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Supplementary information

Partisan differences in physical distancing are linked to health outcomes during the COVID-19 pandemic

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Supplements for: Partisan Differences in Physical Distancing are Linked to Health Outcomes During the COVID-19 Pandemic

Supplemental Notes

The following notes are referenced by number in the main text and should be treated as footnotes/endnotes.

1. Days prior to March 9 were treated by Unacast (the software company that shared these data with the authors) as pre-COVID.
2. We simulated 1000 bootstrapped datasets conditional on estimated random effects incorporating variance from fixed effects estimates and residuals. Predictions were generated from the model refit to each such dataset. Prediction intervals are the 2.5% and 97.5% quantile prediction.
3. Models without the additional covariates had marginal R^2s of .25 and .30, respectively.
4. The model with visitations to nonessential services as the dependent variable did not include random slope of partisanship at the county level and did not include random slopes of time due to convergence issues.
5. Including percent of population aged 18-64 induces rank deficiency in the model as all age proportions necessarily sum to one.
6. Given the observed estimates, our model indicates that an average Trump-leaning county (41% vote-share preference for Trump) verses an average Clinton-leaning county (23% vote-share preference for Clinton) exhibited 7.23% points less reduction in overall

movement and 8.06% points less reduction in visiting nonessential services across the examined date range (March 9 to May 29, 2020).

7. Partisanship was also one of the strongest predictors for the saturated models (the models that included the interactions between partisanship and all control variables, all z-scored; state-policy and population density were stronger predictors; see our analysis outputs hosted here).
8. We also examined whether we would find similar results at the state level—specifically, when assessing partisanship via state-level Trump approval (in 2020) rather than county-level vote gap. We found that Trump approval predicted decreased state physical distancing, *p*s $< .001$. However, this link was not robust to the inclusion of all possible control variables (see Supplements: Partisanship and physical distancing: February 2020 Trump approval*;* pgs. 48-50). These results likely occurred because of the small sample size in terms of states (N = 50), the large number of included control terms in our models, and the resulting reduction in sensitivity due to collapsing across counties of varying make-up and political identity. These findings indicate that future research examining the link between partisanship (and related constructs) and physical distancing should do so at the county rather than state level.
9. In the preregistration we had planned for our analyses to include only data from March 24 onward. Here we report analyses for March 9 onward, however, because this does not substantively change the results and because including all available data provides more accurate estimates. Additionally, in our preregistration we had planned to remove counties with a population of less than 5,000 people. Ultimately, we instead decided to

exclude counties with a population less than 2,000 people to include as much data in our analyses as possible. These decisions did not substantively affect our results.

10. The preregistration does not include clear analysis plans or model specifications and thus solely qualifies as a preregistration of hypotheses. It does not qualify as a preregistration of analyses or model specifications.
11. We also found an interaction with the quadratic time term (B_{movement} = 0.229, 95% CI[0.215, 0.243] and $B_{\text{visitation}}$ = -0.055, 95% CI[-0.079, -0.031], ps < .001; Figure 4). These interactions indicated that for general movement, Trump-leaning counties exhibited a more concave trend over time, while for visitation, they exhibited more of a convex trend over time.
12. Given that the quadratic term did not capture visitation over time well, and because the fit of the included time terms will change with new data, we also reran these models using a General Additive Model approach in which we applied a smoothed time term (GAM; see Supplemental Results).
13. In these analyses, we included all covariates and interactions between vote gap and covariates as controls (see the Saturated Model in Supplementary Tables 22 and 23).
14. In Supplementary Figures 5 and 6 we plot model predictions derived from our main model, analogous to Figure 4. in the main text, but split by states. And finally, we ensured that our findings are not accounted for by effects of State-level policy and Governor party through interactions between those terms not captured in our main model (see Supplements: Additional state-policy models, especially Supplementary Figures 7-9 and Supplementary Table 31).

15. Vote gap for Trump over Clinton in the 2016 election correlated moderately with Fox News preference at the U.S. county level, $r(3005) = .44$, $p < .001$.
16. Because several of the mediation models failed to converge when including random slopes, only random intercepts of county and state were included.
17. Our mediation findings do not rest on the total effects and direct effects being significant. That is, indirect effects can be significant even if total effect and direct effects are not. This is because indirect effects quantify the *change* between total and direct effects. Thus, the marginal total effect observed between partisanship and infection growth rate (when visiting nonessential services was the mediator) does not impact our findings or conclusions.
18. Regarding the total effect, while infection growth rate was larger in Trump-leaning counties in the examined date range, fatality growth rate was *smaller*. First, these differences do not impact the observed mediations (for both infection and fatality growth rate the observed indirect effect was significant). Second, this difference is likely driven by infection growth rate rising around ~May, 2020 in more Trump-leaning counties than Clinton-leaning counties, meaning that fatality growth rate will likely catch up to infection growth rate over summer 2020 until Trump-leaning counties exhibit a larger fatality growth rate as well (this may then change again over the upcoming months/years depending on preventative measures and how coronavirus spreads). Third, we examine the observed mediation when including a broader date range in the *Mediation at Earlier Date Range* section below and found the expected results in that the indirect effects remained while the total and direct effects changed as expected (infection growth rate

was higher in more liberal counties when considering an earlier date range, *p*s < .073 (Supplementary Table 33).

19. Given that we assigned a change from 0 cases to some number of cases in a county as a growth rate of 0, the average reported daily growth rate is likely an underestimation of the actual growth rate.
20. Aside from these analyses, the fact that the mediations were conducted using mixed models in which county was nested within state also should help account for random variation among states, including potential reporting bias.
21. This was the day that we completed the hypothesis preregistration.
22. We excluded counties with less than 2,000 inhabitants because the GPS physical distancing estimates are likely to become unreliable in such counties (we estimated that by including only counties of over 2,000 inhabitants that we would have at least 125 participants per county).
23. Nonessential retail and services are those that fall into the categories of restaurants; department stores; clothing; footwear; discount stores; jewelry; computers and consumer electronics; gifts; seasonal products; books; office supplies; hair; cosmetics and beauty supplies; gyms and fitness; communications; new and used cars; hotels; used products; crafts, toys, and hobbies; travel; spa, massage, and aesthetics; sports and recreation; weight loss; furnishings; home and housewares; home improvement and building supplies; printing, copying, and publishing; theaters; music; amusement; furnishing rentals; shared offices and coworking; car wash; cannabis retail; flowers; bars; pubs; cafes; nightclubs; cinemas; and casinos.

24. Days prior to March 9 were treated by Unacast (the software company that shared this data with the authors) as pre-COVID. For more detail how these scores were calculated see here (the two included measures are metrics one and two). The data provided by Unacast is not shared publicly by us for proprietary reasons but can be accessed by contacting Unacast. For analysis code and for details of the sources of all included measures see here.

Supplemental Materials

Reduction in general movement and visiting nonessential services. Unacast gathers GPS data from thousands of different app providers in the US (all opt-in consent) which provide a unique device ID, a timestamp that the device was "pinged," and the corresponding latitude and longitude. Unacast then clusters these raw pings into dwells (based on if a device is stationary using a certain number of pings over a period of time) and travel events (based on if a device is moving due to the dispersity of the pings). The change in distance traveled, then, is calculated using those travel events. Specifically, percent reduction total distance traveled is calculated by taking the total distance traveled for each device in a county and then averaging across all the devices in a county. Devices were assigned to counties based on where a specific device was recorded for the longest time on a specific day.

The general movement measure is defined by Unacast as the "Percent reduction in total distance traveled per device, averaged across all devices located in the county." The visiting nonessential services measure is defined by Unacast as the "Difference in visitation of nonessential POIs on a specific Post-COVID-19 day compared to a corresponding Pre-COVID-19 baseline." Post-COVID-19 indicates any day after March 8. The Pre-COVID-19 baseline was calculated as a counties' general movement and visiting nonessential services from the same day of the week during the four weeks leading up to March 9. For example, a county's level of physical distancing on Monday, March 9 was calculated as the percent reduction in movement and nonessential visits from the average levels of movement and nonessential visits on the four pre-COVID Mondays (February 10, February 17, February 24, and March 2) in that county.

Regarding the nonessential visitations measure, according to Unacast, this measure includes visiting: "nonessential POIs combine (1) venues from the VDP output and (2) additional BYOPOI (Bring Your Own Points of Interests) added by Unacast based on categories from OpenStreetMaps." These POIs include:

Retail and Services: Restaurant (multiple kinds), Department Store, Clothing (multiple kinds), Footwear, Discount Stores, Jewelry, Computers + Consumer Electronics, Gifts, Seasonal, Books, Office Supplies, Hair, Cosmetics + Beauty Supplies, Gyms + Fitness Facilities, Communications, New/Used Car Dealers, Hotels, Used Products, "Crafts, Toys, and Hobbies", Travel, "Spa, Massage, + Esthetics," Sports + Recreation, Weight Loss, Furnishings, Home + Housewares, Home Improvement +Building Supplies, "Printing, Copying + Publishing", Theatres, Music, Amusement, Furnishing Rentals, Shared Offices + Coworking, Car Wash, Cannabis Retail, Flowers

OpenStreetMaps POIs: Amenity: bar, pub, cafe, restaurant, theatre, nightclub, cinema, casino. Leisure: bowling_alley, fitness_centre, cafe, restaurant, theatre, nightclub. Shop: department_store, mall, clothes, shoes, doityourself, furniture, sports

Further details regarding how the two physical distancing measures were calculated can be found in the "UnacastMethodologyAndAccess" folder in our open-science framework project page (here).

Covariates (control variables). We included numerous control variables in the models. For a detailed overview of these covariates, including descriptions, descriptive statistics, and ranges, see Supplementary Tables 1 and 2, and our dataset references file ("References_Datasets_CovidPolitics_June14.pdf" hosted on our OSF page here). Additionally, for a detailed rmarkdown file of visualizations of these control variables see the file named "partisan_geotracking_00" hosted on our OSF project page (here).

Supplementary Table 1. Descriptions of all covariates, including control variables.

Variable	Description	Source	County or State Level
Time (linear)	Linear time variable from 3/9/20 to 5/29/20	Unacast (2020)	County
Time (quadratic)	Quadratic time variable from 3/9/20 to 5/29/20	Unacast (2020)	County
Weekend	Dummy, 0 weekday, 1 weekend	Unacast (2020)	County
Median Household Income	Median household income in US$ (2018). In model, centered & in units of 10K	United States Department of Agriculture Economic Research Service (2020)	County
Population Density	Population density per square mile of land area as per 2010 census. In model, log- and z-transformed.	Killeen et al. (2020)	County
Median Age	Median county age. In model centered & in decade units.	United States Census Bureau (2018a)	County
Proportion Age 0-17	Proportion in county 0-17. Centered in model.	Killeen et al. (2020)	County

Proportion Age 18-64	Proportion in county 18-64. Centered in model.	Killeen et al. (2020)	County
Proportion Age 65-85	Proportion in county 65-85. Centered in model.	Killeen et al. (2020)	County
Proportion Age 85+	Proportion in county 85+. Centered in model.	Killeen et al. (2020)	County
Grocery Stores per 1000 People	Number of grocery stores per 1,000 people, 2014. Centered in model.	United States Department of Agriculture (2018)	County
Percent of Residents with Low Access to Grocery Stores	Percent of residents in county with ‘low access’ to grocery stores, as of 2015 (low access = composite rating considering distance, vehicle access, and income level). Centered in model.	United States Department of Agriculture (2018)	County
Religious Adherents per 1000 People	Rate of religious adherents per 1,000 people, as of 2010. In model, per capita & centered.	Hoover (2010)	County
Percent Employed	Number of people employed divided by county population 2018. Centered in model.	United States Department of Agriculture Economic Research Service (2020)	County
Governor (Republican)	Dummy, 0 Democrat, 1 Republican, centered in model.	Ballotpedia (2020)	State
State Policy (Stay-at-home)	Dummy, 0 no order, 1 stay-at-home order, centered in model.	Mervosh, Lee, Gamio, & Popovich (2020, June 5)	State (NYC at county)
Commute Time (hours)	Mean travel time to work (hours) of workers 16 and over who did not work at home, 2018. Centered in model.	United States Census Bureau (2018b)	County
Gini Coefficient	Gini Index estimate, 2018, centered in model.	United States Census Bureau (2018c)	County
Difference in Life Expectancy 1985-2010	Difference in life expectancy, 1985-2010 (years)	Institute for Health Metrics and Evaluation (2019)	County
Proportion Black	Percent estimate - Black alone or in combination with one or more other races 2018. Centered in model.	United States Census Bureau (2018a)	County
Proportion Asian	Percent estimate - Asian alone or in combination with one or more other races 2018. Centered in model.	United States Census Bureau (2018a)	County
Proportion Hispanic or Latinx	Percent estimate - Hispanic or Latinx (of any race) 2018. Centered in model.	United States Census Bureau (2018a)	County

State Policy - K-12 Schools Closed	Dummy, 0 no order, 1 state order, centered in model.	Raifman et al. (2020)	State
State Policy - Daycares Closed	Dummy, 0 no order, 1 state order, centered in model.	Raifman et al. (2020)	State
State Policy - Restaurants Closed (except take-out)	Dummy, 0 no order, 1 state order, centered in model.	Raifman et al. (2020)	State
State Policy - Religious Gatherings Closed	Dummy, 0 no order, 1 state order, centered in model. Takes into account states with exemptions for religious gatherings.	Raifman et al. (2020)	State
State Policy - Non-essential Businesses Closed	Dummy, 0 no order, 1 state order, centered in model.	Raifman et al. (2020)	State
Percent Employees in Agriculture, Forestry, Fishing and Hunting	2016 percent of employees in Agriculture, Forestry, Fishing and Hunting	Social Explorer (2016)	County
Percent Employees in Mining, Quarrying, and Oil and Gas Extraction	2016 percent of employees in Mining, Quarrying, and Oil and Gas Extraction	Social Explorer (2016)	County
Percent Employees in Utilities	2016 percent of employees in Utilities	Social Explorer (2016)	County
Percent Employees in Construction	2016 percent of employees in Construction	Social Explorer (2016)	County
Percent Employees in Manufacturing	2016 percent of employees in Manufacturing	Social Explorer (2016)	County
Percent Employees in Wholesale Trade	2016 percent of employees in Wholesale Trade	Social Explorer (2016)	County
Percent Employees in Retail Trade	2016 percent of employees in Retail Trade	Social Explorer (2016)	County
Percent Employees in Transportation	2016 percent of employees in Transportation	Social Explorer (2016)	County
Percent Employees in Information	2016 percent of employees in Information	Social Explorer (2016)	County
Percent Employees in Finance and Insurance	2016 percent of employees in Finance and Insurance	Social Explorer (2016)	County
Percent Employees in Real Estate and Rental and Leasing	2016 percent of employees in Real Estate and Rental and Leasing	Social Explorer (2016)	County

Percent Employees in Professional Scientific, and Technical Services	2016 percent of employees in Professional Scientific, and Technical Services	Social Explorer (2016)	County
Percent Employees in Management of Companies and Enterprises	2016 percent of employees in Management of Companies and Enterprises	Social Explorer (2016)	County
Percent Employees in Administrative and Support and WasteManagement and Remediation Services	2016 percent of employees in Administrative and Support and WasteManagement and Remediation Services	Social Explorer (2016)	County
Percent Employees in Educational Services	2016 percent of employees in Educational Services	Social Explorer (2016)	County
Percent Employees in Health Care and Social Assistance	2016 percent of employees in Health Care and Social Assistance	Social Explorer (2016)	County
Percent Employees in Arts, Entertainment, and Recreation	2016 percent of employees in Arts, Entertainment, and Recreation	Social Explorer (2016)	County
Percent Employees in Accommodation and Food Services	2016 percent of employees in Accommodation and Food Services	Social Explorer (2016)	County

Supplementary Table 2. Descriptives of all covariates, including control variables.

Variable	**Descriptives**	**Overall (N=248050)**
Time (linear)	Mean (SD)	0.000000000000000000756 (0.110)
	Median [Min, Max]	0.00000000000000000412 [-0.189, 0.189]
Time (quadratic)	Mean (SD)	-0.00000000000000000171 (0.110)
	Median [Min, Max]	-0.0309 [-0.123, 0.238]
Weekend	Mean (SD)	0.268 (0.443)
	Median [Min, Max]	0 [0, 1.00]
Median Household Income (thousands)	Mean (SD)	52.9 (14.0)
	Median [Min, Max]	50.6 [25.4, 140]

Population Density	Mean (SD)	269 (1760)
	Median [Min, Max]	47.3 [0.100, 69500]
	Missing	164 (0.1%)
Median Age	Mean (SD)	41.1 (5.25)
	Median [Min, Max]	41.1 [21.7, 67.0]
Proportion Age 0-17	Mean (SD)	0.221 (0.0341)
	Median [Min, Max]	0.221 [0.0707, 0.420]
Proportion Age 18-64	Mean (SD)	0.588 (0.0373)
	Median [Min, Max]	0.587 [0.353, 0.820]
Proportion Age 65-85	Mean (SD)	0.167 (0.0398)
	Median [Min, Max]	0.164 [0.0428, 0.533]
Proportion Age 85+	Mean (SD)	0.0234 (0.00818)
	Median [Min, Max]	0.0223 [0.00367, 0.0754]
Grocery Stores per 1000 People	Mean (SD)	0.234 (0.164)
	Median [Min, Max]	0.192 [0, 1.73]
	Missing	164 (0.1%)
Percent of Residents with Low Access to Grocery Stores	Mean (SD)	0.211 (0.159)
	Median [Min, Max]	0.187 [0, 1.00]
	Missing	1722 (0.7%)
Religious Adherents per 1000 People	Mean (SD)	512 (176)
	Median [Min, Max]	495 [51.3, 1920]
	Missing	164 (0.1%)
Percent Employed	Mean (SD)	0.448 (0.0703)
	Median [Min, Max]	0.452 [0.176, 0.704]
Governor (Republican)	Mean (SD)	0.564 (0.496)
	Median [Min, Max]	1.00 [0, 1.00]

State Policy (Stay-at-home)	Mean (SD)	0.488 (0.500)
	Median [Min, Max]	0 [0, 1.00]
Commute Time (hours)	Mean (SD)	2.14 (0.923)
	Median [Min, Max]	2.10 [0.0167, 5.12]
Gini Coefficient	Mean (SD)	592 (293)
	Median [Min, Max]	580 [2.00, 1220]
Difference in Life Expectancy 1985-2010	Mean (SD)	2.73 (1.40)
	Median [Min, Max]	2.70 [-1.55, 10.7]
Proportion Black	Mean (SD)	0.102 (0.148)
	Median [Min, Max]	0.0340 [0, 0.875]
Proportion Asian	Mean (SD)	0.0183 (0.0337)
	Median [Min, Max]	0.00900 [0, 0.612]
Proportion Hispanic or Latinx	Mean (SD)	0.0925 (0.137)
	Median [Min, Max]	0.0410 [0, 0.991]
State Policy - K-12 Schools Closed	No Order	34,727 (14/0%)
	State Order	213,323 (86.0%)
State Policy - Daycares Closed	No Order	202,133 (81.5%)
	State Order	45,917 (18.5%)
State Policy - Restaurants Closed (except take-out)	No Order	85,978 (34.7%)
	State Order	162,072 (65.3%)
State Policy- Religious Gatherings Closed	No Order	145,632 (58.7%)
	State Order	102,418 (41.3%)
State Policy- Non-essential Businesses Closed	No Order	223,532 (90.1%)
	State Order	24,518 (9.9%)

Percent of Employees in Agriculture, Forestry, Fishing and Hunting	Mean (SD)	0.612 (1.86)
	Median [Min, Max]	0.0200 [0, 31.6]
	Missing	246 (0.1%)
Percent of Employees in Mining, Quarrying, and Oil and Gas Extraction	Mean (SD)	1.29 (4.32)
	Median [Min, Max]	0 [0, 46.1]
	Missing	246 (0.1%)
Percent of Employees in Utilities	Mean (SD)	0.343 (0.870)
	Median [Min, Max]	0 [0, 14.5]
	Missing	246 (0.1%)
Percent of Employees in Construction	Mean (SD)	5.52 (3.87)
	Median [Min, Max]	4.74 [0, 38.7]
	Missing	328 (0.1%)
Percent of Employees in Manufacturing	Mean (SD)	14.3 (12.0)
	Median [Min, Max]	11.5 [0, 71.2]
	Missing	2706 (1.1%)
Percent of Employees in Wholesale Trade	Mean (SD)	4.28 (3.57)
	Median [Min, Max]	3.46 [0, 36.7]
	Missing	2952 (1.2%)
Percent of Employees in Retail Trade	Mean (SD)	15.9 (4.73)
	Median [Min, Max]	15.6 [0.490, 45.2]
	Missing	246 (0.1%)
Percent of Employees in Transportation	Mean (SD)	3.74 (3.55)
	Median [Min, Max]	2.78 [0, 32.5]
	Missing	1804 (0.7%)
Percent of Employees in Information	Mean (SD)	1.22 (1.27)
	Median [Min, Max]	0.970 [0, 17.1]

	Missing	5494 (2.2%)
Percent of Employees in Finance and Insurance	Mean (SD)	3.66 (2.23)
	Median [Min, Max]	3.13 [0, 33.2]
	Missing	574 (0.2%)
Percent of Employees in Real Estate and Rental and Leasing	Mean (SD)	1.06 (0.965)
	Median [Min, Max]	0.880 [0, 11.9]
	Missing	5904 (2.4%)
Percent of Employees in Professional, Scientific, and Technical Services	Mean (SD)	3.35 (3.30)
	Median [Min, Max]	2.60 [0, 74.6]
	Missing	1066 (0.4%)
Percent of Employees in Management of Companies and Enterprises	Mean (SD)	0.835 (1.65)
	Median [Min, Max]	0.0900 [0, 35.2]
	Missing	66420 (26.8%)
Percent of Employees in Administrative & Support & Waste Mgmt. & Remediation Services	Mean (SD)	3.40 (2.85)
	Median [Min, Max]	2.86 [0, 31.0]
	Missing	3198 (1.3%)
Percent of Employees in Educational Services	Mean (SD)	1.20 (2.17)
	Median [Min, Max]	0.440 [0, 22.8]
	Missing	42148 (17.0%)
Percent of Employees in Health Care and Social Assistance	Mean (SD)	17.3 (7.83)
	Median [Min, Max]	16.7 [0, 80.2]
	Missing	410 (0.2%)
Percent of Employees in Arts, Entertainment, and Recreation	Mean (SD)	1.28 (2.20)
	Median [Min, Max]	0.840 [0, 51.5]
	Missing	10496 (4.2%)

Percent of Employees in Accommodation and Food Services	Mean (SD)	11.1 (5.78)
	Median [Min, Max]	10.3 [0, 76.8]
	Missing	656 (0.3%)

We also examine several measures of partisanship and partisan media consumption. For a detailed overview of these measures, including descriptions, descriptive statistics, and ranges, see Supplementary Tables 3 and 4, and our datasets references file (here).

Supplementary Table 3. Descriptions of partisanship and partisan media measures.

Variable	**Description**	**Source**	**County or State Level**
GOP Advantage (2016 vote gap)	Percent Republican vote minus percent Democrat vote, 2016	US County Level Election Results 08-16 (2016)	County
Fox News Lean	Proportion of people reporting watching Fox News minus proportion of people reporting watching CNN and MSNBC, 2019	SimplyAnalytics (2020)	County
Trump Approval Feb 2020	Trump net approval (i.e., approval minus disapproval), -1 to 1 scale, February 2020	Morning Consult (2020)	State

Supplementary Table 4. Descriptives of partisanship and partisan media measures.

Variable	**Descriptives**	**Overall (N=248050)**
GOP Advantage (2016 vote gap)	Mean (SD)	0.310 (0.305)
	Median [Min, Max]	0.375 [-0.887, 0.849]
	Missing	1476 (0.6%)

Fox News Lean	Mean (SD)	0.0761 (0.00375)
	Median [Min, Max]	0.0765 [0.0588, 0.0975]
	Missing	164 (0.1%)
Trump Approval Feb 2020	Mean (SD)	0.0219 (0.132)
	Median [Min, Max]	0.0400 [-0.390, 0.280]
	Missing	82 (0.0%)

We also utilized data on COVID-19 cases and deaths. For a detailed overview of these measures, including descriptions, descriptive statistics, and ranges, see Supplementary Tables 5, 6, 7, and 8, and our datasets references file (here).

Supplementary Table 5. Descriptions of COVID-19 case and death measures.

Variable	Description	Source	County or State Level
COVID-19 Cases per Capita	Daily cumulative number of COVID-19 cases divided by county population	The New York Times (2020); New York State Department of Health (2020); Unacast (2020)	County
COVID-19 Deaths per Capita	Daily cumulative number of COVID-19 deaths divided by county population	The New York Times (2020); USA Facts (2020)	County

Supplementary Table 6 Descriptives of COVID-19 case and death measures.

Variable	Descriptives	Overall (N=248050)

COVID-19 Cases per Capita	Mean (SD)	0.00116 (0.00343)
	Median [Min, Max]	0.000275 [0, 0.126]
COVID-19 Deaths per Capita	Mean (SD)	0.0000482 (0.000164)
	Median [Min, Max]	0 [0, 0.00307]

Supplementary Table 7. Descriptions of COVID-19 case and death growth rate measures.

Variable	Description	Source	County or State Level
COVID-19 Case Growth Rate	Crude Growth Rate. Calculated as: [p_d+p_d-1+…+p_d-6]/7; d = {35, 34, 7} where d = lag-day number and p = physical distancing score	The New York Times (2020); New York State Department of Health (2020); Unacast (2020)	County
COVID-19 Death Growth Rate	Crude Growth Rate. Calculated as: [p_d+p_d-1+…+p_d-6]/7; d = {35, 34, 7} where d = lag-day number and p = physical distancing score	The New York Times (2020); USA Facts (2020)	County

Supplementary Table 8. Descriptives of COVID-19 case and death growth rate measures.

Variable	Descriptives	Overall (N=196625)
COVID-19 Case Growth Rate	Mean (SD)	5.76 (23.3)
	Median [Min, Max]	0 [-100, 1930]
COVID-19 Death Growth Rate	Mean (SD)	1.65 (13.2)
	Median [Min, Max]	0 [-100, 1500]

Supplemental Results

Descriptives of behavioral physical distance. Physical distancing was assessed via counties' daily *percent reduction* in general movement and *percent reduction* in visiting nonessential services as compared to pre-COVID (before March, 9th). Percent reduction in general movement: $M = 0.21$, $SD = 0.19$, min = -2.82, max = 0.98. Percent reduction in general movement: $M = 0.31$, $SD = 0.30$, min = -12.01, max = 1.00. These values indicate that on average there was a ~21% decrease in general movement and a ~31% decrease in visiting nonessential services across the included dates - March 9 to May 29th - as compared to before COVID-19 (before March 9). For a detailed overview of these measures, including descriptions, descriptive statistics, and ranges, see Supplementary Tables 9 and 10, and our datasets references file (here).

Supplementary Table 9. Descriptions of physical distancing measures.

Variable	Description	Source	County or State Level
Daily General Movement Difference	Percent reduction of average distance traveled from baseline (avg. distance traveled for same day of week during non-COVID-19 time period for a specific county)	Unacast (2020)	County
Daily Nonessential Visitation Difference	Percent reduction of visits to nonessential retail and services from baseline (avg. visits for same day of week during non-COVID-19 time period for a specific county)	Unacast (2020)	County

Supplementary Table 10. Descriptives of physical distancing measures.

Variable	Descriptives	Overall (N=248050)
Daily General Movement Difference	Mean (SD)	0.213 (0.194)
	Median [Min, Max]	0.220 [-2.82, 0.975]
Daily Nonessential Visitation Difference	Mean (SD)	0.314 (0.296)
	Median [Min, Max]	0.351 [-12.0, 1.00]
	Missing	78160 (31.5%)

Validation of behavioral physical distancing measures. We first performed several analyses to validate the included behavioral physical distancing measures (the code for these analyses, which were conducted in R, and detailed outputs of these analyses can be found in the "partisan_geotracking_validation.html" hosted here). We entered percent reduction in daily distance traveled (reverse-coded, such that greater values corresponded to increased physical distancing) into mixed effects models, and time as a linear fixed factor and as a quadratic fixed factor. Linear and quadratic time in these analyses (and all other analyses) were calculated to be orthogonal terms. In each of these validation models, we included random intercepts of county and state and random slopes of linear and quadratic time at the state-level. As expected, we found quadratic effects of time (above and beyond linear effects) for percent reduction in general movement and visiting nonessential services between 3/9/2020 and 5/29/2020, such that general movement and visitation reduction increased over time, peaked, and then began to decline (see Supplementary Tables 11 and 12; negative *b*s indicate a convex distribution). On top of these quadratic relationships, we also found that physical distancing decreased over time linearly (see Supplementary Tables 11 [general movement] and 12 [visiting nonessential services]; see Figure 1 in the main text for visualization).

Supplementary Table 11. Validation of percent reduction in general movement over time.

	Reduction in General Movement		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	0.240	0.216 – 0.263	**<0.001**
time_day_linear	-0.336	-0.341 – -0.331	**<0.001**
time_day_quad	-0.858	-0.863 – -0.854	**<0.001**
Random Effects			
σ^2	0.016		
$\tau_{00\ county\_fips}$	0.008		
$\tau_{00\ state\_name}$	0.007		
ICC	0.475		
N_{county_fips}	3025		
N_{state_name}	51		
Observations	248050		
Marginal R^2 / Conditional R^2	0.250 / 0.606		

Supplementary Table 12. Validation of percent reduction in visiting nonessential services over time.

	Reduction in Visiting Nonessential Services		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	0.340	0.315 – 0.365	**<0.001**
time_day_linear	-0.734	-0.741 – -0.726	**<0.001**
time_day_quad	-1.317	-1.325 – -1.309	**<0.001**

Random Effects	
σ^2	0.031
$\tau_{00\ county\_fips}$	0.024
$\tau_{00\ state\_name}$	0.007
ICC	0.503
$N_{\ county\_fips}$	2073
$N_{\ state\_name}$	51
Observations	169890
Marginal R^2 / Conditional R^2	0.309 / 0.657

Next, given the numerous peaks in Figure 1, we examined whether physical distancing was higher on the weekends. We added weekend as a fixed-effects factor (1 = *weekend,* 0 = *weekday*) to our previously described linear mixed effects model (and added a random slope of weekend at the state-level as well for general movement)[1]. We observed large weekend effects, such that reductions in general movement and visitation reduction are both considerably greater on weekends (see Supplementary Tables 13 and 14). Specifically, on the weekends people exhibited an additional ~8.7% reduction in general movement and ~2.5% reduction in visiting nonessential services. These findings are likely driven by fewer people traveling for work on weekends.

Supplementary Table 13. Validation of weekend effects on percent reduction in general movement.

	Reduction in General Movement		
Predictors	*Estimates*	*CI*	*p*

[1] The random slope of weekend was not added for the visiting nonessential services model as this led to convergence issues.

(Intercept)	0.219	0.194 – 0.244	**<0.001**
time_day_linear	-0.271	-0.355 – -0.187	**<0.001**
time_day_quad	-0.866	-0.918 – -0.813	**<0.001**
weekend	0.087	0.086 – 0.088	**<0.001**
Random Effects			
σ^2	0.014		
$\tau_{00\ \mathrm{county\_fips}}$	0.008		
$\tau_{00\ \mathrm{state\_name}}$	0.008		
$\tau_{11\ \mathrm{state\_name.time\_day\_linear}}$	0.092		
$\tau_{11\ \mathrm{state\_name.time\_day\_quad}}$	0.036		
$\rho_{01\ \mathrm{state\_name.time\_day\_linear}}$	0.709		
$\rho_{01\ \mathrm{state\_name.time\_day\_quad}}$	-0.735		
ICC	0.547		
$N_{\mathrm{county\_fips}}$	3025		
$N_{\mathrm{state\_name}}$	51		
Observations	248050		
Marginal R^2 / Conditional R^2	0.277 / 0.672		

Supplementary Table 14. Validation of weekend effects on percent reduction in visiting nonessential services.

	Reduction in Visiting Nonessential Services		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	0.337	0.309 – 0.365	**<0.001**
time_day_linear	-0.669	-0.799 – -0.539	**<0.001**
time_day_quad	-1.357	-1.410 – -1.303	**<0.001**
weekend	0.025	0.023 – 0.027	**<0.001**

Random Effects	
σ^2	0.029
$\tau_{00\ county\_fips}$	0.024
$\tau_{00\ state\_name}$	0.009
$\tau_{11\ state\_name.time\_day\_linear}$	0.223
$\tau_{11\ state\_name.time\_day\_quad}$	0.036
$\rho_{01\ state\_name.time\_day\_linear}$	0.890
$\rho_{01\ state\_name.time\_day\_quad}$	0.184
ICC	0.558
N_{county_fips}	2073
N_{state_name}	51
Observations	169890
Marginal R^2 / Conditional R^2	0.301 / 0.691

Additionally, we looked at the relationship between income and physical distancing. We conducted the same mixed effects model analysis again, but added median household income (2018) to the model as a fixed effect. Median income was mean centered and in units of 10k (i.e., a score of 1 indicates 10k above the mean median income, a score of 2 indicates 20k above the mean and so on). As anticipated, median household income was associated with increased physical distancing (3% and 4% higher distancing on average for general movement and visiting nonessential services, respectively; see Supplementary Tables 15 & 16).

Supplementary Table 15. Validation of relationship between income and percent reduction in general movement.

	Reduction in General Movement		
Predictors	*Estimates*	*CI*	*p*

(Intercept)	0.208	0.188 – 0.228	**<0.001**
time_day_linear	-0.271	-0.355 – -0.187	**<0.001**
time_day_quad	-0.865	-0.918 – -0.813	**<0.001**
weekend	0.087	0.086 – 0.088	**<0.001**
median_income_10k_c	0.030	0.027 – 0.032	**<0.001**
Random Effects			
σ^2	0.014		
$\tau_{00\ \mathrm{county\_fips}}$	0.007		
$\tau_{00\ \mathrm{state\_name}}$	0.005		
$\tau_{11\ \mathrm{state\_name.time\_day\_linear}}$	0.092		
$\tau_{11\ \mathrm{state\_name.time\_day\_quad}}$	0.036		
$\rho_{01\ \mathrm{state\_name.time\_day\_linear}}$	0.707		
$\rho_{01\ \mathrm{state\_name.time\_day\_quad}}$	-0.743		
ICC	0.481		
$N_{\mathrm{county\_fips}}$	3025		
$N_{\mathrm{state\_name}}$	51		
Observations	248050		
Marginal R^2 / Conditional R^2	0.334 / 0.654		

Supplementary Table 16. Validation of relationship between income and percent reduction in visiting nonessential services.

	Reduction in Visiting Nonessential Services		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	0.327	0.305 – 0.349	**<0.001**
time_day_linear	-0.671	-0.801 – -0.540	**<0.001**

time_day_quad	-1.356	-1.409 – -1.302	**<0.001**
weekend	0.025	0.023 – 0.027	**<0.001**
median_income_10k_c	0.040	0.036 – 0.045	**<0.001**
Random Effects			
σ^2	0.029		
$\tau_{00\ \text{county\_fips}}$	0.021		
$\tau_{00\ \text{state\_name}}$	0.006		
$\tau_{11\ \text{state\_name.time\_day\_linear}}$	0.223		
$\tau_{11\ \text{state\_name.time\_day\_quad}}$	0.036		
$\rho_{01\ \text{state\_name.time\_day\_linear}}$	0.926		
$\rho_{01\ \text{state\_name.time\_day\_quad}}$	0.200		
ICC	0.511		
$N_{\text{county\_fips}}$	2073		
$N_{\text{state\_name}}$	51		
Observations	169890		
Marginal R^2 / Conditional R^2	0.350 / 0.682		

We also assessed whether physical distancing is higher when states have issued stay-at-home orders. Specifically, we added state policy (0 = *stay-at-home order not in effect for a specific state on a specific day in the included date range* and 1 = *stay-at-home order in effect for a specific state on a specific day in the included date range*) as a fixed effect to the model. State policy was quantified at the state level, except for counties in New York City which continued to have stay-at-home orders in effect even when New York State lifted its order. As one would expect, we found greater physical distancing when there was a stay-at-home policy in place, both for general movement (see *Supplementary* Table 17) and visiting nonessential services (see *Supplementary* Table 18). Physical distancing was on average ~5.5% and ~6.2% higher, respectively, when stay-at-home orders were in place as compared to when they were not.

Supplementary Table 17. Validation of relationship between state policy and percent reduction in general movement.

	Reduction in General Movement		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	0.217	0.193 – 0.240	**<0.001**
time_day_linear	-0.297	-0.379 – -0.216	**<0.001**
time_day_quad	-0.740	-0.793 – -0.687	**<0.001**
weekend	0.088	0.087 – 0.090	**<0.001**
state_policy_c	0.055	0.053 – 0.057	**<0.001**
Random Effects			
σ^2	0.014		
$\tau_{00\ county\_fips}$	0.008		
$\tau_{00\ state\_name}$	0.007		
$\tau_{11\ state\_name.time\_day\_linear}$	0.088		
$\tau_{11\ state\_name.time\_day\_quad}$	0.036		
$\rho_{01\ state\_name.time\_day\_linear}$	0.640		
$\rho_{01\ state\_name.time\_day\_quad}$	-0.711		
ICC	0.536		
N_{county_fips}	3025		
N_{state_name}	51		
Observations	248050		
Marginal R^2 / Conditional R^2	0.295 / 0.673		

Supplementary Table 18. Validation of relationship between state policy and percent reduction in visiting nonessential services.

	Reduction in Visiting Nonessential Services		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	0.334	0.308 – 0.360	**<0.001**
time_day_linear	-0.700	-0.823 – -0.576	**<0.001**
time_day_quad	-1.216	-1.273 – -1.158	**<0.001**
weekend	0.026	0.025 – 0.028	**<0.001**
state_policy_c	0.062	0.059 – 0.065	**<0.001**
Random Effects			
σ^2	0.029		
$\tau_{00\ \text{county\_fips}}$	0.024		
$\tau_{00\ \text{state\_name}}$	0.008		
$\tau_{11\ \text{state\_name.time\_day\_linear}}$	0.200		
$\tau_{11\ \text{state\_name.time\_day\_quad}}$	0.041		
$\rho_{01\ \text{state\_name.time\_day\_linear}}$	0.842		
$\rho_{01\ \text{state\_name.time\_day\_quad}}$	0.195		
ICC	0.547		
$N_{\text{county\_fips}}$	2073		
$N_{\text{state\_name}}$	51		
Observations	169890		
Marginal R^2 / Conditional R^2	0.316 / 0.690		

Finally, we combined all covariates into one model, which is reported in the main text and in Supplementary Tables 19 and 20 below.

Supplementary Table 19. Validation of relationship between state policy, income, weekday effects and percent reduction in general movement.

	Reduction in General Movement		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	0.206	0.187 – 0.225	**<0.001**
time_day_linear	-0.297	-0.379 – -0.216	**<0.001**
time_day_quad	-0.739	-0.792 – -0.686	**<0.001**
weekend	0.088	0.087 – 0.090	**<0.001**
state_policy_c	0.055	0.053 – 0.057	**<0.001**
median_income_10k_c	0.030	0.027 – 0.032	**<0.001**
Random Effects			
σ^2	0.014		
$\tau_{00\ \text{county\_fips}}$	0.007		
$\tau_{00\ \text{state\_name}}$	0.004		
$\tau_{11\ \text{state\_name.time\_day\_linear}}$	0.088		
$\tau_{11\ \text{state\_name.time\_day\_quad}}$	0.036		
$\rho_{01\ \text{state\_name.time\_day\_linear}}$	0.652		
$\rho_{01\ \text{state\_name.time\_day\_quad}}$	-0.715		
ICC	0.469		
$N_{\text{county\_fips}}$	3025		
$N_{\text{state\_name}}$	51		
Observations	248050		
Marginal R^2 / Conditional R^2	0.354 / 0.657		

Supplementary Table 20. Validation of relationship between state policy, income, weekday effects and percent reduction in visiting nonessential services.

	Reduction in Visiting Nonessential Services		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	0.314	0.294 – 0.333	**<0.001**
time_day_linear	-0.701	-0.824 – -0.577	**<0.001**
time_day_quad	-1.215	-1.272 – -1.158	**<0.001**
weekend	0.026	0.025 – 0.028	**<0.001**
state_policy_c	0.062	0.059 – 0.065	**<0.001**
median_income_10k_c	0.041	0.036 – 0.046	**<0.001**
Random Effects			
σ^2	0.029		
$\tau_{00\ \text{county\_fips}}$	0.021		
$\tau_{00\ \text{state\_name}}$	0.004		
$\tau_{11\ \text{state\_name.time\_day\_linear}}$	0.200		
$\tau_{11\ \text{state\_name.time\_day\_quad}}$	0.041		
$\rho_{01\ \text{state\_name.time\_day\_linear}}$	0.899		
$\rho_{01\ \text{state\_name.time\_day\_quad}}$	0.222		
ICC	0.499		
$N_{\text{county\_fips}}$	2073		
$N_{\text{state\_name}}$	51		
Observations	169890		
Marginal R^2 / Conditional R^2	0.367 / 0.683		

Further, for validation and a test of the sensitivity of this final model, we reconducted this model but with generalized additive models (GAMs). Specifically, we modeled general movement and visitation to nonessential services with time as a smoothed predictor function rather than as a linear and quadratic time predictor. The model included the smoothed predictor function (based off of linear time), county, and state as smoothed functions and included linear controls for weekend, state policy, and median income (coded as in the previous models). Importantly, the GAM approach yielded similar results. Again, we found that enacted state policies, weekends, and median income all predicted greater physical distancing (*p*s<.001, Supplementary Table 21).

Supplementary Table 21. Validation of links between state-policy, weekend, and median income with reduction in general movement and visitation to nonessential services when applying a general additive model (GAM) rather than a linear mixed-effects model.

	General Movement				**Visiting Nonessential Services**			
Predictors	*Estimates*	*SE*	*t*	*p*	*Estimates*	*SE*	*t*	*p*
(Intercept)	0.207	0.001	336.9	<.001	-0.025	0.064	-0.392	0.695
weekend	0.104	0.001	136.8	<.001	0.047	0.001	34.346	<.001
state_policy	0.158	0.001	201.0	<.001	0.240	0.001	171.038	<.001
median_income	0.032	<0.001	117.0	<.001	0.040	<0.001	82.201	<.001
	edf	*Ref.df*	*F*	*p*	*edf*	*Ref.df*	F	*p*
s(time_day_linear)	1	1	11612.7	<.001	1	1	22225	<0.001
s(county_fips)	5.74E-08	1	0	<.001	0.806	1	430031551	<0.001
s(state_name)	49.02	50	305.3	<.001	48.22	49	2719	<0.001
Observations	168668				168668			
R^2	0.392				0.298			

Partisanship and physical distancing: 2016 vote gap. In our main analyses, we examined whether partisanship, as assessed via the county-level voting gap in the 2016 election, predicted counties' degree of physical distancing between March 9th and May 29th, 2020. We conducted a series of three-level mixed-effects models (observations were nested within county and county within state) varying in model specification and saturation to examine the robustness of this claim. In each of these models, we included random intercepts of county and state and the random slope of partisanship at the state-level (we also included random slopes of linear time, quadratic time, and the interactions between partisanship and time where possible, that is, when doing so did not led to convergence failures).

First, as base models, we conducted two mixed effects models with the two physical distancing measures as the outcome variables (general distance and visiting nonessential services, respectively), and voting gap (percent of total votes for Donald Trump in 2016 minus percent of total votes for Hillary Clinton; $M = 0.31$, $SD = 0.30$, min = -0.89, max = .85), linear time and quadratic time (as orthogonal time terms), and the two-way interactions between vote gap and time (linear and quadratic) as fixed effects. We observed a main effect of vote gap in that voting in favor of Donald Trump predicted decreased physical distancing both in terms of general movement and in terms of visiting nonessential services, ps < .001 (see Base Models in Supplementary Tables 22 and 23).[2] We also observed an interaction between vote gap and linear time. The observed negative interaction indicated that the link between voting in favor of Trump in 2016 and reduced physical distancing increased with time, ps < .001 (see Base Models in Supplementary Tables 22 and 23).[3]

To examine the robustness of the observed association between partisanship and physical distancing, we reran these models while adding numerous covariates. Namely, we ran two further

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[2] Counties in Alaska were excluded as we did not have vote-gap data accessible for these counties.
[3] We also observed significant quadratic interactions. For Clinton voting counties as compared to Trump voting ones, the change in general movement over time was more convex, while the change in visiting nonessential services was more concave (these findings are not particularly relevant for our conclusions, however, and are thus noted in this footnote).

model specifications, a main effects model (including main effect of all controls and the interactions between partisanship and linear and quadratic time), and a fully saturated model (including all controls, all interactions between controls and partisanship, and the interactions between partisanship and linear and quadratic time). We added the following covariates to these models (see Supplementary Tables 22 and 23): COVID-19 cases per capita (cumulative cases divided by county population; included for each specific day in the included date range; mean centered), state policy (dummy coded as 1 and 0 and then mean centered; -0.49 = *stay-at-home order not in effect for a specific state on a specific day in the included date range* and 0.51 = *stay-at-home order in effect for a specific state on a specific day in the included date range*), state governor political affiliation (dummy coded as 1 and 0 and then mean centered; -0.56 = *Republican governor*, 0.44 = *Democrat governor*), weekend (0 = *Weekday*, 1 = *Weekend*), median income (mean centered and in units of 10k [see validation analyses above]), median age (mean centered and in units of 10 years), percent of population aged 0-17 (mean centered), percent of population aged 65-85 (mean centered), percent of population older than 85 (mean centered), change in life expectancy from 1985 to 2010 (mean centered), population density (log-transformed and *z*-scored), access to grocery stores (mean centered), number of grocery stores per 1,000 people (mean centered), religiosity (mean centered and divided by 1000; original variable was rate of religious adherents per 1000 people - note that several counties had more religious adherents than residents, perhaps due to registration at multiple denominations, or from registration from non-county residents), percent employment (mean centered), economic inequality (Gini coefficient; mean centered), average time to travel to work (divided by 60 and mean centered), percent of population Black (divided by 100 and mean centered), percent

Hispanic (divided by 100 and mean centered), and percent Asian (divided by 100 and mean centered). All the noted models were re-conducted when *z*-scoring all the included continuous controls (see the "Standardized models" tab for each of the following rmarkdown files, "partisan_geotracking_01_partisanship," "partisan_geotracking_01_foxnews," and "partisan_geotracking_01_trumpapproval" hosted on our OSF project page, here).

Crucially, even when adjusting for these variables and for interactions between these variables and partisanship, we still found a significant association between partisanship (vote gap) and physical distancing for both general movement and visiting nonessential services, $ps < .001$ (see Row 2 of the main models and saturated models in Supplementary Tables 22 and 23). And, again we found a negative interaction between partisanship and linear time, $ps < .001$, suggesting that counties favoring Trump exhibited weaker physical distancing as time progressed (see Supplementary Tables 22 and 23, Row 5).

Supplementary Table 22. Predicting reduction in general movement. Base model, main model, and fully saturated models.

	Base Model			**Main Model**			**Saturated Model**		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.263	0.245 – 0.280	**<0.001**	0.220	0.209 – 0.231	**<0.001**	0.214	0.203 – 0.225	**<0.001**
gop_advantage_2016	-0.159	-0.196 – -0.122	**<0.001**	-0.114	-0.140 – -0.087	**<0.001**	-0.099	-0.127 – -0.072	**<0.001**
time_day_linear	-0.184	-0.240 – -0.129	**<0.001**	-0.241	-0.248 – -0.234	**<0.001**	-0.249	-0.256 – -0.241	**<0.001**
time_day_quad	-0.943	-0.986 – -0.901	**<0.001**	-0.814	-0.821 – -0.807	**<0.001**	-0.803	-0.810 – -0.795	**<0.001**

gop_advantage_2016* time_day_linear	-0.585	-0.689 – -0.481	**<0.001**	-0.382	-0.396 – -0.367	**<0.001**	-0.363	-0.379 – -0.346	**<0.001**
gop_advantage_2016* time_day_quad	0.263	0.191 – 0.335	**<0.001**	0.229	0.215 – 0.243	**<0.001**	0.194	0.177 – 0.211	**<0.001**
weekend				0.089	0.088 – 0.090	**<0.001**	0.087	0.085 – 0.088	**<0.001**
median_income_10k_c				0.020	0.017 – 0.024	**<0.001**	0.022	0.018 – 0.026	**<0.001**
pop_density_log_s				0.029	0.024 – 0.034	**<0.001**	0.032	0.026 – 0.037	**<0.001**
cases_capita_100_c				0.013	0.011 – 0.016	**<0.001**	0.016	0.013 – 0.019	**<0.001**
supermarkets_c				0.055	0.034 – 0.076	**<0.001**	0.070	0.038 – 0.103	**<0.001**
supermarkets_low_accesstores_c				0.004	-0.015 – 0.022	0.691	0.017	-0.012 – 0.047	0.253
religion_c				-0.010	-0.031 – 0.010	0.323	-0.029	-0.055 – -0.003	**0.029**
percent_employed_c				-0.080	-0.138 – -0.022	**0.007**	-0.023	-0.106 – 0.059	0.578
median_age_county_2018_10y_c				0.044	0.028 – 0.060	**<0.001**	0.044	0.023 – 0.065	**<0.001**
age_proportion_85plus_c				0.170	-0.449 – 0.790	0.590	-0.932	-1.883 – 0.019	0.055
age_proportion_65to85_c				-0.344	-0.556 – -0.132	**0.001**	-0.096	-0.418 – 0.225	0.557
age_proportion_0to17_c				0.029	-0.093 – 0.151	0.638	0.114	-0.035 – 0.263	0.133
state_policy_c				0.038	0.036 – 0.039	**<0.001**	0.043	0.041 – 0.045	**<0.001**
governor_c				0.012	-0.007 – 0.032	0.222	0.012	-0.009 – 0.034	0.253
gini_c				0.232	0.134 – 0.329	**<0.001**	0.291	0.164 – 0.417	**<0.001**
prop_hisp_latin_c				-0.078	-0.113 – -0.044	**<0.001**	-0.063	-0.101 – -0.024	**0.001**
prop_asian_c				0.171	0.041 – 0.301	**0.010**	0.171	0.015 – 0.328	**0.032**
prop_black_c				-0.140	-0.181 – -0.099	**<0.001**	-0.119	-0.164 – -0.074	**<0.001**
life_expectancy_diff_19852010_c				0.004	0.001 – 0.006	**0.001**	0.005	0.002 – 0.008	**0.003**
commute_time_h_c				-0.047	-0.086 – -0.007	**0.021**	-0.102	-0.156 – -0.049	**<0.001**
gop_advantage_2016* weekend							0.006	0.003 – 0.009	**0.001**
gop_advantage_2016 * median_income_10k_c							-0.012	-0.023 – -0.002	**0.024**
gop_advantage_2016 *							-0.015	-0.028 – -0.001	**0.032**

pop_density_log_s			
gop_advantage_2016 * cases_capita_100_c	-0.013	-0.020 – -0.006	**<0.001**
gop_advantage_2016 * supermarkets_c	-0.075	-0.141 – -0.009	**0.027**
gop_advantage_2016 * supermarkets_low_accesstores_c	-0.024	-0.088 – 0.039	0.456
gop_advantage_2016 * religion_c	0.073	0.011 – 0.135	**0.021**
gop_advantage_2016 * percent_employed_c	-0.187	-0.375 – 0.000	0.051
gop_advantage_2016 * median_age_county_2018_10y_c	-0.016	-0.068 – 0.037	0.559
gop_advantage_2016 * age_proportion_85plus_c	3.263	1.126 – 5.399	**0.003**
gop_advantage_2016 * age_proportion_65to85_c	-0.514	-1.267 – 0.239	0.181
gop_advantage_2016 * age_proportion_0to17_c	-0.197	-0.576 – 0.182	0.309
gop_advantage_2016 * state_policy_c	-0.017	-0.022 – -0.013	**<0.001**
gop_advantage_2016 * governor_c	0.006	-0.039 – 0.051	0.796
gop_advantage_2016 * gini_c	-0.319	-0.614 – -0.024	**0.034**
gop_advantage_2016 * prop_hisp_latin_c	-0.018	-0.101 – 0.065	0.670
gop_advantage_2016 * prop_asian_c	0.288	-0.116 – 0.693	0.163
gop_advantage_2016 * prop_black_c	0.005	-0.077 – 0.087	0.906
gop_advantage_2016 * life_expectancy_diff_19852010_c	-0.004	-0.012 – 0.004	0.305
gop_advantage_2016 * commute_time_h_c	0.212	0.087 – 0.337	**0.001**

Random Effects			
σ^2	0.0150	0.0138	0.0138
τ_{00}	0.0062 county_fips	0.0038 county_fips	0.0037 county_fips
	0.0036 state_name	0.0010 state_name	0.0011 state_name
τ_{11}	0.0107 county_fips.gop_advantage_2016	0.0074 county_fips.gop_advantage_2016	0.0068 county_fips.gop_advantage_2016
	0.0147 state_name.gop_advantage_2016	0.0043 state_name.gop_advantage_2016	0.0039 state_name.gop_advantage_2016
	0.0382 state_name.time_day_linear		
	0.0218 state_name.time_day_quad		
	0.1304 state_name.gop_advantage_2016:time_day_linear		
	0.0575 state_name.gop_advantage_2016:time_day_quad		
ρ_{01}	-0.4283 county_fips	-0.1172 county_fips	-0.0944 county_fips
	-0.5126 state_name.gop_advantage_2016	-0.1336 state_name	-0.1227 state_name
	0.1617 state_name.time_day_linear		
	-0.3826 state_name.time_day_quad		
	-0.3978 state_name.gop_advantage_2016:time_day_linear		
	0.1415 state_name.gop_advantage_2016:time_day_quad		
ICC	0.4207	0.3163	0.3157
N	3007 county_fips	2987 county_fips	2987 county_fips
	50 state_name	50 state_name	50 state_name
Observations	246574	244934	244934
Marginal R^2 / Conditional R^2	0.343 / 0.619	0.462 / 0.632	0.463 / 0.633

Supplementary Table 23. Predicting reduction in visiting nonessential services. Base model, main model, and fully saturated models.

	Base Model			**Main Model**			**Saturated Model**		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.415	0.394 – 0.437	**<0.001**	0.346	0.332 – 0.360	**<0.001**	0.347	0.332 – 0.363	**<0.001**
gop_advantage_2016	-0.351	-0.394 – -0.307	**<0.001**	-0.125	-0.162 – -0.088	**<0.001**	-0.109	-0.148 – -0.070	**<0.001**
time_day_linear	-0.453	-0.539 – -0.367	**<0.001**	-0.503	-0.514 – -0.492	**<0.001**	-0.494	-0.506 – -0.482	**<0.001**

time_day_quad	-1.342	-1.391 – -1.294	**<0.001**	-1.192	-1.203 – -1.181	**<0.001**	-1.182	-1.194 – -1.169	**<0.001**
gop_advantage_201* time_day_linear	-1.084	-1.112 – -1.056	**<0.001**	-1.030	-1.054 – -1.005	**<0.001**	-1.064	-1.093 – -1.035	**<0.001**
gop_advantage_201* time_day_quad	-0.061	-0.089 – -0.034	**<0.001**	-0.055	-0.079 – -0.031	**<0.001**	-0.094	-0.125 – -0.064	**<0.001**
weekend				0.026	0.024 – 0.028	**<0.001**	0.038	0.036 – 0.040	**<0.001**
median_income_10k_c				0.022	0.016 – 0.028	**<0.001**	0.016	0.008 – 0.023	**<0.001**
pop_density_log_s				0.048	0.041 – 0.055	**<0.001**	0.044	0.035 – 0.052	**<0.001**
cases_capita_100_c				0.033	0.029 – 0.037	**<0.001**	0.028	0.024 – 0.032	**<0.001**
supermarkets_c				-0.097	-0.158 – -0.035	**0.002**	-0.080	-0.153 – -0.007	**0.033**
supermarkets_low_accesstores_c				0.151	0.103 – 0.199	**<0.001**	0.082	0.017 – 0.148	**0.014**
religion_c				-0.024	-0.064 – 0.016	0.233	-0.030	-0.076 – 0.016	0.205
percent_employed_c				0.288	0.164 – 0.412	**<0.001**	0.499	0.321 – 0.677	**<0.001**
median_age_county_2018_10y_c				-0.139	-0.171 – -0.108	**<0.001**	-0.126	-0.167 – -0.086	**<0.001**
age_proportion_85plus_c				0.174	-1.248 – 1.596	0.810	0.116	-1.846 – 2.078	0.908
age_proportion_65to85_c				0.509	0.058 – 0.959	**0.027**	0.567	-0.084 – 1.219	0.088
age_proportion_0to17_c				-1.319	-1.581 – -1.058	**<0.001**	-1.097	-1.415 – -0.778	**<0.001**
state_policy_c				0.044	0.042 – 0.047	**<0.001**	0.047	0.043 – 0.050	**<0.001**
governor_c				-0.015	-0.039 – 0.010	0.244	-0.019	-0.045 – 0.007	0.149
gini_c				0.426	0.232 – 0.621	**<0.001**	0.537	0.293 – 0.781	**<0.001**
prop_hisp_latin_c				0.081	0.019 – 0.144	**0.011**	0.081	0.014 – 0.148	**0.018**
prop_asian_c				-0.034	-0.219 – 0.152	0.722	0.393	0.137 – 0.648	**0.003**
prop_black_c				-0.103	-0.172 – -0.035	**0.003**	-0.104	-0.181 – -0.027	**0.008**
life_expectancy_diff_19852010_c				0.001	-0.003 – 0.005	0.588	0.002	-0.004 – 0.007	0.548
commute_time_h_c				-0.164	-0.245 – -0.084	**<0.001**	-0.137	-0.245 – -0.030	**0.012**
gop_advantage_2016 * weekend							-0.045	-0.051 – -0.039	**<0.001**
gop_advantage_2016 * median_income_10k_c							0.015	-0.003 – 0.033	0.097

gop_advantage_2016 * pop_density_log_s	0.007	-0.015 – 0.029	0.523
gop_advantage_2016 * cases_capita_100_c	0.030	0.018 – 0.042	**<0.001**
gop_advantage_2016 * supermarkets_c	-0.045	-0.204 – 0.114	0.581
gop_advantage_2016 * supermarkets_low_accesstores_c	0.168	0.011 – 0.326	**0.036**
gop_advantage_2016 * religion_c	0.096	-0.015 – 0.207	0.090
gop_advantage_2016 * percent_employed_c	-0.643	-1.056 – -0.230	**0.002**
gop_advantage_2016 * median_age_county_2018_10y_c	-0.094	-0.203 – 0.015	0.089
gop_advantage_2016 * age_proportion_85plus_c	1.294	-3.340 – 5.928	0.584
gop_advantage_2016 * age_proportion_65to85_c	0.012	-1.619 – 1.643	0.988
gop_advantage_2016 * age_proportion_0to17_c	-1.235	-2.001 – -0.470	**0.002**
gop_advantage_2016 * state_policy_c	-0.009	-0.016 – -0.001	**0.030**
gop_advantage_2016 * governor_c	0.026	-0.023 – 0.076	0.292
gop_advantage_2016 * gini_c	-0.185	-0.745 – 0.375	0.518
gop_advantage_2016 * prop_hisp_latin_c	0.018	-0.122 – 0.158	0.804
gop_advantage_2016 * prop_asian_c	1.047	0.424 – 1.669	**0.001**
gop_advantage_2016 * prop_black_c	-0.080	-0.216 – 0.056	0.248
gop_advantage_2016 * life_expectancy_diff_19852010_c	-0.003	-0.016 – 0.009	0.612
gop_advantage_2016 * commute_time_h_c	0.153	-0.094 – 0.401	0.225

Random Effects			
σ^2	0.0278	0.0283	0.0283
τ_{00}	0.0161 $_{\text{county\_fips}}$	0.0106 $_{\text{county\_fips}}$	0.0104 $_{\text{county\_fips}}$
	0.0047 $_{\text{state\_name}}$	0.0013 $_{\text{state\_name}}$	0.0013 $_{\text{state\_name}}$
τ_{11}	0.0164 $_{\text{state\_name.gop\_advantage\_2016}}$	0.0020 $_{\text{state\_name.gop\_advantage\_2016}}$	0.0017 $_{\text{state\_name.gop\_advantage\_2016}}$
	0.0942 $_{\text{state\_name.time\_day\_linear}}$		
	0.0282 $_{\text{state\_name.time\_day\_quad}}$		
ρ_{01}	-0.7232 $_{\text{state\_name.gop\_advantage\_2016}}$	-0.0452 $_{\text{state\_name}}$	-0.0417 $_{\text{state\_name}}$
	0.4437 $_{\text{state\_name.time\_day\_linear}}$		
	0.0402 $_{\text{state\_name.time\_day\_quad}}$		
ICC	0.4375	0.3008	0.2966
N	2068 $_{\text{county\_fips}}$	2057 $_{\text{county\_fips}}$	2057 $_{\text{county\_fips}}$
	50 $_{\text{state\_name}}$	50 $_{\text{state\_name}}$	50 $_{\text{state\_name}}$
Observations	169480	168586	168586
Marginal R^2 / Conditional R^2	0.459 / 0.696	0.536 / 0.676	0.539 / 0.676

We reran the Saturated model (see Supplementary Tables 22 and 23) again when additionally controlling for the percent employment in various types of professions (e.g., agriculture, finance, manufacturing). These models were run separately because the percent employment type variables included substantial amounts of missing data and thus reduced sample size. We included percent employment in agriculture (which also includes forestry, fishing, and hunting), mining (which also includes quarrying, oil, and gas extraction), utilities, construction, manufacturing, wholesale trade, retail trade, transportation and warehousing, information, finance and insurance, real estate, professional services (also include scientific and technical services), management of companies and enterprises, administrative, educational services, health care and social assistance, arts (including entertainment and recreation), and finally, accommodation and food services (all mean centered; see Supplementary Table 1 for more detail). When doing so, partisanship still predicted a smaller reduction in general movement and visiting nonessential services. The interactions with linear time remained as well (see Supplementary Table 24).

Supplementary Table 24. Predicting reduction in general movement and nonessential visitation when also including percent employment type in the saturated model.

	Reduction in General Movement			**Reduction in Non-Essential Visitation**		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.216	0.203 – 0.228	**<0.001**	0.352	0.337 – 0.367	**<0.001**
gop_advantage_2016	-0.058	-0.089 – -0.028	**<0.001**	-0.091	-0.131 – -0.052	**<0.001**
time_day_linear	-0.219	-0.226 – -0.212	**<0.001**	-0.494	-0.506 – -0.482	**<0.001**
time_day_quad	-0.827	-0.834 – -0.820	**<0.001**	-1.186	-1.199 – -1.174	**<0.001**
weekend	0.086	0.084 – 0.087	**<0.001**	0.040	0.037 – 0.042	**<0.001**
median_income_10k_c	0.014	0.010 – 0.018	**<0.001**	0.013	0.005 – 0.020	**0.001**
pop_density_log_s	0.030	0.025 – 0.036	**<0.001**	0.041	0.032 – 0.051	**<0.001**
cases_capita_100_c	0.015	0.012 – 0.017	**<0.001**	0.029	0.025 – 0.034	**<0.001**
supermarkets_c	0.034	-0.004 – 0.072	0.077	-0.109	-0.185 – -0.033	**0.005**
supermarkets_low_accesstores_c	0.010	-0.025 – 0.045	0.572	0.090	0.022 – 0.159	**0.009**
religion_c	-0.007	-0.032 – 0.018	0.565	-0.006	-0.051 – 0.039	0.782
percent_employed_c	0.125	0.024 – 0.226	**0.015**	0.488	0.297 – 0.680	**<0.001**
median_age_county_2018_10y_c	0.060	0.038 – 0.083	**<0.001**	-0.112	-0.153 – -0.070	**<0.001**
age_proportion_85plus_c	-0.740	-1.819 – 0.339	0.179	3.095	1.043 – 5.146	**0.003**
age_proportion_65to85_c	-0.143	-0.495 – 0.209	0.426	-0.069	-0.745 – 0.607	0.842
age_proportion_0to17_c	0.120	-0.060 – 0.301	0.190	-0.989	-1.327 – -0.652	**<0.001**

state_policy_c	0.038	0.036 – 0.040	**<0.001**	0.046	0.043 – 0.050	**<0.001**
governor_c	0.001	-0.022 – 0.024	0.931	-0.022	-0.046 – 0.002	0.070
gini_c	0.211	0.080 – 0.341	**0.002**	0.415	0.167 – 0.664	**0.001**
prop_hisp_latin_c	0.036	-0.004 – 0.076	0.081	0.079	0.010 – 0.147	**0.024**
prop_asian_c	0.239	0.091 – 0.386	**0.002**	0.313	0.067 – 0.559	**0.013**
prop_black_c	-0.036	-0.085 – 0.013	0.146	-0.074	-0.153 – 0.005	0.067
life_expectancy_diff_19852010_c	0.004	0.001 – 0.007	**0.007**	0.001	-0.004 – 0.006	**0.673**
commute_time_h_c	-0.080	-0.137 – -0.022	**0.006**	-0.106	-0.217 – 0.004	**0.058**
pct_emp_agri_2016_prop_c	0.428	0.126 – 0.731	**0.005**	0.625	0.011 – 1.239	**0.046**
pct_emp_mini_2016_prop_c	0.153	0.037 – 0.268	**0.009**	0.266	0.061 – 0.470	**0.011**
pct_emp_util_2016_prop_c	-0.372	-0.825 – 0.081	0.108	0.123	-0.684 – 0.930	0.764
pct_emp_cons_2016_prop_c	0.114	0.014 – 0.213	**0.025**	0.068	-0.127 – 0.263	**0.495**
pct_emp_manu_2016_prop_c	-0.020	-0.069 – 0.030	0.442	-0.065	-0.167 – 0.036	0.206
pct_emp_whol_2016_prop_c	-0.142	-0.265 – -0.020	**0.023**	-0.150	-0.378 – 0.078	**0.197**
pct_emp_reta_2016_prop_c	-0.025	-0.115 – 0.065	0.587	-0.172	-0.342 – -0.001	**0.049**
pct_emp_tran_2016_prop_c	-0.201	-0.291 – -0.110	**<0.001**	0.013	-0.153 – 0.180	**0.877**
pct_emp_info_2016_prop_c	0.253	0.015 – 0.492	**0.037**	0.142	-0.285 – 0.570	**0.513**
pct_emp_fina_2016_prop_c	0.113	-0.020 – 0.246	0.097	-0.076	-0.322 – 0.171	0.546
pct_emp_real_2016_prop_c	0.645	0.295 – 0.996	**<0.001**	-0.651	-1.307 – 0.006	**0.052**
pct_emp_prof_2016_prop_c	0.154	0.029 – 0.279	**0.016**	-0.032	-0.252 – 0.188	**0.775**
pct_emp_mana_2016_prop_c	-0.023	-0.205 – 0.158	0.801	0.200	-0.118 – 0.519	0.218
pct_emp_admi_2016_prop_c	0.062	-0.060 – 0.185	0.316	0.266	0.043 – 0.489	**0.019**
pct_emp_educ_2016_prop_c	0.110	-0.018 – 0.238	0.092	0.041	-0.191 – 0.273	0.729
pct_emp_heal_2016_prop_c	-0.008	-0.074 – 0.058	0.806	0.045	-0.086 – 0.175	0.500
pct_emp_arts_2016_prop_c	0.396	0.215 – 0.577	**<0.001**	0.370	0.028 – 0.712	**0.034**

pct_emp_acco_2016_prop_c	0.126	0.046 – 0.206	**0.002**	0.491	0.328 – 0.655	**<0.001**
gop_advantage_2016 * time_day_linear	-0.360	-0.378 – -0.343	**<0.001**	-1.042	-1.073 – -1.012	**<0.001**
gop_advantage_2016 * time_day_quad	0.181	0.162 – 0.199	**<0.001**	-0.100	-0.132 – -0.068	**<0.001**
gop_advantage_2016 * weekend	0.017	0.013 – 0.020	**<0.001**	-0.038	-0.044 – -0.031	**<0.001**
gop_advantage_2016 * median_income_10k_c	-0.003	-0.014 – 0.008	0.553	0.014	-0.004 – 0.033	0.119
gop_advantage_2016 * pop_density_log_s	-0.007	-0.021 – 0.008	0.356	0.019	-0.005 – 0.043	0.116
gop_advantage_2016 * cases_capita_100_c	-0.007	-0.015 – 0.000	0.061	0.026	0.014 – 0.039	**<0.001**
gop_advantage_2016 * supermarkets_c	0.017	-0.069 – 0.102	0.697	-0.149	-0.323 – 0.025	0.094
gop_advantage_2016 * supermarkets_low_accesstores_c	-0.049	-0.141 – 0.043	0.296	-0.064	-0.234 – 0.105	0.457
gop_advantage_2016 * religion_c	-0.020	-0.087 – 0.046	0.551	0.045	-0.068 – 0.158	0.439
gop_advantage_2016 * percent_employed_c	-0.539	-0.787 – -0.291	**<0.001**	-0.784	-1.226 – -0.342	**0.001**
gop_advantage_2016 * median_age_county_2018_10y_c	0.005	-0.060 – 0.070	0.882	-0.084	-0.199 – 0.031	0.152
gop_advantage_2016 * age_proportion_85plus_c	6.226	3.541 – 8.910	**<0.001**	-0.269	-5.255 – 4.717	**0.916**
gop_advantage_2016 * age_proportion_65to85_c	-1.374	-2.298 – -0.450	**0.004**	0.459	-1.270 – 2.188	**0.603**
gop_advantage_2016 * age_proportion_0to17_c	0.172	-0.309 – 0.653	0.483	-0.508	-1.351 – 0.334	0.237
gop_advantage_2016 * state_policy_c	-0.016	-0.021 – -0.011	**<0.001**	-0.009	-0.017 – -0.000	**0.043**
gop_advantage_2016 * governor_c	0.020	-0.029 – 0.069	0.426	0.014	-0.036 – 0.063	0.584
gop_advantage_2016 * gini_c	-0.140	-0.466 – 0.187	0.402	0.056	-0.528 – 0.639	0.852
gop_advantage_2016 * prop_hisp_latin_c	-0.183	-0.276 – -0.091	**<0.001**	-0.060	-0.205 – 0.086	**0.422**
gop_advantage_2016 * prop_asian_c	0.258	-0.112 – 0.628	0.172	1.071	0.463 – 1.679	**0.001**
gop_advantage_2016 * prop_black_c	-0.077	-0.166 – 0.012	0.089	-0.039	-0.184 – 0.105	0.595
gop_advantage_2016 * life_expectancy_diff_19852010_c	-0.007	-0.014 – 0.001	0.087	-0.005	-0.017 – 0.008	0.448

gop_advantage_2016 * commute_time_h_c	0.093	-0.052 – 0.239	0.208	-0.112	-0.378 – 0.154	0.409

Random Effects	
σ^2	0.0099
$\tau_{00\ county\_fips}$	0.0024
$\tau_{00\ state\_name}$	0.0014
$\tau_{11\ county\_fips.gop\_advantage\_2016}$	0.0031
$\tau_{11\ state\_name.gop\_advantage\_2016}$	0.0051
$\rho_{01\ county\_fips}$	0.2016
$\rho_{01\ state\_name}$	-0.1195
ICC	0.3404
N_{county_fips}	1960
N_{state_name}	50
Observations	160720
Marginal R^2 / Conditional R^2	0.552 / 0.704

Random Effects	
σ^2	0.0263
$\tau_{00\ county\_fips}$	0.0085
$\tau_{00\ state\_name}$	0.0010
$\tau_{11\ state\_name.gop\_advantage\_2016}$	0.0019
$\rho_{01\ state\_name}$	-0.0344
ICC	0.2727
N_{county_fips}	1733
N_{state_name}	50
Observations	142046
Marginal R^2 / Conditional R^2	0.562 / 0.682

Testing the Models with GAMs

Further, for validation and a test of the sensitivity of this final model, we reconducted the base model, main model, and saturated model (see Supplementary Tables 22 and 23) but with generalized additive models (GAMs). Specifically, we modeled general movement and visitation to nonessential services with time as a smoothed predictor function rather than as a linear and quadratic time predictor. The model included (linear) time, partisanship, and weekend as fixed terms, linear time as a smoothed random effect, and county and state as random effects (smoothed as a random effect via ‘re’; see GAM documentation in R), and all the controls as fixed effects (depending on the specific model, base model, main model, or saturated model; see Supplementary Tables 22 and 23 above). Importantly, the GAM approach yielded similar results. GOP advantage was associated with decreased general movement and daily visitation to nonessential businesses in each of the 3 models, *p*s < .001 (Supplementary Table 25). For full results see the rmarkdown file named "GAM_analysis" in the OSF Project page (here).

Supplementary Table 25. Validation of the link between partisanship and physical distancing for the 3 conducted models (base model, main model, saturated model) when applying a general additive model (GAM) rather than a linear mixed-effects model.

	Reduction in General Movement				**Reduction in Visiting Nonessential Services**			
GOP-Advantage (2016)	*Estimate*	*SE*	*t*	*p*	*Estimate*	*SE*	*t*	*p*
Base Model	-0.135	0.002	-87.14	<0.001	-0.317	0.002	-128.42	<0.001
Main Model	-0.086	0.002	-37.32	<0.001	-0.130	0.004	-29.85	<0.001
Saturated Model	-0.068	0.003	-22.54	<0.001	-0.128	0.005	-25.14	<0.001

Link Between Partisanship and Physical Distancing Over Time

We next explored how the observed links between partisanship and physical distancing varied over time. First, for the main model reported above, we found interactions between vote gap and the linear time terms ($B_{movement}$ = -.382, 95% CI[-.396, -.367], and $B_{visitation}$ = -1.03, 95% CI[-1.054, -1.005], *p*s < .001) as well as the quadratic time terms ($B_{movement}$ = .229, 95% CI[.215, .243], and $B_{visitation}$ = -0.055, 95% CI[-0.079, -0.031], *p*s < .001; Figure 4; Table 1). These significant interactions were also found in the base and saturated models (see Supplementary Tables 22 and 23). Together, these interaction terms indicate accelerated decreases in physical distancing with time as a result of increasing Trump advantage in the 2016 vote, as well as moderation of the quadratic trend.

Second, we conducted mixed effects models for each date in the included date range (March 9 to May 29) with physical distancing (general movement and nonessential visitation) as the dependent variables (multiplied by 100 to create a percent), and vote gap and all the controls noted above as predictors (except weekend because weekday vs. weekend does not vary within a day and employment type because we wished to include as much data as possible). The random intercept of state was included (random slopes at the county level failed to converge). We then extracted the specific coefficient for partisanship predicting physical distancing from each of these models and plotted them over time (see Figure 5). We then empirically examined whether these coefficients change over time. Linear models with *z*-scored linear time and quadratic time terms (orthogonal) indicated that the link between counties' pro-Trump voting and weaker physical distancing strengthened over time (i.e., the coefficient became increasingly negative) both for general movement and visiting nonessential services (Supplementary Table 26; Figure 5). Furthermore, the relationship appeared to be quadratic, such that more pro-Trump voting counties (as compared to pro-Clinton counties) increasingly exhibited decreased physical distancing over time until this link plateaued in the end of April and begin to somewhat reverse (albiet visitation was only marginal; Supplementary Table 26; Figure 5).

We also conducted the same model but with Time as a non-parametric smoother (generalized additive model; GAM) because the linear and quadratic time terms did not perfectly capture the links between partisanship and physical distancing over time (see Supplementary Figure 1), and because these links will likely change outside of the date range observed here (March 9 to May 29). Again, the link between counties' pro-Trump voting and weaker physical distancing varied over time, both for general movement, edf = 8.65, df = 8.96, $F = 57.09$, $p < .001$, and for nonessential visitation, edf = 6.09, df = 7.25, $F = 19.72$, $p < .001$.

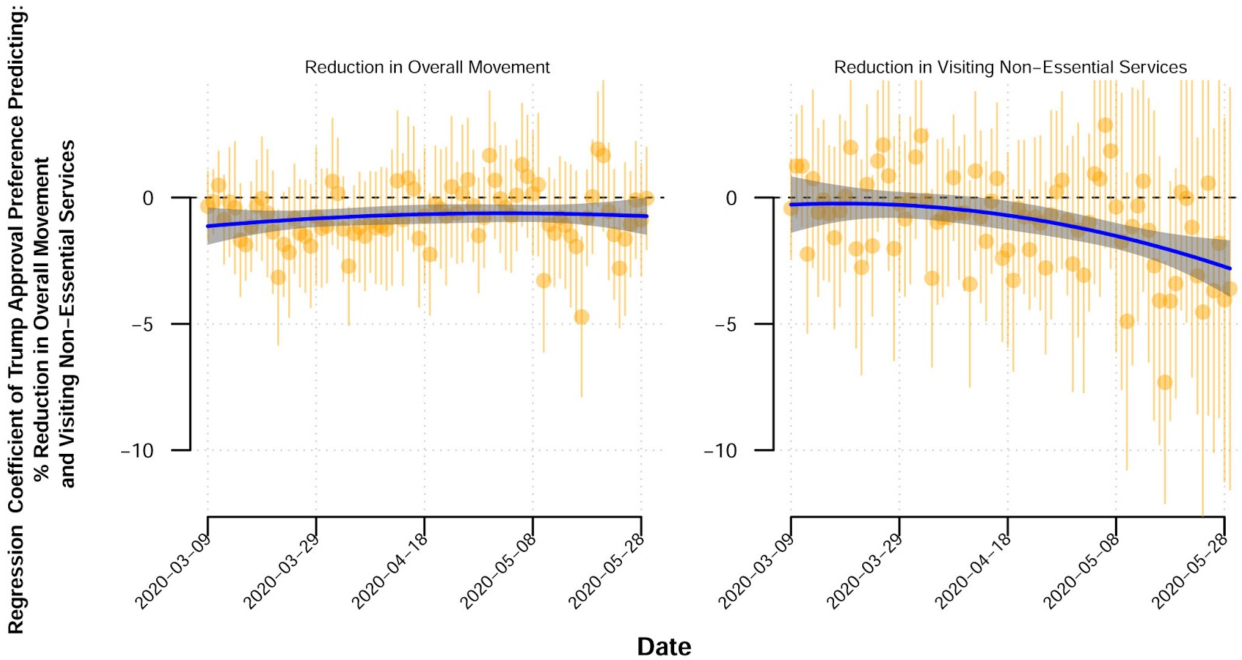
Supplementary Table 26. The negative link between vote-gap (2016 voting for Trump over Clinton) and reduction in general movement and visiting nonessential services (while controlling for covariates) strengthened over time (a negative linear trajectory) for general movement and visiting nonessential services. For general movement, a concave quadratic trajectory was also observed (marginal for visitation; see Figure 5).

	Reduction in General Movement			**Reduction in Visiting Nonessential Services**		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	-4.309	-4.497 – -4.121	**<0.001**	-5.374	-5.674 – -5.075	**<0.001**
time_day_linear	-0.956	-1.145 – -0.767	**<0.001**	-1.297	-1.599 – -0.996	**<0.001**
time_day_quad	0.861	0.672 – 1.050	**<0.001**	0.364	0.062 – 0.665	**0.019**

Partisanship and physical distancing: February 2020 Trump approval. We also examined whether the above results extend to the state-level. Specifically, we reconducted the base model, main model, and saturated model when replacing county partisanship (vote gap) with February 2020 *state*-level Trump approval as our measure of partisanship. We found that state-level trump approval predicted lower physical distancing in our base model, b_{movement} = -0.293, 95% CI[-0.413, -0.172], $p < .001$, and, $b_{\text{visitation}}$ = -0.404, 95% CI[-0.524, -0.285], $p <$ .001, but did not do so in the main model, b_{movement} = -0.042, 95% CI[-0.136, 0.052], $p = .378$, and $b_{\text{visitation}}$ = -0.026, 95% CI[-0.125, 0.074], $p = .613$, and did not do so in the saturated model, b_{movement} = 0.011, 95% CI[-0.081, 0.102], $p = .821$, and $b_{\text{visitation}}$ = 0.011, 95% CI[-0.095, 0.116], p

= .842. Similarly, the expected negative interactions between trump approval and linear time predicting physical distancing were observed in the base model, $b_{movement}$ = -0.563, 95% CI[-1.065, -0.061], p = .028, and, $b_{visitation}$ = -1.416, 95% CI[-2.084, -0.747], $p < .001$, but these interactions were inconsistent (i.e., varied in terms of general movement vs. visiting nonessential services for the main and saturated models (see rmarkdownfile named "partisan_geotracking_03_trump" on our OSF page, here, for detailed analyses).

These results were likely found due to a combination of the large number of included control terms in our models, the small *n* in terms of states (50), and the associated reduced sensitivity of collapsing across counties of varying make-up and political identity. Indeed, illustrating this reduced sensitivity, the daily coefficient estimates of physical distancing predicting Trump approval varied drastically between specific days (the yellow lines in Supplementary Figure 1; see (see rmarkdownfile named "OverTimeAnalyses" on our OSF page, here, for detailed analyses). In sum, these findings indicate that future research examining the link between partisanship (and related constructs) and physical distancing should do so at the county rather than state level.



Supplementary Figure 1. Coefficients of U.S. State-level Trump approval predicting percent reduction in general movement and visiting nonessential services for each of the included dates while controlling for covariates as a function of time (March 9 to May 29, 2020). Individual points represent regression coefficients. Blue lines represent predictions from linear regression models with linear and quadratic time terms. For GAM models of these data see Supplements. Error bands: +/- 2 *SE*.

State orders, partisanship, and physical distancing. We examined whether our observed partisanship findings are moderated by government intervention, specifically state-policy. To do so, we examined the interaction term between partisanship and state policy in the fully saturated mixed models we had calculated (see Supplementary Tables 22 and 23). We found that stay-at-home orders were less effective for Trump-voting counties, as evident by the negative interaction between vote gap and state policy, general movement: b = -0.17, 95% CI[-0.022, -0.013], p < .001, and visitation: b = -0.009, 95% CI[-0.016, -0.001], p = .030. This implies that when predicting reduction in movement for an average Clinton leaning county, the model predicted a 23.6% reduction in overall movement and a 35.8% reduction in visiting nonessential services *when not* under a state order, but a 28.3% and 40.6% reduction, respectively, *when under* a state order. For an average Trump leaning county, the model predicted a 18.0% reduction in overall movement and 28.1% reduction in visiting nonessential services *when not* under a state order but a 21.6% and 32.4% reduction, respectively *when under* a state order. Finally, these results remained when including type of employment in these models, $p < .001$, and $p = .043$ (see Supplementary Table 24).

Media consumption and physical distancing. We also examined whether counties' type of media consumption is predictive of physical distancing behavior. In particular, is physical distancing lower in areas that watch Fox News more so than CNN and MSNBC. We first created a Fox News preference score variable by subtracting the average media consumption of CNN and MSNBC from the average media consumption of Fox News per U.S. County (see Supplementary Tables 3 and 4 for descriptives). We then conducted the same mixed effects models (base model, main model, and saturated model) as we did for county vote-gap but with vote-gap replaced by Fox News preference (mean centered and multiplied by 100 to create a percent). As expected, Fox News preference was associated with decreased physical distancing as assessed via general movement and via visiting nonessential services in each of these models, *p*s < .001 (see Row 2 in Supplementary Tables 27 and 28). And, as we found for vote-gap, Fox News preference interacted with linear time in that the link between counties watching Fox News (more than MSNBC and CNN) and reduced physical distancing strengthened over time, *p*s < .001 (see Row 5 in Supplementary Tables 27 and 28. Critically, these findings were observed even in the most saturated model (i.e., when including all covariates and interactions between Fox News preference and these covariates; Supplementary Tables 27 and 28). And, these results also were observed when adding type of employment to these models, *p*s < .001 (see RMarkDown file named "partisan_geotracking_02_foxnews" on our OSF page, here, for analysis details).

Supplementary Table 27. Consuming Fox News (over CNN and MSNBC) predicts a smaller reduction in general movement. Base model, main model, and saturated model.

	Base Model			**Main Model**			**Saturated Model**		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.231	0.208 – 0.254	**<0.001**	0.193	0.179 – 0.206	**<0.001**	0.191	0.177 – 0.204	**<0.001**
media_foxnews_lean_percent_c	-0.069	-0.087 – -0.052	**<0.001**	-0.053	-0.076 – -0.030	**<0.001**	-0.042	-0.065 – -0.019	**<0.001**
time_day_linear	-0.294	-0.373 – -0.216	**<0.001**	-0.363	-0.367 – -0.358	**<0.001**	-0.362	-0.367 – -0.357	**<0.001**
time_day_quad	-0.887	-0.938 – -0.837	**<0.001**	-0.732	-0.737 – -0.727	**<0.001**	-0.732	-0.738 – -0.727	**<0.001**
media_foxnews_lean_percent_c* time_day_linear	-0.355	-0.368 – -0.343	**<0.001**	-0.332	-0.344 – -0.321	**<0.001**	-0.317	-0.330 – -0.304	**<0.001**
media_foxnews_lean_percent_c* time_day_quad	0.108	0.096 – 0.121	**<0.001**	0.109	0.097 – 0.120	**<0.001**	0.116	0.102 – 0.131	**<0.001**
weekend				0.089	0.088 – 0.090	**<0.001**	0.089	0.088 – 0.090	**<0.001**
median_income_10k_c				0.021	0.017 – 0.024	**<0.001**	0.020	0.017 – 0.024	**<0.001**
pop_density_log_s				0.037	0.032 – 0.041	**<0.001**	0.036	0.031 – 0.042	**<0.001**
cases_capita_100_c				0.015	0.013 – 0.018	**<0.001**	0.012	0.010 – 0.015	**<0.001**
supermarkets_c				0.057	0.036 – 0.079	**<0.001**	0.062	0.039 – 0.085	**<0.001**
supermarkets_low_accesstores_c				0.002	-0.016 – 0.021	0.801	0.007	-0.012 – 0.026	0.493
religion_c				-0.012	-0.033 – 0.009	0.269	-0.007	-0.028 – 0.014	0.537
percent_employed_c				-0.061	-0.121 – -0.001	**0.046**	-0.063	-0.125 – -0.001	**0.047**
median_age_county_2018_10y_c				0.036	0.019 – 0.053	**<0.001**	0.028	0.009 – 0.046	**0.003**
age_proportion_85plus_c				0.199	-0.462 – 0.859	0.555	-0.402	-1.128 – 0.324	0.278
age_proportion_65to85_c				0.209	-0.042 – 0.460	0.103	0.362	0.083 – 0.641	**0.011**

age_proportion_0to17_c	-0.109	-0.234 – 0.016	0.086	-0.151	-0.293 – -0.009	**0.037**
state_policy_c	0.042	0.041 – 0.044	**<0.001**	0.042	0.041 – 0.044	**<0.001**
governor_c	0.015	-0.012 – 0.042	0.271	0.014	-0.013 – 0.041	0.306
gini_c	0.332	0.234 – 0.430	**<0.001**	0.302	0.203 – 0.401	**<0.001**
prop_hisp_latin_c	0.056	0.026 – 0.087	**<0.001**	0.040	0.007 – 0.073	**0.018**
prop_asian_c	0.294	0.162 – 0.425	**<0.001**	0.341	0.170 – 0.513	**<0.001**
prop_black_c	-0.006	-0.034 – 0.022	0.665	-0.009	-0.038 – 0.020	0.548
life_expectancy_diff_19852010_c	0.003	0.001 – 0.005	**0.015**	0.003	0.001 – 0.005	**0.016**
commute_time_h_c	0.001	-0.040 – 0.042	0.952	-0.009	-0.051 – 0.032	0.658
media_foxnews_lean_percent_c* weekend				0.004	0.001 – 0.006	**0.015**
media_foxnews_lean_percent_c* median_income_10k_c				-0.009	-0.018 – 0.001	0.068
media_foxnews_lean_percent_c* pop_density_log_s				-0.008	-0.020 – 0.004	0.199
media_foxnews_lean_percent_c* cases_capita_100_c				-0.019	-0.026 – -0.012	**<0.001**
media_foxnews_lean_percent_c* supermarkets_c				-0.081	-0.140 – -0.021	**0.008**
media_foxnews_lean_percent_c* supermarkets_low_accesstores_c				-0.046	-0.101 – 0.008	0.095
media_foxnews_lean_percent_c * religion_c				0.067	0.015 – 0.118	**0.012**
media_foxnews_lean_percent_c * percent_employed_c				-0.089	-0.250 – 0.072	0.280
media_foxnews_lean_percent_c* median_age_county_2018_10y_c				-0.010	-0.053 – 0.033	0.654
media_foxnews_lean_percent_c * age_proportion_85plus_c				3.848	2.085 – 5.611	**0.001**
media_foxnews_lean_percent_c * age_proportion_65to85_c				-0.573	-1.124 – -0.023	**0.041**
media_foxnews_lean_percent_c * age_proportion_0to17_c				-0.389	-0.707 – -0.072	**0.016**
media_foxnews_lean_percent_c * state_policy_c				0.002	-0.002 – 0.005	0.410
media_foxnews_lean_percent_c * governor_c				0.009	-0.022 – 0.040	0.577
media_foxnews_lean_percent_c * gini_c				-0.434	-0.685 – -0.183	**0.001**

media_foxnews_lean_percent_c * prop_hisp_latin_c							-0.076	-0.160 – 0.007	0.074
media_foxnews_lean_percent_c * prop_asian_c							0.291	-0.070 – 0.652	0.114
media_foxnews_lean_percent_c * prop_black_c							-0.017	-0.097 – 0.063	0.671
media_foxnews_lean_percent_c *life_expectancy_diff_19852010_c							-0.002	-0.008 – 0.005	0.596
media_foxnews_lean_percent_c * commute_time_h_c							0.142	0.025 – 0.259	**0.017**
Random Effects									
σ^2	0.0156			0.0139			0.0139		
τ_{00}	0.0054 county_fips			0.0043 county_fips			0.0044 county_fips		
	0.0067 state_name			0.0021 state_name			0.0021 state_name		
τ_{11}	0.0116 county_fips.media_foxnews_lean_percent_c			0.0048 county_fips.media_foxnews_lean_percent_c			0.0036 county_fips.media_foxnews_lean_percent_c		
	0.0023 state_name.media_foxnews_lean_percent_c			0.0020 state_name.media_foxnews_lean_percent_c			0.0016 state_name.media_foxnews_lean_percent_c		
	0.0807 state_name.time_day_linear								
	0.0327 state_name.time_day_quad								
ρ_{01}	-0.1119 county_fips			0.1747 county_fips			0.1898 county_fips		
	-0.3764 state_name.media_foxnews_lean_percent_c			0.0840 state_name			-0.0350 state_name		
	0.6527 state_name.time_day_linear								
	-0.6507 state_name.time_day_quad								
ICC	0.4971			0.3462			0.3412		
N	3023 county_fips			2986 county_fips			2986 county_fips		
	51 state_name			49 state_name			49 state_name		
Observations	247886			244852			244852		
Marginal R^2 / Conditional R^2	0.272 / 0.634			0.441 / 0.635			0.445 / 0.635		

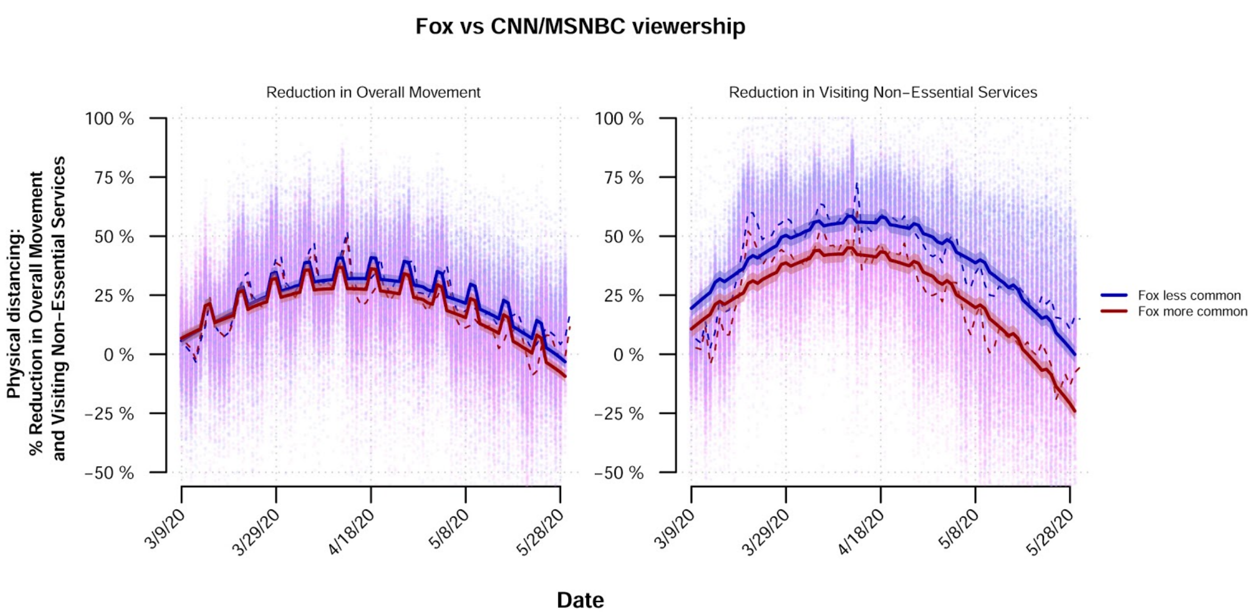
Supplementary Table 28. Consuming Fox News (over CNN and MSNBC) predicts a smaller reduction in visiting nonessential services. Base model, main model, and saturated model.

	Base Model	Main Model	Saturated Model

Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.329	0.300 – 0.357	**<0.001**	0.316	0.304 – 0.329	**<0.001**	0.320	0.307 – 0.332	**<0.001**
media_foxnews_lean_percent_c	-0.279	-0.308 – -0.249	**<0.001**	-0.099	-0.136 – -0.062	**<0.001**	-0.098	-0.135 – -0.061	**<0.001**
time_day_linear	-0.734	-0.741 – -0.726	**<0.001**	-0.795	-0.803 – -0.787	**<0.001**	-0.794	-0.802 – -0.785	**<0.001**
time_day_quad	-1.317	-1.324 – -1.310	**<0.001**	-1.173	-1.182 – -1.164	**<0.001**	-1.173	-1.182 – -1.164	**<0.001**
media_foxnews_lean_percent_c * time_day_linear	-0.721	-0.741 – -0.700	**<0.001**	-0.709	-0.729 – -0.688	**<0.001**	-0.697	-0.720 – -0.673	**<0.001**
media_foxnews_lean_percent_c * time_day_quad	-0.074	-0.095 – -0.054	**<0.001**	-0.058	-0.079 – -0.038	**<0.001**	-0.090	-0.115 – -0.064	**<0.001**
weekend				0.026	0.025 – 0.028	**<0.001**	0.026	0.025 – 0.028	**<0.001**
median_income_10k_c				0.020	0.014 – 0.026	**<0.001**	0.017	0.011 – 0.024	**<0.001**
pop_density_log_s				0.051	0.045 – 0.058	**<0.001**	0.054	0.047 – 0.062	**<0.001**
cases_capita_100_c				0.045	0.041 – 0.049	**<0.001**	0.043	0.038 – 0.047	**<0.001**
supermarkets_c				-0.070	-0.130 – -0.010	**0.023**	-0.069	-0.130– -0.007	**0.028**
supermarkets_low_accesstores_c				0.147	0.099 – 0.195	**<0.001**	0.128	0.080 – 0.176	**<0.001**
religion_c				-0.033	-0.071 – 0.005	0.091	-0.019	-0.059 – 0.022	0.369
percent_employed_c				0.357	0.238 – 0.475	**<0.001**	0.342	0.215 – 0.470	**<0.001**
median_age_county_2018_10y_c				-0.118	-0.150 – -0.086	**<0.001**	-0.118	-0.154 – -0.081	**<0.001**
age_proportion_85plus_c				0.676	-0.815 – 2.166	0.374	0.617	-0.897 – 2.132	0.424
age_proportion_65to85_c				0.784	0.249 – 1.319	**0.004**	0.697	0.123 – 1.271	**0.017**
age_proportion_0to17_c				-1.510	-1.748 – -1.271	**<0.001**	-1.740	-2.026 – -1.453	**<0.001**
state_policy_c				0.059	0.057 – 0.062	**<0.001**	0.059	0.057 – 0.062	**<0.001**
governor_c				-0.018	-0.043 – 0.006	0.147	-0.018	-0.043 – 0.006	0.137
gini_c				0.497	0.310 – 0.685	**<0.001**	0.506	0.308 – 0.705	**<0.001**
prop_hisp_latin_c				0.173	0.122 – 0.225	**<0.001**	0.201	0.144 – 0.259	**<0.001**
prop_asian_c				0.008	-0.160 – 0.171	0.921	0.281	0.077 – 0.485	**0.007**
prop_black_c				0.023	-0.025 – 0.071	0.352	0.007	-0.043 – 0.058	0.774
life_expectancy_diff_19852010_c				0.001	-0.003 – 0.005	0.529	0.001	-0.003 – 0.004	0.783
commute_time_h_c				-0.127	-0.207- -0.047	**0.002**	-0.078	-0.161 – 0.005	0.064

media_foxnews_lean_percent_c * weekend	-0.045	-0.050 – -0.040	**<0.001**
media_foxnews_lean_percent_c * median_income_10k_c	-0.001	-0.016 – 0.014	0.898
media_foxnews_lean_percent_c * pop_density_log_s	0.031	0.015 – 0.048	**<0.001**
media_foxnews_lean_percent_c * cases_capita_100_c	-0.012	-0.024 – 0.001	0.062
media_foxnews_lean_percent_c * supermarkets_c	-0.229	-0.375 – -0.082	**0.002**
media_foxnews_lean_percent_c *supermarkets_low_accesstores_c	0.070	-0.049 – 0.190	0.248
media_foxnews_lean_percent_c * religion_c	0.055	-0.020 – 0.130	0.153
media_foxnews_lean_percent_c * percent_employed_c	-0.147	-0.417 – 0.123	0.287
media_foxnews_lean_percent_c *median_age_county_2018_10y_c	-0.066	-0.141 – 0.009	0.086
media_foxnews_lean_percent_c * age_proportion_85plus_c	2.202	-1.351 – 5.756	0.224
media_foxnews_lean_percent_c * age_proportion_65to85_c	0.637	-0.353 – 1.627	0.207
media_foxnews_lean_percent_c * age_proportion_0to17_c	-0.443	-1.035 – 0.149	0.143
media_foxnews_lean_percent_c * state_policy_c	-0.007	-0.014 – -0.001	**0.026**
media_foxnews_lean_percent_c * governor_c	-0.031	-0.065 – 0.002	0.068
media_foxnews_lean_percent_c * gini_c	-0.007	-0.467 – 0.453	0.976
media_foxnews_lean_percent_c * prop_hisp_latin_c	0.194	0.062 – 0.326	**0.004**
media_foxnews_lean_percent_c * prop_asian_c	0.663	0.196 – 1.129	**0.005**
media_foxnews_lean_percent_c * prop_black_c	-0.067	-0.192 – 0.059	0.298
media_foxnews_lean_percent_c *life_expectancy_diff_19852010_c	-0.001	-0.011 – 0.009	0.893

media_foxnews_lean_percent_c * commute_time_h_c			0.179	-0.030 – 0.389	0.094
Random Effects					
σ^2	0.0299	0.0287	0.0286		
τ_{00}	0.0149 $_{\text{county\_fips}}$	0.0095 $_{\text{county\_fips}}$	0.0098 $_{\text{county\_fips}}$		
	0.0099 $_{\text{state\_name}}$	0.0015 $_{\text{state\_name}}$	0.0013 $_{\text{state\_name}}$		
τ_{11}	0.0067 $_{\text{county\_fips.media\_foxnews\_lean\_percent\_c}}$	0.0099 $_{\text{county\_fips.media\_foxnews\_lean\_percent\_c}}$	0.0062 $_{\text{county\_fips.media\_foxnews\_lean\_percent\_c}}$		
	0.0059 $_{\text{state\_name.media\_foxnews\_lean\_percent\_c}}$	0.0016 $_{\text{state\_name.media\_foxnews\_lean\_percent\_c}}$	0.0006 $_{\text{state\_name.media\_foxnews\_lean\_percent\_c}}$		
ρ_{01}	0.3949 $_{\text{county\_fips}}$	0.5484 $_{\text{county\_fips}}$	0.6964 $_{\text{county\_fips}}$		
	0.2848 $_{\text{state\_name}}$	0.0970 $_{\text{state\_name}}$	0.4225 $_{\text{state\_name}}$		
ICC	0.4703	0.3027	0.2953		
N	2073 $_{\text{county\_fips}}$	2056 $_{\text{county\_fips}}$	2056 $_{\text{county\_fips}}$		
	51 $_{\text{state\_name}}$	49 $_{\text{state\_name}}$	49 $_{\text{state\_name}}$		
Observations	169890	168504	168504		
Marginal R^2 / Conditional R^2	0.408 / 0.686	0.529 / 0.672	0.535 / 0.672		



Supplementary Figure 2. U.S. counties' average physical distancing (percent reduction in general movement and visits to nonessential services) as a function of time and Fox News preference (as compared to MSNBC and CNN). For the purposes of this figure, counties were binned as "Fox more common" if a county had a greater Fox advantage than average and as "Fox less common" if a county had a smaller Fox advantage than average. Each point represents one county. Dashed line is the daily average across counties, split by Fox commonness as defined above. Bold blue and red lines represent the average predictions of Fox News preference from the medium-saturated multilevel model described in Supplementary Table 15 and 16 above. Error bands are bootstrapped 95% prediction intervals.

We also examined whether the negative link between right-leaning media (Fox News lean) and physical distancing remains when accounting for partisanship as assessed by vote gap (see section above). To test this, we reconducted the Main model (see Supplementary Table 29) when also including vote gap, the interactions between vote gap and linear and quadratic time, and the interaction between vote gap and Fox News lean. When doing so, Fox News consumption (over MSNBC and CNN) still negatively predicted physical distancing (Supplementary Table 29). These results indicate that consuming right-leaning media content and partisan vote (in 2016) both account for independent variance in terms of predicting lower physical distancing. Furthermore, we note that the coefficient of partisanship vote-gap slightly decreased when including Fox News lean in the model (see Table 1 and Supplementary Table 29), indicating that a portion of the variance between vote-gap and lower physical distancing may be accounted for by consuming right-leaning media (and/or vice-versa).

Supplementary Table 29. Fox News lean predicting reduction in general movement and visiting nonessential services when accounting for GOP advantage (2016 vote-gap for Trump over Clinton). The Main Model was utilized.

	Reduction in General Movement	**Reduction in Visiting Nonessential Services**

Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.216	0.204 – 0.228	**<0.001**	0.344	0.329 – 0.359	**<0.001**
media_foxnews_lean_percent_c	-0.038	-0.063 – -0.014	**0.002**	-0.053	-0.092 – -0.013	**0.009**
gop_advantage_2016	-0.106	-0.137 – -0.074	**<0.001**	-0.111	-0.153 – -0.069	**<0.001**
time_day_linear	-0.279	-0.286 – -0.272	**<0.001**	-0.559	-0.571 – -0.548	**<0.001**
time_day_quad	-0.803	-0.810 – -0.796	**<0.001**	-1.188	-1.200 – -1.176	**<0.001**
weekend	0.089	0.088 – 0.090	**<0.001**	0.026	0.024 – 0.028	**<0.001**
median_income_10k_c	0.020	0.016 – 0.023	**<0.001**	0.018	0.012 – 0.024	**<0.001**
pop_density_log_s	0.028	0.023 – 0.033	**<0.001**	0.046	0.039 – 0.053	**<0.001**
cases_capita_100_c	0.010	0.008 – 0.012	**<0.001**	0.028	0.024 – 0.032	**<0.001**
supermarkets_c	0.046	0.025 – 0.068	**<0.001**	-0.064	-0.125 – -0.002	**0.042**
supermarkets_low_accesstores_c	0.008	-0.010 – 0.027	0.376	0.133	0.086 – 0.181	**<0.001**
religion_c	-0.002	-0.022 – 0.018	0.839	-0.018	-0.055 – 0.020	0.358
percent_employed_c	-0.095	-0.154 – -0.036	**0.002**	0.324	0.206 – 0.443	**<0.001**
median_age_county_2018_10y_c	0.047	0.030 – 0.063	**<0.001**	-0.111	-0.143 – -0.080	**<0.001**
age_proportion_85plus_c	0.319	-0.331 – 0.969	0.337	0.419	-1.067 – 1.905	0.580
age_proportion_65to85_c	-0.145	-0.394 – 0.104	0.253	0.477	-0.063 – 1.016	0.083
age_proportion_0to17_c	0.056	-0.065 – 0.176	0.364	-1.385	-1.632 – -1.138	**<0.001**
state_policy_c	0.040	0.038 – 0.041	**<0.001**	0.048	0.046 – 0.051	**<0.001**
governor_c	0.019	-0.001 – 0.039	0.059	-0.013	-0.036 – 0.011	0.285
gini_c	0.206	0.109 – 0.303	**<0.001**	0.469	0.281 – 0.657	**<0.001**
prop_hisp_latin_c	-0.051	-0.086 – -0.017	**0.004**	0.079	0.019 – 0.138	**0.010**
prop_asian_c	0.093	-0.039 – 0.225	0.169	-0.028	-0.213 – 0.157	0.766
prop_black_c	-0.137	-0.179 – -0.095	**<0.001**	-0.094	-0.162 – -0.027	**0.006**
life_expectancy_diff_19852010_c	0.004	0.002 – 0.006	**<0.001**	0.001	-0.002 – 0.005	0.523
commute_time_h_c	-0.029	-0.069 – 0.011	0.156	-0.126	-0.206 – -0.046	**0.002**
media_foxnews_lean_percent_c	-0.245	-0.258 – -0.232	**<0.001**	-0.407	-0.430 – -0.384	**<0.001**

* time_day_linear						
media_foxnews_lean_percent_c * time_day_quad	0.032	0.019 – 0.045	**<0.001**	-0.052	-0.075 – -0.030	**<0.001**
gop_advantage_2016 * time_day_linear	-0.253	-0.269 – -0.237	**<0.001**	-0.807	-0.834 – -0.779	**<0.001**
gop_advantage_2016 * time_day_quad	0.211	0.195 – 0.226	**<0.001**	-0.027	-0.054 – 0.000	0.051
media_foxnews_lean_percent_c * gop_advantage_2016	0.055	0.028 – 0.083	**<0.001**	-0.085	-0.132 – -0.038	**<0.001**
N	$2986_{\text{county\_fips}}$			$2056_{\text{county\_fips}}$		
	$49_{\text{state\_name}}$			$49_{\text{state\_name}}$		
Observations	244852			168504		

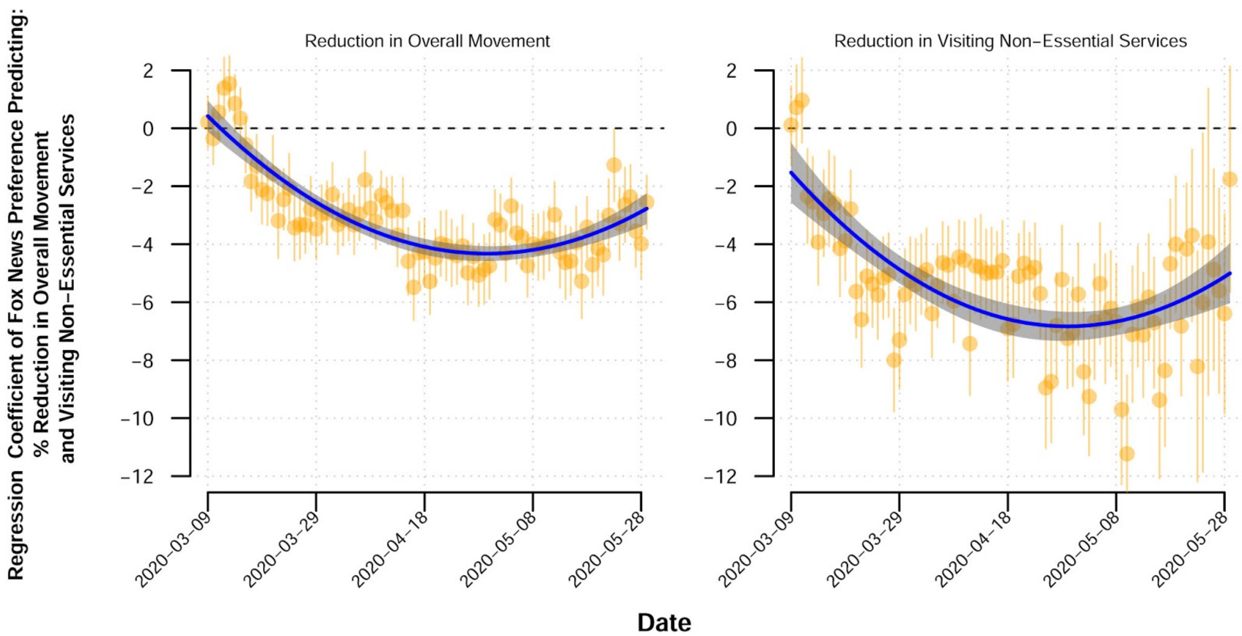
We next explored how the observed links between Fox News preference and physical distancing vary over time. As was true for vote-gap, the observed partisan media consumption differences in physical distancing strengthened with time. First, negative interactions between Fox News lean and linear time were observed for both general movement and visiting nonessential services, (B_{movement} = -0.332, 95% CI[-0.344, -0.321] and $B_{\text{visitation}}$ = -0.709, 95% CI[-0.729,-0.688], *p*s < .001, see Supplementary Tables 27-28 and Supplementary Figure 2).

We also conducted the alternate over-time analysis we had conducted for the observed links between vote gap and physical distancing over time (see above by Supplementary Table 26). That is, we conducted a mixed-effects model for each date in the included date range (March 9th to May 29th) with physical distancing (general movement and nonessential visitation) as the dependent variables (multiplied by 100 to create a percent), respectively, and Fox News lean and all the controls noted above (random intercept of state was included; random slopes failed to converge). We then extracted the specific coefficient for partisanship predicting physical distancing from each of these models and plotted them over time (see Supplementary Figure 3). Linear models with *z*-scored linear time and quadratic time terms (calculated to be orthogonal) indicated that the link between counties' Fox News preference and weaker physical distancing strengthened over time (i.e., the coefficient became increasingly negative) both for general movement and visiting nonessential services, $B_{movement}$ = -0.98, 95% CI[-1.16, -0.79] and $B_{visitation}$ = -0.98, 95% CI[-1.34, -0.62], *p*s < .001 (Supplementary Table 30; Supplementary Figure 3). Furthermore, the quadratic time term explained additional variance both for general movement and nonessential visitation, *p*s < .001. Counties watching more Fox News (as compared to MSNBC and CNN) increasingly exhibited decreased physical distancing over time until this link plateaued in the end of April and began to somewhat reverse, $B_{movement}$ = 0.89, 95% CI[0.70, 1.07], and $B_{visitation}$ = 0.94, 95% CI[0.58, 1.30], *p*s < .001; see Supplementary Figure 3 and Supplementary Table 30.

Supplementary Table 30. The negative link between Fox News preference and reduction in general movement and visiting nonessential services (while controlling for covariates) strengthened over time (a negative linear trajectory) for general movement and visiting nonessential services. For both physical distancing measures, a concave quadratic trajectory was also observed (see Supplementary Figure 3).

	General Movement			**Visiting Nonessential Services**		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	-3.191	-3.375 – -3.008	**<0.001**	-5.375	-5.733 – -5.016	**<0.001**

time_day_linear	-0.975	-1.160 – -0.790	**<0.001**	-0.978	-1.338 – -0.617	**<0.001**
time_day_quad	0.888	0.703 – 1.073	**<0.001**	0.936	0.575 – 1.296	**<0.001**



Supplementary Figure 3. Coefficients of county Fox News preference predicting percent reduction in general movement and visiting nonessential services for each of the included dates while controlling for covariates as a function of time (March 9 to May 29, 2020). Individual points represent regression coefficients. Blue lines represent predictions from linear regression models with linear and quadratic time terms. For GAM models of these data see Supplements. As the pandemic progressed, Fox News leaning counties increasingly exhibited less physical distancing. This difference plateaued around the start of May and then began to weaken. Error bands: +/- 2 *SE*.

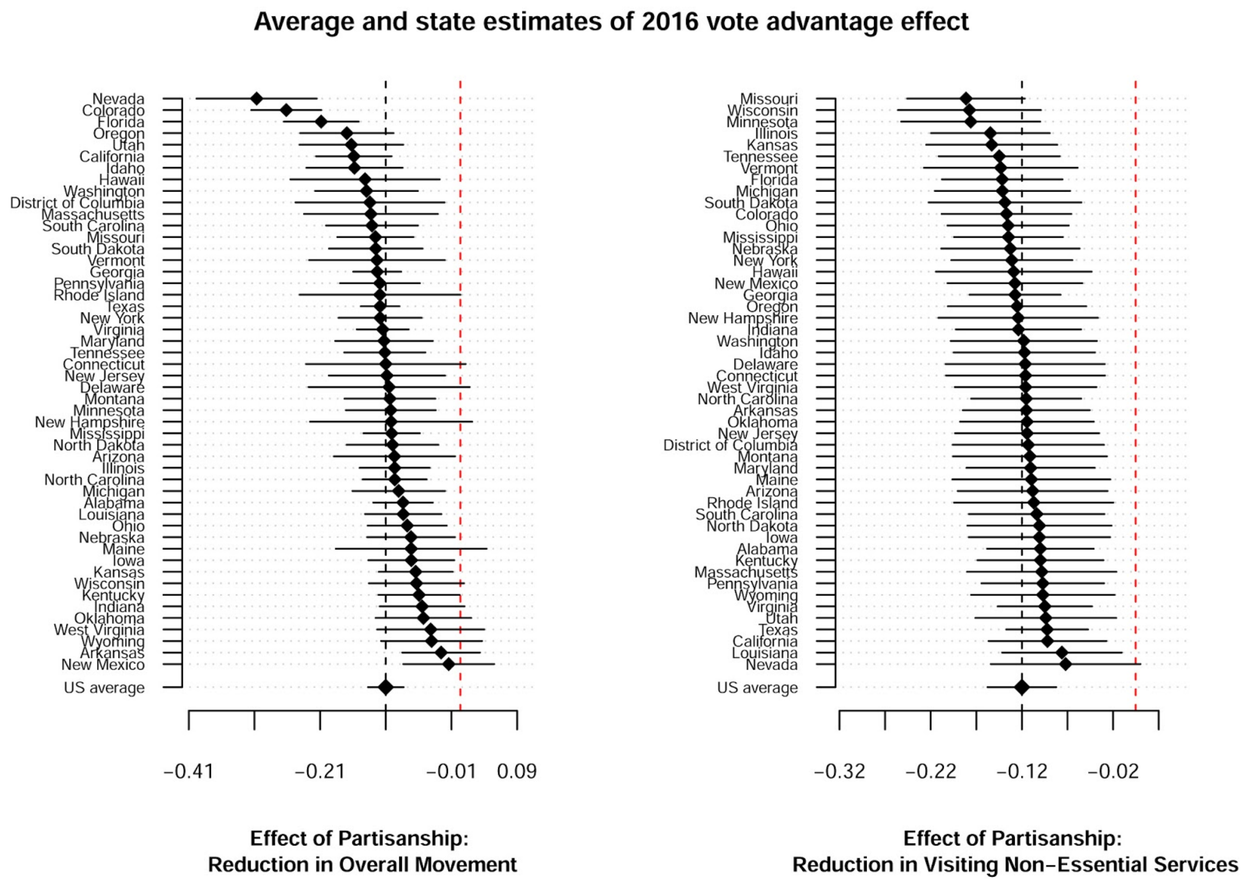
Finally, we again conducted the same model but with time as a non-parametric smoother (generalized additive model; GAM) because the linear and quadratic time terms did not perfectly capture the links between partisanship and physical distancing over time (see Supplementary

Figure 2), and because these links will likely change outside of the date range observed here (March 9 to May 29). Again, the link between counties' pro-Trump voting and weaker physical distancing varied over time, both for general movement, edf = 7.95, df = 8.71, $F = 34.48$, $p < .001$, and nonessential visitation, edf = 5.51, df = 6.65, $F = 14.86$, $p < .001$ (see rmarkdown named "OverTimeAnalyses" on on our OSF project page (here).

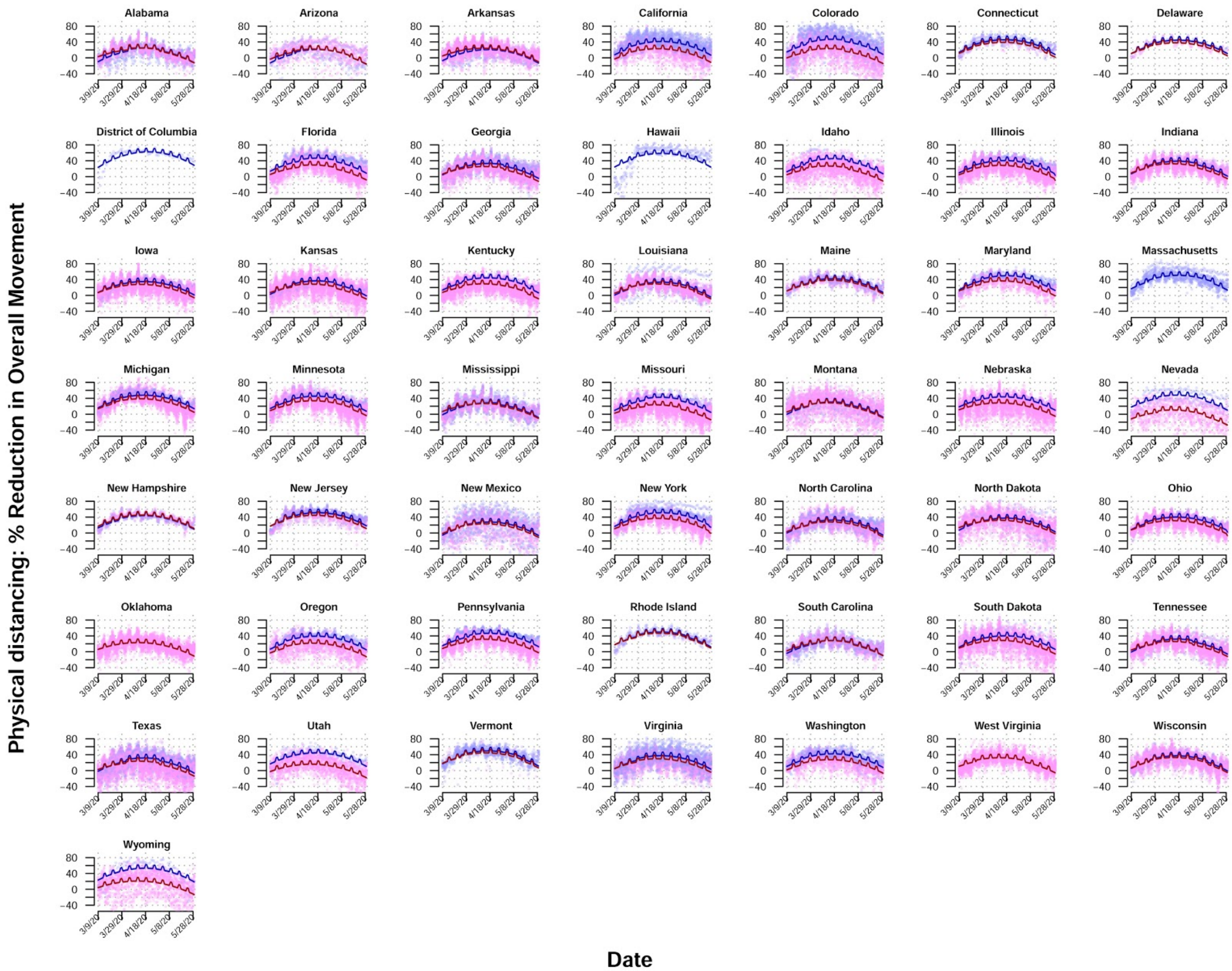
Potential State-Policy Confound

As noted in the main text, one could make the argument that state policies and not county differences in partisanship explain our findings. For instance, stay-at-home orders may have been more stringent and remained in place longer in more Democratic than Republican states or in states run by Democratic than Republican governors, in turn resulting in Republican leaning counties (which are more common in Republican states) exhibiting lower physical distancing (and in this gap increasing when stay-at-home policies are in place). We address this both based on the main models presented in the text and with additional models presented in the next subsection.

State-policy based on main models. First, we observed partisan differences in physical distancing when including the length of state policies and the political affiliation of states' governors as control variables in our models. Additionally all our main analyses were conducted using mixed effects models that nested counties within state. These models account for random variance within states, and as such, can partly account for state-level factors such as variation in the strictness of state-policy. We also examined whether states' contributions to the observed county-level partisan effect differ greatly. As can be seen in Supplementary Figure 4, while there is variation between states, most states' contributions are in line with the population average (i.e., the CIs overlap with the population average). These results further indicate that our findings cannot fully be explained with reference to differences at the state level rather than by differences in county partisanship. Additionally, in Supplementary Figures 5 and 6 we plot model predictions derived from our main model, analogous to Figure 4 in the main text, but split by states.



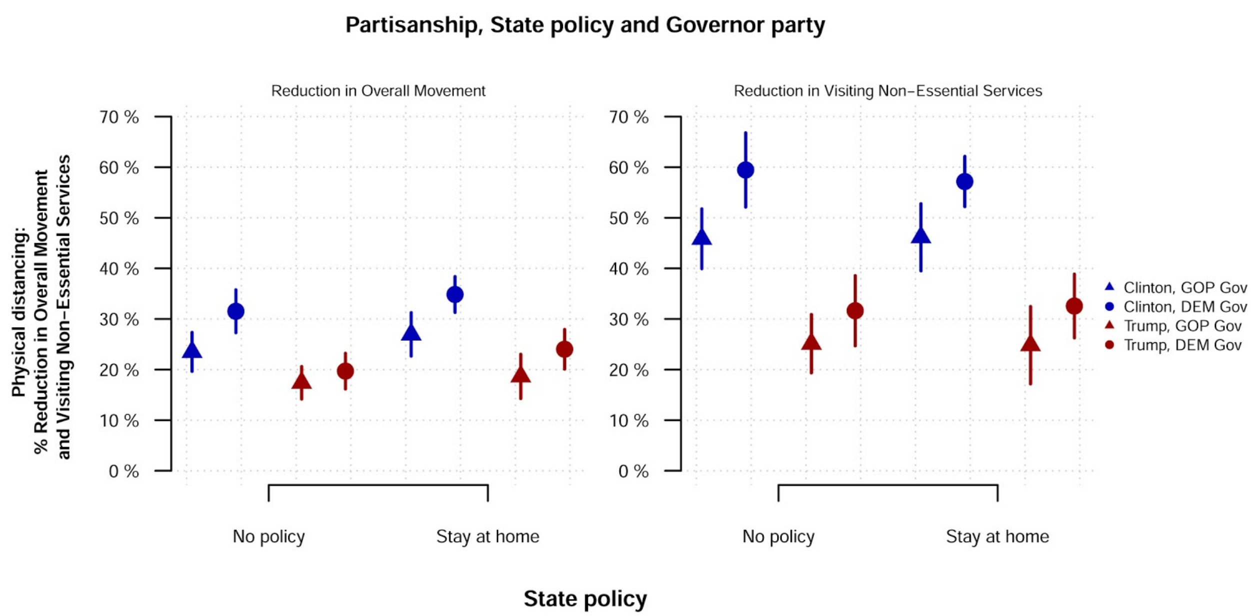
Supplementary Figure 4. Coefficient forest plot from models reported in main text (Table 1), showing by-state estimated slopes of partisan vote advantage at the county level. Estimated population average (fixed effect) plotted for reference and also indicated by dashed black line. Dashed red line indicates 0 effect of partisanship. Error bars +/- 2 *SE*.



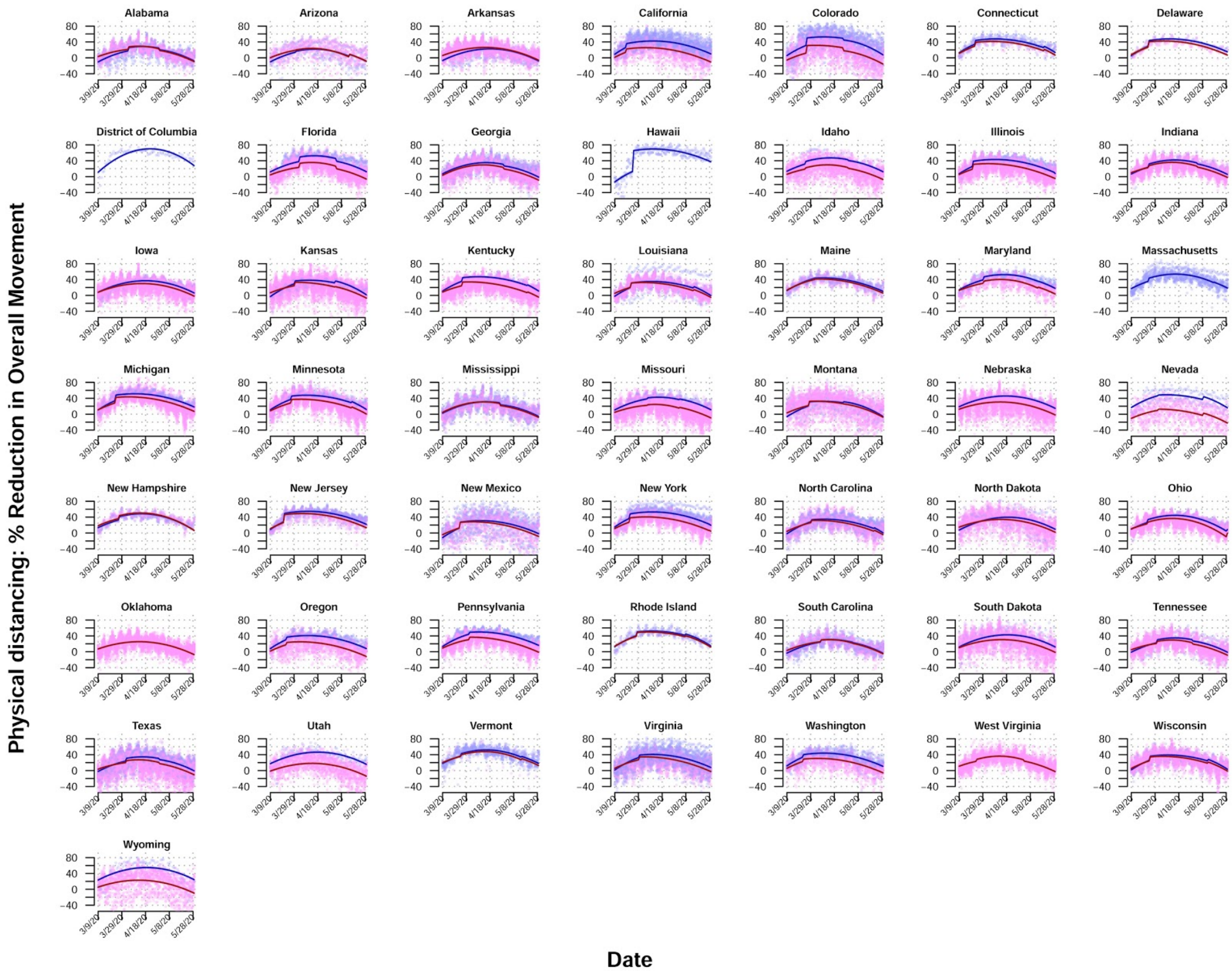
Supplementary Figure 5. Counties' average reduction in general movement as a function of time and partisanship (Trump vs. Clinton vote gap in 2016), split by state. For the purposes of this figure, counties were binned as Trump Lean if a greater percentage of inhabitants voted for Trump, and Clinton Lean if a greater percentage of inhabitants voted for Clinton. Each point represents one county. Bold blue and red lines represent the average predictions of vote gap from the multilevel models described in Table 1 and main text. Error bands are bootstrapped 95% prediction intervals.

Supplementary Figure 6. Counties' average reduction in visits to nonessential services as a function of time and partisanship (Trump vs. Clinton vote gap in 2016), split by state. For the purposes of this figure, counties were binned as Trump Lean if a greater percentage of inhabitants voted for Trump, and Clinton Lean if a greater percentage of inhabitants voted for Clinton. Each point represents one county. Bold blue and red lines represent the average predictions of vote gap from the multilevel models described in Table 1 and main text. Error bands are bootstrapped 95% prediction intervals.

Additional state-policy models. Second, it remains possible that our observed effects of partisanship are moderated by effects of state-level policy and governor party through interactions not captured in our main model. We tested this by fitting additional models. Models included the full three-way interaction between partisanship (2016 vote gap), governor party and state policy, together with orthogonal linear and quadratic time terms. The first three predictors and these two-way interactions were interacted with the linear and quadratic time terms. Random intercepts were fit at both county and state level. Random slopes of partisanship, governor party and state policy were fit at the state level. For the distancing model, random slopes of partisanship at the county level were also included. Our main findings were robust, even when allowing for full moderation of our main effects. Plotting the marginal effects of partisanship, by governor party and state policy in Supplementary Figure 7, clearly shows a partisan gap across all combinations of these terms. See also Supplementary Table 31 for model coefficients and Supplementary Figures 8 & 9 for by-state model predictions.



Supplementary Figure 7. Marginal predictions for an average Clinton or Trump leaning county split by Governor partisanship and State policy derived from the model presented in Supplementary Table 31. Error bands: +/- 2 *SE*.



Supplementary Figure 8. Counties' average reduction in general movement as a function of time and partisanship (Trump vs. Clinton vote gap in 2016), split by state. For the purposes of this figure, counties were binned as Trump Lean if a greater percentage of inhabitants voted for Trump, and Clinton Lean if a greater percentage of inhabitants voted for Clinton. Each point represents one county. Bold blue and red lines represent the average predictions of vote gap from the multi-level model described in Supplementary Table 31. Error bands are bootstrapped 95% prediction intervals.

Supplementary Figure 9. Counties' average reduction in visits to nonessential services as a function of time and partisanship (Trump vs. Clinton vote gap in 2016), split by state. For the purposes of this figure, counties were binned as Trump Lean if a greater percentage of inhabitants voted for Trump, and Clinton Lean if a greater percentage of inhabitants voted for Clinton. Each point represents one county. Bold blue and red lines represent the average predictions of vote gap from the multi-level model described in Supplementary Table 31. Error bands are bootstrapped 95% prediction intervals.

Supplementary Table 31. Predicting reduction in general movement and nonessential visitation, results from multilevel models. Models included the full three-way interaction between partisanship (2016 vote gap), governor party and state policy, together with orthogonal linear and quadratic time terms. The first three predictors and their two-way interactions were interacted with the linear and quadratic time terms. Random intercepts were fit at both county and state level. Random slopes of partisanship, governor party and state policy were fit at the state level. For the distancing model random slopes of partisanship at the county level were also included.

	Reduction in General Movement			Reduction in Visiting Nonessential Services		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.270	0.248 – 0.291	**<0.001**	0.433	0.412 – 0.454	**<0.001**
gop_advantage_2016	-0.160	-0.198 – -0.123	**<0.001**	-0.362	-0.410 – -0.314	**<0.001**
state_policy_c	0.037	0.013 – 0.060	**0.003**	0.001	-0.017 – 0.019	0.916
governor_c	-0.055	-0.096 – -0.015	**0.007**	-0.107	-0.148 – -0.067	**<0.001**
time_day_linear	-0.292	-0.300 – -0.283	**<0.001**	-0.627	-0.640 – -0.614	**<0.001**
time_day_quad	-0.846	-0.855 – -0.837	**<0.001**	-1.322	-1.336 – -1.308	**<0.001**
gop_advantage_2016 * state_policy_c	-0.013	-0.018 – -0.007	**<0.001**	0.017	0.007 – 0.026	**<0.001**
gop_advantage_2016 * governor_c	0.065	-0.009 – 0.139	0.086	0.082	-0.014 – 0.178	0.095
state_policy_c * governor_c	-0.010	-0.057 – 0.037	0.671	0.012	-0.023 – 0.047	0.498
gop_advantage_2016 * time_day_linear	-0.480	-0.499 – -0.462	**<0.001**	-1.100	-1.129 – -1.070	**<0.001**
gop_advantage_2016 * time_day_quad	0.155	0.135 – 0.175	**<0.001**	-0.019	-0.051 – 0.014	0.262
state_policy_c * time_day_linear	-0.422	-0.440 – -0.404	**<0.001**	-0.683	-0.710 – -0.656	**<0.001**
state_policy_c * time_day_quad	0.094	0.076 – 0.113	**<0.001**	0.403	0.374 – 0.431	**<0.001**
governor_c * time_day_linear	0.078	0.061 – 0.094	**<0.001**	-0.123	-0.149 – -0.098	**<0.001**
governor_c * time_day_quad	-0.082	-0.100 – -0.063	**<0.001**	-0.107	-0.135 – -0.078	**<0.001**
(gop_advantage_2016 * state_policy_c) * time_day_linear	0.074	0.032 – 0.115	**0.001**	0.014	-0.053 – 0.081	0.677
(gop_advantage_2016 * state_policy_c) * time_day_quad	-0.303	-0.346 – -0.261	**<0.001**	-0.514	-0.585 – -0.444	**<0.001**
(gop_advantage_2016 * governor_c) * time_day_linear	0.066	0.030 – 0.102	**<0.001**	0.195	0.135 – 0.254	**<0.001**
(gop_advantage_2016 * governor_c) * time_day_quad	-0.227	-0.271 – -0.182	**<0.001**	-0.165	-0.240 – -0.091	**<0.001**
(state_policy_c * governor_c) * time_day_linear	0.272	0.245 – 0.298	**<0.001**	0.234	0.192 – 0.276	**<0.001**

(state_policy_c * governor_c) * time_day_quad	-0.599	-0.628 – -0.571	**<0.001**	-1.534	-1.580 – -1.489	**<0.001**
(gop_advantage_2016 * state_policy_c) * governor_c	-0.050	-0.062 – -0.038	**<0.001**	-0.059	-0.079 – -0.039	**<0.001**
Random Effects						
σ^2	0.0148			0.0267		
τ_{00}	0.0062 $_{\text{county\_fips}}$			0.0161 $_{\text{county\_fips}}$		
	0.0041 $_{\text{state\_name}}$			0.0035 $_{\text{state\_name}}$		
τ_{11}	0.0106 $_{\text{county\_fips.gop\_advantage\_2016}}$					
	0.0140 $_{\text{state\_name.gop\_advantage\_2016}}$			0.0198 $_{\text{state\_name.gop\_advantage\_2016}}$		
	0.0059 $_{\text{state\_name.state\_policy\_c}}$			0.0033 $_{\text{state\_name.state\_policy\_c}}$		
	0.0023 $_{\text{state\_name.governor\_c}}$			0.0019 $_{\text{state\_name.governor\_c}}$		
ρ_{01}	-0.43 $_{\text{county\_fips.gop\_advantage\_2016}}$					
	-0.41 $_{\text{state\_name.gop\_advantage\_2016}}$			-0.80 $_{\text{state\_name.gop\_advantage\_2016}}$		
	0.44 $_{\text{state\_name.state\_policy\_c}}$			-0.03 $_{\text{state\_name.state\_policy\_c}}$		
	0.61 $_{\text{state\_name.governor\_c}}$			0.37 $_{\text{state\_name.governor\_c}}$		
N	2987 $_{\text{county\_fips}}$			2057 $_{\text{county\_fips}}$		
	50 $_{\text{state\_name}}$			50 $_{\text{state\_name}}$		
Observations	244934			168586		
Marginal R^2 / Conditional R^2	0.344 / 0.641			0.475 / 0.701		

Detailed State Policies. Third, we reconducted our models when considering more nuanced state policy variables. Specifically, we added the following variables to our model in terms of whether a specific state policy was in effect or not on a specific date: closed schools (kindergarten through 12th grade), closed childcare, closed restaurants (except for take-out), closed non-essential businesses more generally, and whether religious gatherings were forbidden. These variables took into account if/when these mandates were lifted (e.g., when restaurants reopened). These data were sourced from CUSP (COVID-19 US State Policy Database; see here).

To examine whether these more specific state policy variables account for our results, we reconducted the main and saturated models for general movement and visiting non-essential services when including the two-way interactions between each of these specific state policy variables and partisanship (2016 vote gap) and the two-way interactions between each of these specific state policy variables and governor political affiliation. Importantly, these latter interactions should account for the possibility that specific state policy orders may have been varyingly enforced depending on the political orientation of the governor of a state (and that this may explain the observed county partisan difference in physical distancing). Random intercepts were fit at both county and state level. Random slopes of partisanship were fit at the state level. For the general movement model, the random slope of partisanship at the county level was also included (the random slope did not converge for the visitation models).

Even when including these interactions, partisanship in terms of voting for Trump over Clinton still predicted lower physical distancing. This was true both for general movement and visitation, as well as for the main model and the saturated model. See Supplementary Tables 32 and 33 for model coefficients. Furthermore, we found that our results remained when reconducting these models while including counties' percent of employment in different professions (see the rmarkdown file "partisan_geotracking_01_partisanship" on our OSF project page, here). And finally, at least for general movement, all the interactions between specific types of state policies and partisanship were negative except for closing child-care and closing non-essential businesses (see Supplementary Table 32; these findings echo the main text results regarding the general state policy variable). This was not true for reduction visitation, however. Though negative interactions were observed between partisanship and closing child-care and closing restaurants, a null interaction was observed between partisanship and closing non-essential business, and a positive interaction was observed between partisanship and closing schools (as was the interaction for the general state policy variable; see Supplementary Table 33). These inconsistent interactions may indicate that the link between partisanship and social distancing strengthened or weakened depending on whether *specific* state policies were in effect or, more likely, these inconsistent interactions may be driven by the specific state policy variables correlating with one-another (i.e., including all these variables in the same model controls for overlapping variance leading coefficients to shift).

In sum, however, while differences in the timing of state policies (including specific state policies; e.g., closing restaurants) and governor's political orientation undoubtedly contribute to variation in county-level physical distancing, and these variables interact with county-level partisanship in important ways, our conclusions remain that county-level partisanship, as captured by the 2016 vote-gap, contributes to our understanding of variation in physical distancing.

Supplementary Table 32. Predicting reduction in general movement when considering specific types of state policies (closed school kindergarten through 12th grade, closed child-care, closed restaurants [except for take-out], closed non-essential businesses more generally, and whether religious gatherings were forbidden). Models included the two-way interactions between partisanship (2016 vote gap) and specific type of state policy, and the two-way interactions between governor political party and specific type of state policy.

	Reduction in General Movement (Main Model)			**Reduction in General Movement (Saturated Model)**		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.216	0.205 – 0.227	**<0.001**	0.210	0.198 – 0.222	**<0.001**
gop_advantage_2016	-0.111	-0.138 – -0.084	**<0.001**	-0.097	-0.125 – -0.069	**<0.001**
time_day_linear	-0.424	-0.434 – -0.415	**<0.001**	-0.430	-0.439 – -0.420	**<0.001**

time_day_quad	-0.603	-0.612 – -0.593	**<0.001**	-0.604	-0.614 – -0.595	**<0.001**
gop_advantage_2016 * time_day_linear	-0.296	-0.317 – -0.276	**<0.001**	-0.280	-0.302 – -0.258	**<0.001**
gop_advantage_2016 * time_day_quad	0.118	0.096 – 0.140	**<0.001**	0.123	0.102 – 0.145	**<0.001**
governor_c	0.020	-0.001 – 0.041	0.059	0.020	-0.002 – 0.042	0.082
state_policy_c	0.038	0.036 – 0.041	**<0.001**	0.039	0.036 – 0.041	**<0.001**
state_policy_k12_schools_c	0.101	0.098 – 0.104	**<0.001**	0.101	0.098 – 0.104	**<0.001**
state_policy_childcare_c	0.011	0.007 – 0.015	**<0.001**	0.011	0.007 – 0.015	**<0.001**
state_policy_restaurant_c	0.015	0.013 – 0.018	**<0.001**	0.015	0.013 – 0.018	**<0.001**
state_policy_religious_c	0.015	0.011 – 0.018	**<0.001**	0.014	0.011 – 0.018	**<0.001**
state_policy_non_essential_c	-0.013	-0.053 – 0.028	0.547	-0.006	-0.049 – 0.037	0.777
weekend	0.091	0.090 – 0.092	**<0.001**	0.089	0.088 – 0.091	**<0.001**
median_income_10k_c	0.020	0.016 – 0.023	**<0.001**	0.022	0.018 – 0.026	**<0.001**
pop_density_log_s	0.028	0.024 – 0.033	**<0.001**	0.031	0.026 – 0.037	**<0.001**
cases_capita_100_c	0.014	0.012 – 0.016	**<0.001**	0.017	0.014 – 0.019	**<0.001**
supermarkets_c	0.054	0.033 – 0.075	**<0.001**	0.070	0.037 – 0.102	**<0.001**
supermarkets_low_accesstores_c	0.003	-0.015 – 0.022	0.729	0.016	-0.014 – 0.046	0.288
religion_c	-0.011	-0.031 – 0.010	0.312	-0.030	-0.056 – -0.004	**0.025**
percent_employed_c	-0.081	-0.140 – -0.023	**0.006**	-0.023	-0.105 – 0.060	0.586
median_age_county_2018_10y_c	0.044	0.028 – 0.060	**<0.001**	0.043	0.022 – 0.065	**<0.001**
age_proportion_85plus_c	0.150	-0.472 – 0.771	0.637	-0.940	-1.897 – 0.016	0.054
age_proportion_65to85_c	-0.336	-0.549 – -0.124	**0.002**	-0.082	-0.404 – 0.241	0.620
age_proportion_0to17_c	0.035	-0.087 – 0.157	0.576	0.120	-0.030 – 0.269	0.116
gini_c	0.232	0.134 – 0.329	**<0.001**	0.290	0.164 – 0.416	**<0.001**
prop_hisp_latin_c	-0.075	-0.110 – -0.040	**<0.001**	-0.057	-0.096 – -0.018	**0.004**
prop_asian_c	0.187	0.055 – 0.319	**0.006**	0.189	0.031 – 0.347	**0.019**
prop_black_c	-0.138	-0.181 – -0.096	**<0.001**	-0.119	-0.166 – -0.073	**<0.001**
life_expectancy_diff_19852010_c	0.004	0.001 – 0.006	**0.002**	0.004	0.001 – 0.008	**0.005**
commute_time_h_c	-0.048	-0.087 – -0.008	**0.019**	-0.105	-0.159 – -0.051	**<0.001**
gop_advantage_2016 * state_policy_c	-0.008	-0.014 – -0.003	**0.002**	-0.009	-0.014 – -0.003	**0.001**
gop_advantage_2016 * state_policy_k12_schools_c	-0.049	-0.057 – -0.041	**<0.001**	-0.050	-0.057 – -0.042	**<0.001**
gop_advantage_2016 * state_policy_childcare_c	0.007	-0.002 – 0.016	0.148	0.007	-0.002 – 0.016	0.110

gop_advantage_2016 * state_policy_restaurant_c	-0.013	-0.019 – -0.008	**<0.001**	-0.013	-0.018 – -0.007	**<0.001**
gop_advantage_2016 * state_policy_religious_c	-0.029	-0.036 – -0.022	**<0.001**	-0.028	-0.035 – -0.021	**<0.001**
gop_advantage_2016 * state_policy_non_essential_c	0.016	-0.065 – 0.097	0.705	-0.013	-0.094 – 0.068	0.752
governor_c * state_policy_c	-0.006	-0.010 – -0.003	**<0.001**	-0.006	-0.010 – -0.003	**<0.001**
governor_c * state_policy_k12_schools_c	0.024	0.020 – 0.028	**<0.001**	0.024	0.020 – 0.028	**<0.001**
governor_c * state_policy_childcare_c	-0.025	-0.030 – -0.019	**<0.001**	-0.025	-0.030 – -0.019	**<0.001**
governor_c * state_policy_restaurant_c	0.013	0.010 – 0.016	**<0.001**	0.013	0.009 – 0.016	**<0.001**
governor_c * state_policy_religious_c	-0.009	-0.013 – -0.004	**<0.001**	-0.009	-0.013 – -0.004	**<0.001**
gop_advantage_2016 * weekend				0.005	0.002 – 0.008	**0.004**
gop_advantage_2016 * median_income_10k_c				-0.012	-0.023 – -0.002	**0.022**
gop_advantage_2016 * pop_density_log_s				-0.014	-0.028 – -0.001	**0.041**
gop_advantage_2016 * cases_capita_100_c				-0.014	-0.021 – -0.007	**<0.001**
gop_advantage_2016 * supermarkets_c				-0.074	-0.140 – -0.007	**0.030**
gop_advantage_2016 * supermarkets_low_accesstores_c				-0.022	-0.086 – 0.042	0.496
gop_advantage_2016 * religion_c				0.075	0.013 – 0.138	**0.018**
gop_advantage_2016 * percent_employed_c				-0.186	-0.374 – 0.002	0.053
gop_advantage_2016 * median_age_county_2018_10y_c				-0.013	-0.066 – 0.039	0.617
gop_advantage_2016 * age_proportion_85plus_c				3.235	1.085 – 5.386	**0.003**
gop_advantage_2016 * age_proportion_65to85_c				-0.548	-1.302 – 0.207	0.155
gop_advantage_2016 * age_proportion_0to17_c				-0.208	-0.588 – 0.171	0.282
gop_advantage_2016 * gini_c				-0.316	-0.612 – -0.020	**0.036**

gop_advantage_2016 * prop_hisp_latin_c				-0.025	-0.108 – 0.058	0.556
gop_advantage_2016 * prop_asian_c				0.272	-0.134 – 0.679	0.189
gop_advantage_2016 * prop_black_c				0.009	-0.074 – 0.092	0.831
gop_advantage_2016 * life_expectancy_diff_19852010_c				-0.004	-0.012 – 0.004	0.335
gop_advantage_2016 * commute_time_h_c				0.219	0.094 – 0.345	**0.001**
Random Effects						
σ^2	0.0134			0.0134		
τ_{00}	0.0038 $_{county\_fips}$			0.0037 $_{county\_fips}$		
	0.0011 $_{state\_name}$			0.0012 $_{state\_name}$		
τ_{11}	0.0075 $_{county\_fips.gop\_advantage\_2016}$			0.0069 $_{county\_fips.gop\_advantage\_2016}$		
	0.0046 $_{state\_name.gop\_advantage\_2016}$			0.0042 $_{state\_name.gop\_advantage\_2016}$		
ρ_{01}	-0.1214 $_{county\_fips}$			-0.0955 $_{county\_fips}$		
	-0.2297 $_{state\_name}$			-0.2130 $_{state\_name}$		
ICC	0.3243			0.3236		
N	2987 $_{county\_fips}$			2987 $_{county\_fips}$		
	50 $_{state\_name}$			50 $_{state\_name}$		
Observations	244934			244934		
Marginal R^2 / Conditional R^2	0.475 / 0.645			0.476 / 0.646		

Supplementary Table 33. Predicting reduction in nonessential visitation when considering specific types of state policies (closed school kindergarten through 12th grade, closed child-care, closed restaurants [except for take-out], closed non-essential businesses more generally, and whether religious gatherings were forbidden). Models included the two-way interactions between partisanship (2016 vote gap) and specific type of state policy, and the two-way interactions between governor political party and specific type of state policy.

	Reduction in Visiting Non-Essential Services (Main Model)			**Reduction in Visiting Non-Essential Services (Saturated Model)**		
Predictors	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
(Intercept)	0.338	0.321 – 0.355	**<0.001**	0.341	0.323 – 0.358	**<0.001**

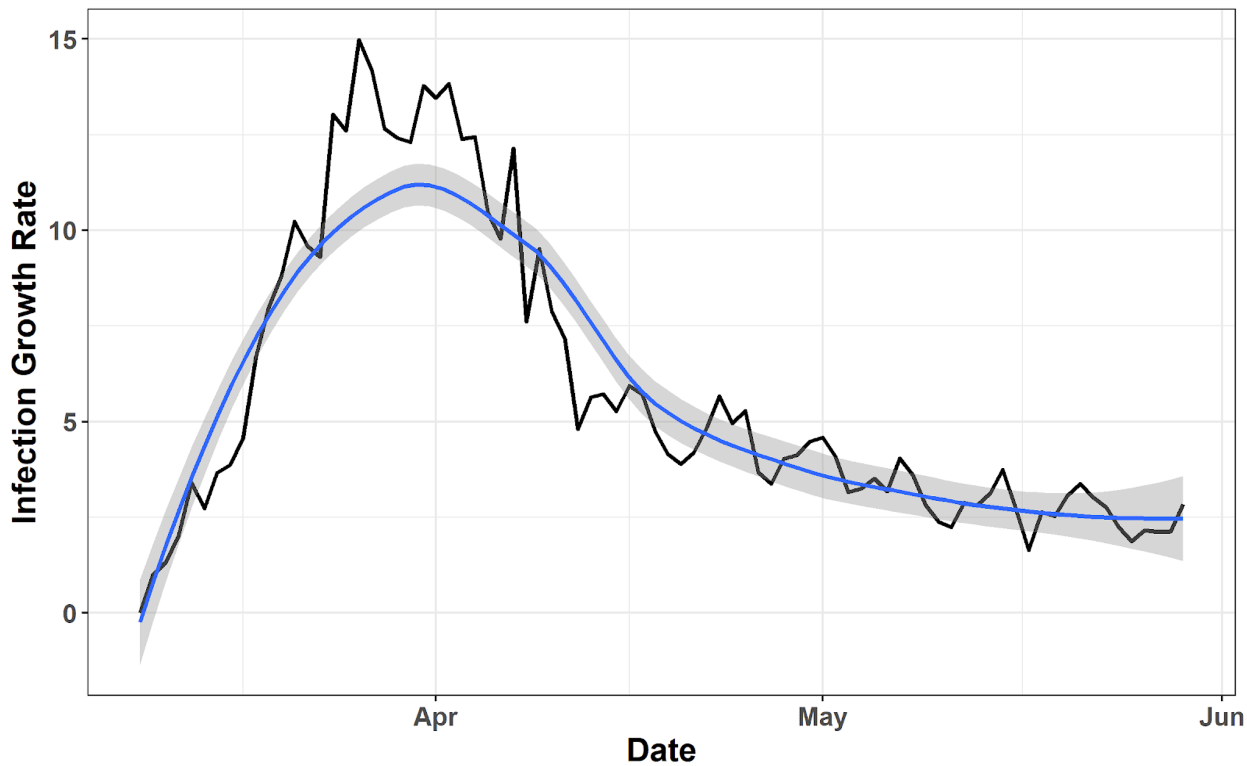
gop_advantage_2016	-0.121	-0.159 – -0.082	**<0.001**	-0.104	-0.145 – -0.064	**<0.001**
time_day_linear	-0.791	-0.806 – -0.777	**<0.001**	-0.783	-0.798 – -0.768	**<0.001**
time_day_quad	-0.740	-0.755 – -0.726	**<0.001**	-0.732	-0.747 – -0.717	**<0.001**
gop_advantage_2016 * time_day_linear	-0.994	-1.028 – -0.959	**<0.001**	-1.026	-1.063 – -0.988	**<0.001**
gop_advantage_2016 * time_day_quad	-0.078	-0.114 – -0.041	**<0.001**	-0.112	-0.148 – -0.075	**<0.001**
governor_c	-0.009	-0.042 – 0.023	0.579	-0.008	-0.039 – 0.023	0.615
state_policy_c	0.022	0.018 – 0.026	**<0.001**	0.023	0.019 – 0.026	**<0.001**
state_policy_k12_schools_c	0.184	0.179 – 0.189	**<0.001**	0.184	0.179 – 0.190	**<0.001**
state_policy_childcare_c	0.018	0.012 – 0.025	**<0.001**	0.019	0.013 – 0.025	**<0.001**
state_policy_restaurant_c	0.092	0.088 – 0.096	**<0.001**	0.092	0.089 – 0.096	**<0.001**
state_policy_religious_c	-0.002	-0.007 – 0.003	**0.429**	-0.001	-0.007 – 0.004	**0.620**
state_policy_non_essential_c	0.005	-0.055 – 0.066	0.860	-0.003	-0.064 – 0.058	0.920
weekend	0.031	0.029 – 0.033	**<0.001**	0.043	0.041 – 0.045	**<0.001**
median_income_10k_c	0.021	0.015 – 0.027	**<0.001**	0.015	0.007 – 0.022	**<0.001**
pop_density_log_s	0.048	0.041 – 0.056	**<0.001**	0.044	0.035 – 0.053	**<0.001**
cases_capita_100_c	0.033	0.029 – 0.037	**<0.001**	0.028	0.023 – 0.032	**<0.001**
supermarkets_c	-0.100	-0.162 – -0.037	**0.002**	-0.077	-0.151 – -0.003	**0.042**
supermarkets_low_accesstores_c	0.147	0.098 – 0.195	**<0.001**	0.078	0.012 – 0.145	**0.021**
religion_c	-0.025	-0.066 – 0.015	0.217	-0.029	-0.076 – 0.017	**0.219**
percent_employed_c	0.287	0.162 – 0.412	**<0.001**	0.501	0.322 – 0.681	**<0.001**
median_age_county_2018_10y_c	-0.137	-0.169 – -0.105	**<0.001**	-0.127	-0.168 – -0.086	**<0.001**
age_proportion_85plus_c	0.176	-1.278 – 1.630	0.813	0.061	-1.943 – 2.065	0.953
age_proportion_65to85_c	0.467	0.010 – 0.924	**0.045**	0.559	-0.100 – 1.219	0.096
age_proportion_0to17_c	-1.307	-1.572 – -1.042	**<0.001**	-1.074	-1.396 – -0.752	**<0.001**
gini_c	0.424	0.227 – 0.621	**<0.001**	0.535	0.287 – 0.782	**<0.001**
prop_hisp_latin_c	0.088	0.023 – 0.154	**0.008**	0.089	0.019 – 0.159	**0.013**

prop_asian_c	-0.030	-0.224 – 0.164	**0.762**	0.435	0.173 – 0.697	**0.001**
prop_black_c	-0.109	-0.183 – -0.035	**0.004**	-0.107	-0.190 – -0.024	**0.011**
life_expectancy_diff_19852010_c	0.001	-0.003 – 0.005	**0.672**	0.001	-0.004 – 0.007	**0.647**
commute_time_h_c	-0.170	-0.251 – -0.088	**<0.001**	-0.144	-0.252 – -0.036	**0.009**
gop_advantage_2016 * state_policy_c	0.035	0.026 – 0.044	**<0.001**	0.033	0.024 – 0.042	**<0.001**
gop_advantage_2016 * state_policy_k12_schools_c	0.041	0.028 – 0.054	**<0.001**	0.038	0.025 – 0.052	**<0.001**
gop_advantage_2016 * state_policy_childcare_c	-0.031	-0.045 – -0.016	**<0.001**	-0.032	-0.047 – -0.018	**<0.001**
gop_advantage_2016 * state_policy_restaurant_c	-0.077	-0.086 – -0.067	**<0.001**	-0.078	-0.087 – -0.069	**<0.001**
gop_advantage_2016 * state_policy_religious_c	-0.058	-0.071 – -0.046	**<0.001**	-0.061	-0.073 – -0.049	**<0.001**
gop_advantage_2016 * state_policy_non_essential_c	-0.032	-0.116 – 0.052	0.455	-0.013	-0.098 – 0.071	0.759
governor_c * state_policy_c	0.022	0.017 – 0.028	**<0.001**	0.022	0.016 – 0.028	**<0.001**
governor_c * state_policy_k12_schools_c	-0.023	-0.029 – -0.016	**<0.001**	-0.023	-0.030 – -0.016	**<0.001**
governor_c * state_policy_childcare_c	-0.022	-0.031 – -0.013	**<0.001**	-0.022	-0.031 – -0.014	**<0.001**
governor_c * state_policy_restaurant_c	-0.001	-0.007 – 0.004	**0.641**	-0.001	-0.007 – 0.005	**0.736**
governor_c * state_policy_religious_c	-0.030	-0.037 – -0.022	**<0.001**	-0.029	-0.036 – -0.021	**<0.001**
gop_advantage_2016 * weekend				-0.045	-0.051 – -0.040	**<0.001**
gop_advantage_2016 * median_income_10k_c				0.016	-0.001 – 0.034	**0.072**
gop_advantage_2016 * pop_density_log_s				0.007	-0.015 – 0.029	**0.535**
gop_advantage_2016 * cases_capita_100_c				0.032	0.021 – 0.044	**<0.001**
gop_advantage_2016 * supermarkets_c				-0.039	-0.198 – 0.120	**0.632**
gop_advantage_2016 * supermarkets_low_accesstores_c				0.161	0.002 – 0.320	**0.047**
gop_advantage_2016 * religion_c				0.097	-0.015 – 0.209	**0.089**
gop_advantage_2016 * percent_employed_c				-0.644	-1.059 – -0.229	**0.002**

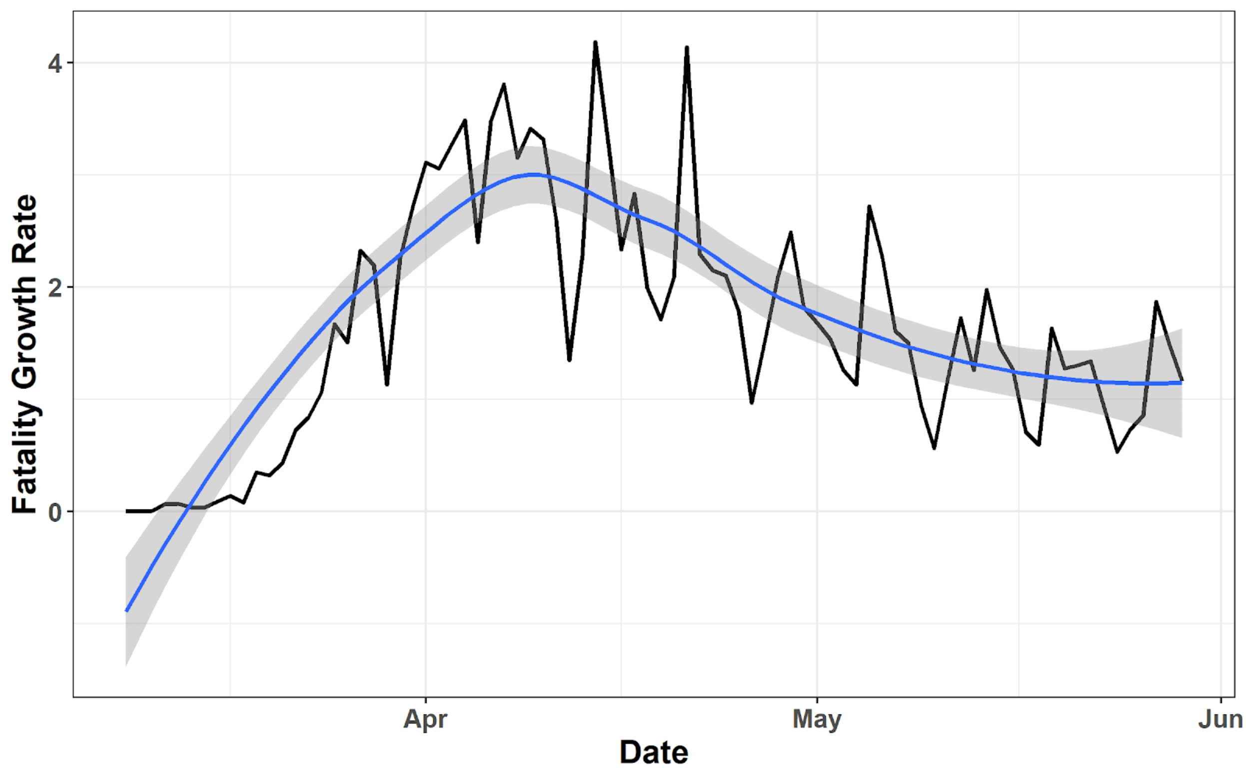
gop_advantage_2016 * median_age_county_2018_10y_c				-0.088	-0.197 – 0.021	0.115
gop_advantage_2016 * age_proportion_85plus_c				1.265	-3.431 – 5.962	**0.597**
gop_advantage_2016 * age_proportion_65to85_c				-0.044	-1.677 – 1.589	0.958
gop_advantage_2016 * age_proportion_0to17_c				-1.308	-2.070 – -0.546	**0.001**
gop_advantage_2016 * gini_c				-0.162	-0.726 – 0.403	**0.575**
gop_advantage_2016 * prop_hisp_latin_c				0.019	-0.122 – 0.160	0.791
gop_advantage_2016 * prop_asian_c				1.103	0.474 – 1.731	**0.001**
gop_advantage_2016 * prop_black_c				-0.056	-0.193 – 0.082	0.427
gop_advantage_2016 * life_expectancy_diff_19852010_c				-0.003	-0.015 – 0.010	0.655
gop_advantage_2016 * commute_time_h_c				0.173	-0.076 – 0.421	**0.173**
Random Effects						
σ^2	0.0256			0.0256		
τ_{00}	0.0107 county_fips			0.0105 county_fips		
	0.0023 state_name			0.0023 state_name		
τ_{11}	0.0023 state_name.gop_advantage_2016			0.0018 state_name_.gop_advantage_2016		
ρ_{01}	0.0621 state_name			-0.2080 state_name		
ICC	0.3447			0.3340		
N	2057 county_fips			2057 county_fips		
	50 state_name			50 state_name		
Observations	168586			168586		
Marginal R^2 / Conditional R^2	0.564 / 0.714			0.569 / 0.713		

Mediation Analyses

Linking reduced physical distancing to increases in COVID-19 infections and deaths. In order to test whether the observed partisan differences are linked to actual COVID-19 infections and deaths (i.e., the proposed mediation model), we first examined whether physical distancing is linked to infection and fatality growth rate (Path B of the mediation pathway) and then examined the full mediation models (STATA analysis software was used for all these analyses). Growth rate was used because the main goal of physical distancing is to “flatten the curve,” or the growth rate of coronavirus. Growth rate was calculated as the cumulative number of infections (fatalities) on the current day (n) minus the cumulative number of infections (fatalities) on the previous day (n-1), divided by the cumulative number of infections (fatalities) on the previous day (n-1), multiplied by 100 (to create a percent). Calculated as such, growth rate is identical to growth rate in cases per capita because counties’ populations did not vary during the sample period. A change in the number of cases from 0 to 0 the next day was assigned a growth rate of zero to avoid undefined values, as was a change of 0 to some integer (which is infinity). Growth rate on the first day of included data (March 9th) was set to 0 since given our growth rate formula, growth rate on that day would be undefined. Calculated as such, we observed that both infection and fatality growth rates first increased and then declined (between March 9 and May 29), as expected. That is, COVID-19 initially spread at a rapid rate and then this spread weakened (likely as a function of preventative measures; Supplementary Figures 10 and 11). Finally, we note that we also replicated the conducted mediation models when calculating *exponential* infection and fatality growth rate instead of the crude infection and fatality growth rate noted above. Applying an exponential growth rate is illustrative from an epidemiological perspective (28, 33, 34, 43, 44), as COVID-19 would initially spread exponentially in the idealized scenario of an early disease spreading on a closed, homogeneous population without interventions. For exponential growth rate results, see the end of this section.



Supplementary Figure 10. Crude infection growth rate across time.



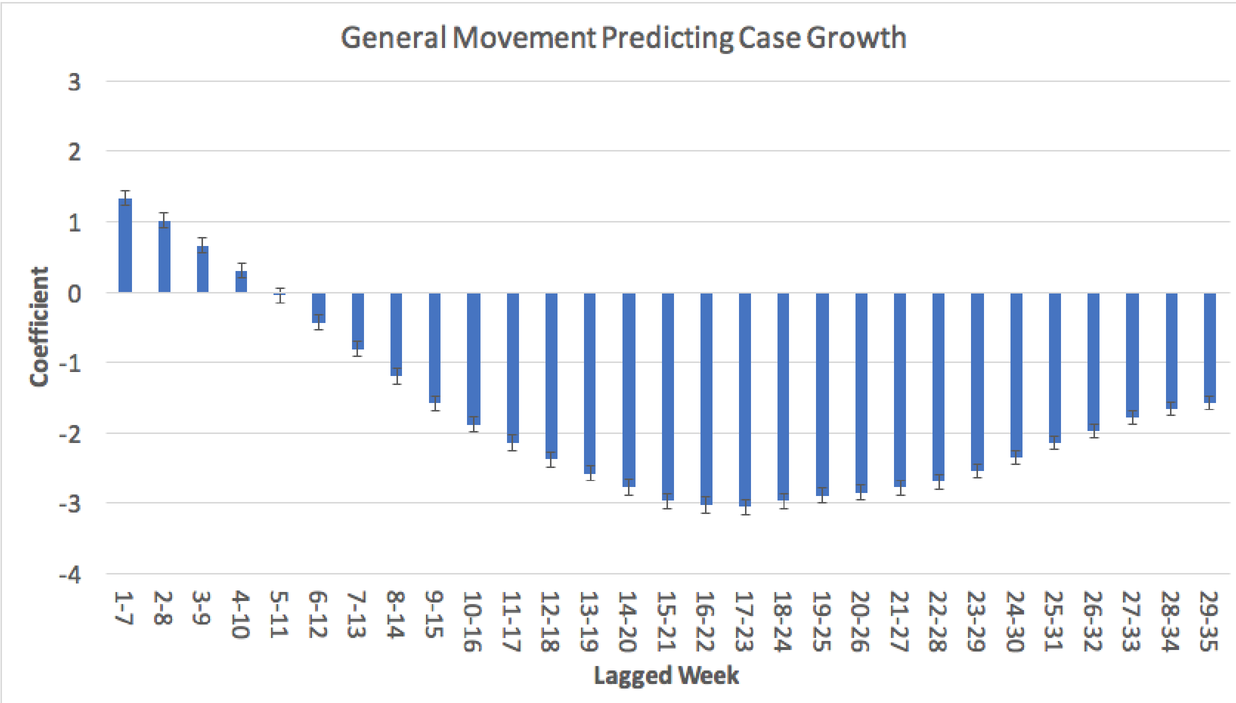
Supplementary Figure 11. Crude fatality growth rate across time.

As in previous work, we defined the incubation period of COVID-19 as the time from exposure to first symptoms (35-38). Although this period may include a period of asymptomatic viral shedding, we did not account for it in our analysis (39). Based on previous work, we estimated the incubation period of COVID-19 to be between 2 to 11 days (median ~4-5 days) (36). This is within the estimates provided by previous work: median: 5.1 days, 95% CI: 4.5 to 5.8 days, with 97.5% developing symptoms within ~11.5 days (37); 95% confidence interval [CI]: 2 to 14 days (38); range: 3 to 11 days from epidemiologic evidence (39). We then estimated that receiving positive test results takes at the very least 1 day. Given these estimates, physical distancing measures could begin to reduce counties' infection growth rate as early as 3 days thereafter, but more likely begins to have a measurable impact on infection rate around 7-8 days later (~5 day incubation and ~3 days to seek and receive test results). Importantly, this estimate is not when the impact of physical distancing is likely strongest, however. That is, physical distancing should predict decreased growth rate more and more strongly as residual infections die out and cases with long incubation periods pass until eventually, this link peaks and then starts to decline (see Supplementary Figures 12-15) (40).

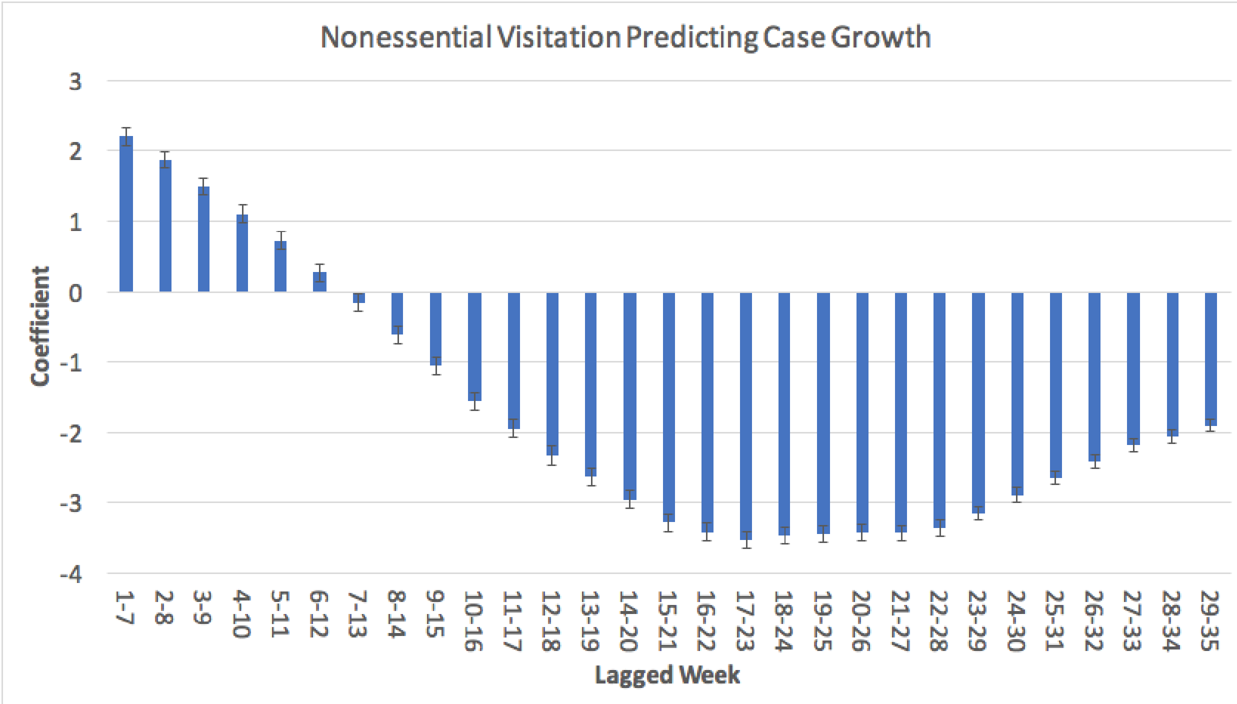
We first considered the link between lagged physical distancing and infection growth rate. Specifically, we conducted a series of mixed effects models with infection growth rate as our dependent variable and observations nested within county and county within state. The predictor variables of interest were, as noted in the main text, the rolling 7-day averages of general movement and visiting nonessential services ($[(p_t + p_{t-1} + \ldots + p_{t-6})/7; t = \{35, 34, \ldots, 7\}]$, where t = lag day and p = physical distancing score) on infection growth. For efficiency's sake, controls were not included in these models. To retain the largest possible date range of data, a 7-day average lag was counted as soon as one day within a 7-day lag was available (though this somewhat reduces sensitivity of the lag estimates, this loss of sensitivity is superseded by efforts to include as large a date-range of data as possible).

For general movement, we found that the 7-day average between lagged day 17 and 23 to most strongly predict lower infection growth rate, $B = -3.05$, 95% CI[-3.15, -2.94], $SE = 0.05$, $z = -56.29$, $p < .001$. That is, counties' physical distancing averaged between 17 and 23 days before a given date most strongly predicted a lower infection growth rate on that date (Supplementary Figure 12). For nonessential visitation, this 7-day lagged average was also between day 17 and 23, $B = -3.53$, 95% CI[-3.65, -3.41], $SE = 0.06$, $z = -57.41$, $p < .001$ (Supplementary Figure 13).

The specific coefficients of each of the 7-day lags can be found in the excel file named "7-Day-LagEstimates" hosted on our OSF project page (here).



Supplementary Figure 12. Rolling 7-day averages of general movement predicting infection growth rate.



Supplementary Figure 13. Rolling 7-day averages of nonessential visitation predicting infection growth rate.

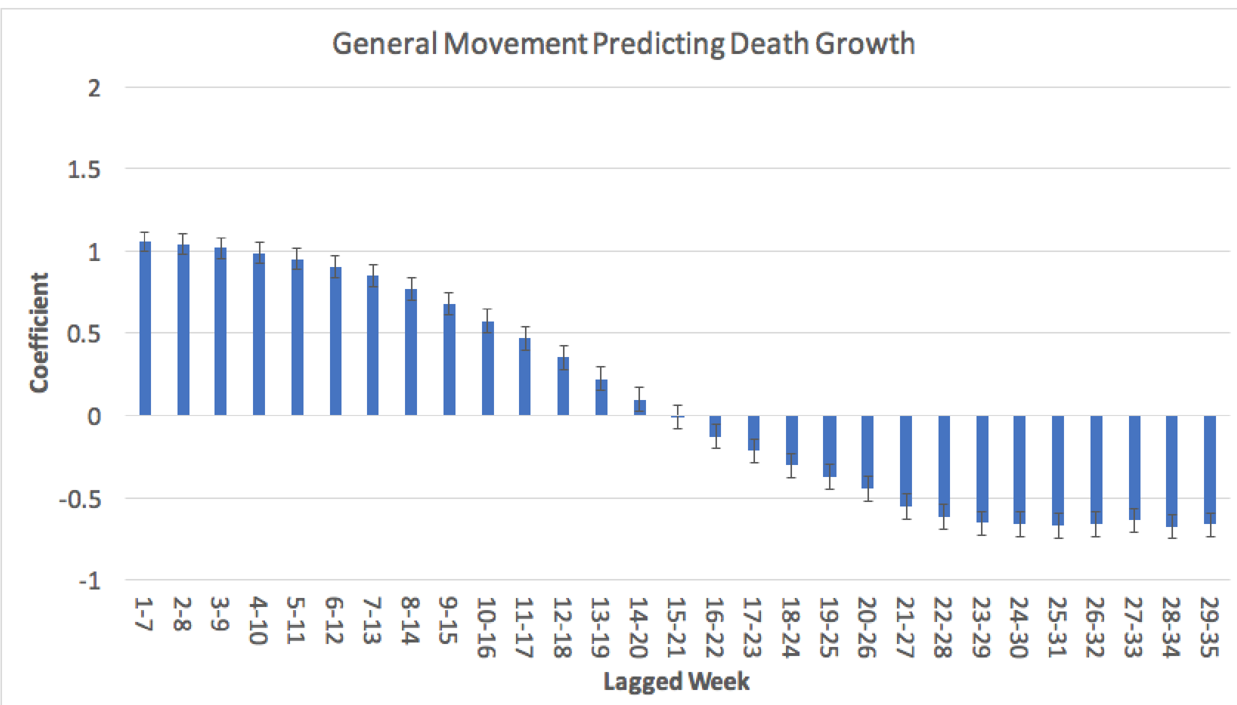
Given these results, we reran the mixed effects models with the identified most predictive 7-day physical distancing lag for infection growth rate but when also including numerous control variables (as main effects). In these mixed-models, county was nested within state and random intercepts of county and state were included. The included control variables were: State policy (1 = State policy in effect on a specific day), governor political affiliation (1 = Democrat), weekend (1 = Weekend), median income (z-scored), median age (z-scored), percent of population aged 0-17 (z-scored), percent of population aged 65-85 (z-scored), percent of population older than 85 (z-scored), change in life expectancy from 1985 to 2010 (z-scored), population density (z-scored), access to grocery stores (z-scored), number of grocery stores per 1,000 people (z-scored), religiosity (z-scored), percent employment (z-scored), economic inequality (z-scored), average time to travel to work (z-scored), percent of population Black (z-scored), percent Hispanic (z-scored), and percent Asian (z-scored). Weight effect coding (58) was used for binary variables (state policy, governor political affiliation, and weekend). The date range of the analysis was restricted to March 26 through May 29, 2020 (infection growth rate: n = 196,625 observations; 51 states [including D.C.], 3,003 counties; $M = 5.72$, $SD = 21.33$), as 7-day lags between 17 and 23 days could not be calculated for any days before March 26 (i.e., March 26 - March 9 = 17 days).[4]

Importantly, when controlling for all the noted covariates, the identified 7-day average lag of 17 to 23 days still predicted lower infection growth rate, ps < .001 (Table 2). Further, these results remained when including counties' non-lagged social distancing in these model as a control, ps < .001 (Table 2). And, supporting the unique predictive validity of our results, counties' non-lagged physical distancing (i.e., same-day physical distancing in a model without lagged physical distancing) predicted higher infection growth rate, ps < .001 (Table 2). All these results remained when including employment type as further control variables, ps < .001 (see the results file named "B-path_summaries" hosted on our OSF project page (here).

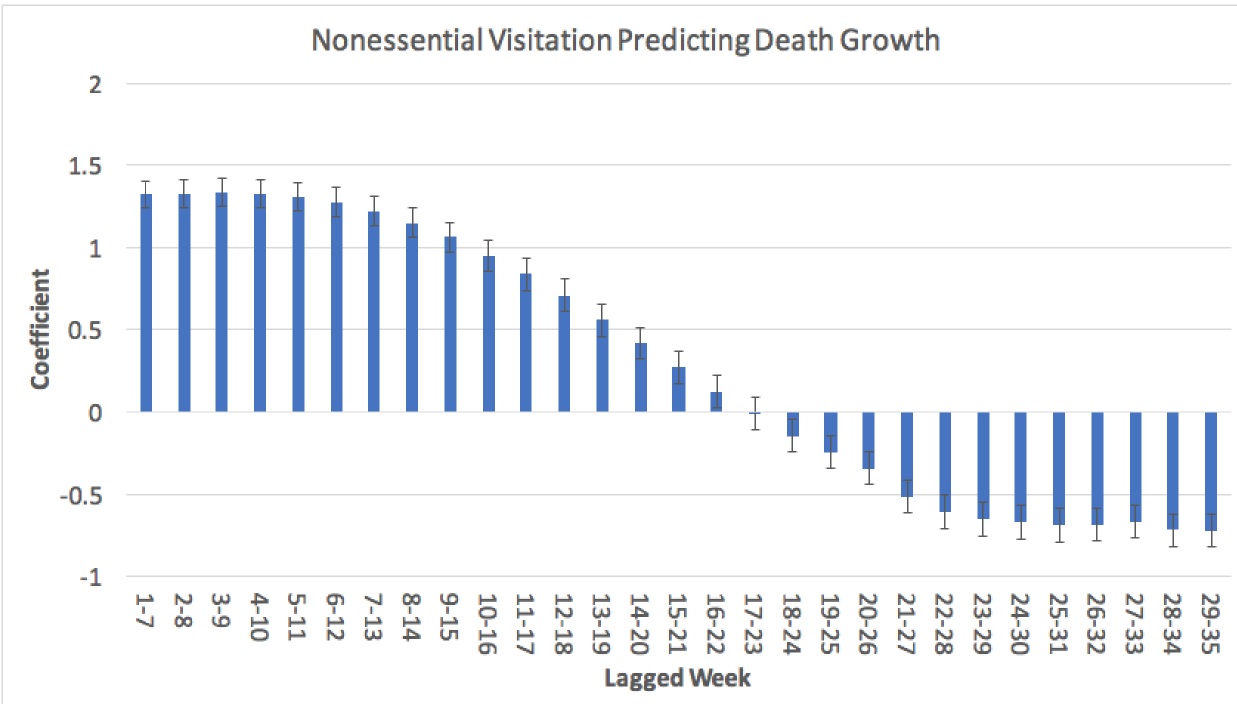
We next considered the link between lagged physical distancing and fatality growth rate in the same manner as we did for infection growth rate. Again, we tested which rolling 7-day average of general movement and visiting nonessential services best predicts reduced fatality growth rate. The 7-day physical distancing lagged average most predictive of lower fatality growth rate was between day 25 and 31 earlier for general movement, $B_{visitation} = -0.67$, 95% CI[-0.74, -0.59], $SE = 0.04$, $z = -17.65$, $p < .001$ (Table 2; Supplementary Figure 14), and

[4] The final number of observations included in the analyses was slightly lower, n = 195,195, because several of the control variables in the model were missing data.

between day 29 and 35 earlier for visiting nonessential services, $B_{visitation}$ = -0.72, 95% CI[-0.82, -0.62], SE = 0.05, z = -14.37, p < .001 (see Supplementary Figure 15). Given that the day 25 to 31 span was very close in terms of predictive power as between day 29 and 35 for visiting nonessential services (see Table 2 and Supplementary Figure 15), $B_{visitation}$ = -0.69, 95% CI[-0.79, -0.59], SE = 0.05, z = -13.37, p < .001, we chose to use the 25 to 31 lag for both physical distancing measures when predicting fatality growth rate for consistency's sake. Doing so did not change the results. Supporting the validity of these results, the identified 7-day lag for fatality growth rate was later in time than the lag for infection growth rate (25 to 31 vs. 17 to 23). The specific coefficients of each of the 7-day lags can be in the excel file named "7-Day-LagEstimates" hosted on our OSF project page (here).



Supplementary Figure 14. Rolling 7-day averages of general movement predicting fatality growth rate.



Supplementary Figure 15. Rolling 7-day averages of nonessential visitation predicting fatality growth rate.

As for infection growth rate, we examined these links again while controlling for covariates. The date range of the analysis was restricted to April 3 through May 29, 2020 (fatality growth rate: n = 172,425 observations; 51 states [including D.C.], 3,003 counties; M = 1.94, SD = 13.64), as 7-day lags between 25 and 31 days could not be calculated for any days before April 3 (i.e., April 3 - March 9 = 25 days). Counties' reduction in general movement and visiting nonessential services averaged between 25 and 31 lagged-days still predicted a lower fatality growth rate, ps < .001 (Table 2). These results also remained when including counties' non-lagged social distancing in the models as a control variable, *p*s < .001 (Table 2). Supporting the unique predictive validity of these findings, non-lagged physical distancing (i.e., same-day physical distancing in a model without lagged physical distancing) predicted greater rather than reduced fatality growth rate, *p*s < .001 (Table 2). Again, these results remained when adding the type of employment variables into the models (e.g., agriculture, finance, manufacturing), *p*s < .001 (see the results file named "B-path_summaries" hosted on our OSF project page; here). Collectively, these results indicate that counties' degree of physical distancing predicts a strong reduction in the growth rate of COVID-19 infections and fatalities in those counties approximately 17-23 and 25-31 days later.

Cross-lagged analyses. We considered the potential effect of infection growth rate on physical distancing (the cross-lagged effect).[5] Mixed effects models with all the above noted controls included, indicated that lagged infection growth rate (between 1 and 14 days earlier) *positively* predicted physical distancing (collapsed across general movement and visitations. Specifically, in line with an increase in infection growth rate leading people to engage in greater physical distancing, counties' infection growth rate averaged between 1 and 14 days earlier predicted greater physical distancing, $B = 3.49$, 95% CI[3.42, 3.56], $SE = .04$, $z = 96.90$, $p < .001$. Similarly, we found that counties' fatality growth rate averaged between 1 and 14 days earlier also predicted greater physical distancing, $B = 0.68$, 95% CI[0.60, 0.75], $SE = .68$, $z = 17.24$, $p < .001$.[6] For more details, see the results file named "Cross-lagged_summaries" hosted on our OSF project page (here).

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[5] The type of employment variables were not included in these analyses, but all other control variables were.
[6] The mixed-models failed to converge when including a random intercept of state. Thus, for these models, only a random intercept of county was included.

Mediation analyses. Finally, and most importantly, we tested the indirect (i.e., mediated) link of partisan differences on infection and fatality growth rate. The analyses were conducted in STATA and followed mixed-model mediation procedures as outlined by (43) with county nested within state; the mediation models included 3-level mixed-effects models as in the models reported throughout this article. Because several of the mediation models failed to converge when including random slopes, only random intercepts of county and state were included. All the above noted control variables (see Path B analyses above) were included. Further, we added Region (dummy-coded and weighted) as an additional control to account for differences in infection rates based on geographical region in the United States. Alaska was excluded from the analyses because of missing partisanship (vote-gap) values, and D.C. was excluded for missing Region values. The examined date ranges were March 26 to May 29, 2020, for infections (general movement: n = 194,090 observations, 49 states, 2,986 countie, 65 days; visitation: n = 133,640 observations; 49 states, 2,056 counties, 65 days) and April 3 to May 29, 2020, for fatalities (general movement: n = 170,202 observations; 49 states, 2,986 counties, 57 days; visitation: n = 117,192 observations; 49 states, 2,056 counties, 57 days).

The indirect relationships between counties' pro-Trump voting (z-scored) and infection growth rate via physical distancing (lagged 17 to 23 days earlier; z-scored) were significant, ps < .001 (see Table 3). Specifically, we found that Trump-leaning counties exhibited a greater infection growth rate than Clinton-leaning ones, ps < .068 (between March 26 and May 29, 2020; see Total Effects, Table 3).[7] Importantly, this would not have been the case if

[7] Our mediation findings do not rest on the total effects and direct effects being significant. That is, indirect effects can be significant even if total effect and direct effects are not. This is because indirect effects quantify the *change* between total and direct effects. Thus, the marginal total effect observed between partisanship and infection growth

Trump-leaning counties had physically distanced to the same extent as more Clinton-leaning ones, however. Indeed, if Trump-leaning counties physically distanced like Clinton-leaning counties, Trump-leaning counties would actually have had a smaller infection growth rate than Clinton-leaning ones, ps < .002 (see Direct Effects in Table 3).

The mediation was also observed for counties' fatality growth rate, ps < .001 (lagged 25 to 31 days earlier; Table 3). Specifically, we found that Trump-leaning counties exhibited a *smaller* fatality growth rate than Clinton-leaning ones, ps < .006 (between April 3 and May 29, 2020; see Total Effects, Table 3), but importantly, would have exhibited an even comparatively smaller fatality growth rate had they physically distanced to the same extent as more Clinton-leaning counties, ps < .001 (see Direct Effects in Table 3).[8]

More specifically, our model indicated that extremely pro-Trump voting counties (+2 z-score in the vote gap variable) experienced an infection growth rate of .59 percentage points higher on average (between March 26 and May 29, 2020; average infection growth rate across all counties in the model was 5.72% points). Such pro-Trump counties, however, would have experienced a growth rate of 1.17 percentage points less than the average if they had socially distanced to the same extent as more Democratic-voting counties - a swing of 1.76 percentage

rate (when visiting nonessential services was the mediator) influences neither our overall mediation findings nor conclusions.

[8] Regarding the total effect, while infection growth rate was larger in Trump-leaning counties in the examined date range, fatality growth rate was *smaller*. First, these differences do not impact the observed mediations (for both infection and fatality growth rate the observed indirect effect was significant). Second, this difference is likely driven by infection growth rate rising more recently in more Trump-leaning counties than Clinton-leaning counties (~May, 2020), meaning that fatality growth rate will likely catch up to infection growth rate over summer 2020 until Trump-leaning counties exhibit a larger fatality growth rate as well (this may then change again over the upcoming months/years depending on preventative measures and how COVID-19 spreads). Third, we examine the observed mediation when including a broader date range in the *Mediation at Earlier Date Range* section below and found the expected results in that the indirect effects remained while the total and direct effects changed as expected (infection growth rate was higher in more liberal counties in this earlier date range, ps < .073 (Supplementary Table 33).

points in infection growth rate. Notably, if a county had started with 1 case on day 1 of our data (March 26th), 65 days later (the number of days included in our date range), that county would have had ~53 infections if the growth rate was 6.31% (the approximate growth rate in Trump leaning counties; +2 *SD*). The county would have only had ~18 infections, however, if the growth rate was 4.55% (the approximate growth rate in Trump leaning counties when accounting for differences in physical distancing).[9] In other words, approximately triple the amount of people would have been infected in heavily pro-Trump counties as a result of poorer physical distancing if all counties had 1 case on March 26, 2020. In sum, then, these findings tentatively suggest that partisan differences in physical distancing predicted a higher growth rate of infections and deaths in Republican counties than was necessary.

Mediations when including employment type. The observed mediations remained consistent when including the type of employment variables (see Supplementary Table 1) as additional control variables (Supplementary Table 34).

Supplementary Table 34. Output of mediation models when additionally including employment types as control variables. The link between partisanship (Trump vs. Clinton vote gap in 2016; z-scored) and COVID-19 infection and fatality growth rate was mediated by time-lagged physical distancing (reduction in general movement and reduction in visiting nonessential services 17-23 days and 25-31 days earlier; z-scored).

	Predictor Variable		**Mediator**		**Outcome Variable**
Mediation 1:	Partisanship		Lagged Reduction in General Movement (17-23 days prior)		Infection Growth Rate
Total Effect	$B = 0.215$	$SE = 0.143$	$z = 1.50$	$p = .133$	95% CI: [-0.065, 0.495]
Direct Effect	$B = -0.595$	$SE = 0.169$	$z = -3.53$	$p < .001$	95% CI: [-0.926, -0.264]

[9] Given that there are approximately 3,000 counties, this difference would amount to ~159,000 number of people becoming infected rather than ~54,000 if all counties had behaved as Trump leaning counties did.

Indirect Effect	B = 0.810	SE = 0.165	z = 4.90	p < .001	95% CI: [0.486, 1.134]
Mediation 2:	Partisanship	Lagged Reduction in Visiting Nonessential Services (17-23 days prior)			Infection Growth Rate
Total Effect	B = 0.335	SE = 0.159	z = 2.11	p = .035	95% CI: [0.023, 0.646]
Direct Effect	B = -0.432	SE = 0.182	z = -2.37	p = .018	95% CI: [-0.790, -0.075]
Indirect Effect	B = 0.767	SE = 0.154	z = 4.97	p < .001	95% CI: [0.465, 1.070]
Mediation 3:	Partisanship	Lagged Reduction in General Movement (25-31 days prior)			Fatality Growth Rate
Total Effect	B = -0.315	SE = 0.189	z = -1.66	p = .097	95% CI: [-0.686, 0.057]
Direct Effect	B = -0.493	SE = 0.186	z = -2.65	p = .008	95% CI: [-0.857, -0.129]
Indirect Effect	B = 0.178	SE = 0.051	z = 3.47	p = .001	95% CI: [0.077, 0.278]
Mediation 4:	Partisanship	Lagged Reduction in Visiting Nonessential Services (25-31 days prior)			Fatality Growth Rate
Total Effect	B = -0.294	SE = 0.224	z = -1.31	p = .190	95% CI: [-0.733, 0.145]
Direct Effect	B = -0.453	SE = 0.236	z = -1.92	p = .055	95% CI: [-0.915, -0.009]
Indirect Effect	B = 0.159	SE = 0.050	z = 3.16	p = .002	95% CI: [0.061, 0.258]

Mediations at an earlier date range. Given that the conducted meditations included lags of 17 to 23 days and 25 to 31 days, the date range included in these analyses was restricted to March 26 to May 29, and April 3 to May 29, respectively. Thus, the findings that Trump leaning counties exhibited a higher infection growth rate is limited to this date range. Indeed, when including all dates (March 9 to May 29, 2020), Trump-leaning counties exhibited a smaller infection growth rate, B = -0.354, 95% CI[-0.532, -0.176], SE = .09, z = -3.89, p < .001 (see the results file named "C-path" hosted on our OSF project page here). These results are explained by Democratic-leaning counties being hit harder at the start of the pandemic as they are more highly traveled and because New York City was the epicenter at the start of the outbreak. To ensure that our results also hold true for these earlier date range, we reran the conducted mediations but with a physical distancing lag 7 to 14 days for infection growth rate, and 19 to 25 days for fatality growth rate (to include a larger date range; March 16 to May 29 and March 28 to May 29). When doing so, we still found the observed mediations (we collapsed across general movement and visiting nonessential services in these analyses for simplicity; Supplementary Table 35).

Supplementary Table 35. Output of mediation models when testing an earlier physical distancing lag for infections (7 to 14 days) and fatalities (19 to 25 days) to include a larger overall date range (March 16 to May 29 and March 28 to May 29).

	Predictor Variable		**Mediator**		**Outcome Variable**
Mediation 1:	Partisanship		Lagged Reduction in Physical Distancing (7-14 days prior)		Infection Growth Rate
Total Effect	B = -0.250	SE = 0.150	z = -1.67	p = .095	95% CI: [-0.544, 0.043]
Direct Effect	B = -0.717	SE = 0.161	z = -4.46	p < .001	95% CI: [-1.032, -0.401]
Indirect Effect	B = 0.466	SE = 0.106	z = 4.41	p < .001	95% CI: [0.259, 0.674]
Mediation 2:	Partisanship		Lagged Reduction in Physical Distancing (19-25 days prior)		Fatality Growth Rate
Total Effect	B = -0.510	SE = 0.124	z = -4.11	p < .001	95% CI: [-0.754,-0.267]
Direct Effect	B = -0.634	SE = 0.143	z = -4.43	p < .001	95% CI: [-0.914, -0.354]
Indirect Effect	B = 0.123	SE = 0.043	z = 2.88	p = .004	95% CI: [0.039, 0.207]

Mediations as a function of other analysis choices. Additionally, we note that the observed mediations also remained consistent when removing all cases where infection and fatality growth rate were zero (Supplementary Table 36). That is, our results remained when excluding all instances in which a county's infections (fatalities) did not grow, respectively (we calculated these analyses because infection and fatality growth rate exhibited zero-inflation). These latter analyses also indicate that our results hold when only considering dates in which the growth rate of COVID-19 and COVID-19 fatalities increased in a county. And, the observed mediation findings also remained the same when calculating infection and fatality growth rates via a moving average (to account for outlier days and infection and fatality spikes [see Supplementary Figures 10 and 11]; Supplementary Table 37). Finally, the findings also remained when including the more specific state policy variables (e.g., closing restaurants, closing child-care; see Supplementary Tables 1 and 2) as additional control variables (Supplementary Table 38).

Supplementary Table 36. Mediation models when only including non-zero growth rates (all cases in which a county's infections [fatalities] did not grow were excluded). Physical distancing was calculated by collapsing across general movement and visiting nonessential services for simplicity.

	Predictor Variable		Mediator		Outcome Variable
Mediation 1:	Partisanship		Lagged Reduction in Physical Distancing (17-23 days prior)		Infection Growth Rate
Total Effect	$B = 4.499$	$SE = 0.842$	$z = 5.34$	$p < .001$	95% CI: [2.848, 6.150]
Direct Effect	$B = 1.759$	$SE = 0.949$	$z = 1.85$	$p = .064$	95% CI: [-0.101, 3.620]
Indirect Effect	$B = 2.740$	$SE = 0.296$	$z = 9.24$	$p < .001$	95% CI: [2.159, 3.321]
Mediation 2:	Partisanship		Lagged Reduction in Physical Distancing (25-31 days prior)		Fatality Growth Rate
Total Effect	$B = 7.539$	$SE = 2.967$	$z = 2.54$	$p = .011$	95% CI: [1.723, 13.354]
Direct Effect	$B = 4.653$	$SE = 3.040$	$z = 1.53$	$p = .126$	95% CI: [-1.304, 10.611]
Indirect Effect	$B = 2.885$	$SE = 0.600$	$z = 4.81$	$p < .001$	95% CI: [1.709, 4.061]

Supplementary Table 37. Mediation models when calculating infection and fatality growth rates via moving averages (r = ((r(d) + r(d+1) + r(d-1))/3 where r = growth rate and d = day). Physical distancing was calculated by collapsing across general movement and visiting nonessential services for simplicity.

	Predictor Variable		**Mediator**		**Outcome Variable**
Mediation 1:	Partisanship		Lagged Reduction in Physical Distancing (17-23 days prior)		Infection Growth Rate
Total Effect	B = 0.280	SE = 0.148	z = 1.90	p = .058	95% CI: [-0.009, 0.569]
Direct Effect	B = -0.738	SE = 0.171	z = -4.32	p < .001	95% CI: [-1.073, -0.403]
Indirect Effect	B = 1.018	SE = 0.121	z = 8.39	p < .001	95% CI: [0.780, 1.255]
Mediation 2:	Partisanship		Lagged Reduction in Physical Distancing (25-31 days prior)		Fatality Growth Rate
Total Effect	B = -0.426	SE = 0.119	z = -3.58	p < .001	95% CI: [-0.660, -0.193]
Direct Effect	B = -0.640	SE = 0.136	z = -4.71	p < .001	95% CI: [-0.906, -0.374]
Indirect Effect	B = 0.213	SE = 0.050	z = 4.24	p < .001	95% CI: [0.115, 0.312]

Supplementary Table 38. Mediation models when including the specific state policy variables (e.g., closing restaurants, closing schools) as additional control variables.

	Predictor Variable		**Mediator**		**Outcome Variable**
Mediation 1:	Partisanship		Lagged Reduction in General Movement (17-23 days prior)		Infection Growth Rate
Total Effect	B = 0.231	SE = 0.156	z = 1.48	p = .139	95% CI: [-0.075, 0.537]
Direct Effect	B = -0.577	SE = 0.180	z = -3.20	p = .001	95% CI: [-0.930, -0.223]
Indirect Effect	B = 0.808	SE = 0.123	z = 6.56	p < .001	95% CI: [0.566, 1.049]
Mediation 2:	Partisanship		Lagged Reduction in Visiting Nonessential Services (17-23 days prior)		Infection Growth Rate
Total Effect	B = 0.323	SE = 0.156	z = 2.08	p = .038	95% CI: [0.018, 0.628]

Direct Effect	*B* = -0.586	*SE* = 0.161	*z* = -3.63	*p* < .001	95% CI: [-0.902, -0.270]
Indirect Effect	*B* = 0.909	*SE* = 0.109	*z* = 8.38	*p* < .001	95% CI: [0.697, 1.122]
Mediation 3:	Partisanship	Lagged Reduction in General Movement (25-31 days prior)			Fatality Growth Rate
Total Effect	*B* = -0.410	*SE* = 0.100	*z* = -4.11	*p* < .001	95% CI: [-0.605, -0.215]
Direct Effect	*B* = -0.591	*SE* = 0.115	*z* = -5.14	*p* < .001	95% CI: [-0.817, -0.366]
Indirect Effect	*B* = 0.182	*SE* = 0.049	*z* = 3.71	*p* < .001	95% CI: [0.086, 0.278]
Mediation 4:	Partisanship	Lagged Reduction in Visiting Nonessential Services (25-31 days prior)			Fatality Growth Rate
Total Effect	*B* = -0.517	*SE* = 0.146	*z* = -3.53	*p* < .001	95% CI: [-0.804, -0.230]
Direct Effect	*B* = -0.689	*SE* = 0.161	*z* = -4.29	*p* < .001	95% CI: [-1.004, -0.375]
Indirect Effect	*B* = 0.172	*SE* = 0.047	*z* = 3.69	*p* < .001	95% CI: [0.081, 0.264]

Exponential infection and fatality growth rate. Finally, we also reconducted the mediations when modeling the growth rate for an exponential model of disease dynamics (i.e., the exponential growth rate), which is expected to apply for the idealized case of an early epidemic in a closed population without interventions. Importantly, we confirmed that the key mediations remain when using an exponential growth rate, calculated as the natural log of cumulative infections (fatalities: I(t+1)) on the next day (t+1) divided by cumulative infections (fatalities: I(t)) on the current day (n)--i.e., $r(t) = \ln(I(t+1)/I(t)) = \ln(I(t+1)) - \ln(I(t))$ (35). Finally, we multiplied this number by 100 to have a percent score. We excluded the final day in the date range of analysis since the growth rate on a given day depends on the cumulative case counts on the following day. A change in the number of cases from 0 to 0 the next day was assigned a growth rate of zero to avoid undefined values (to do so, all 0s were first replaced with 1s). When using exponential growth rate as the dependent variable in our models, we still observed the same mediations (see Supplementary Table 39).

Supplementary Table 39. Output of mediation models when calculating infection and fatality growth rate via exponential growth rate. The link between partisanship (Trump vs. Clinton vote gap in 2016; z-scored) and exponential infection and fatality growth rate was mediated by physical distancing (reduction in general movement and in visiting nonessential services; z-scored).

	Predictor Variable	**Mediator**			**Outcome Variable**
Mediation 1:	Partisanship	Lagged Reduction in General Movement (17-23 days prior)			Infection Growth Rate
Total Effect	$B = 0.141$	$SE = 0.108$	$z = 1.30$	$p = .194$	95% CI: [-0.072, 0.353]
Direct Effect	$B = -0.539$	$SE = 0.125$	$z = -4.30$	$p < .001$	95% CI: [-0.785, -0.294]
Indirect Effect	$B = 0.680$	$SE = 0.091$	$z = 7.46$	$p < .001$	95% CI: [0.501, 0.859]
Mediation 2:	Partisanship	Lagged Reduction in Visiting Nonessential Services (17-23 days prior)			Infection Growth Rate
Total Effect	$B = 0.195$	$SE = 0.107$	$z = 1.82$	$p = .069$	95% CI: [-0.015, 0.406]
Direct Effect	$B = -0.503$	$SE = 0.128$	$z = -3.92$	$p < .001$	95% CI: [-0.755, -0.252]
Indirect Effect	$B = 0.699$	$SE = 0.086$	$z = 8.13$	$p < .001$	95% CI: [0.530, 0.867]
Mediation 3:	Partisanship	Lagged Reduction in General Movement (25-31 days prior)			Fatality Growth Rate
Total Effect	$B = -0.316$	$SE = 0.090$	$z = -3.51$	$p < .001$	95% CI: [-0.493, -0.140]
Direct Effect	$B = -0.463$	$SE = 0.100$	$z = -4.64$	$p < .001$	95% CI: [-0.659, -0.267]
Indirect Effect	$B = 0.147$	$SE = 0.038$	$z = 3.89$	$p < .001$	95% CI: [0.073, 0.221]
Mediation 4:	Partisanship	Lagged Reduction in Visiting Nonessential Services (25-31 days prior)			Fatality Growth Rate
Total Effect	$B = -0.386$	$SE = 0.123$	$z = -3.13$	$p = .002$	95% CI: [-0.628, -0.144]
Direct Effect	$B = -0.526$	$SE = 0.132$	$z = -3.98$	$p < .001$	95% CI: [-0.785, -0.267]
Indirect Effect	$B = 0.140$	$SE = 0.037$	$z = 3.80$	$p < .001$	95% CI: [0.068, 0.213]

Meta-analysis of within state mediations. Possibly, the observed indirect effects are driven by differences in *reporting* infections rather than actual infections (this seems less likely for fatalities given that these are harder to falsely report/under-report). To examine this possibility, we tested whether the observed indirect effect results for infection growth rate remained when individually testing these effects *within* states and then aggregating these results via a meta-analysis. We only included states with 50 or more counties (n = 28), given that smaller numbers of counties would lead to unreliable estimates. Specifically, we took the indirect effect coefficient for each of the within state analyses and meta-analyzed these coefficients (using the metafor package in R). Our meta-analysis revealed that the indirect effect was significant, B = 0.417, SE = 0.122, z = 3.43, p = .0006, 95% CI[0.179, 0.656]. These findings suggest that infection reporting bias at the U.S. State-level are unlikely to account for our results, given that it is unlikely that reporting differences exist *within* states. Aside from these analyses, we also note that the conducted mediations were conducted using mixed-models in which county was nested within state. This should also account for potential random variation among states, including variation in reporting infections.

Supplemental Discussion

We note two caveats. First, the objective degree of physical distancing required to halt the exponential spread of COVID-19 has yet to be determined. Said another way, less stringent physical distancing, involving opening business but still banning large gatherings and nonessential travel, may be enough to keep the R_0 value of coronavirus under 1 and thus allow people to carry on relatively unchanged lives without hospitals being overwhelmed. If true, then the observed partisan differences in physical distancing may be largely inconsequential, and may even have allowed for less disruption of people's lives in Republican counties. Though possible, we still found physical distancing to predict actual COVID-19 infections and deaths at the county level. In other words, the question of whether pro-Trumps counties' lower degree of physical distancing was appropriate or not depends on how one quantifies mobility and social freedoms versus infections and fatalities, something which we are not qualified to quantify.

Second, just as pro-Trump counties neglected physical distancing comparatively to pro-Clinton counties, liberal enclaves neglected physical distancing (until it was too late) comparatively to European counties that were already struggling with COVID-19 (e.g., Italy). However, this group-based approach to COVID-19 in terms of perceiving the pandemic as limited to foreign nations seems to extend to *within* the United States. That is, Republican counties acted and continue to act as if COVID-19 can only hit "foreign" liberal areas. Unfortunately, this approach may directly have led Republican counties to exhibit a greater amount of infections than necessary, and may explain the recent rise of infections in Republican areas (as of mid May, 2020) (59). Our results thus suggest that this rise in infections in pro-Trump counties could have been avoided if partisan effects were weaker within the U.S.