × Population density								-0.011
								(0.016)
Observations	51940	51940	51940	51940	51940	51940	51940	51940
R^2	0.985	0.985	0.985	0.985	0.985	0.985	0.985	0.985
Trump margin × Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographics × Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation shares × Day FE	No	Yes	No	Yes	Yes	Yes	Yes	Yes
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other tweets	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Orders	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors clustered at the state level. The sample is 94,690 county days from 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. Republican counties are those in which Trump's 2016 vote margin was greater than zero. All other variables that interacted with the treatment indicator are centered around their county-level median values. County-level demographic controls are median age, log household income, population density, share of population over 65, share black, share Hispanic, and share male. Occupation shares are the county-level employment shares of retail, services, and manufacturing workers. "COVID controls" include controls for county-level confirmed cases and state-level COVID-19 deaths. "Other tweets" includes controls for post-COVID and social distancing-related tweets."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-5: Governors' stay home tweets and mobility, robustness to media exposure

Outcome	Median time at home						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Full sample							
Post stay home message	13.262***	13.357***	17.052***	17.073***	17.343***	16.937***	17.144***
	(3.746)	(3.732)	(4.736)	(4.717)	(4.710)	(4.803)	(4.713)
Post stay home message × Trump vote margin			-1.285*	-1.303*	-1.324*	-1.266	-1.276
			(0.764)	(0.769)	(0.766)	(0.777)	(0.767)
Post stay home message × TV news share				-0.032			
				(0.047)			
Post stay home message × Cable news share					-0.090*		
					(0.051)		
Post stay home message × Social media share						-0.040	
						(0.075)	
Post stay home message × Social media politics share							-0.056
							(0.050)
Observations	81947	81947	81947	81947	81947	81947	81947
R^2	0.988	0.988	0.988	0.988	0.988	0.988	0.988
Panel B: Democratic governors							
Post stay home message	15.555***	15.532***	12.774***	12.998***	12.767***	12.739***	12.808***
	(3.581)	(3.538)	(4.284)	(4.207)	(4.185)	(4.382)	(4.217)
Post stay home message × Trump vote margin			1.201	1.220	1.187	1.182	1.178
			(0.751)	(0.757)	(0.744)	(0.757)	(0.763)
Post stay home message × TV news share				0.068			
				(0.072)			
Post stay home message × Cable news share					0.020		
					(0.070)		
Post stay home message × Social media share						-0.014	
						(0.113)	
Post stay home message × Social media politics share							-0.004
							(0.064)
Observations	37995	37995	37995	37995	37995	37995	37995
R^2	0.987	0.987	0.987	0.987	0.987	0.987	0.987
Panel C: Republican governors							
Post stay home message	7.632	7.609	19.079**	18.804**	19.237**	19.023**	19.124**
	(5.036)	(4.990)	(7.614)	(7.548)	(7.533)	(7.771)	(7.530)
Post stay home message × Trump vote margin			-3.042**	-3.085***	-3.091***	-3.048**	-3.041**
			(1.097)	(1.096)	(1.094)	(1.132)	(1.111)
Post stay home message × TV news share				-0.099*			
				(0.055)			
Post stay home message × Cable news share					-0.152**		
					(0.064)		
Post stay home message × Social media share						-0.021	
						(0.096)	
Post stay home message × Social media politics share							-0.056
							(0.074)
Observations	43952	43952	43952	43952	43952	43952	43952
R^2	0.989	0.989	0.989	0.989	0.989	0.989	0.989
Trump margin × Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographics × Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation shares × Day FE	No	Yes	No	Yes	Yes	Yes	Yes
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other tweets	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Orders	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors clustered at the state level. The sample is 81,947 county-days from March 1-March 31, 2020, for which CCES media exposure data is available. 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. Republican counties are those in which Trump's vote margin in 2016 was greater than zero. All other variables that interacted with the treatment indicator are centered around their county-level median values. County-level demographic controls are median age, log household income, population density, share of population over 65, share black, share Hispanic, and share male. Occupation shares are the county-level employment shares of retail, services, and manufacturing workers. "COVID controls" include controls for county-level confirmed cases and state-level COVID-19 deaths. "Other tweets" includes controls for post-COVID and social distancing-related tweets."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 Other outcome variables

We have argued that time spent at home is 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-6, 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 0.18 percentage points per day and reduce the distance traveled by 4.2%, the latter being significant at the 5% level. 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 coefficient for stay-home messaging is now significant in the Democratic sample (column 1) and more than five times the magnitude of the insignificant coefficient for Republican counties (column 2). In Panel C, we find some evidence that the triple-interaction effects observed in Table 2 carry over to these other outcome variables, though the triple-interaction terms are not significant. Overall, the finding that tweets matter, and differentially so by county partisan lean, appears robust. However, the final finding is that these effects vary depending on the governor's identity and hold only for the median time at home outcomes.

Table SI-6: 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 message	0.186	0.778**	-0.042**	-0.025
	(0.278)	(0.339)	(0.017)	(0.019)
Post stay home message × Trump vote margin		-0.188***		-0.006
		(0.054)		(0.004)
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 message	1.035***	0.206	-0.030*	-0.039**
	(0.338)	(0.284)	(0.017)	(0.016)
Observations	14708	79982	14708	79982
R^2	0.993	0.989	0.999	0.999
Panel C: Triple interactions				
Post stay home message	1.024**	1.475***	-0.026	-0.014
	(0.426)	(0.529)	(0.016)	(0.023)
Post stay home message × GOP governor	-0.464	-0.400	-0.003	-0.018
	(0.697)	(1.127)	(0.032)	(0.039)
Post stay home message × Trump vote margin	-0.236***		-0.003	
	(0.081)		(0.004)	
Post stay home message × GOP governor × Trump vote margin	0.074		-0.003	
	(0.119)		(0.006)	
Post stay home message × GOP county		-1.306***		-0.021
		(0.466)		(0.026)
Post stay home message × GOP governor × GOP county		-0.191		-0.012
		(1.034)		(0.044)
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
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
Other tweets	Yes	Yes	Yes	Yes
Orders	Yes	Yes	Yes	Yes

Standard errors in parentheses clustered at the state level. The sample is 93,030 county-days from 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 household income, population density, share of population over 65, share black, share Hispanic, and share male. "Orders" includes controls for whether the state has issued the following orders: emergency declarations, banning large gatherings, school closures, restaurant/bar closures, non-essential business closures, and stay-at-home orders. The footer at the bottom of the table refers to all specifications, while the footer after Panel C refers only to that panel. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

D.4 Definition of treatment variable

Throughout the paper, we exploit a "staggered adoption" differences-in-differences design where the treatment indicator of interest equals one in all periods after the governor initially issues a stay-at-home tweet. In this section, we consider the robustness of the main results concerning different definitions of the treatment variable. We begin in Table SI-7 by investigating whether the main effects differ when considering tweets that recommend social distancing but fall short of calling on citizens to stay home. As Figure 1 in the main text shows, these communications typically precede those about staying at home. They are therefore also of interest in understanding changes in voluntary social distancing behavior in the earliest phase of the pandemic.

In Table SI-7, we compare the magnitude of the behavior change induced by a social distancing tweet to that of the stay-home tweet across our four 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 14.5 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 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 3.8 minutes per day, though this difference is not statistically significant. This greater effect is likely because governors' social distancing tweets predominantly occurred during the earlier phase of the pandemic – before prohibitions of large gatherings and closures of schools and businesses – 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-8 replicates the main results of Table 2, using social distancing tweets instead of stay-at-home tweets as the treatment of interest. Generally, the differential effects of partisan and governor identities observed in the main results are not obtained when considering social distancing tweets. In particular, the responses do not differ by Trump's 2016 margin (Panel A) and are 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-7: 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 message	10.648***		10.594***	0.035***		0.035***	0.195		0.194	-0.043**		-0.043**
	(3.875)		(3.549)	(0.010)		(0.009)	(0.281)		(0.280)	(0.018)		(0.017)
Post social distancing message		14.518***	14.467***		0.046***	0.046***		0.171	0.170		-0.049**	-0.049**
		(4.266)	(3.896)		(0.014)	(0.012)		(0.244)	(0.242)		(0.020)	(0.019)
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	0.997	0.997	0.997	0.990	0.990	0.990	0.999	0.999	0.999

Standard errors clustered at the state level. The 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 household income, population density, share of population over 65, share black, share Hispanic, and share male. "COVID controls" include controls for county-level confirmed cases and state-level COVID-19 deaths. "Orders" includes controls for whether the state has issued the following 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-8: 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 message	14.518***	15.599***	0.046***	0.041**
	(4.266)	(5.479)	(0.014)	(0.017)
Post social distancing message × Trump vote margin		-0.327		0.001
		(0.926)		(0.003)
Observations	94690	94690	94690	94690
R^2	0.984	0.984	0.997	0.997
Panel B: By county party				
County party	Dem	GOP	Dem	GOP
Post social distancing message	16.152**	14.921***	0.022	0.046***
	(6.341)	(4.344)	(0.020)	(0.013)
Observations	14708	79982	14708	79982
R^2	0.985	0.984	0.997	0.998
Panel C: Triple interaction				
Post social distancing message	15.681**	16.435*	0.037*	0.045*
	(7.786)	(8.340)	(0.020)	(0.026)
Post social distancing message × GOP governor	-2.455	3.063	0.010	0.018
	(10.268)	(12.949)	(0.032)	(0.042)
Post social distancing message × Trump vote margin	-0.931		0.003	
	(1.456)		(0.004)	
Post social distancing message × GOP governor × Trump vote margin	1.249		-0.002	
	(1.831)		(0.007)	
Post social distancing message × GOP county		-3.283		0.002
		(7.748)		(0.022)
Post social distancing message × GOP governor × GOP county		-4.721		-0.023
		(12.346)		(0.041)
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	0.984	0.984	0.997	0.997
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. The sample is 94,690 county days from 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. Republican counties are those in which Trump's 2016 vote margin was greater than zero. County-level demographic controls are median age, log household income, population density, share of population over 65, share black, share Hispanic, and share male. "COVID controls" include controls for county-level confirmed cases and state-level COVID-19 deaths. "Orders" includes controls for whether the state has issued the following orders: emergency declarations, banning large gatherings, school closures, restaurant/bar closures, non-essential business closures, and stay-at-home orders. The footer at the bottom of the table refers to all specifications, while the footer after Panel C refers only to that panel. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

D.5 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 a different estimation approach, namely, allowing for random intercepts at the county level. Table SI-9 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 random effects results are generally very similar to those in Table 2, 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 12.2 minutes per day, compared with 10.4 under fixed effects. This corresponds to a 3.5% increase, significant at the 1% level. In column 2, the interaction with Trump's vote share is larger; 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 45% smaller in magnitude, though still significant under fixed effects.

In Panel B, columns 1 and 2 reveal very similar partisanship patterns – Trump-voting counties respond less than half as much to stay-at-home tweets, comparable 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, suggests that assumptions over the structure of county-specific heterogeneity are not particularly important. This indicates that time-invariant county-level heterogeneity is not substantially correlated with governors' messaging.

Table SI-9: 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 message	12.184***	21.023***	0.035***	0.046***
	(3.469)	(4.989)	(0.009)	(0.011)
Post stay home message × Trump vote margin		-2.878***		-0.003
		(0.942)		(0.002)
Observations	94690	94690	94690	94690
R^2	0.371	0.373	0.178	0.179
Panel B: By county party				
County party	Dem	GOP	Dem	GOP
Post stay home message	23.024***	10.891***	0.048***	0.034***
	(6.026)	(3.338)	(0.018)	(0.009)
Observations	14708	79982	14708	79982
R^2	0.509	0.381	0.300	0.185
Panel C: Triple interaction				
Post stay home message	15.749**	15.910*	0.033*	0.020
	(7.124)	(8.413)	(0.017)	(0.024)
Post stay home message × GOP governor	6.757	23.276*	0.028	0.092***
	(9.887)	(13.477)	(0.022)	(0.030)
Post stay home message × Trump vote margin	0.297		0.004	
	(1.529)		(0.005)	
Post stay home message × GOP governor × Trump vote margin	-4.477**		-0.013**	
	(1.944)		(0.005)	
Post stay home message × GOP county		0.610		0.027
		(6.900)		(0.022)
Post stay home message × GOP governor × GOP county		-39.872***		-0.127***
		(12.667)		(0.031)
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
Observations	94690	94690	94690	94690
R^2	0.375	0.376	0.181	0.183
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
Other tweets	Yes	Yes	Yes	Yes
Orders	Yes	Yes	Yes	Yes

Standard errors clustered at the state level. The sample is 94,690 county days from 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. Republican counties are those in which Trump's vote margin in 2016 was greater than zero. County-level demographic controls are median age, log household income, population density, share of population over 65, share black, share Hispanic, and share male. "COVID controls" include controls for county-level confirmed cases and state-level COVID-19 deaths. "Other tweets" includes controls for post-COVID and social distancing-related tweets. "Orders" includes controls for whether the state has issued the following orders: emergency declarations, banning large gatherings, school closures, restaurant/bar closures, non-essential business closures, and stay-at-home orders. The footer at the bottom of the table refers to all specifications, while the footer after Panel C refers only to that panel. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

D.6 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 to estimate the average county-level effect. Under population weighting, results will likely be driven primarily by larger, typically Democratic-leaning urban areas, whereas unweighted regressions allow us to uncover the effects across the political spectrum. This section considers how population weighting affects the main estimates.

Table SI-10 re-estimates the results from Table 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 10.2 more daily minutes at home, on average. However, in column (2), we find that the negative interaction term with Trump's 2016 vote margin is no longer statistically significant. This is likely because smaller pro-Trump counties previously driving this interaction effect have been down-weighted. In Panel B, the effect is positive and significant for both Republicans and Democrats but larger for Republicans, in contrast to the main results. Looking at the nonlinear pattern of effects in Figure SI-11, 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 be further left and have smaller effects than more centrist Democratic areas. Panel C of Table SI-10 reveals that the triple-interaction effect is still of the correct sign but smaller in magnitude and only significant for the logged dependent variable.

Table SI-11 re-estimates the results from Table SI-3 with county-level population weights. As in the unweighted regression, effects are still larger in Democratic rather than Republican states. The interaction terms with Trump's 2016 vote margin remain of the same sign, though the size and significance in Panel B are greatly diminished. The negative marginal effect slope in Republican states and the mildly positive marginal effect slope in Democratic states have both flattened.

Table SI-10: 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 message	10.162***	10.204***	0.019***	0.019***
	(3.506)	(3.543)	(0.007)	(0.007)
Post stay home message × Trump vote margin		-0.643		0.001
		(0.815)		(0.001)
Observations	94690	94690	94690	94690
R^2	1.000	1.000	1.000	1.000

Panel B: By county party

Outcome	Median time at home		Log time at home	
County party	Dem	GOP	Dem	GOP
Post stay home message	9.367**	11.754***	0.010	0.027***
	(4.425)	(3.563)	(0.008)	(0.007)
Observations	14708	79982	14708	79982
R^2	1.000	1.000	1.000	1.000

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 message	13.917**	12.862*	0.017*	0.008
	(5.458)	(6.757)	(0.009)	(0.012)
Post stay home message × GOP governor	-9.246	-5.307	0.003	0.017
	(8.197)	(10.749)	(0.011)	(0.016)
Post stay home message × Trump vote margin	0.581		0.003**	
	(0.847)		(0.001)	
Post stay home message × GOP governor × Trump vote margin	-1.418		-0.004	
	(1.597)		(0.002)	
Post stay home message × GOP county		2.243		0.018
		(5.692)		(0.011)
Post stay home message × GOP governor × GOP county		-10.039		-0.032**
		(8.864)		(0.015)
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	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
Other tweets	Yes	Yes	Yes	Yes
Orders	Yes	Yes	Yes	Yes

Standard errors in parentheses clustered at the state level. All estimates are weighted by county-level population. The 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. Republican counties are those in which Trump's 2016 vote margin was greater than zero. County-level demographic controls are median age, log household income, population density, share of population over 65, share black, share Hispanic, and share male. "COVID controls" include controls for county-level confirmed cases and state-level COVID-19 deaths. "Other tweets" includes controls for post-COVID and social distancing-related tweets. "Orders" includes controls for whether the state has issued the following orders: emergency declarations, banning large gatherings, school closures, restaurant/bar closures, non-essential business closures, and stay-at-home orders. The footer at the bottom of the table refers to all specifications, while the footer after Panel C refers only to that panel.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table SI-11: 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 message	13.060**	13.305**	0.016	0.017*
	(5.091)	(4.888)	(0.009)	(0.009)
Post stay home message × Trump vote margin		0.605		0.003**
		(0.801)		(0.001)
Observations	42750	42750	42750	42750
R^2	1.000	1.000	1.000	1.000
Panel B: Republican governors				
Post stay home message	7.305*	8.341*	0.023***	0.024***
	(4.042)	(4.653)	(0.007)	(0.008)
Post stay home message × Trump vote margin		-0.841		-0.001
		(1.113)		(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
Other tweets	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. Republican counties are those in which Trump's vote margin in 2016 was greater than zero. County-level demographic controls are median age, log household income, population density, share of population over 65, share black, share Hispanic, and share male. "COVID controls" include controls for county-level confirmed cases and state-level COVID-19 deaths. "Other tweets" includes controls for post-COVID and social distancing related tweets. "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.7 Robustness: outliers

In Table SI-12, we re-estimate the primary results after dropping outliers or county-days with low device coverage. We define outliers as county-days where the median time at home was in the bottom or top 2.5% of the county-day distribution. Observations with low device coverage are those in which the number of reporting devices is less than 5% of the county population. After trimming outliers in columns 1-2, we find that the results are similar to the main results in Table 2. However, in columns 3-4, we find that after dropping county days with low device coverage, the main results in Panels A and B are stronger than in the full-sample. At the same time, the triple-interaction terms in Panel C are of the correct sign but no longer significant at the 5% level but only at the 10% level.

Table SI-12: Governors' tweets, partisanship, and mobility, robustness to outliers

Outcome	Median time at home			
Drop	Outliers		Low device count	
	(1)	(2)	(3)	(4)
Panel A: Full sample				
Post stay home message	9.874***	14.339***	12.997***	22.550***
	(3.389)	(4.474)	(3.462)	(5.122)
Post stay home message × Trump vote margin		-1.406*		-2.487***
		(0.724)		(0.858)
Observations	89981	89981	69394	69394
R^2	0.986	0.986	0.988	0.988
Panel B: By county party				
County party	Dem	GOP	Dem	GOP
Post stay home message	18.426**	9.498***	18.809***	12.964***
	(7.289)	(3.197)	(5.184)	(3.613)
Observations	13326	76655	6404	62990
R^2	0.987	0.987	0.991	0.988
Panel C: Triple interactions				
Interaction	Cont. vote margin	Binary	Cont. vote margin	Binary
Post stay home message	9.304	5.697	18.532**	20.646**
	(5.726)	(6.629)	(7.341)	(8.534)
Post stay home message × GOP governor	10.157	26.716**	1.250	15.223
	(7.598)	(10.461)	(9.267)	(18.455)
Post stay home message × Trump vote margin	1.709*		0.682	
	(0.930)		(1.694)	
Post stay home message × GOP governor × Trump vote margin	-5.137***		-3.439*	
	(1.195)		(1.840)	
Post stay home message × GOP county		10.151**		0.944
		(4.806)		(9.136)
Post stay home message × GOP governor × GOP county		-43.854***		-34.859*
		(9.297)		(17.955)
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
Other tweets	Yes	Yes	Yes	Yes
Orders	Yes	Yes	Yes	Yes
Observations	89981	89981	69394	69394
R^2	0.987	0.986	0.988	0.988
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
Other tweets	Yes	Yes	Yes	Yes
Orders	Yes	Yes	Yes	Yes

Standard errors in parentheses clustered at the state level. The sample is indicated in the table header. Outliers are county-days below the bottom 2.5% and above the top 2.5% of the distribution of median time at home. Low device counts are county days where the number of devices sampled is less than 5% of the population. 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. Republican counties are those in which Trump's 2016 vote margin was greater than zero. County-level demographic controls are median age, log household income, population density, share of population over 65, share black, share Hispanic, and share male. "COVID controls" include controls for county-level confirmed cases and state-level COVID-19 deaths. "Other tweets" includes controls for post-COVID and social distancing-related tweets. "Orders" includes controls for whether the state has issued the following orders: emergency declarations, banning large gatherings, school closures, restaurant/bar closures, non-essential business closures, and stay-at-home orders. The footer at the bottom of the table refers to all specifications, while the footer after Panel C refers only to that panel. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

D.8 Robustness: local orders

Local social distancing policies often pre-dated state-level policies. According to data from the COVID-19 Local Action Tracker, 178 US cities covering 62.9 million inhabitants independently implemented COVID-19 containment or curve-flattening policies – up to and including full lockdowns – during March. The earliest such policy occurred on March 4th, just one day after the first governor in our sample began tweeting about social distancing. These local actions may be correlated across time and space with governors' messaging and could, therefore, bias our difference-in-differences results. Furthermore, given the geography of US partisanship, if these local actions are concentrated primarily in urban areas, they will affect mainly democratic counties. Therefore, These local policies could account for the differential partisan response to governors' messages if they correlate in time with these state-level messages and are concentrated in Democratic-leaning urban areas of states where governors send these messages.

To rule out this confounding effect, we re-estimate the main specifications controlling directly for time-varying local policies. We consider all local policies that are in any way directed at "prevention/ cure-flattening," using the coding system of the COVID-19 Local Action Tracker. Since these orders are issued at the city level, we define an indicator variable equal to one if a county contains a city implementing a COVID-19 containment policy. We also test the robustness of interacting this variable with the share of the county population affected by the order or measuring it as the cumulative number of local policy orders.

The results are presented in Table SI-13. Columns 1-4 estimate the main effect of governors' messaging, while columns 5-8 estimate the differential effect by partisanship. The baseline results are re-printed in columns (1) and (5) for reference. Overall, the estimates indicate that neither the main effects nor the interactions with partisanship are changed by including controls for local policy actions. Once local policy controls are included, all effects retain the same sign, significance, and magnitude. Reassuringly, the coefficients on the local policy covariate are of the correct sign and significant for all measures except the population share. The results suggest that local policies also lead to a significant reduction in county-level mobility but are largely orthogonal to governors' messaging and local patterns of partisan response to this messaging.

Table SI-13: Governors' tweets, partisanship, and mobility, robustness to local orders

Outcome	Median time at home							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post stay home message	10.409***	10.439***	10.364***	10.387***	15.694***	15.682***	15.446***	15.621***
	(3.542)	(3.545)	(3.555)	(3.546)	(4.697)	(4.688)	(4.696)	(4.705)
Post stay home message × Trump vote margin					-1.679**	-1.666**	-1.614**	-1.662**
					(0.707)	(0.704)	(0.703)	(0.709)
Local policy active		12.287**				12.190**		
		(5.114)				(5.022)		
Cumulative local policies			3.941***				3.835***	
			(1.258)				(1.235)	
County population share covered by local policy				0.174				0.170
				(0.128)				(0.128)
Observations	94690	94690	94690	94690	94690	94690	94690	94690
R^2	0.984	0.984	0.984	0.984	0.984	0.984	0.984	0.984
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Demographics × Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Trump margin × Day FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
COVID controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other tweets	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Orders	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses clustered at the state level. 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. "Local policy active" is a dummy variable equaling one every day after the first city-level containment order occurs in a given county. "Cumulative local policies" is the cumulative number of city-level orders in a given county as of time t. "County population share covered by local policy" interacts the "local policy active" dummy with the maximum share of the county-level population affected by an order. County-level demographic controls are median age, log household income, population density, share of population over 65, share black, share Hispanic, and share male. "COVID controls" include controls for county-level confirmed cases and state-level COVID-19 deaths. "Other tweets" includes controls for post-COVID and social distancing-related tweets. "Orders" includes controls for whether the state has issued the following 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.9 Robustness: block-group-level data

Our main results use counties as the unit of analysis, which geographically aggregates individual political preferences, which we do not observe. As such, they may be affected by an ecological inference problem — we cannot say whether Democratic vs. Republican *voters* are responding differentially, only that the effects vary by average county-level partisan skew. For us to observe the county-level results of Table 2 in the absence of any differential partisan response at the individual level, it must be the case that Republicans respond more than Democrats in Democratic counties. At the same time, the reverse is true in Republican counties. We see no reason ex-ante that this would be the case; in fact, we note that recent survey evidence is supportive of individual-level partisan differences in self-reported social distancing beliefs and behavior [1, 2].

Still, we attempt to allay this ecological inference critique using more disaggregated data. Individual voter-level mobility and partisanship data are not available. However, Safegraph mobility data is available at the census block group level, a standardized census unit containing 600-3000 people. Electoral data is available at the precinct level, the smallest voting unit defined by the state government, containing an average of 833 voters in 2016. At this level of disaggregation, political preferences are substantially more homogenous, and it is difficult to argue that offsetting individual effects drives the results. Figure SI-12 plots the distribution of Trump's vote margin separately at the block-group and county levels. The tails of the distribution, particularly the left tail, have much greater mass at the block-group level, indicating a greater density of extreme voting in the disaggregated data.

Several issues arise when replicating our main specifications at the census block group level. Firstly, electoral precincts and block groups vary in geographic extent, and there is no precise geographic mapping between the two (in some states, the former is larger, in others, the latter). To match census block groups to electoral precincts, we identify the geographical intersections between each set of units. We then define the political preferences at the block-group level as the weighted average of Trump's 2016 vote margin for all precincts that intersect a given block group, where the weights are the share of the block-group geographic area that falls within a given electoral precinct.

Secondly, precinct-level electoral data with accompanying geographic information is only available for 38 states.[2] Since the variation of interest (governors' statements) occurs at the state-level, this substantially reduces an already-small number of clusters, with implications for statistical power. These states also may not be representative of the whole country.

[2] These states are AZ, AR, CA, CO, DE, FL, GA, HI, IA, IL, KS, KY, LA, MA, MD, ME, MI, MN, MO, MT, NC, ND, NE, NH, NM, NV, OK, OR, RI, SC, TN, TX, UT, VA, VT, WA, WI, WY

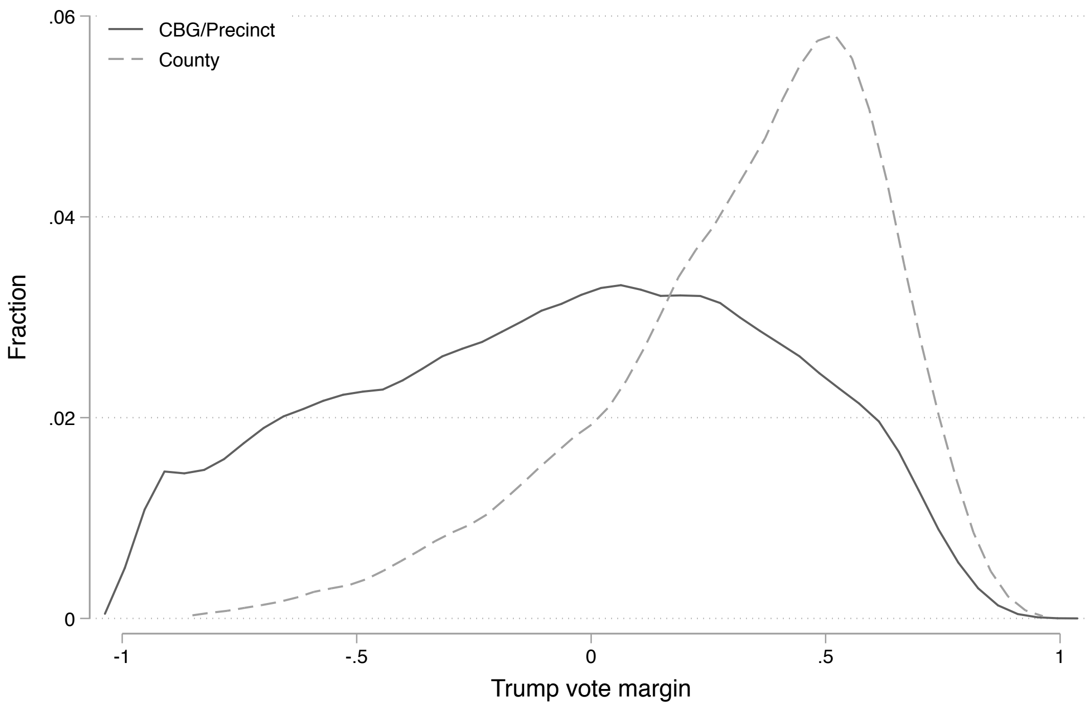
Finally, there is substantially less heterogeneity in population size at the block-group level than at the county level. As such, unweighted estimates at the block group level cannot be directly compared to unweighted county-level estimates and are, in fact, closer to the population-weighted estimates in SI D.6. To address this issue, we also present re-weighted block-group-level estimates, where the weights are the inverse of the number of block groups in a county. This serves to up-weight more sparsely populated counties with fewer block groups so that the weights more closely resemble those implicit in the main unweighted county-level specification. For these reasons, we emphasize the county-level results of our main specifications.

We present the block-group-level estimates in Table SI-14. To ensure a comparable sample, we first re-estimate the main (column 1) and partisan interaction (column 2) effects on the county-level data for the subsample of 38 states for which precinct-level data is available, presenting results for the pooled sample (Panel A), Democratic governors (Panel B), and Republican governors (Panel C). We then re-estimate the main (column 3) and partisan interaction (columns 4-6) effects on the block-group-level data. For the partisan interaction effects, we consider county fixed effects (column 4), block-group fixed effects (column 5), and block-group fixed effects with inverse county size weights (column 6).

Column 1, Panel A shows that the county-level effect in the 38-state sample is smaller in magnitude than in the full sample in Table 2 (8.4 minutes vs. 10.4 minutes). However, the interaction, in effect, is somewhat larger. The main effects at the precinct level in Panel A, column 3 remain positive and significant – governors' messaging leads to 13.8 additional minutes spent at home per day on average. The baseline and interaction effects in column (4) are smaller than the county-level effects in column (2), and the interaction term is no longer significant. The interaction term is negative but much smaller in column (5). However, when we re-weight in column (6) to match the county-level results, the interaction term is negative, significant, and very similar in magnitude to the county-level results of column (2).

The main result of Table SI-3 and Table 2 Panel C is that the differential partisan response is greatest under Republican governors. The block-group-level results of Table SI-14 Panels B and C generally support these findings. In Democratic states (Panel B), there is no differential partisan response regardless of the specification choice. In contrast, in Republican-controlled states (Panel B), the interaction effect is negative and significant except in the unweighted specification with block-group fixed effects (column 5), where it is still negative but smaller in magnitude and insignificant. Note that in Panel C, the interaction terms in columns (4) and (6) – both 3.1 – are similar to the 3.81 estimated in column (2). At the same time, note that the unweighted estimates in Panels B and C column (5) are similar in magnitude to the population-weighted county-level results in Table SI-10 column (2) Panels A and B, respectively. This suggests that the more uniform size of census block groups drives the divergence between unweighted county and block-group-level results, implying that re-weighting is necessary to preserve comparability with the main county-level results.

Figure SI-12: Distribution of Trump's 2016 vote margin



Note: Figure shows the distribution of Trump's vote margin in the 2016 presidential election at the counties and census-block-groups (CBG) level.

Table SI-14: Governors' stay home tweets and mobility by governor's party, census block-group-level

Outcome	Median time at home					
Unit	County		Census block-group			
Weights			Unweighted			Re-weighted
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full sample						
Post stay home message	8.379*	18.599***	13.848***	12.784***	13.607***	13.449**
	(4.282)	(5.954)	(3.675)	(3.498)	(3.530)	(5.124)
Post stay home message × Trump vote margin		-2.254**		-1.528	-0.100	-1.964**
		(1.077)		(0.959)	(0.733)	(0.841)
Observations	74709	74709	4680873	4680873	4680873	4680873
R^2	0.787	0.789	0.709	0.268	0.710	0.671
Panel B: Democratic governors						
Post stay home message	9.546*	9.413	5.632	6.367	6.426	6.553
	(4.873)	(6.880)	(4.189)	(4.227)	(4.256)	(4.989)
Post stay home message × Trump vote margin		0.442		0.894	1.438**	0.324
		(1.308)		(0.943)	(0.662)	(0.624)
Observations	36157	36157	2597094	2597094	2597094	2597094
R^2	0.794	0.795	0.708	0.275	0.708	0.664
Panel C: Republican governors						
Post stay home message	1.109	20.759**	10.303**	12.140**	11.275**	12.405**
	(3.653)	(8.296)	(3.888)	(4.310)	(4.075)	(5.742)
Post stay home message × Trump vote margin		-3.807**		-3.081**	-0.818	-3.116***
		(1.611)		(1.106)	(0.942)	(1.005)
Observations	38552	38552	2083779	2083779	2083779	2083779
R^2	0.783	0.785	0.708	0.244	0.708	0.680
County FE	Yes	Yes	No	Yes	No	No
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
CBG FE	No	No	Yes	No	Yes	Yes
Trump margin × Day FE	No	Yes	No	Yes	Yes	Yes
Other tweets	Yes	Yes	Yes	Yes	Yes	Yes
Orders	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors clustered at the state level. The sample is 74,709 county days or 4,680,873 block group days from March 1-March 31, 2020, for 38 states. Treatment indicator equals one for all days after the governor of state s issues a tweet about social distancing. Re-weighted specifications weight the estimates by the inverse of county size, measured by the number of block groups. "Trump vote margin" is census block group i's vote margin for Donald Trump in the 2016 presidential election, calculated as the weighted average Trump margin of all of the electoral precincts geographically intersecting i, where the weights are the share of area intersected. "Other tweets" includes controls for post-COVID and social distancing-related tweets. "Orders" includes controls for whether the state has issued the following 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.10 Robustness: specification choice and county-specific time trends

In Figure SI-7, we present evidence that there are no differential pre-trends in social distancing outcomes before a governor's initial stay-at-home messaging, increasing our confidence in the identification assumption of parallel trends required for the main estimates to be interpreted as causal effects of governors' messaging. In this section, we consider an additional test of this identification assumption. In particular, counties receiving stay-home messaging may follow differential trends in outcomes after the message for unrelated reasons, biasing our causal estimate even without obvious pre-trends.

To address this concern, in Table SI-15, we augment the main difference-in-differences specification with interactions between the county fixed-effects and linear time trends, allowing for county-specific linear trends in social distancing outcomes. We also consider robustness to removing or including the main control variables — COVID case counts, state-level policy orders, other governors' messaging, and interacted county demographics. In general, we find that the main results hold. Conditional on county-specific linear time trends, governors' stay-at-home messaging still increases time at home from 5-9 minutes daily, on average, depending on specification choice. As before, these effects are more pronounced in Democratic counties (Panel B) than in Republican ones (Panel C). However, the results lose significance in column (8).

In general, the effects are smaller when county-specific time trends are included. We maintain that county-specific time trends are too exacting for a robustness test. This test requires that social distancing rises in treated counties relative to control ones and that it does so supra-linearly. Treatment effects now measure deviations above the linear trend in treatment relative to control counties rather than level differences. In practice, this requires a large jump in social distancing in treated counties at the time of the messaging rather than a gradual increase. Of course, Figure SI-7 demonstrates that we indeed find a gradual increase in social distancing behavior in response to governors' messaging. This dynamic pattern is consistent with governors' repeated messaging after an initial statement. As such, including county-specific time trends may not be appropriate in our setting. Even so, we find that the results hold, albeit at somewhat smaller magnitudes.

Table SI-15: Governors' stay-home tweets and mobility, county-specific time trends

Outcome	Median time at home					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full sample						
Post stay home message	20.859***	9.308***	10.617***	6.354**	8.617**	5.033*
	(3.855)	(3.109)	(3.911)	(2.547)	(3.953)	(2.774)
Observations	94690	94690	94690	94690	94690	94690
R^2	0.790	0.822	0.792	0.823	0.803	0.828
Panel B: Democratic counties						
Post stay home message	34.723***	7.890	21.187***	7.338	21.363***	8.479
	(7.852)	(5.711)	(6.112)	(5.633)	(7.693)	(5.621)
Observations	14708	14708	14708	14708	14708	14708
R^2	0.841	0.880	0.844	0.881	0.868	0.894
Panel C: Republican counties						
Post stay home message	17.876***	9.612***	9.015**	6.073**	8.458**	4.547
	(3.891)	(3.099)	(3.954)	(2.464)	(3.468)	(2.955)
Observations	79982	79982	79982	79982	79982	79982
R^2	0.778	0.806	0.779	0.807	0.789	0.813
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE $\times$ linear time trends	No	Yes	No	Yes	No	Yes
Demographics $\times$ Day FE	No	No	No	No	Yes	Yes
COVID controls	No	No	Yes	Yes	Yes	Yes
Other tweets	No	No	Yes	Yes	Yes	Yes
Orders	No	No	Yes	Yes	Yes	Yes

Standard errors clustered at the state level. The sample is 94,690 county days from March 1-March 31, 2020. Treatment indicator equals one for all days after the governor of state s issues a tweet about social distancing. Republican counties are those in which Trump's 2016 vote margin was greater than zero. County-level demographic controls are median age, log household income, population density, share of population over 65, share black, share Hispanic, and share male. "COVID controls" include controls for county-level confirmed cases and state-level COVID-19 deaths. "Other tweets" includes controls for post-COVID and social distancing-related tweets. "Orders" includes controls for whether the state has issued the following 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.11 Robustness: Facebook data as proxy for messaging

Our analysis uses Twitter posts as a proxy for governors' public messaging around COVID-19. We do not believe that Twitter is the only or even the most important, channel through which governors release public statements on COVID-19. However, we use tweets because they are a widely available public data source that succinctly captures governors' positions on these issues. They serve merely as a convenient and reliable proxy for messaging. Similar content, however, is released via other forums, notably governors' Facebook accounts. In Figure SI-3, we show that governors' content is highly correlated across social media platforms. The timing of governors' tweets encouraging citizens to stay-at-home behavior is highly correlated with the timing of Facebook posts with the same content.

Given this observation, we consider whether the main results replicate when we use Facebook activity as a proxy for messaging instead of Twitter activity. This may allay concerns that Twitter posts are not as widely seen as Facebook posts since Facebook is a more widely used social media platform. Table SI-16 estimates the main regressions on the full sample (Panel A), Democratic governors (Panel B), and Republican governors (Panel C) using the date of the first Facebook post encouraging residents to stay home to construct the treatment indicator. We find nearly identical direction, magnitude, and significance results to the main results using Twitter data.

Table SI-16: Governors' stay home Facebook posts and mobility

Outcome	Median time at home			
	(1)	(2)	(3)	(4)
Panel A: Full sample				
Post stay home message	12.827***	18.856***	0.040***	0.044***
	(4.630)	(5.518)	(0.012)	(0.015)
Post stay home message × Trump vote margin		-1.952**		-0.001
		(0.730)		(0.002)
Observations	94690	94690	94690	94690
R^2	0.984	0.984	0.997	0.997
Panel B: Democratic governors				
Post stay home message	19.160***	20.371***	0.035**	0.032*
	(5.552)	(5.942)	(0.017)	(0.016)
Post stay home message × Trump vote margin		-0.488		0.001
		(0.782)		(0.002)
Observations	42750	42750	42750	42750
R^2	0.983	0.983	0.997	0.997
Panel C: Republican governors				
Post stay home message	2.632	14.731*	0.033**	0.058**
	(5.651)	(8.113)	(0.015)	(0.026)
Post stay home message × Trump vote margin		-3.053***		-0.006
		(1.020)		(0.005)
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
Other tweets	Yes	Yes	Yes	Yes
Orders	Yes	Yes	Yes	Yes

Standard errors clustered at the state level. The sample is 94,690 county days from March 1-March 31, 2020. Treatment indicator equals one for all days after the governor of state s issues a Facebook post about social distancing. "Trump vote margin" is county i's vote margin for Donald Trump in the 2016 presidential election. County-level demographic controls are median age, log household income, population density, share of population over 65, share black, share Hispanic, and share male. "COVID controls" include controls for county-level confirmed cases and state-level COVID-19 deaths. "Other tweets" includes controls for post-COVID and social distancing-related Facebook posts. "Orders" includes controls for whether the state has issued the following orders: emergency declarations, banning large gatherings, school closures, restaurant/bar closures, non-essential business closures, and stay-at-home orders. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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