

Supplementary Materials for

Partisan pandemic: How partisanship and public health concerns affect individuals' social mobility during COVID-19

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This PDF file includes:

Materials and Methods
Figs. S1 to S18
Tables S1 to S3

Materials and Methods

Section S1: Study design materials and methods

All the data and code needed to replicate the study is available in Dryad at:

<https://doi.org/10.5061/dryad.3bk3j9khg>

To obtain our data, we interview of 1,135,638 randomly selected respondents from the Survey Monkey platform between April 4, 2020 and September 29, 2020. These individuals are randomly sampled from the approximately 2 million individuals who take Survey Monkey surveys every day.

The data we analyze was collected by Survey Monkey using respondents who have consented to participate in the Survey Monkey audience panel and surveys.

The privacy policy that Survey Monkey respondents agree to is available at:

<https://www.surveymonkey.com/mp/legal/privacy-policy/>

The privacy policy pertaining to survey research that respondents consent to when participating in Survey Monkey is available at:

<https://www.surveymonkey.com/mp/legal/survey-research-privacy-notice/>

The policy governing the content of Survey Monkey surveys is available at:

<https://www.surveymonkey.com/mp/legal/content-policy/>

The survey was written and administered by Survey Monkey and provided to the other collaborators on this project. Because the surveys were designed, administered, and collected by Survey Monkey and provided to the researchers, IRB approval was not required. In addition, because the survey data being provided to the researchers is anonymous and includes only non-sensitive data, the project would be IRB exempt even had the collaborators designed the survey questions being analyzed.

The anonymized data are weighted for age, race, sex, education, and geography using the Census Bureau's American Community Survey to reflect the demographic composition of the United States. An additional smoothing parameter for political party identification based on aggregates of SurveyMonkey research surveys is included. Weights are generated each day using daily interviews Monday through Friday, and once over combined interviews on Saturday and Sunday. Party identification parameters are refreshed bi-weekly.

Figure S1 Displays the number of valid responses to our key dependent variable on each day from April 4th to September 29, 2020.

The following question is asked to determine an individual's degree of social activity, which serves as our main dependent variable.

In the past 24 hours, have you left your home to do any of the following? (Select all that apply)

[Response order randomized]

- Go to work
- Go grocery shopping

- Exercise
- Go for a walk/get some fresh air
- Visit with friends of family
- Eat at a restaurant or bar
- Get medical care
- None of the above

To measure each individual's level of activity in the previous 24-hours, we add up the number of activities they reported participating in. We are cognizant of the fact that this combines activities that are voluntary (like going to a restaurant) and those that are involuntary (like getting medical care). Figure S2 displays the trends in each of these activities over our time, and clearly there is much more variation in more voluntary activities. To probe these differences, in Figure S4 and S5 below we report the partisan differences in each of these activities. While there is notable heterogeneity, in each activity the same pattern of partisan-motivated activity is present.

The following question was asked to gauge an individual's level of worried about COVID-19:

How worried are you that you or someone in your family will be exposed to the coronavirus?

- Very worried
- Somewhat worried
- Not too worried
- Not worried at all

To classify individuals as partisans they are asked the following questions:

In politics today, do you consider yourself a Republican, Democrat, or Independent?

- Republican
- Democrat
- Independent

[If respondent selects "Independent"] *As of today, do you lean more to the Republican or Democratic Party?*

- Republican
- Democrat
- Neither

If respondent answers Republican or Democrat in the first question, or leans towards either of those parties in the second question, they are classified accordingly. Respondents who select "Neither" on the second question are classified as "independent".

We also include two media questions to help determine whether partisan values are activated by media consumption.

To determine overall media diet we ask:

How much do you keep up with the news, regardless of whether you get it from television, newspapers, radio, or any other source?

- A lot
- Some
- Not Much
- Not Much at all

Individuals who answer “A lot” are coded as High News Consumers, and those that any otherwise are coded as non-High News Consumers.

To determine the proportion of an individual’s media diet that is made up of right-wing news sources we ask the following question:

Do you follow political news coverage by any of the following media organizations on a daily or almost daily basis?

- Breitbart
- BuzzFeed
- CNN
- Drudge Report
- FOX News
- MSNBC
- New York Times
- NPR
- Washington Post
- Wall Street Journal
- None of the above

Individuals are given a right-wing media score by dividing the number of right-wing media sources they report following (FOX News and Breitbart) by the total number of media sources they report following. As such, the maximum of this score is 1, and the minimum 0.

Data on COVID-19 prevalence comes from COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University. These data report, on each day, the number of COVID-19 cases in each county in the United States.

As a first data processing step, we use county population estimates from the American Community Survey to transform county cases to be cases per 1000 residents.

We then calculate for each county, for each week, the change in the number of cases from the previous week in that county, using the median number of cases in each county for each week.

Consider, for example, interviewing an individual in zip-code 37206 (in Davidson county on Nashville's East Side) on April 4th. On the week of April 4th in Davidson county (in which the zip-code is wholly contained) the median number of cases per 1000 was 1.001. In the week previous, the median number of cases per 1000 was .428. This individual, therefore, would be given the value .573 for change in county cases per 1000. This value is a fair representation of the fact that this individual, on this day, was witnessing a worsening public health situation in their immediate surrounding.

Survey Monkey respondents self-report their zip-code. To assign respondents to a county we determine the county in which the majority of the residents of that zip-code live in. For 86% of respondents, their zip-code is entirely contained within one county.

Finally, we merge the data on how the number of COVID-19 cases is changing in each county on each day to the Survey Monkey data.

Section S2. Method of Statistical Analysis

Our methodology estimates the following 4 models separately on each day t for individuals i in states j .

Equation 1

$$Last24_i = \alpha_j + \beta K_i + \epsilon_{ij}$$

Equation 2

$$Last24_i = \alpha_j + \gamma Democrat_i + \zeta Republican_i + \beta K_i + \epsilon_{ij}$$

Equation 3

$$Last24_i = \alpha_j + \eta County.Change.in.COVID.Cases_i + \beta K_i + \epsilon_{ij}$$

Equation 4

$$Last24_i = \alpha_j + \gamma Democrat_i + \zeta Republican_i + \eta County.Change.in.COVID.Cases_i + \beta K_i + \epsilon_{ij}$$

On each day, we regress the level of self-reported activity in the last 24 hours for individual i in state j on state fixed-effects (α_j) (to control for between-state differences) and a matrix of individual-level and zip-code level demographics (K_i). These demographics are gender (dummy for female), age (dummies for 18-24, 25-34, 34-44, 45-54, 55-64, 65+), race (dummies for White, Black, Asian, Hispanic, and other), education (dummies for less than high school, high school only, associates or some college, bachelor degree, postgraduate degree), income (dummies for below 29.9k, 30k-74.9k, 75k-149.9k, +150k), zip code population density (dummies for urban, suburban, and rural), and employment status (dummy for unemployed).

In all models, standard errors are clustered at the state level.

To estimate the coefficients of partial determination for Figure 2, we calculate the following equation using specifications 1, 2, & 3:

$$\delta_{2|3} = (SS_{res2|3} - SS_{res1})/SS_{res1}$$

Thus, the quantity $\delta_{2|3}$ is the proportion of unexplained variance in specification 1 that is explained by adding partisanship (in specification 2) or public health (in specification 3).

To obtain standard errors for these estimates we perform a bootstrapping procedure. On each day we randomly sample (with replacement) rows from the dataset to construct a bootstrap sample the same length as the day's original sample. In this bootstrap sample we estimate specifications 1-3 and record the coefficients of partial determination. We complete this procedure 1000 times per day. The standard errors in Figure 2 represent the 95% distribution of these bootstrap estimates.

Figure 3 represents the daily coefficients on the two-party variables and change in county cases on each day from specification (4). The 95% confidence intervals are derived from the standard errors from the OLS model, which are clustered by state.

The coefficients in Figure 4 come from regressions using specification (4) run separately in each state. For these regressions, individuals are pooled across days, so a polynomial time trend is employed. The values on the x axis are, for each state, the aggressiveness of their COVID-19 mitigation policy. The details of this measure can be found below in section S6.

Section S3. Robustness of Results: Using Specific Activity Measures instead of Sum Total

Our main dependent variable is an additive index of activities the respondent has participated in over the previous 24-hours. This scale includes both voluntary and involuntary activities. A reasonable critique is that partisanship's effects on this measure is being driven entirely by differential activity in voluntary activity.

To investigate this, we repeat our main analysis separately for each activity.

Figure S4 presents results from specification (4) run separately on each activity, pooled across time with a polynomial time trend. While there are important differences, in each activity partisanship is a significant differentiator for activity. As with the main results in the paper, these results cannot be explained by differences between states (as the models include state fixed effects), nor can they be explained by an individual's age, race, income, education, unemployment status, or population density of their community.

Figure S5 presents results from running specification (4) on each activity on each day, to determine the trends in the impact of partisanship. Interestingly, some activities (like going to work or walking) have seen persistent partisan differences across time. Others seem to be far more affected by time.

Section S4. Robustness of Results: Differences in Leaners and Identified Partisans

In Table S1 we present a pooled model using specification (4) where party "leaners" are separated. As mentioned in the main text, political science literature has consistently found that leaners behave in ways broadly similar to identified partisans. The results in this case support that conclusion. Democrat leaners and identified Democrats are similarly less likely to be socially active compared to Independents, and Republican leaners and identified Republicans are similarly more likely to be socially active compared to Independents. Indeed, in the case of levels of activity during this pandemic, being a leaner is *more* impactful than being an identified partisan. Table S2 presents a more restrictive model with Zip-Code fixed effects – which does

even more to control for the statutory environment an individual is living in. The results are unchanged: party has a robust effect on social behavior.

Section S5. Robustness of Results: Alternative Measures of COVID-19 Impact

For our main analyses we used as a measure of public health the weekly change in the number of cases per 1000 in a respondent's county. We believe that this is a reasonable measure of how an individual's immediate public health situation is changing. However, to show the robustness of our findings in this section we replicate Figure 2 in the paper using various other measures of public health: the weekly change in the number of deaths in an individual's county, the total number of cases in an individual's county, the total number of deaths in an individual's county, the weekly change in the number of cases in an individual's state, and the weekly change in the number of deaths in an individual's state. Note that for these last two measures we drop the state fixed effects from the specification, as otherwise the model would not be able to be estimated. All specifications show identical results to those found in the paper.

There is slightly more evidence of an effect of COVID-19 using the statewide measure. It may be that statewide numbers are more apparent to an individual through news reports than COVID incidence in their counties. We further investigate this possibility in Table S3, which re-runs specifications 1-4 using state change in COVID-19 cases in the previous week per 1000 state residents. Indeed, in this specification, the marginal effect on this variable is slightly higher. The coefficient of partial determination for change in state cases/1000 is .26, meaning that .26% of the residual variation in specification 1 is explained by the changing level of COVID-19 at the state level. This is slightly higher than .22% of variance explained by change in county cases/1000. Regardless, this state-level measure is still swamped by party. Overall, the two party variables explain 23 times more variation than the state-level measure of COVID-19 change.

An additional note is that it is impossible to determine whether a larger relationship between COVID incidence and social mobility at the state level is due to individuals reactions to the incidence of COVID in their community, or to statewide regulations. That is, individuals may be less mobile in states with a higher incidence of COVID simply because that state has taken more aggressive steps to limit mobility.

S6: Robustness in Results: Trends in Partisan Effects by State

Our main estimates of the impact of partisanship use state fixed-effects to rule out the relationships being driven by statutory regulations in different states. That is, these fixed-effects rule out democrats being less socially mobile because more democrats live in states which have more restrictive COVID mitigation laws. This being said, it may still be the case that the relationship between partisanship and distancing might be driven by the partisans in certain states, while other states have no differences.

Figure 4 in the main body of the paper displays the results of a pooled model between partisanship and distancing in each state, showing that there is a remarkably similar effect of being a partisan on distancing in every state. Figure S15 extends this analysis, graphing the average number of activities practiced by Democrats and Republicans on each day and in each state. Again, this figure shows a remarkable degree of similarity in partisan behavior across the

country. In every state, the average Republican participates in more activities than the average Democrat throughout the time series. Nearly every state follows the same pattern as well: with Republicans rapidly increasing their activity levels in April and May, before cutting down on activity through the summer. Recent months has seen Republicans in nearly every state begin to increase their activity levels again, however.

S7: Robustness of Results: Varying Relationships Based on Media Consumption

A key finding from Figure 4 in the main text is that the effect of party does not vary a great deal from state-to-state. That is, Republicans are more socially active (and Democrats less) than independents at approximately the same rate regardless of state. One explanation for this uniformity is an increasingly nationalized communication environment (31,33), whereby all individuals in the country consume an ever greater share of national over local news. Instead of receiving news about local conditions, high news consumers are likely to receive a national partisan message about how Democrats and Republicans are expected to behave.

A testable implication of the theory that national partisan messaging is driving these trends is that the relationship between party and social activity should be stronger for individuals who consume more news. For 82930 individuals from May 27th to June 8th, and an additional 32568 individuals from September 21th to September 29th, Survey Monkey asked respondents: "How much do you keep up with the news, regardless of whether you get it from television, newspapers, radio, or any other source?". We coded those who answered "A lot" as high news consumers (1), and those who answered "Some", "Not Much", and "Not at all" non-high news consumers (0). To understand the degree to which watching the news changes the impact of partisanship, we interact this variable with the indicators for Democrat, Republican, and Case Change in our pooled model (i.e. Table S1). The results of this model can be found in Figure S16. These results confirm the hypothesis: individuals who are high news consumers have a significantly higher association between their partisanship and social activity than those individuals who are not high news consumers. Our belief is that this is due to those individuals being more likely to receive partisan cues about behavior. Being a high news consumer, on the other hand, does not affect the impact of the number of cases in an individual's immediate area on social activities. While the amount of news significantly moderates the effect of party on distancing behavior, it should be noted that news consumption does not fully explain the effect. Low news Republicans are still massively more socially mobile than low news Democrats.

A subset of this question is whether specific types of media sources which push a particular type of message influence an individual's behavior. Consistent with the President's stated strategy, right-wing news sources have consistently downplayed the virus. An important research question is whether this messaging is associated with decreased concern about COVID-19 among Republicans. For 5811 individuals from March 9th to March 13th, and an additional 24822 respondents from September 21st to September 29th Survey Monkey asked whether they viewed several prominent media sources on a "daily or almost daily basis".¹ From these data we create a variable that measures the proportion of their media diet which consists of two right wing sources – FOX News and Breitbart. For example: if an individual reported reading 6 news

¹ The full list of sources asked about is: Breitbart, Buzzfeed, CNN, Drudge Report, FOX News, MSNBC, New York Times, NPR, Washington Post, and the Wall Street Journal.

sources, and two of those were Breitbart and FOX News, they would receive a score of .33. The median Republican has a score of 0.5 of this variable. A full 40% of Republicans score 1 on this measure, indicating that their only reported news sources are right-wing news sources.

This right-wing media variable was then interacted with the party and case change variables. The result of this model can be found in Figure S17.

The results confirm the expectation that viewing right wing media sources is associated with less concern for COVID-19 among Republicans. Republicans who do not watch these news sources are predicted to be 23 percentage points less worried about COVID-19 than independents. Republicans whose entire reported media diet consist of right-wing news sources, on the other hand, are 30 percentage points less worried about COVID-19 than independents. While this change in marginal effects is significant, it is also important to note that media viewership does not fully explain the difference between Democrats and Republicans. Even Republicans who completely abstain from FOX and Breitbart are far less concerned about the virus than are Democrats or Independents.

S8: Measuring Variation in Social Mitigation by State

Figure 4 in the main text requires the creation of a state-by-state measure of the policy response to COVID-19. To do so we collected data on several indicators of policy. All data was collected on August 13th, 2020.

- (1) The length of the states' stay-at-home order, measured in days. California's stay at home order was (as of this writing) never rescinded. As such it was coded as being 10 days longer than the next longest SAH order (a total of 90 days).
- (2) Whether the state had no mask order (0), a limited mask order (for example, only for essential workers) (1), or a broad mask order (2).
- (3) Whether the state put any restriction on travel (1) or not (0), such as quarantines for visitors from COVID-19 hotspots.
- (4) The proportion of total COVID-19 tests for every positive case, to measure testing capacity.
- (5) The proportion of contact tracers hired to contact tracers needed (excluding reserve capacity), to measure contact tracing capacity.

Data on stay at home length, mask orders, and travel restrictions was collected from the National Academy for State Health Policy.² Testing data was collected from The COVID Tracking Project.³ Data on contact tracing capacity and need was collected from NPR.⁴

Because each of these measures are on a different scale, the first data processing step was standardizing the variables by mean centering each and dividing by the standard error. To scale

² <https://www.nashp.org/governors-prioritize-health-for-all/>

³ <https://covidtracking.com/data/download>

⁴ <https://www.npr.org/sections/health-shots/2020/06/18/879787448/as-states-reopen-do-they-have-the-workforce-they-need-to-stop-coronavirus-outbre>

the measures together we used Principal Component Analysis⁵ with 1 factor. Factor loadings ranged from .62 for mask orders to .69 for travel restrictions. This tight band of loadings gives confidence that each of these underlying components is an important part of robust policy response. Figure S18 displays how each of the underlying components relates to the recovered measure of policy mitigation.

⁵ Specifically, we used the `principal()` command from the “psych” package in R.

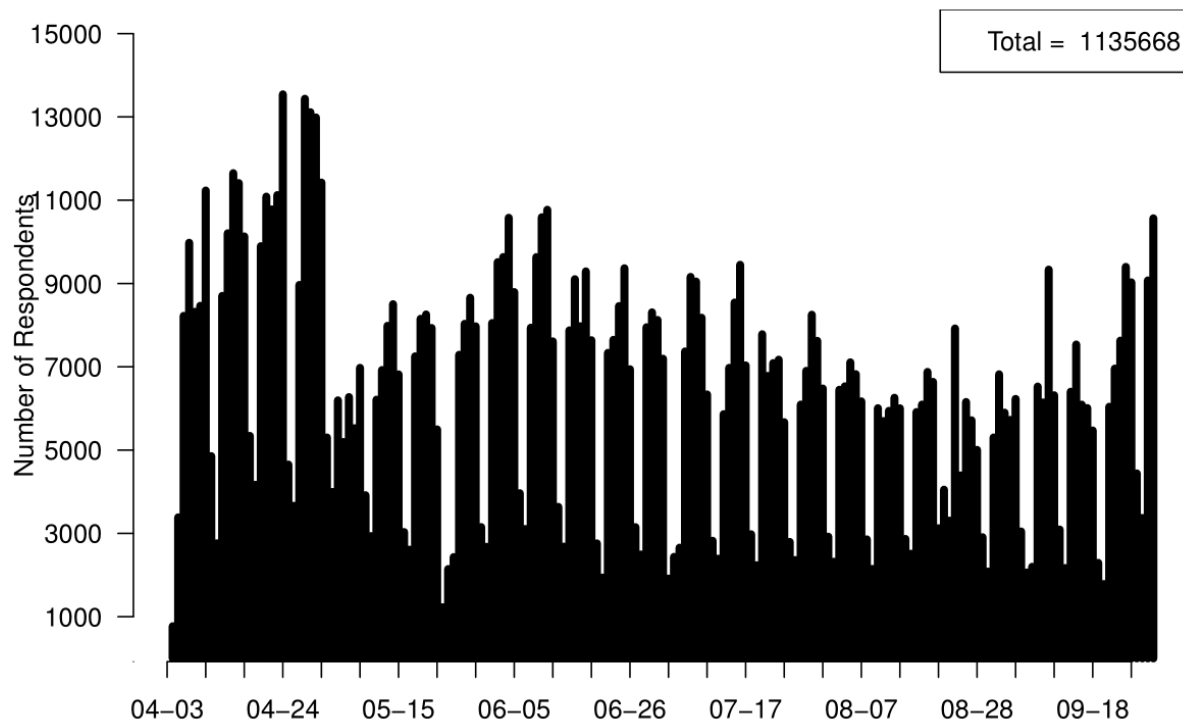


Figure S1: Daily Number of Respondents to “Last 24-hr activity measure.” The number of responses fluctuates daily due to the differences in the number of respondents who were invite to participate each day because of demands for other surveys as well as in the timing of when respondents choose to respond to a request to take a survey. A total of 1,135,668 responses were analyzed.

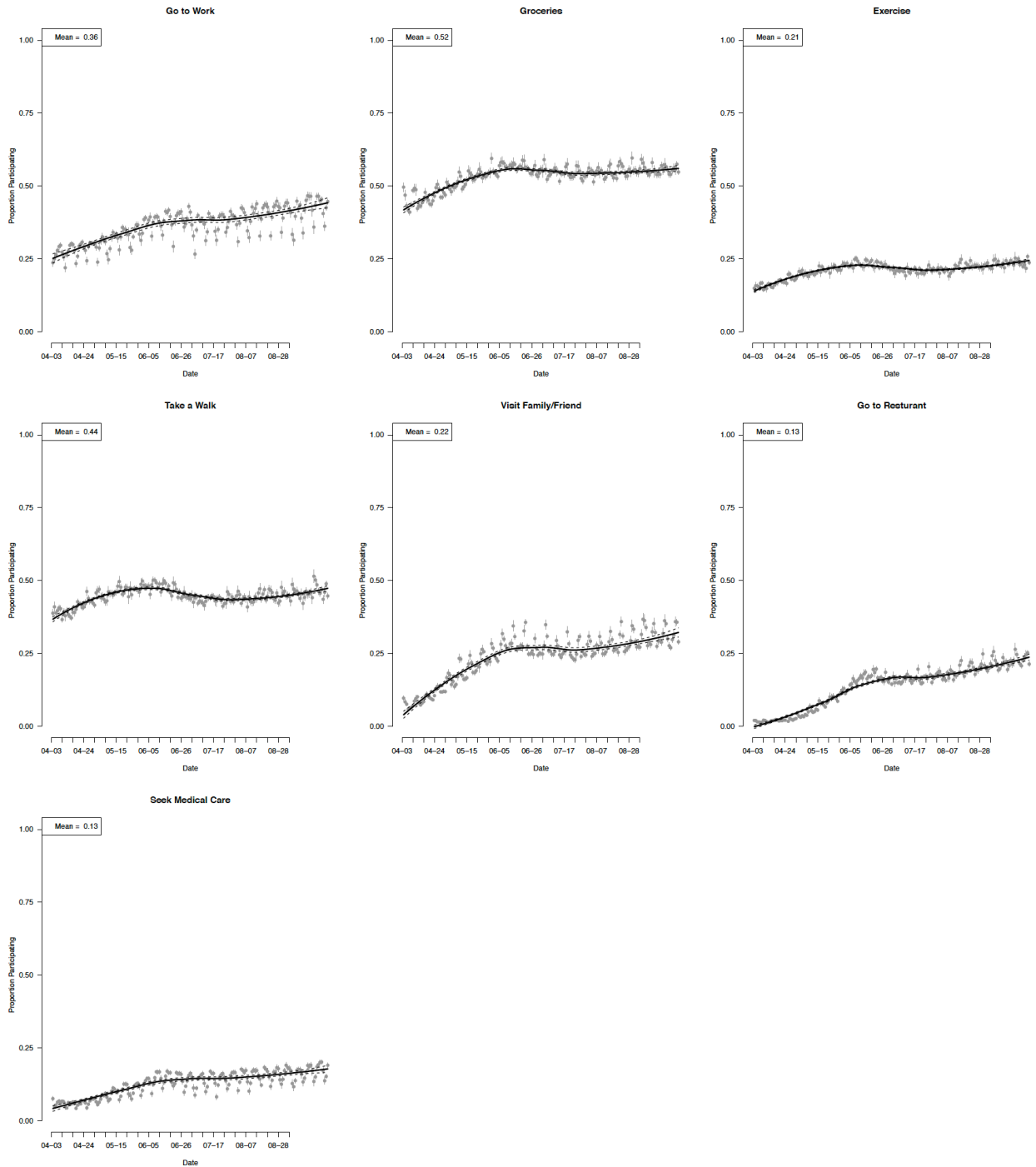


Figure S2: Overall Daily Trends in each Social Activity used to create the “Last 24hr activity” measure. Each response was weighted equally to create the measure analyzed in the text. Lines characterize the smoothed trend. While there are differences in the level of activity by activity the trend change similarly over time. Daily estimates are weighted to US adult population.

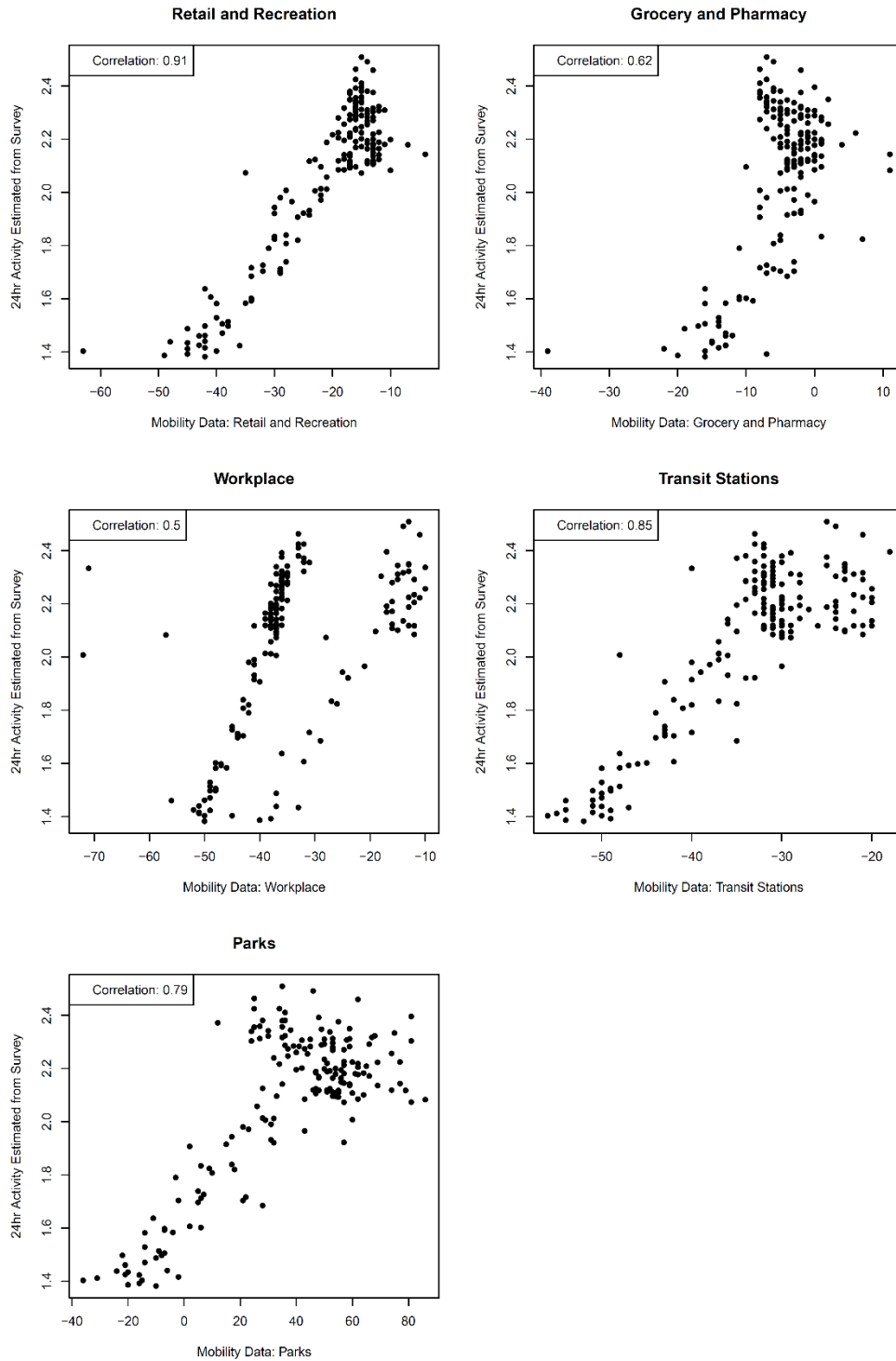


Figure S3: Comparison of Statewide Average of Total Self-Reported Activity to Google Mobility Data. To validate the survey-based measures of social mobility we analyze, figure plots the average number of total social activities by state pooled over time (y-axis, weighted by US adult population) against Google’s mobility measure for various geographic locations (x-axis). The Google mobility data was obtained: October 12, 2020. Our survey measure of mobility correlates strongly to this behavioral measure.

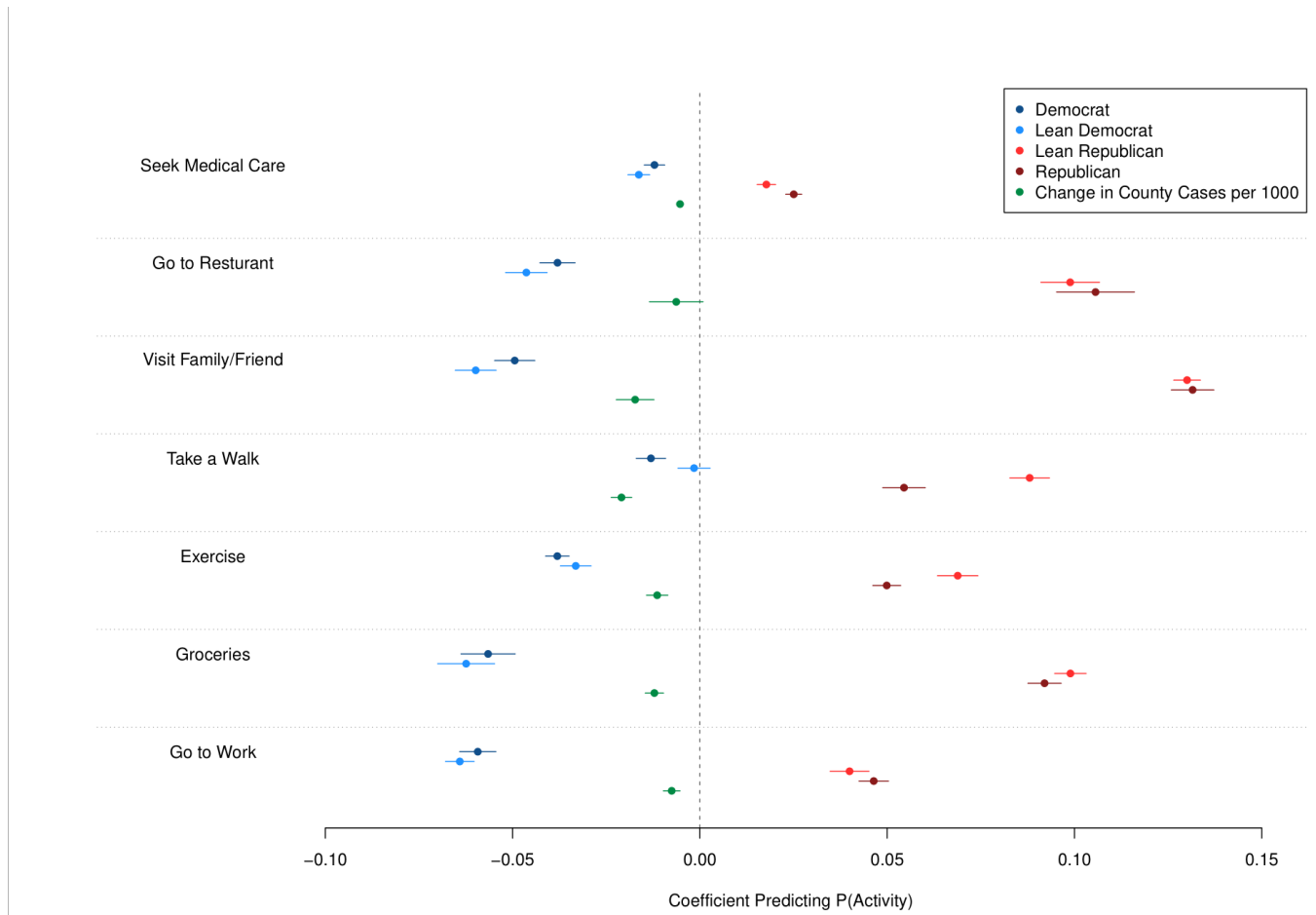


Figure S4. Coefficient plot of Specification (4) by Social Activity. Results predict the probability of engaging in each of the social activities by partisanship and COVID-19 incidence to show robustness of partisan differences across activities. Each row graphs the coefficient estimates from a separate pooled regression that includes a polynomial time trend, state fixed effects, and a battery of demographics. For party variables, reference is pure independents. Standard errors are clustered by state. Estimated weighted by US adult population. There are large and statistically significant partisan gaps in behavior for behaviors of all types. Further, the incidence of COVID in an individuals area negatively influences the degree of social mobility, though to a much smaller degree.

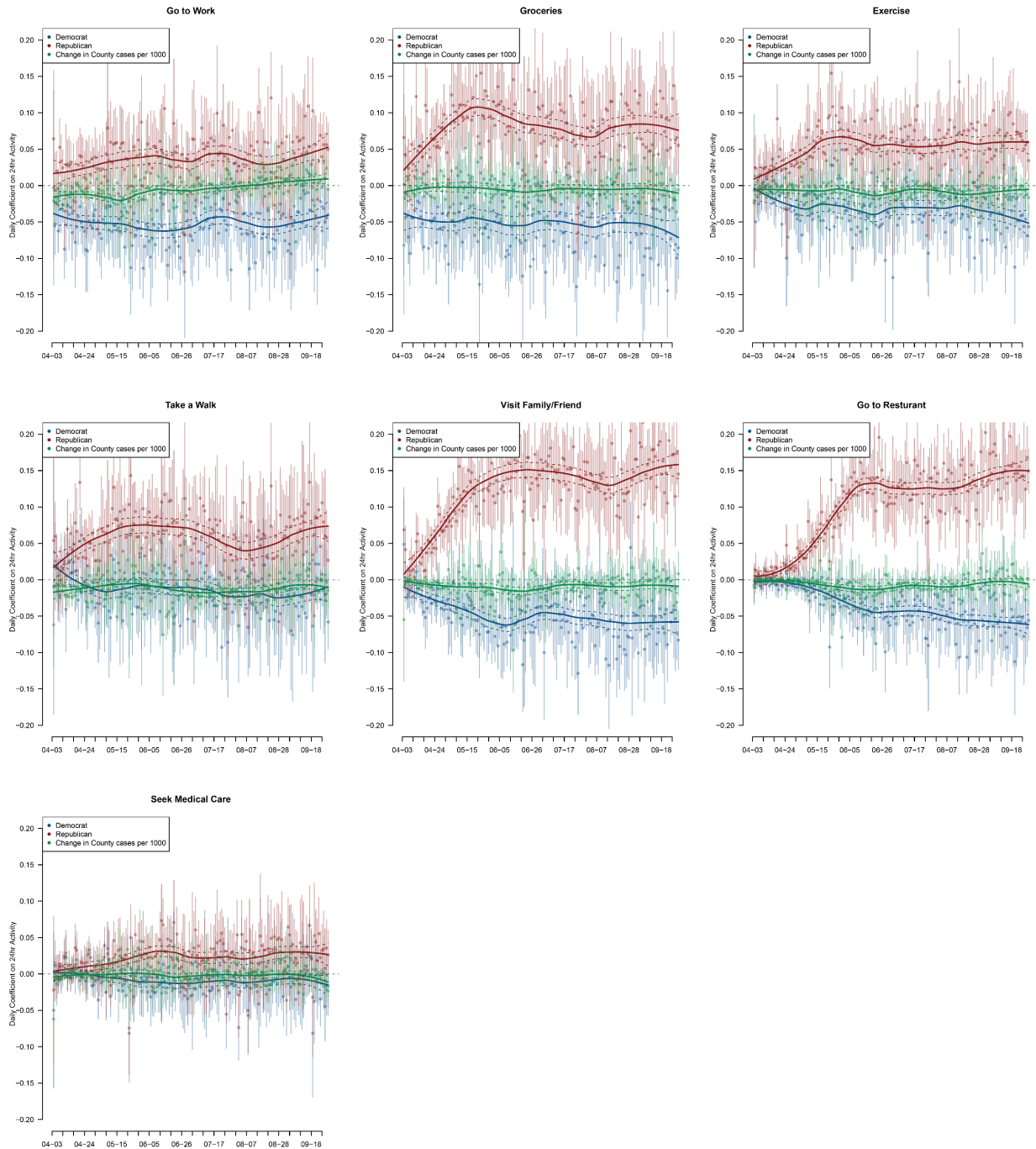


Figure S5: Effect of Partisanship and COVID-19 on Individual Activities Over Time. Coefficients are from OLS regression using specification (4) run separately on each day. Observations weighted to the US adult population. For party variables, reference is pure independents. Partisan leaners are included with identifying partisans. 95% confidence intervals from OLS standard errors clustered by state. Trend is local regression weighted by inverse of each estimates standard error.

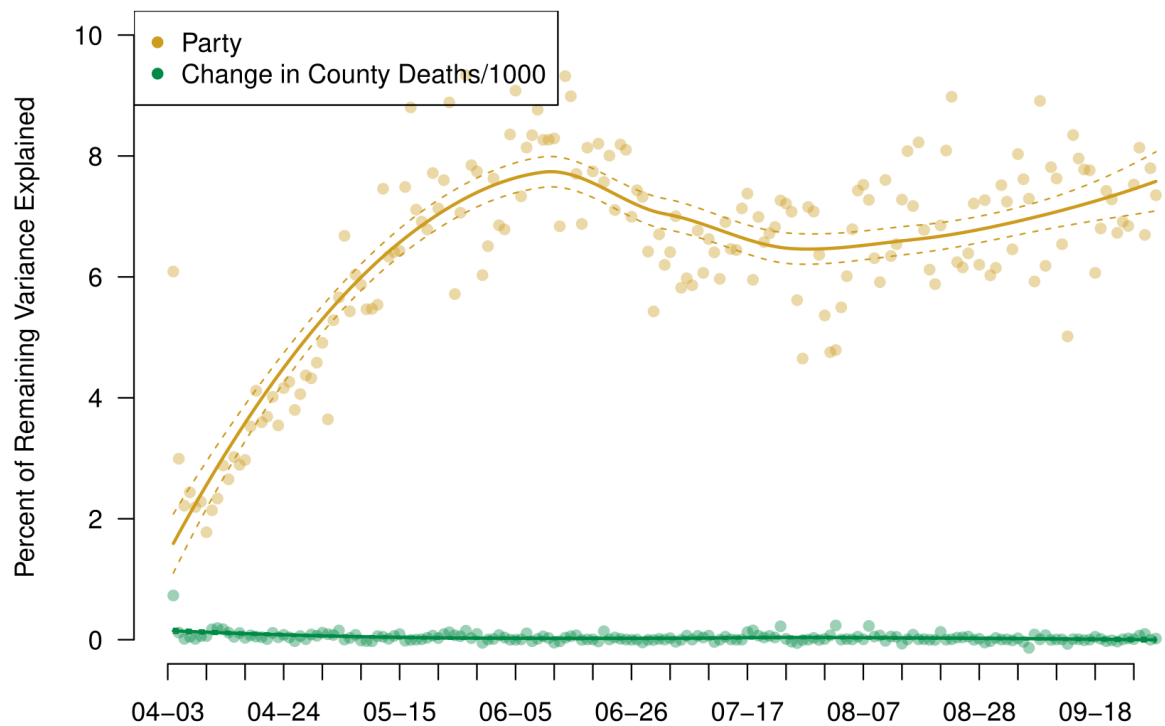


Fig. S6. Variation in Social Mobility Behavior Explained by Partisanship and the Impact of COVID-19 in the Community (Change in County Deaths/1000). The daily coefficients of partial determinations are computed via OLS regression using specifications (1-3) run separately on each day. Observations weighted to the US adult population. Point estimates describe the percent of residual variation in specification (1) using the weighted national responses for each day being explained by each variable. The smoothed trend-line is a local regression fitted to the estimates over time. Variation in changes in the population adjusted COVID-19 reported death rate in the county do not explain variation in self-reported social mobility.

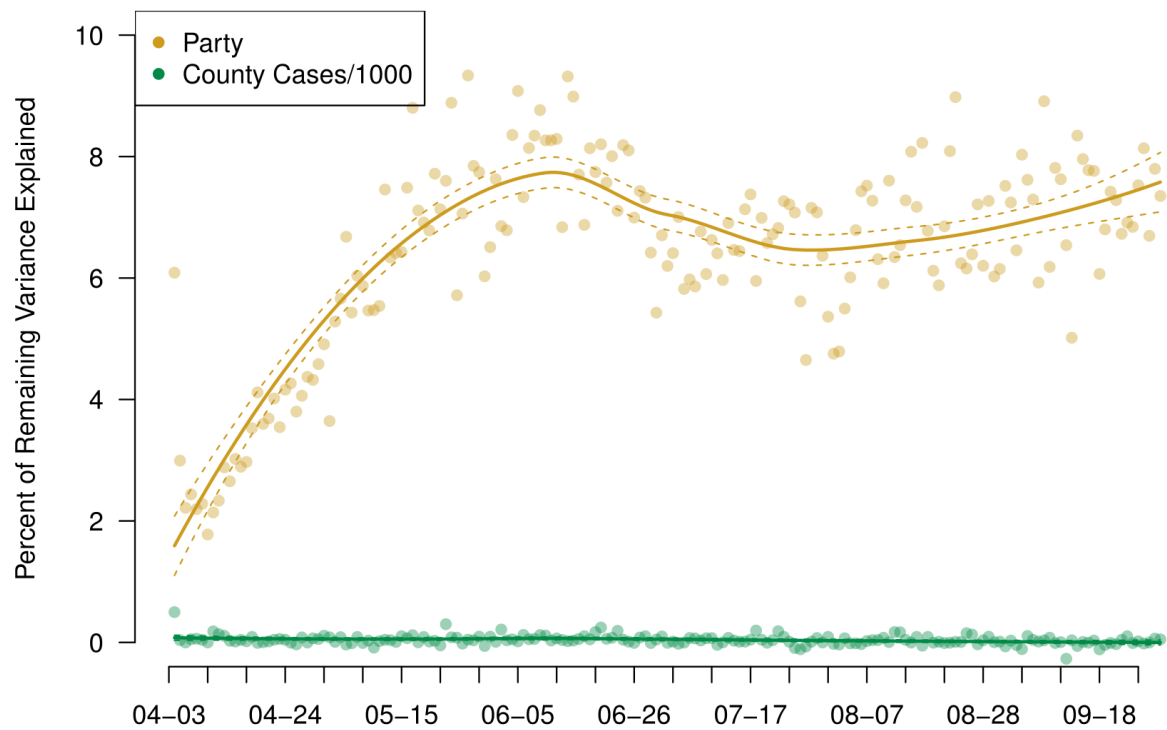


Fig. S7. Variation in Social Mobility Behavior Explained by Partisanship and the Impact of COVID-19 in the Community (County Cases/1000). The daily coefficients of partial determinations are computed via OLS regression using specifications (1-3) run separately on each day. Observations weighted to the US adult population. Point estimates describe the percent of residual variation in specification (1) using the weighted national responses for each day being explained by each variable. The smoothed trend-line is a local regression fitted to the estimates over time. Variation in the population adjusted COVID-19 reported number of cases in the county do not explain variation in self-reported social mobility.

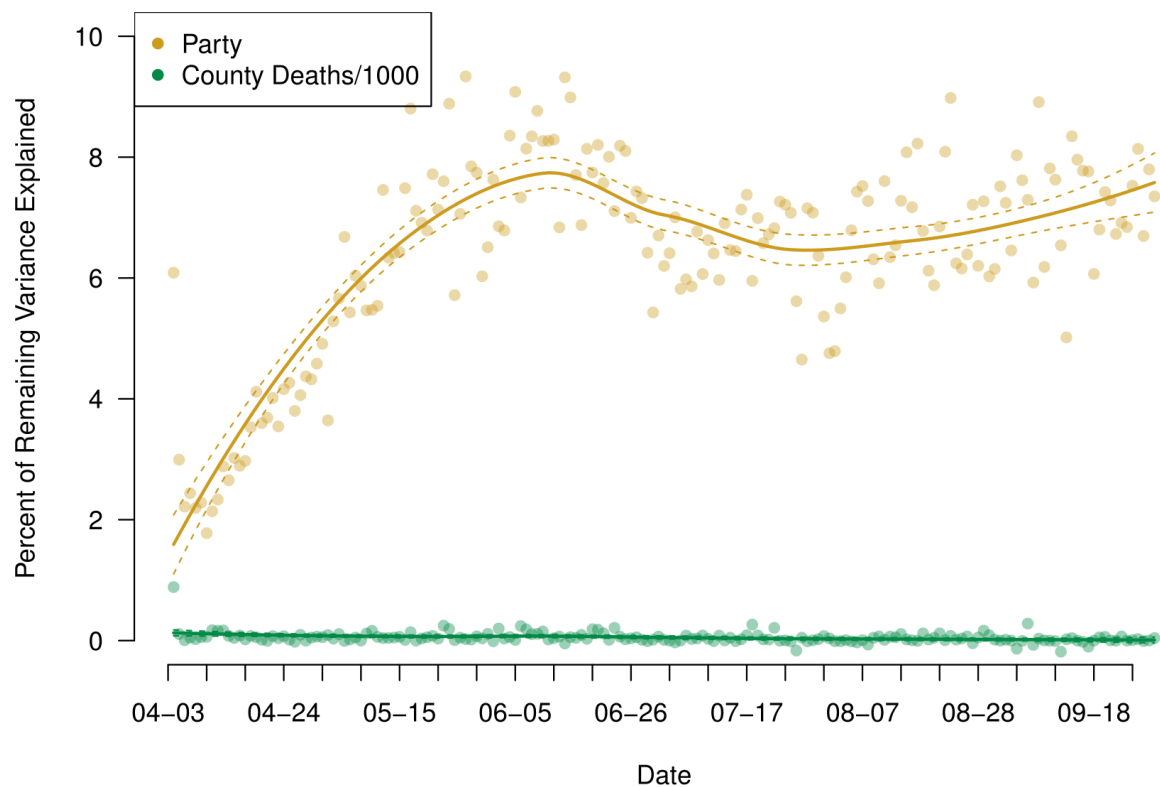


Fig. S8. Variation in Social Mobility Behavior Explained by Partisanship and the Impact of COVID-19 in the Community (County Deaths/1000). The daily coefficients of partial determinations are computed via OLS regression using specifications (1-3) run separately on each day. Observations weighted to the US adult population. Point estimates describe the percent of residual variation in specification (1) using the weighted national responses for each day being explained by each variable. The smoothed trend-line is a local regression fitted to the estimates over time. Variation in in the population adjusted COVID-19 reported number of deaths in the county do not explain variation in self-reported social mobility.

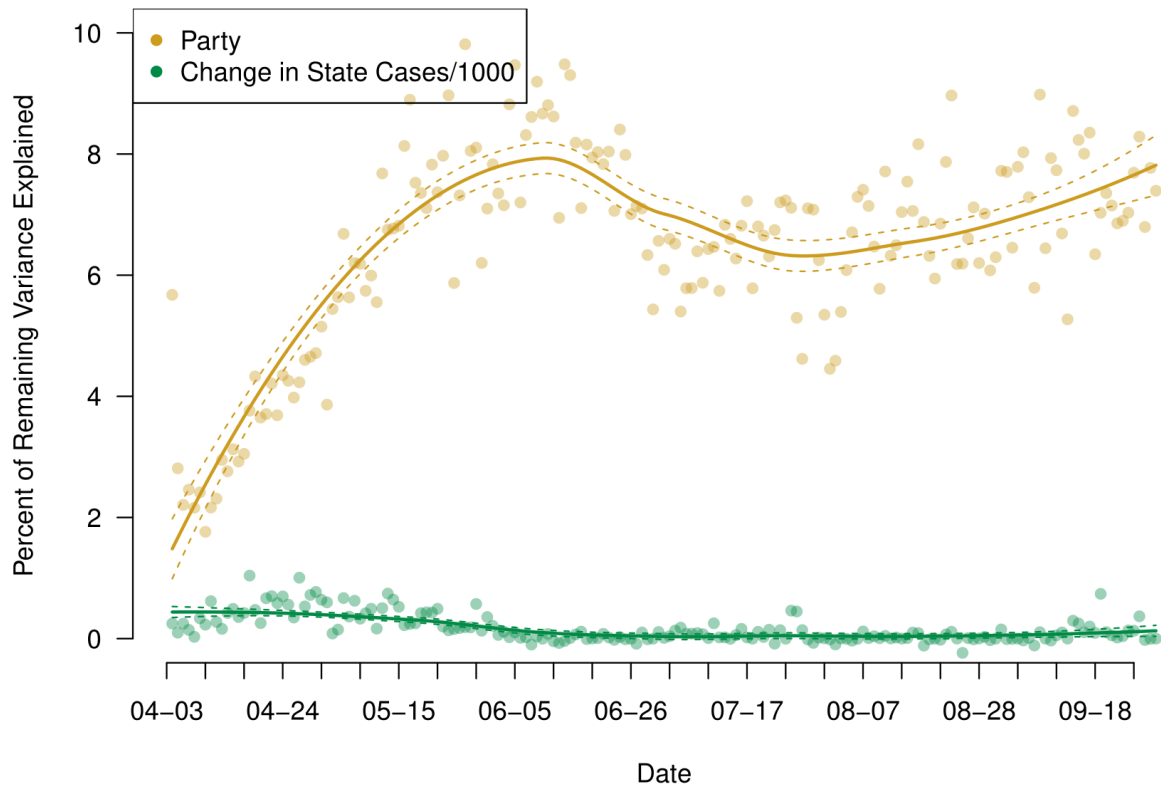


Fig. S9. Variation in Social Mobility Behavior Explained by Partisanship and the Impact of COVID-19 in the Community (Change in State Cases/1000). The daily coefficients of partial determinations are computed via OLS regression using specifications (1-3) run separately on each day. Observations weighted to the US adult population. Point estimates describe the percent of residual variation in specification (1) using the weighted national responses for each day being explained by each variable. The smoothed trend-line is a local regression fitted to the estimates over time. Variation in in the population adjusted COVID-19 reported change in the number of cases in the state do not explain variation in self-reported social mobility.

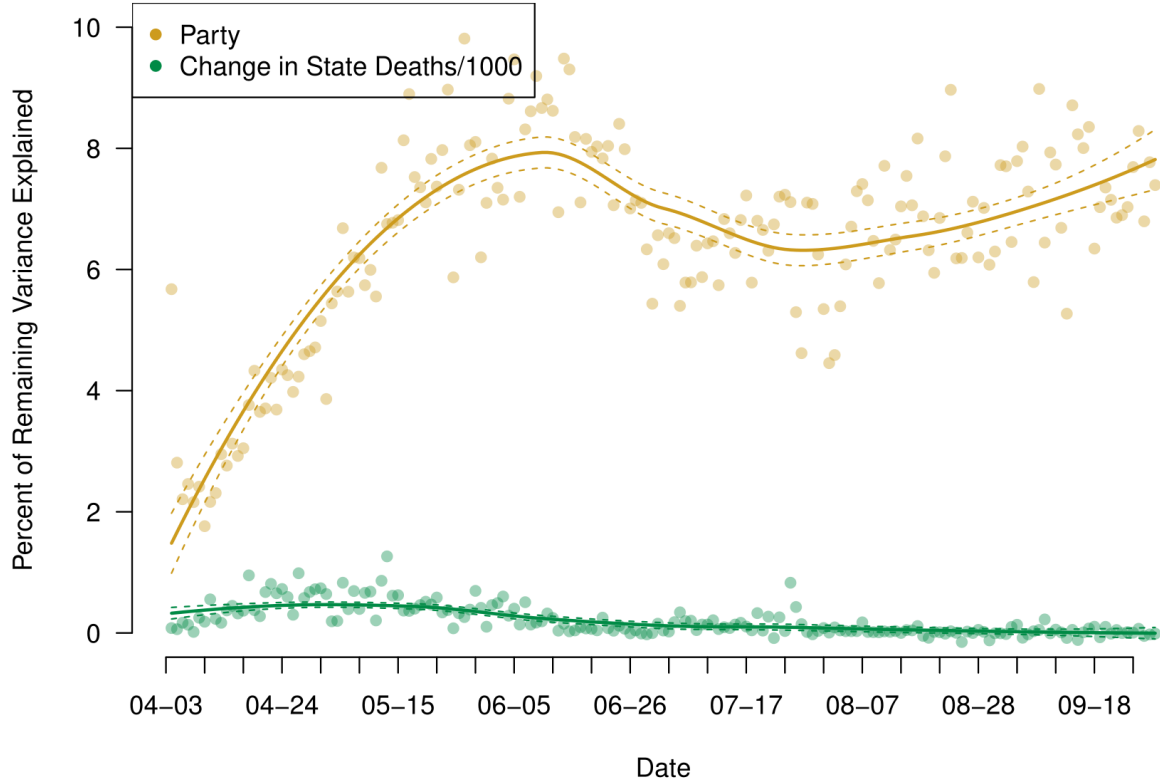


Fig. S10. Variation in Social Mobility Behavior Explained by Partisanship and the Impact of COVID-19 in the Community (Change in State Deaths/1000). The daily coefficients of partial determinations are computed via OLS regression using specifications (1-3) run separately on each day. Observations weighted to the US adult population. Point estimates describe the percent of residual variation in specification (1) using the weighted national responses for each day being explained by each variable. The smoothed trend-line is a local regression fitted to the estimates over time. Variation in in the population adjusted COVID-19 reported change in the number of deaths in the state do not explain variation in self-reported social mobility.

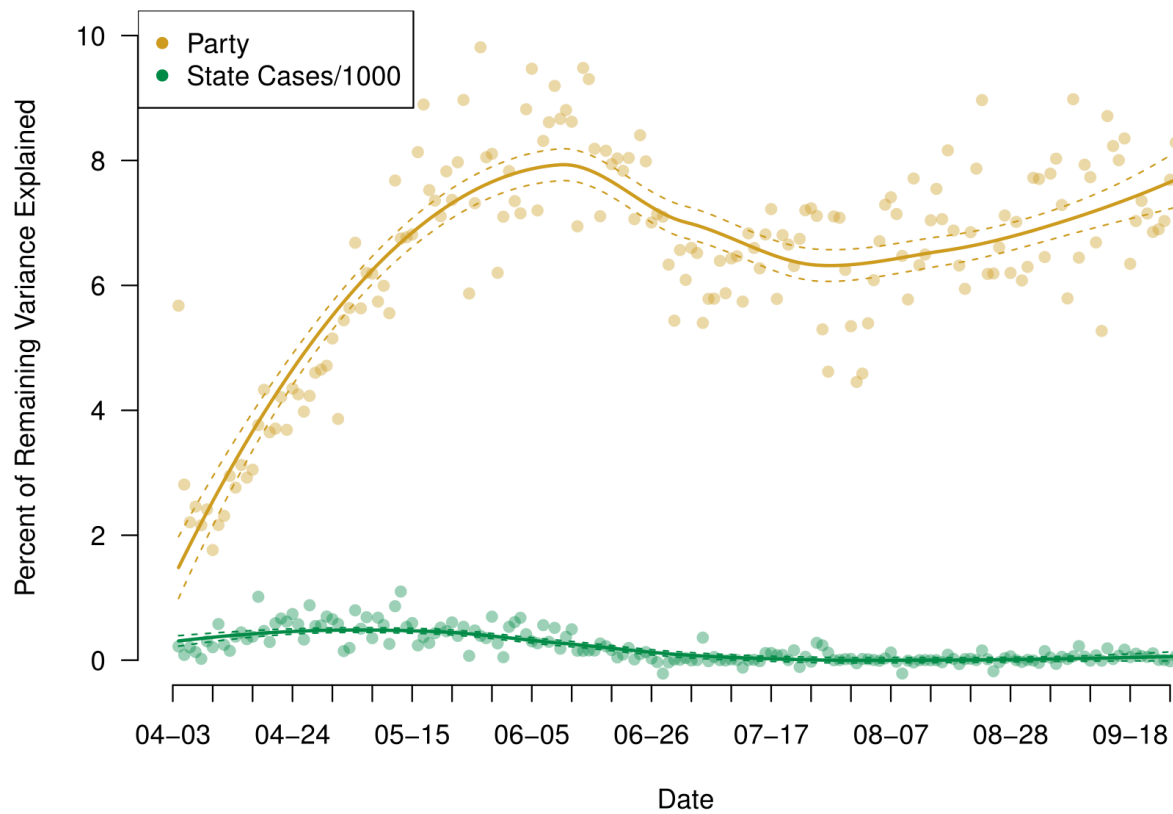


Fig. S11. Variation in Social Mobility Behavior Explained by Partisanship and the Impact of COVID-19 in the Community (State Cases/1000). The daily coefficients of partial determinations are computed via OLS regression using specifications (1-3) run separately on each day. Observations weighted to the US adult population. Point estimates describe the percent of residual variation in specification (1) using the weighted national responses for each day being explained by each variable. The smoothed trend-line is a local regression fitted to the estimates over time. Variation in the population adjusted COVID-19 reported number of cases in the state do not explain variation in self-reported social mobility.

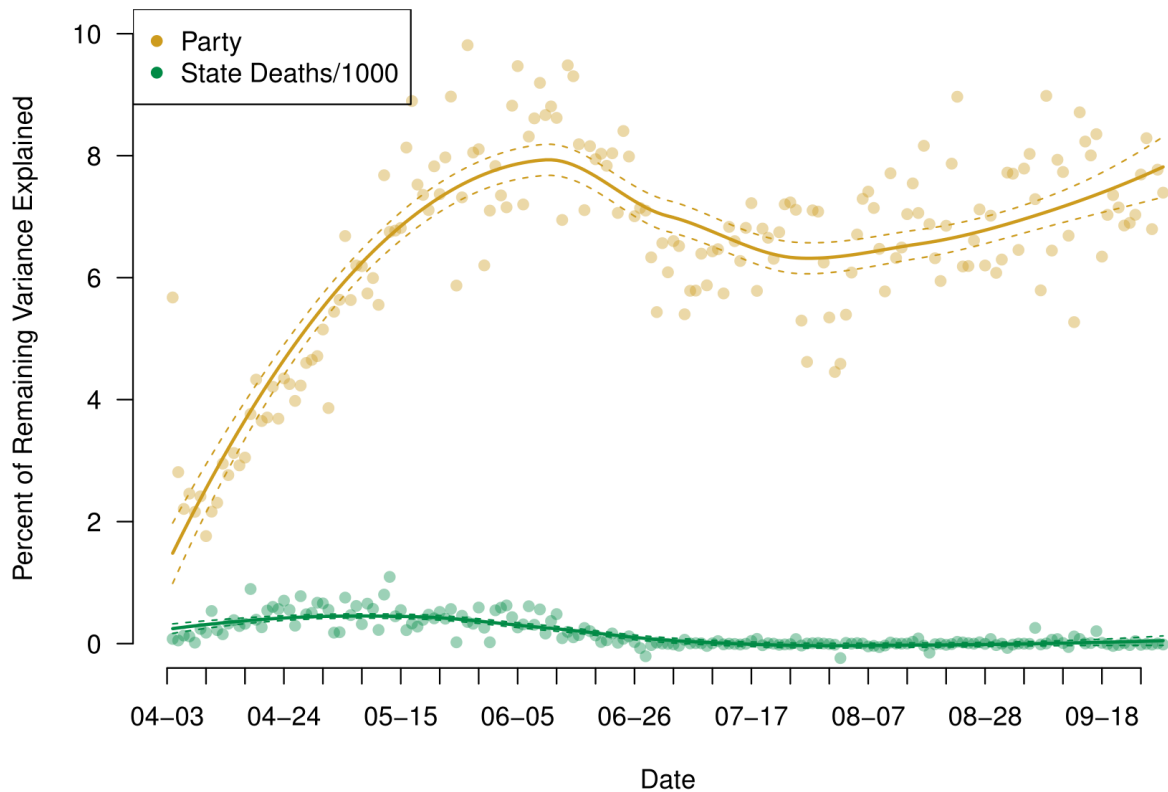


Fig. S12. Variation in Social Mobility Behavior Explained by Partisanship and the Impact of COVID-19 in the Community (State Deaths/1000). The daily coefficients of partial determinations are computed via OLS regression using specifications (1-3) run separately on each day. Observations weighted to the US adult population. Point estimates describe the percent of residual variation in specification (1) using the weighted national responses for each day being explained by each variable. The smoothed trend-line is a local regression fitted to the estimates over time. Variation in in the population adjusted COVID-19 reported the number of deaths in the state do not explain variation in self-reported social mobility.

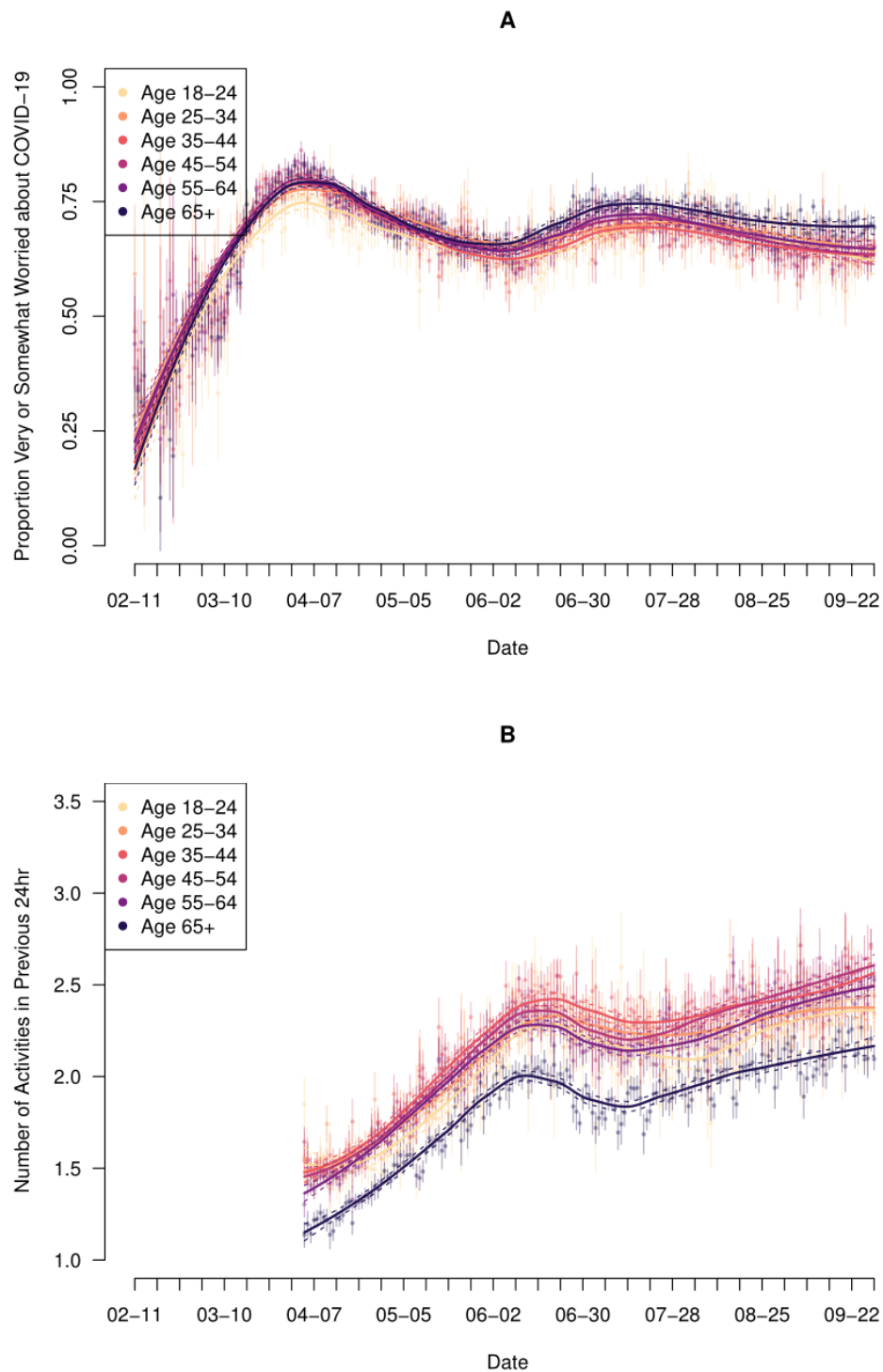


Fig. S13. Concern with Catching COVID-19 and Social Mobility Behavior Over time by Age Group. Plot (A) graphs the nationally weighted daily percentage of respondents who are either “very” or “somewhat” worried about catching COVID-19 by age group. Plot (B) graphs the average number of social activities individuals report doing in the last 24 hours by age group. 95% confidence intervals are reported for each daily average. Estimates weighted to US adult population. Plotted lines are loess smoothers to summarize trends over time.

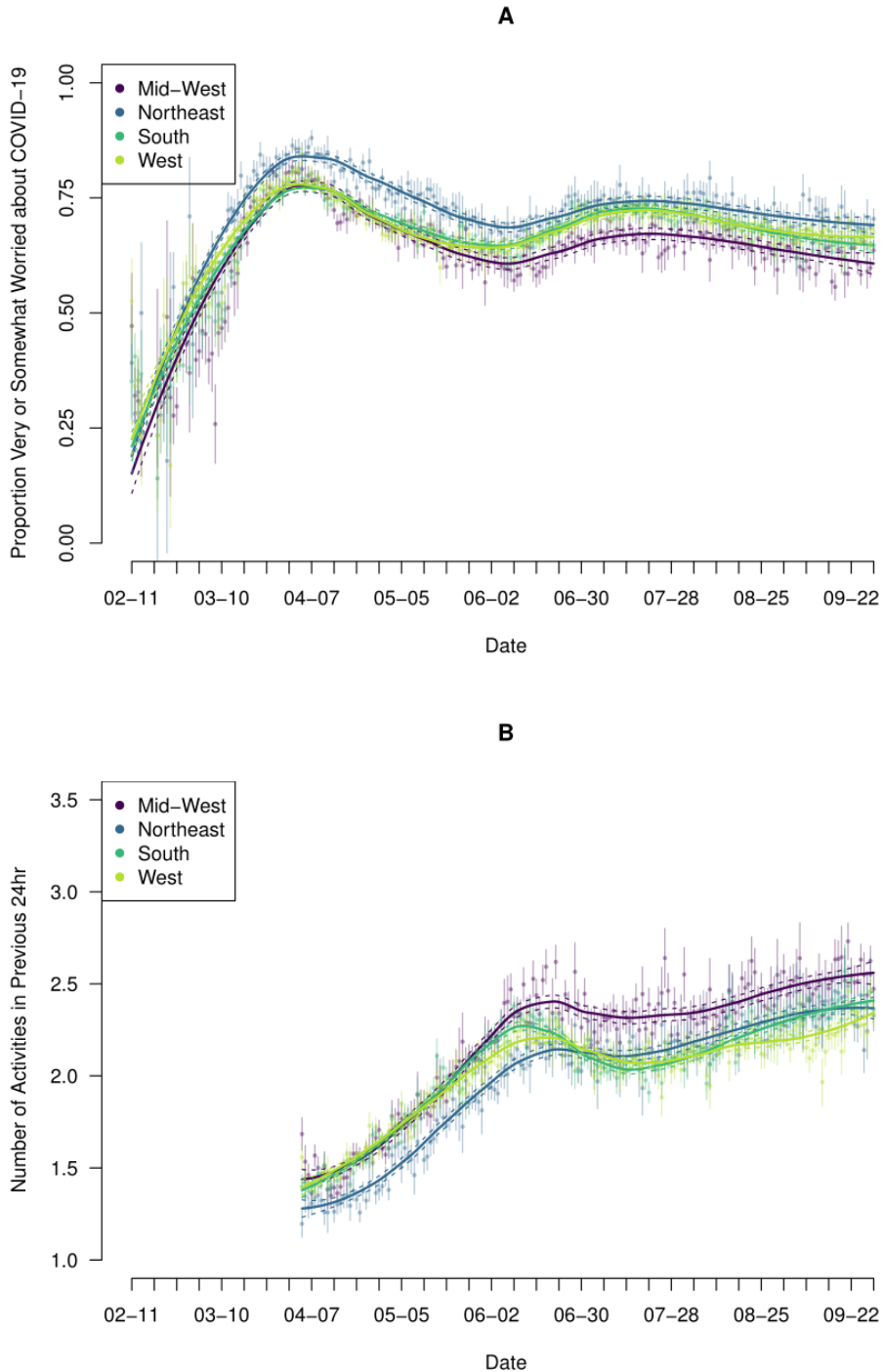


Fig. S14. Concern with Catching COVID-19 and Social Mobility Behavior Over time by Census Region. Plot (A) graphs the nationally weighted daily percentage of respondents who are “very” or “somewhat” worried about catching COVID-19 by region. Plot (B) graphs the average number of social activities individuals report doing in the last 24 hours by region. Estimates weighted to US adult population. 95% confidence intervals are reported for each daily average. Plotted lines are loess smoothers to summarize trends over time.

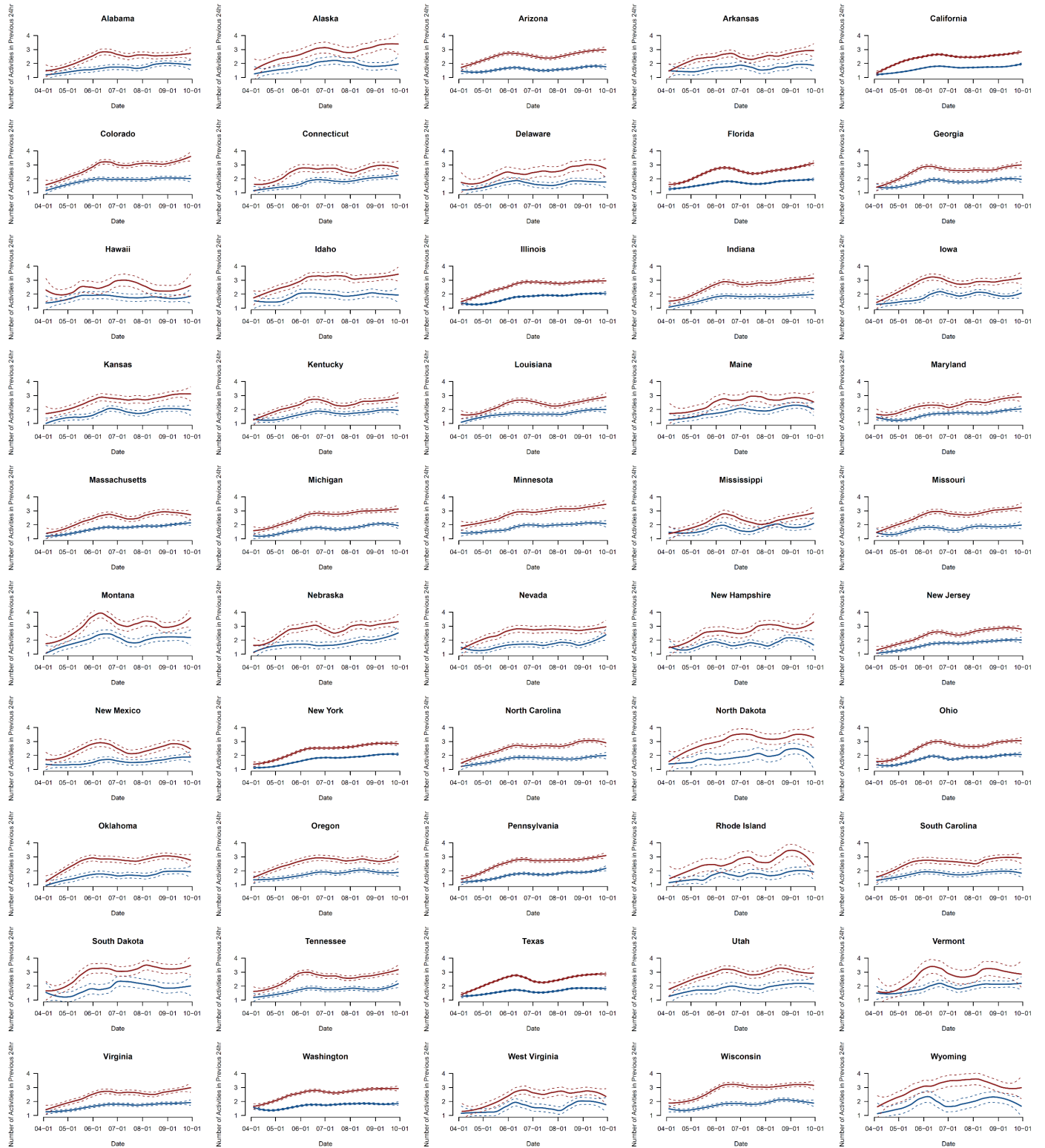


Fig. S15. Trends in Social Mobility for Democrats and Republicans, by State. Each plot graphs the weighted (to state adult population) daily average of the number of social activities individuals reported doing in the last 24 hours. For readability, the point estimates for the daily averages are omitted and a loess smoothed curve is used to show trends over time.

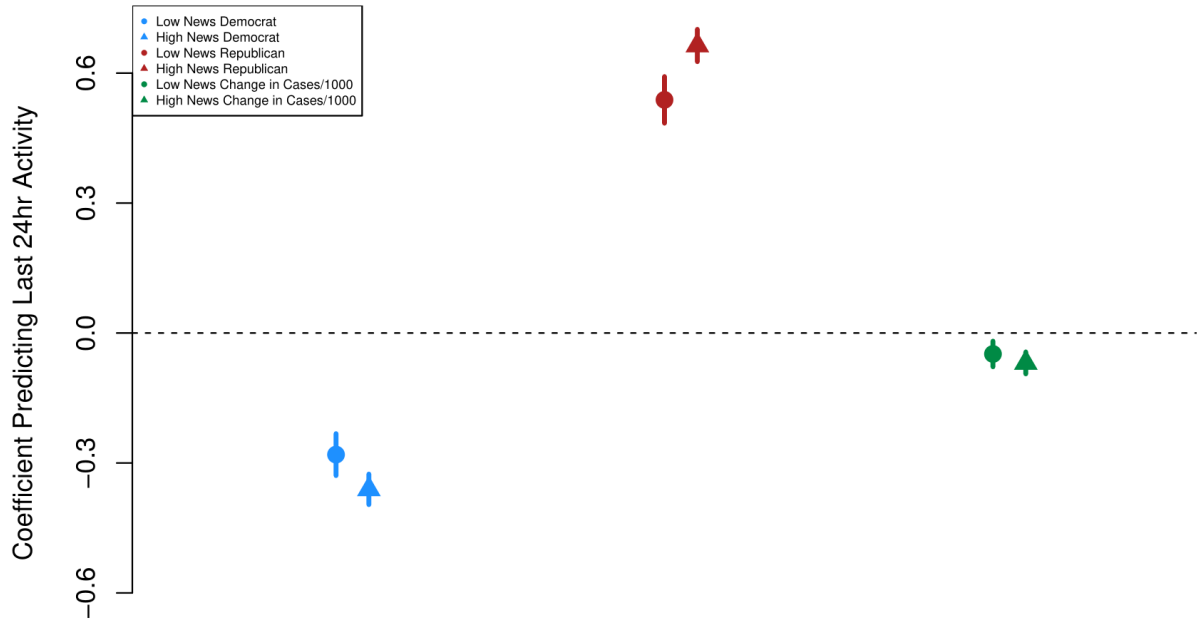


Fig. S16. Effects of Party and Case Change, by News Viewership. Marginal effects from a model predicting number of social activities performed in last 24 hours. Model is pooled across time and includes a polynomial time trend, state fixed effects, and a battery of demographics. Estimates weighted by US adult population. Standard errors are clustered by state. High news consumption significantly increases the effect of party for both Democrats and Republicans, but does not impact the effect of a change in local cases. However, even low news Republicans and Democrats are still extremely different in their behavior.

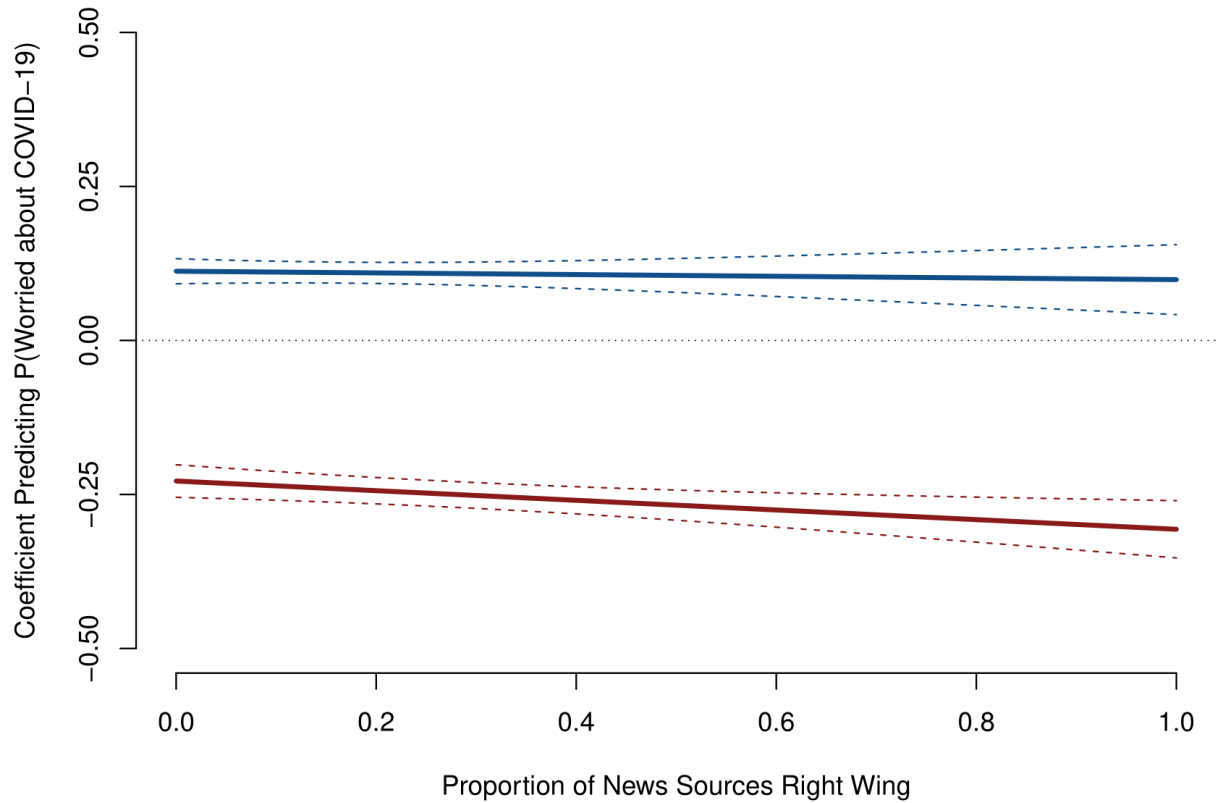


Fig. S17. Effects of Party by Right Wing News Viewership. Marginal effects from a model predicting probability respondents is worried about COVID-19. Model is pooled across time and includes a polynomial time trend, state fixed effects, and a battery of demographics. Estimates weighted to US adult population. Standard errors are clustered by state. Having a media diet with a higher proportion of right wing news (FOX News and Breitbart) is associated with Republicans being less concerned about COVID. While this change in concern is statistically significant, it is not of high substantial importance: Republicans who watch no right-wing media are still far less worried about COVID than Democrats who watch a great deal of these sources.

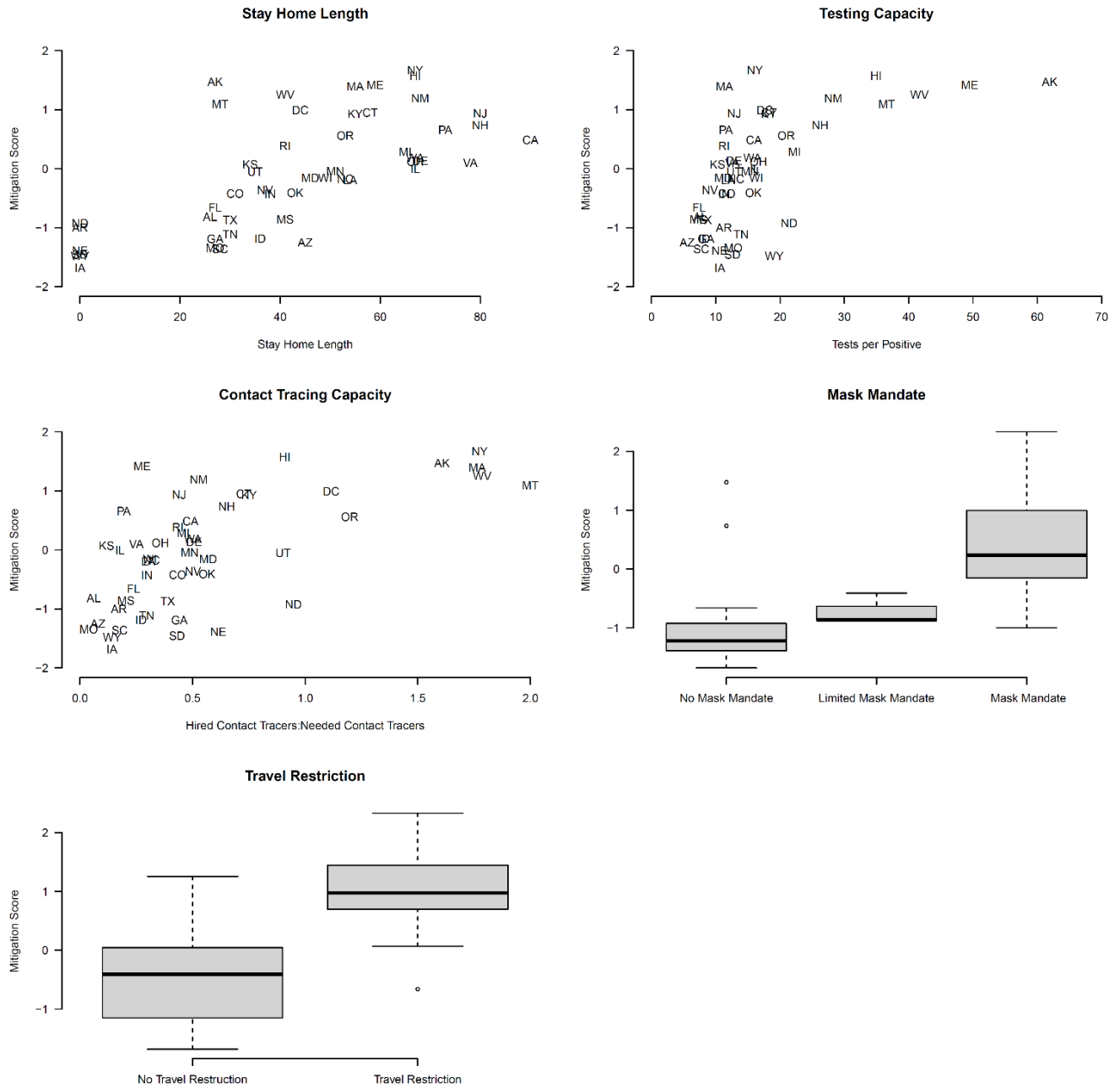


Fig. S18. Relationship of Underlying Measures to Mitigation Score. To summarize the extent to which there was variation in the severity of the regulations used to try to control the spread of COVID-19, we factor analyze the various policy decisions being made by each state to uncover a single factor that summarizes the between-state variation. To do so we standardize each variable and then use a Principal Components Analysis to recover the dominant factor we use to examine the effect of variation in mitigation policies on variation in social mobility.

Determinants of Social Distancing Behavior	
Last 24 Hour Activity (0-7)	
Time	0.01* (0.0005)
Time2	-0.0000* (0.0000)
Democrat	-0.27* (0.01)
Lean Democrat	-0.28* (0.01)
Lean Republican	0.54* (0.01)
Republican	0.50* (0.01)
County Change in Covid Cases/1000	-0.08* (0.01)
Female	-0.34* (0.01)
Income 30k-74K	0.09* (0.01)
Income 75k-149k	0.20* (0.01)
Income 150k+	0.31* (0.01)
Age 25-34	-0.09* (0.01)
Age 34-44	-0.14* (0.01)
Age 45-54	-0.19* (0.02)
Age 55-64	-0.26* (0.02)
Age 65+	-0.31* (0.02)
Race Other	0.10* (0.01)
Black	0.04* (0.01)
Asian	-0.34* (0.02)
Hispanic	-0.06* (0.02)
High School	0.06* (0.02)
Associates/Some College	0.15* (0.02)
College	0.16* (0.02)
Postgraduate	0.13* (0.02)
Unemployed	-0.40* (0.01)
Rural	0.03* (0.01)
Urban	-0.04* (0.01)
State F.E.	Yes
N	1034346
Adj. R-squared	0.15
Residual Std. Error	1.47 (df = 1034268)

p < [.*]; *p < [.**]; †p < .05

Table S1. Number of Social Activities Regression Results with Leaners. Specification analyzes data pooled over time to allow social mobility to vary between “leaners” and “partisans.” The similarity of coefficients reveals the lack of difference and the justification for collapsing. Standard errors are clustered by state. Data weighted to US adult population.

Determinants of Social Distancing Behavior	
	Last 24 Hour Activity (0-7)
Time	0.01* (0.0001)
Time2	-0.0000* (0.0000)
Democrat	-0.26* (0.005)
Lean Democrat	-0.29* (0.01)
Lean Republican	0.54* (0.01)
Republican	0.50* (0.01)
County Change in Covid Cases/1000	-0.08* (0.002)
Female	-0.34* (0.003)
Income 30k-74K	0.08* (0.005)
Income 75k-149k	0.19* (0.01)
Income 150k+	0.29* (0.01)
Age 25-34	-0.08* (0.01)
Age 34-44	-0.13* (0.01)
Age 45-54	-0.18* (0.01)
Age 55-64	-0.26* (0.01)
Age 65+	-0.32* (0.01)
Race Other	0.13* (0.01)
Black	0.10* (0.01)
Asian	-0.29* (0.01)
Hispanic	-0.004 (0.01)
High School	0.05* (0.01)
Associates/Some College	0.14* (0.01)
College	0.15* (0.01)
Postgraduate	0.11* (0.01)
Unemployed	-0.40* (0.004)
Zip Code F.E.	Yes
N	1034870
Adj. R-squared	0.16
Residual Std. Error	1.47 (df= 1006725)

p < [.]; **p < [.**]; *p < [.05]

Table S2. Number of Social Activities Regression Results with Leaners (Zip Code FE). Specification analyzes data pooled over time to allow social mobility to vary between “leaners” and “partisans.” The similarity of coefficients reveals the lack of difference and the justification for collapsing. Standard errors are clustered by Zip-Code. Data weighted to US adult population.

Determinants of Social Distancing Behavior

	Last 24 Hour Activity (0-7)			
	Model 1	Model 2	Model 3	Model 4
Time	0.01*	0.01*	0.02*	0.01*
	(0.001)	(0.001)	(0.001)	(0.001)
Time2	-0.0000*	-0.0000*	-0.0001*	-0.0001*
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Democrat		-0.27*		-0.27*
		(0.01)		(0.01)
Republican		0.51*		0.51*
		(0.01)		(0.01)
State Change in Covid Cases/1000			-0.12*	-0.12*
			(0.02)	(0.02)
Female	-0.43*	-0.34*	-0.43*	-0.34*
	(0.01)	(0.01)	(0.01)	(0.01)
Income 30k-74K	0.11*	0.09*	0.11*	0.09*
	(0.01)	(0.01)	(0.01)	(0.01)
Income 75k-149k	0.25*	0.20*	0.25*	0.20*
	(0.01)	(0.01)	(0.01)	(0.01)
Income 150k+	0.38*	0.31*	0.38*	0.31*
	(0.02)	(0.01)	(0.02)	(0.01)
Age 25-34	-0.06*	-0.09*	-0.06*	-0.09*
	(0.01)	(0.01)	(0.01)	(0.01)
Age 34-44	-0.08*	-0.13*	-0.08*	-0.14*
	(0.01)	(0.01)	(0.01)	(0.01)
Age 45-54	-0.10*	-0.18*	-0.10*	-0.18*
	(0.02)	(0.02)	(0.02)	(0.02)
Age 55-64	-0.17*	-0.26*	-0.17*	-0.26*
	(0.02)	(0.02)	(0.02)	(0.02)
Age 65+	-0.24*	-0.31*	-0.25*	-0.31*
	(0.02)	(0.02)	(0.02)	(0.02)
Race Other	0.07*	0.10*	0.07*	0.10*
	(0.02)	(0.01)	(0.02)	(0.01)
Black	-0.20*	0.04*	-0.20*	0.04*
	(0.02)	(0.01)	(0.02)	(0.01)
Asian	-0.40*	-0.34*	-0.39*	-0.34*
	(0.02)	(0.02)	(0.02)	(0.02)
Hispanic	-0.17*	-0.08*	-0.17*	-0.08*
	(0.03)	(0.02)	(0.03)	(0.02)
High School	0.07*	0.06*	0.07*	0.06*
	(0.02)	(0.02)	(0.02)	(0.02)
Associates/Some College	0.14*	0.15*	0.14*	0.15*
	(0.02)	(0.02)	(0.02)	(0.02)
College	0.09*	0.16*	0.09*	0.16*
	(0.02)	(0.02)	(0.02)	(0.02)
Postgraduate	-0.01	0.13*	-0.01	0.13*
	(0.02)	(0.02)	(0.02)	(0.02)
Unemployed	-0.43*	-0.40*	-0.42*	-0.40*
	(0.01)	(0.01)	(0.01)	(0.01)
Rural	0.09*	0.04*	0.09*	0.04*
	(0.01)	(0.01)	(0.01)	(0.01)
Urban	-0.11*	-0.05*	-0.11*	-0.05*
	(0.01)	(0.01)	(0.01)	(0.01)
State F.E.	Yes			
N	1049411	1034373	1049411	1034373
Adj. R-squared	0.10	0.15	0.11	0.15
Residual Std. Error	1.51 (df= 1049338)	1.47 (df= 1034298)	1.51 (df= 1049337)	1.47 (df= 1034297)

p < [.]; **p < [.**]; *p < [.05]

Table S3. Number of Social Activities Regression Results, State-Wide COVID-19 Measure. Specification analyzes data pooled over time to determine the impact of the change in the number of COVID-19 cases at the state level. COVID-19 cases measured at the state level are slightly more predictive of distancing than the equivalent measure at the county level, though still far less important than partisanship. Standard errors are clustered by State. Data weighted to US adult population.