

NBER WORKING PAPER SERIES

POLARIZATION AND PUBLIC HEALTH:  
PARTISAN DIFFERENCES IN SOCIAL DISTANCING  
DURING THE CORONAVIRUS PANDEMIC

Hunt Allcott  
Levi Boxell  
Jacob C. Conway  
Matthew Gentzkow  
Michael Thaler  
David Y. Yang

Working Paper 26946  
<http://www.nber.org/papers/w26946>

NATIONAL BUREAU OF ECONOMIC RESEARCH  
1050 Massachusetts Avenue  
Cambridge, MA 02138  
April 2020

We thank SafeGraph for providing access to the data and the SafeGraph COVID-19 response community for helpful input. We acknowledge funding from the Stanford Institute for Economic Policy Research (SIEPR), the John S. and James L. Knight Foundation, the Sloan Foundation, the Institute for Humane Studies, and the National Science Foundation (grant number: DGE-1656518). For our survey, we registered a pre-analysis plan on the AEA Registry, with ID AEARCTR-0005632. This study was approved by IRBs at NYU (IRB-FY2017-938) and Harvard (IRB17-1725). The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

At least one co-author has disclosed a financial relationship of potential relevance for this research. Further information is available online at <http://www.nber.org/papers/w26946.ack>

NBER working papers are circulated for discussion and comment purposes. They have not been peer-reviewed or been subject to the review by the NBER Board of Directors that accompanies official NBER publications.

© 2020 by Hunt Allcott, Levi Boxell, Jacob C. Conway, Matthew Gentzkow, Michael Thaler, and David Y. Yang. All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission provided that full credit, including © notice, is given to the source.

Polarization and Public Health: Partisan Differences in Social Distancing during the Coronavirus Pandemic

Hunt Allcott, Levi Boxell, Jacob C. Conway, Matthew Gentzkow, Michael Thaler, and David Y. Yang

NBER Working Paper No. 26946

April 2020

JEL No. D72,I12,I18

**ABSTRACT**

We study partisan differences in Americans' response to the COVID-19 pandemic. Political leaders and media outlets on the right and left have sent divergent messages about the severity of the crisis, which could impact the extent to which Republicans and Democrats engage in social distancing and other efforts to reduce disease transmission. We develop a simple model of a pandemic response with heterogeneous agents that clarifies the causes and consequences of heterogeneous responses. We use location data from a large sample of smartphones to show that areas with more Republicans engage in less social distancing, controlling for other factors including state policies, population density, and local COVID cases and deaths. We then present new survey evidence of significant gaps between Republicans and Democrats in beliefs about personal risk and the future path of the pandemic.

Hunt Allcott  
Department of Economics  
New York University  
19 W. 4th Street, 6th Floor  
New York, NY 10012  
and NBER  
hunt.allcott@nyu.edu

Matthew Gentzkow  
Department of Economics  
Stanford University  
579 Jane Stanford Way  
Stanford, CA 94305  
and NBER  
gentzkow@stanford.edu

Levi Boxell  
Stanford University  
Department of Economics 5  
79 Jane Stanford Way  
Stanford, CA 94305  
Lboxell@stanford.edu

Michael Thaler  
Harvard University  
Department of Economics  
1805 Cambridge St  
Cambridge, MA 02138  
michaelthaler@g.harvard.edu

Jacob C. Conway  
Stanford University  
Department of Economics  
579 Jane Stanford Way  
Stanford, CA 94305  
jconway@stanford.edu

David Y. Yang  
Harvard University  
Department of Economics  
1805 Cambridge Street  
Littauer Center M-31  
Cambridge, MA 02138  
davidyang@fas.harvard.edu

# 1 Introduction

Mobilizing an effective public response to an emerging pandemic requires clear communication and trust (Holmes 2008; Taylor et al. 2009; van der Weerd et al. 2011; Vaughn and Tinker 2011). Risk reduction measures such as social distancing and self-quarantine can rarely be enforced entirely by coercion, particularly in democratic societies. The public must understand what is required of them and be persuaded of the importance of complying.

Partisan differences could play a key role in determining how Americans respond to the COVID-19 pandemic. Prominent officials have sent conflicting messages about the crisis, with President Trump and other Republican officials sometimes saying it was less severe, and Democrats giving more emphasis to its dangers (Beauchamp 2020; Stanley-Becker and Janes 2020; Coppins 2020; McCarthy 2020). Partisan media have tended to echo this division (Aleem 2020; Kantrowitz 2020). This could cause differences between people on the right and left in the extent of risk reduction measures such as social distancing, with potentially important effects on human health and the economy.

In this paper, we combine GPS location data from a large sample of smartphones with a new survey to study partisan differences in the early response to COVID-19. The GPS data are collected by the company SafeGraph, and record daily and weekly visits to points of interest (POIs), including restaurants, hotels, hospitals, and many other public and private businesses. Our primary analysis focuses on the period from January 26, 2020 to April 4, 2020.

We begin with two motivating facts. First, recent nationwide surveys have shown that Democrats are more concerned about the spread of COVID-19 than Republicans. Second, Democrats report taking more steps to avoid infection than Republicans. We note, however, that Democratic areas also have had more coronavirus cases and implemented stay-at-home policies earlier. The raw differences observed on surveys could simply be the expected result of local differences in risk or regulation, rather than an effect of partisanship *per se*.

We then present a simple model that clarifies the potential causes and consequences of divergent social-distancing behavior. It combines a standard epidemiological model of a pandemic with an economic model of optimizing behavior by heterogeneous agents. The model clarifies that divergent responses between groups need not be inefficient. One group might engage in less social distancing because their costs of distancing are greater (e.g., they would lose more income as a result) or because their benefits of distancing are smaller (e.g., they are at lower risk of in-

fection). However, differences in behavior resulting from divergent *beliefs* of otherwise similar agents do suggest systematic inefficiency, as optimizing based on different beliefs means that the marginal costs of social distancing are not equated across people. In that case, society gets less social distancing at higher cost than if agents had the same beliefs.

Our main GPS results show that the strong partisan differences in social distancing behavior that emerged with the rise of COVID-19 are not merely an artifact of differences in state policies or observed risks. Controlling for state-time fixed effects to account for heterogenous policy responses by state governments only attenuates the partisan gap slightly. Including controls to proxy for health and economic variables interacted flexibly with time attenuates the gap more substantially, but it remains statistically and economically significant. After including our full set of controls, we estimate that moving from the 10th to the 90th percentile of Republican county vote share is associated with an 18.6 percent increase in the number of POI visits during the week of March 29.

Our findings are robust to the inclusion or exclusion of control variables, excluding states with early COVID-19 outbreaks, or dropping highly populated counties. Replacing the continuous measure of partisanship with discrete indicators for portions of the Republican vote share distribution or restricting the sample to counties from certain portions of the distribution does not change our qualitative conclusions. Furthermore, there is no evidence of a similar partisan gap during the same period in 2019.

Finally, we use new survey data from April 4-7, 2020 to provide additional evidence on the differences in beliefs that may underlie the partisan gap in behavior. We collect participants' demographics (including party affiliation), beliefs regarding the efficacy of social distancing, self-reported distancing due to COVID-19, and predictions about future COVID-19 cases. Compared to Republicans, we find that Democrats believe the pandemic is more severe and report a greater reduction in contact with others. In our survey, we also randomly vary whether predictions about future COVID-19 cases are incentivized, and do not find evidence that incentives reduce the partisan gap, suggesting that these predictions are less likely to be due to partisan cheerleading (as in Bullock et al. 2015 and Prior et al. 2015), and more likely to reflect true differences in beliefs. A back-of-the-envelope calculation of our model estimates that the deadweight loss cost due to these partisan differences is \$2.8 billion per year.

Several contemporaneous studies also measure partisan differences in responses to COVID-



19.<sup>1</sup> Gadarian et al. (2020) present survey evidence showing partisan gaps in self-reported responses to the pandemic. Barrios and Hochberg (2020) show differences between Republican and Democratic areas in the frequency of COVID-related queries on Google and in movement patterns as measured in GPS data from a different source than the one we use here. Painter and Qiu (2020) examine partisan heterogeneity in response to state-level, stay-at-home orders.

Our work contributes to a broader literature on what drives responses to pandemics (e.g., Blendon et al. 2008; Vaughan and Tinker 2009; Fineberg 2014). Risk perception, behavior changes, and trust in government information sources change as pandemics progress (Ibuka et al. 2010; Bults et al. 2011). Demographic characteristics, such as gender, income, geography, or social interactions, are important determinants of the adoption of recommended public health behaviors (Bish and Michie 2010; Ibuka et al. 2010; Bults et al. 2011; Chuang et al. 2015; Shultz et al. 2016; Gamma et al. 2017).

A related literature focuses on the consequences of political polarization for health behaviors (e.g., Iyengar et al. 2019 and Montoya-Williams and Fuentes-Afflick 2019). Party affiliation is correlated with physician recommendations on politicized health procedures, enrollment in government exchanges created under the Affordable Care Act, and beliefs in the safety of vaccines (Hersh and Goldenberg 2016; Lerman et al. 2017; Sances and Clinton 2019; Trachtman 2019; Krupenkin 2018; Suryadevara et al. 2019). We show how partisan differences can lead to the inefficient allocation of public health goods, such as social distancing, during pandemics.

Our work also relates to a broader literature on partisan differences in trust and beliefs. For instance, a large body of empirical literature documents partisan differences in beliefs about factual events such as unemployment (Bartels 2002; Gaines et al. 2007; Bullock et al. 2015). There exists a growing literature on building theoretical models of opinion polarization to explain observed partisanship (Dixit and Weibull 2007; Benoit and Dubra 2015; Ortoleva and Snowber 2015; Fryer et al. 2019). Furthermore, a substantial empirical literature studies the link between media markets and political polarization (Glaeser and Ward 2006; McCarty et al. 2006; Campante and Hojman 2013; Prior 2013).

Finally, our work adds to the increasing number of papers using GPS or related data to study social interactions. For example, Dubé et al. (2017) test the effectiveness of mobile targeting with coupons to competing movie theaters based on consumers' real-time location. Hanna et al. (2017)

---

<sup>1</sup>Coverage in the media and some studies examine partisan heterogeneity in response to COVID-19 with no or few controls for differential risk exposure or costs of social distancing (e.g., Economist 2020; Andersen 2020). Baker et al. (2020) use transaction-level data and examine heterogeneity in consumption responses to COVID-19.

use data from Google Maps to estimate the effects of lifting high-occupancy vehicle restrictions in Jakarta, Indonesia.<sup>2</sup> Chen and Rohla (2018) and Athey et al. (2019) use SafeGraph data to measure the effects of political polarization on the length of Thanksgiving dinners and to estimate a novel measure of racial segregation, respectively.

Sections 2, 3, 4, 5, and 6, respectively, present our motivating facts, theoretical framework, data, GPS analysis, and survey results.

## **2 Motivating Facts**

In this section, we present two basic facts on partisan differences in social distancing. First, existing surveys document large differences in beliefs and social distancing by political party. Figure 1 presents results from previous national polls. Panel A shows that Democrats were consistently more concerned than Republicans about the spread of coronavirus in the United States from January 26 through the most recent polls in early April.

Second, consistent with beliefs, there exist partisan differences in self-reported social distancing behaviors. Panel B presents results from a March 13th poll, showing that Democrats were more likely to say they were eating at home more often, had stocked up on food and supplies, changed travel plans, and cancelled plans to avoid crowds. Panels C and D show that throughout the month of March, Democrats were more likely than Republicans to say that they were avoiding public places and small gatherings.

To interpret these differences, we need a framework to understand why people from the two political parties might behave differently, and why that might matter. For example, Democratic areas also have had more coronavirus cases and implemented stay-at-home policies earlier.

## **3 Stylized Model**

In this section, we present a stylized model to clarify why it might matter if different types of people choose different amounts of social distancing. We embed an epidemiological model of disease transmission into an economic model with agents who maximize utility considering the expected private cost of disease.

---

<sup>2</sup>See also Blattman et al. (2018) and Davis et al. (2019).

### 3.1 Epidemiological Model

We use a discrete time version of the standard SIR epidemiological model (Kermack and McKendrick 1927). In each period  $t$ , each person is in one of four states  $\sigma \in \{S, I, R, D\}$ , representing Susceptible, Infected, Recovered, and Deceased. The share of the population in each state at time  $t$  is  $s_t, i_t, r_t$ , and  $d_t$ . Let  $\beta$  represent disease infectiousness, and let  $c_t$  denote an individual's amount of risky behavior at time  $t$ —for example, the amount of travel, dining out, failing to wash hands, and other activities that increase risk of becoming Infected.

All people begin in the Susceptible state. A Susceptible person becomes Infected at time  $t + 1$  with probability  $c_t \beta i_t$  and stays Susceptible with probability  $(1 - c_t \beta i_t)$ . Infected people stay Infected for one period, after which they become Deceased with probability  $\psi$  or Recovered with probability  $(1 - \psi)$ . Both  $D$  and  $R$  are absorbing states.

Let  $\theta$  index different types of people—for example, liberals and conservatives. Let  $\omega_{\theta\sigma t}$  be a state variable representing the share of type  $\theta$  that is in state  $\sigma$  at time  $t$ . The population is of measure 1, so  $\sum_{\theta} \sum_{\sigma} \omega_{\theta\sigma t} = 1$ .

### 3.2 Individual Decisions

People of type  $\theta$  earn flow utility  $u_{\theta}(c_t; \sigma_t)$ , which depends on their risky behavior  $c_t$  and their state  $\sigma_t$ . People discount the future at rate  $\delta$  and maximize expected lifetime utility  $\sum_{\tau=t}^{\infty} \delta^{\tau} u_{\theta}(c_{\tau}; \sigma_{\tau})$ . Define  $V_{\theta}(\sigma)$  as the expected lifetime utility of a person currently in state  $\sigma$ ; note that this also implicitly depends on current and future population states  $\omega_{\theta\sigma t}$ . Being infected reduces utility, so we assume  $V_{\theta}(S) > V_{\theta}(I)$ .

We focus on Susceptible people, as they comprise most of the population during the period we study. We can write their maximization problem as a Bellman equation, in which people maximize the sum of utility from risky behavior today and expected future utility:

$$V_{\theta}(S_t) = \max_{c_t} \left\{ \underbrace{u_{\theta}(c_t; S_t)}_{\text{current utility from risky behavior}} + \underbrace{\delta [c_t \beta i_t V_{\theta}(I) + (1 - c_t \beta i_t) V_{\theta}(S)]}_{\text{expected future utility}} \right\}. \quad (1)$$

The first-order condition for privately optimal risky behavior is

$$\underbrace{u'_{\theta}}_{\text{marginal utility of risk}} = \underbrace{\beta i_t}_{\text{marginal infection probability}} \underbrace{\delta (V_{\theta}(S) - V_{\theta}(I))}_{\text{private cost of infection}}. \quad (2)$$

The first-order condition shows that people choose their risky behavior to equate marginal benefit (more utility today) with private marginal cost (higher risk of infection, which reduces future utility). The equation illustrates that there are three reasons why risky behavior might vary across types. First is the marginal utility of risk (or equivalently, the marginal cost of social distancing): for example, people vary in how much they like travel and dining out, as well as in how easy it is to work from home. Second is the marginal infection probability: for example, local infection rate  $i_t$  differs across geographic areas. Third is the private cost of infection: for example, infection is more harmful for people who are older or have underlying health conditions.

### 3.3 Social Optimum

It is difficult to know for sure whether people take too many or too few steps to reduce disease transmission during our study period. Thus, we do not consider the optimal consumption of  $c$ . Instead, we hold constant the total amount of risky behavior and ask whether the allocation across types is optimal. Tangibly, this means that we are not asking, “how much social distancing should people be doing?” Instead, we are asking, “holding constant the amount of social distancing people are doing, would some people ideally be doing less, and others ideally be doing more?”

Social welfare is the sum of utility across all people in all states:

$$W_t = \sum_{\theta} \sum_{\sigma} \omega_{\theta\sigma} V_{\theta}(\sigma_t). \quad (3)$$

Let  $C_t$  denote the total risky behavior at time  $t$  across all people. The (constrained) socially optimal outcome results from maximizing  $W_t$  subject to the constraint that  $C_t = \bar{C}_t$ . Let  $\lambda$  be the shadow price on that constraint; this reflects the loss from having too much or too little social distancing overall.

Consuming  $c$  imposes two types of externalities. First, it imposes a positive pecuniary externality, as travel, dining out, and other risky activities help keep firms in business and workers employed. Second, it imposes a negative externality by increasing the person’s infection probability, which increases the expected stock of infected people in the next period ( $i_{t+1}$ ), which increases other Susceptible people’s infection risk. Let  $\phi_t$  denote the net externality per unit of consumption, which may be positive or negative; this becomes more negative as the contagion externality grows. We assume that these externalities are constant across people, and that people do not account for them when setting their  $c_t^*$ .

In the constrained social optimum, Susceptible people's consumption of  $c_t$  would satisfy the following first-order condition:

$$0 = \underbrace{u'_\theta - \beta i_t \delta (V_\theta(S) - V_\theta(I))}_{\text{private marginal utility}} + \underbrace{\phi_t}_{\text{externality}} + \underbrace{\lambda}_{\text{shadow price}}. \quad (4)$$

### 3.4 Heterogeneous Risk Misperceptions

We now allow people to misperceive risks. These misperceptions cause people to choose too much or too little risky behavior relative to their private optimum, and heterogeneous misperceptions cause transfers across types and efficiency losses.

We now add  $\theta$  subscripts to explicitly denote different parameters by type. Let  $\mu_{t\theta} := \beta i_t \delta (V_\theta(S) - V_\theta(I))$  denote type  $\theta$ 's expected utility cost due to infection from an additional unit of risky consumption. Let  $\tilde{\mu}_{t\theta}$  denote type  $\theta$ 's *perception* of that cost. Susceptible type  $\theta$  consumers then set  $c_{t\theta}$  according to the following modified first-order condition:

$$u'_\theta = \tilde{\mu}_{t\theta}, \quad (5)$$

giving consumption denoted  $c_{t\theta}^*$ .

For illustrative purposes, imagine that there are two types  $\theta \in \{a, b\}$  in equal proportion, and that period  $t$  marginal utility is linear and the same for both types, so  $u'_\theta(c) = u'(c)$  for both types and  $u''$  is a constant. Finally, without loss of generality, assume that type  $a$  perceives greater risk, so  $\tilde{\mu}_{ta} > \tilde{\mu}_{tb}$ . Our survey data show that Democrats perceive greater risk, so one can think of Democrats as type  $a$ . We do not take a stand on which type perceives risk more correctly or which type's behavior is closer to the unconstrained social optimum.

Define  $\bar{\mu}_t := \frac{1}{2} (\tilde{\mu}_{ta} + \tilde{\mu}_{tb})$  as the average risk perception. With homogeneous risk perceptions, both types would set  $c_t$  such that  $u' = \bar{\mu}_t$ , giving homogeneous consumption denoted  $\bar{c}_t$ . With heterogeneous misperceptions, type  $a$  consumes more and type  $b$  consumes less; the consumption difference is  $c_{tb}^* - c_{ta}^* = \frac{\tilde{\mu}_{ta} - \tilde{\mu}_{tb}}{-u''}$ . These consumption differences cause both transfers across types and efficiency losses.

Risk perceptions affect risky consumption, and risky consumption causes externalities, so the heterogeneous misperceptions cause transfers across groups. The net transfer from type  $a$  to type  $b$  from heterogeneous instead of homogeneous misperceptions is

$$\underbrace{\frac{\tilde{\mu}_{ta} - \tilde{\mu}_{tb}}{-u''}}_{\text{consumption difference}} \cdot \underbrace{\phi_t}_{\text{externality}}. \quad (6)$$

If  $\phi_t > 0$ , i.e. the positive pecuniary externality from risky consumption outweighs the negative contagion externality, then heterogeneous misperceptions cause a net transfer from type  $b$  to type  $a$ . Intuitively, we would say that Republicans are doing more to keep the economy going. On the other hand, if  $\phi_t < 0$ , i.e. the negative contagion externality outweighs the positive pecuniary externality, then heterogeneous misperceptions cause a net transfer from type  $a$  to type  $b$ . Intuitively, we would say that Democrats are doing more to reduce the spread of disease.

The efficiency cost in period  $t$  from heterogeneous instead of homogeneous misperceptions are the two deadweight loss triangles around  $\bar{c}_t$ , with total area:

$$\Delta W_t = \frac{s_t}{2} \cdot \frac{\left( \overbrace{\tilde{\mu}_{ta} - \bar{\mu}_t}^{\text{misperception}} \right)^2}{\underbrace{-u''}_{\text{slope of private marginal utility}}}. \quad (7)$$

Intuitively, type  $a$  people (Democrats) are doing too much social distancing, and type  $b$  (Republicans) too little, relative to the (constrained) social optimum with homogeneous risk perceptions. The marginal cost of social distancing is increasing: it's easy to start by avoiding going to a bar once a week, but eventually one's only contact with people is going to the grocery store for food, and it is quite costly to stop buying food. Thus, society could achieve the same amount of social distancing at lower cost if type  $a$  did less and type  $b$  did more.

This model informs the empirical tests in the rest of the paper. In Section 6, we ask if Democrats and Republicans have different risk perceptions, which would generate the transfers and efficiency costs described above. In doing so, we control for factors such as population density that could generate difference in actual risks across types. In Sections 5 and 6, we ask if Democrats and Republicans are reducing risk by different amounts. In doing so, we use proxies to control for differences in actual risks and marginal costs of risk reduction that could cause differential risk reduction to be socially optimal.

## 4 Data

### 4.1 SafeGraph Mobile GPS Location Data

Our analysis uses GPS data from SafeGraph, aggregating GPS pings from numerous mobile applications to measure foot traffic patterns to a collection of points-of-interest (POIs). POIs include retail shops, restaurants, movie theaters, hospitals, and many other public locations individuals may choose to go when leaving their house. For each POI, SafeGraph reports its geographic location, industry, and the total number of visitors in their mobile device panel that have visited each day.<sup>3</sup>

Our primary analysis uses data from a period of ten weeks, from January 26 to April 4, 2020. We aggregate visits across all POIs in a given county for a given week. We also separately aggregate visits by 2-digit NAICS code for each county and week. In a placebo analysis, we analyze data over earlier time periods (starting in January 2019).

We also use data from the SafeGraph Social Distancing data released as a part of their COVID-19 response. This data is available since January 1, 2020 and updated regularly. We use data over the same ten week period. This data contains alternative measures of social distancing beyond POI visits, such as the number of devices leaving their assigned geohash-7 home or the median time spent away from home across devices.

See the Appendix for additional information on the SafeGraph data construction.

We supplement the SafeGraph data with various other sources of county and census block group data. For demographic information on age, race, education, income, and poverty status at the county-level, we aggregate census block group data from SafeGraph Open Census to the county level.<sup>4</sup> For each county, we define county partisanship to be the proportion of total votes received by President Donald Trump in the 2016 election (MIT Election Data and Science Lab 2018). We use county-level data on COVID-19 cases and deaths from The New York Times (2020).

### 4.2 Survey

To supplement these data, we ran an online survey with a sample of American adults to study partisan gaps in beliefs about and responses to COVID-19 at the individual level. The survey

---

<sup>3</sup>SafeGraph removes POIs with fewer than five visitors in a given month for data through February 2020. For the March 2020 data, SafeGraph has released data on a weekly basis, rather than a monthly basis, and include all POIs with at least 1 visitor for these weekly releases.

<sup>4</sup>The SafeGraph Open Census data is derived from the 2016 5-year ACS at the census block group.

was conducted from April 4-7 with Prime Panels from CloudResearch, a market research firm with access to 50 million participants. We recruited 2,000 participants to complete the study; participants are broadly representative of U.S. adults in terms of party affiliation, age, gender, and race.<sup>5</sup> Subjects who completed the survey were paid a show-up fee from CloudResearch and had the chance to earn additional bonus incentives of up to \$100.

Participants were asked for their party affiliation on a seven-point scale, ranging from “Strongly Democrat” to “Strongly Republican.” We interpret party continuously, where 0 represents “Strongly Democrat” and 6 represents “Strongly Republican.” We also classify participants into Republican (including independents who lean Republican) and Democrats (including independents who lean Democrat) for descriptive analyses.

The survey asked for demographic information (zipcode, age, race, gender, income, education, number of children, and health). It then asked about news consumption habits and trust before and during COVID-19. Then, there were several questions about social distancing: self-reported social distancing in response to COVID-19, beliefs about the risk of not distancing, and the appropriate trade-off between going out more to help the economy versus going out less to avoid spreading COVID-19.

We next elicited beliefs about the number of new COVID-19 cases that would be confirmed in the U.S. in April, 2020, as well as the approval rating of Donald Trump’s response to the pandemic on April 30, and randomly vary whether these were incentivized or not. 1,013 (51 percent) subjects made incentivized predictions in which they earn more money if they are closer to the correct answer. They were told that we will randomly select 10 participants who will receive a payment of  $(\$100 - \Delta)$  where  $\Delta$  is the percentage point difference between their answer and the true value. The remaining 987 (49 percent) of subjects were not incentivized. The primary four outcome variables are participants’ answers to the three social-distancing questions and the one prediction question.

All survey questions are listed in Appendix A.2.2.

## 5 SafeGraph Empirical Specification and Results

Figure 2 visualizes geographic variation in this social distancing response, and compares observed variation to analogous distributions of partisanship, COVID-19 confirmed cases, and public policy responses. Panel A maps the social distancing response observed in each county, as measured by

---

<sup>5</sup>In addition, we weighted observations so that age, gender, and race distributions match the 2010 Census data, and party affiliation matches the Gallup survey from March 13-22, 2020 (Gallup 2020).



the percent decrease in SafeGraph visits between the week beginning January 26th and the week beginning March 29th, using data described below. Panel B shades counties by their party affiliation, captured by the Republican vote share in the 2016 presidential election. Panel C maps the number of COVID-19 cases confirmed in a given county by April 4th. Panel D shades states by the effective start date for the earliest statewide “stay-at-home” order issued. Panels A and B exhibit a strong geographic correlation between the counties with weaker social distancing responses and those with higher Republican vote shares. Panel D shows that areas with stronger distancing responses also generally instituted earlier statewide, stay-at-home orders. We also observe stronger social distancing responses in counties with more COVID-19 confirmed cases (Panel C). However, these counties also had more coronavirus cases and were in states that initiated stay-at-home policies earlier. Thus, the partisan differences in social distancing could simply be the expected result of local differences in infection risk or regulation. In order to establish partisan difference in social distancing, we next exploit over time variations.

Figure 4 reports trends in social distancing and COVID-19 prevalence separately for Republican and Democratic counties, defined to be counties above or below the median 2016 Republican vote share respectively. Panel A shows that the overall number of POI visits is relatively constant until COVID-19 cases begin emerging in the United States in March. During this same period, Democratic counties exhibited a sharper drop in weekly POI visits than their Republican counterparts. As Panel B demonstrates, Democratic counties also exhibited a much sharper rise in COVID-19 cases and deaths—accounting for nearly all verified COVID-19 cases and deaths through March 29. Appendix Figure A1 shows that these declining and differential POI trends are not present over the same time period in 2019.

Our main empirical specification takes the following form

$$\log(c_{it}) = \alpha_t \rho_i + X_{it} \cdot \gamma + \varepsilon_{it},$$

where  $c_{it}$  is the number of POI visits in county  $i$  during week  $t$ ,  $\alpha_t$  are the time-varying coefficients on county partisanship  $\rho_i$ ,  $X_{it}$  are potentially time-varying controls, and  $\varepsilon_{it}$  is the county-specific error term.<sup>6</sup> In choosing our control variables  $X_{it}$ , we chose variables to flexibly control for the four channels of divergent behavior highlighted in equation (2). Standard errors are clustered at the county-level throughout unless specified otherwise.

---

<sup>6</sup>In implementing, we normalize  $\alpha_t$  relative to the first week.

Figure 5 reports our estimates of  $\alpha_t$  under various sets of covariates chosen to incrementally control for the mechanisms highlighted by our model.

In Panel A, we only include county and time fixed effects. This measures the extent to which these two groups' behavior diverges with the rise of COVID-19 via any of the aforementioned channels. Throughout February, there are no significant partisan differences in POI visits relative to the January 26 week baseline. However, as COVID-19 begins to emerge in the United States, partisan differences arise and grow throughout the weeks of March.

These results do not control for differences in state policies, which themselves may be a function of the partisan leanings of government officials. In Panel B, adding state-time fixed effects to control for state-level policies in response to COVID-19 along with other state-level temporal shocks causes the partisan differences to attenuate slightly.

In Panel C, we flexibly control for various health<sup>7</sup> and economic<sup>8</sup> characteristics of the county. We view the health controls as proxies for the marginal infection probability and the private cost of infection, and we view the economic controls as proxies for the marginal cost of social distancing, though each group of controls could proxy for other factors as well. We allow the coefficient on these variables  $\gamma_t$  to vary flexibly across time.

Although these controls attenuates the partisan differences to some degree, they remain economically and statistically significant. By the week of March 29, our estimate of  $\alpha_t$  is 0.470. This implies that going from a county with the 10th to the 90th percentile in Republican vote share is associated with an 18.6 percent increase in the number of POI visits during the week of March 29.<sup>9</sup> Appendix Figure A2 shows that these strong partisan differences do not appear over the same time period in 2019. We view these results as evidence of behavioral differences driven by partisan misperceptions of risks at the group-level, consistent with the survey evidence.

In Appendix Figure A3, we report sensitivity to various alternative specifications. Panels A and B use alternative sets of controls. Panel C replaces the measure of partisanship with a discrete indicator for certain quantiles of the Republican vote share distribution. Panel D drops counties with populations above half a million or states with early COVID-19 outbreaks (California, Washington, and New York). Panel E restricts the sample to counties from certain portions of the

---

<sup>7</sup>Health controls include log of one plus the number of confirmed COVID-19 cases in the county, the log of one plus the number of COVID-19 deaths in the county, the log of one plus the county population density (individuals per square kilometer) and the share of the population 65 years or older.

<sup>8</sup>Economic controls include the share of the population with at least a bachelor's degree, the share in poverty, and the shares of white, black, and asians.

<sup>9</sup>The difference between the 90th and 10th percentile of Republican vote share is  $0.807 - 0.411 = 0.396$ .

Republican vote share distribution. And, Panel F weights observations by the county’s population, uses standard errors clustered at the state-level, and examines sensitivity to the start date. None of the alternative specifications change the central conclusion regarding partisan differences in social distancing in March.

Appendix Figure A4 aggregates the number of POI visits at the electoral precinct level and shows that the qualitative conclusion of less social distancing by Republicans holds at the precinct level, even when including county-time fixed effects. Again, these patterns are not present in 2019 (Appendix Figure A5).

Figure 6 examines heterogeneity across 2-digit NAICS codes by re-aggregating POI visits to the county level after restricting to certain NAICS codes. Consistent with the narrative around COVID-19, we see the strongest partisan differences emerge with POIs in the accommodations and food, entertainment, and retail industries. There are no significant partisan differences in visits to health care POIs.

Figure 7 repeats Panel C of 5, but using POI visits aggregated at the day level. The partisan differences emerge in March for both weekdays and weekends, suggesting these differences are not driven solely by differences in work-from-home policies.

Figure 8 considers various alternative measures of social distancing derived from SafeGraph’s Social Distancing data release as described in Section 4. Statistically significant partisan differences emerge in March for the log number of devices leaving home, the share of devices leaving home, and the total number of active devices.<sup>10</sup> For the log of the median time away from home, we see positive, but insignificant, point estimates.

## 6 Survey Results

Turning to the results of our survey, we first confirm that there indeed exists partisan differences in (self-reported) social distancing behaviors and attitudes, consistent with the POI visits results presented above, and then show that beliefs about the effectiveness of social distancing and predictions

---

<sup>10</sup>A key issue with the SafeGraph social distancing data is sample attrition. SafeGraph restricts the panel to devices with observed location pings in a given time period. For some applications, the frequency of location pings depends on device mobility. If devices are immobile at home or turned off, they may not generate location pings and would then be dropped from the sample. The total number of active devices changes over our sample period in a manner consistent with sample attrition. Given these issues, we prefer measures of social distancing derived solely from *external* activity (e.g., POI visits) that do not contain the same measurement error problems. We attempt to correct for the differential attrition in our measure of the share of devices leaving home (see Figure 8 footnotes for correction; see Panel G of Appendix Figure A3 for estimates using the uncorrected measure).

of the spread of COVID-19 follow the same partisan patterns.

Our main empirical specification regresses normalized responses on each question on party:

$$y_i = \kappa + \alpha\rho_i + \gamma X_i + \varepsilon_i,$$

where  $y_i$  is the number of standard deviations above the mean for response  $i$ ,  $\rho_i$  is the continuous measure of party lean from 0 to 1,  $X_i$  are demographic and location controls, and  $\varepsilon_i$  is an error term.

Figure 9 shows consistent evidence for partisan differences in social distancing, both with and without control variables.<sup>11</sup> On average, participants report reducing contact by 70.0 percent, with a standard deviation (SD) of 24.5 percent. After including controls, strong Democrats report engaging in 0.18 SD more of a reduction in contact with others as compared to strong Republicans. This corresponds to a gap in reducing contact with others of 72.2 percent for strong Democrats versus 67.8 percent for strong Republicans. Similarly, Democrats find it significantly more important to stay inside to prevent the spread of the virus versus go outside to help the economy, and the difference between strong partisans is 0.23 SD.

We then examine the extent to which such partisan differences in social distancing attitudes could be attributed to underlying beliefs regarding COVID-19 severity and efficacy of social distancing. We first consider how Republicans and Democrats differ in their perceptions of the risk of not socially distancing, and find that that Democrats believe that the probability of catching COVID-19 in one month without any social distancing is higher than Republicans do. On average, participants assess this probability to be 55.0 percent (SD 31.9 percent). Strong Democrats hold beliefs that the risk of not socially distancing is 0.34 SD larger as compared to strong Republicans. This corresponds to a gap in beliefs about the probability of catching COVID-19 without social distancing of 60.5 percent for strong Democrats versus 49.6 percent for strong Republicans.

We next consider beliefs about future COVID-19 cases in the entire U.S. We tell participants the number of cases by March 31 and ask them to predict the number of cases in April. For half of subjects, these predictions are incentivized. We find that Democrats anticipate more future COVID-19 cases. On average, participants predict 202,810 new cases in the U.S. in April 2020 (SD 233,343 cases, due to a long right tail).<sup>12</sup> Strong Democrats predict 0.24 SD more cases as compared to strong Republicans. This corresponds to a gap in beliefs about future cases of 231,283 for strong Democrats versus 172,336 for strong Republicans.

---

<sup>11</sup>These effects are not due to observation weighting, as shown in Appendix Figure A7.

<sup>12</sup>As pre-specified, these averages are calculated after winsorizing at the 5-percent level to account for outliers.

To explore what could account for partisan differences in COVID-19 related beliefs, we ask whether the partisan gap in beliefs about the number of U.S. cases shrinks when subjects are given incentives for accuracy. Bullock et al. (2015) and Prior et al. (2015) show that partisan differences on factual questions often shrink under incentives, and interpret this as evidence that the differences in survey responses are partly due to “partisan cheerleading” rather than differences in true beliefs. As shown in Figure 10, we find that on an explicitly political question (Trump’s approval rating for his handling of COVID-19), incentives indeed reduce the partisan gap, consistent with the findings in Bullock et al. (2015) and Prior et al. (2015). However, the partisan gap in predicted future cases if anything widens with incentives. This supports the view that Democrats and Republicans genuinely differ in their beliefs about the severity of the outbreak.

In Appendix Figure A6, we find that the partisan gap in social distancing behaviors attenuates by 60 percent when controlling for respondents’ beliefs about the efficacy of social distancing. While suggestive, we note that controlling for beliefs does not cleanly separate the causal role of beliefs versus other factors.

Finally, we use participants’ self-reported willingness-to-accept for social distancing to do a back-of-the-envelope calculation of the deadweight loss from Equation 7. We assume that agents have the same flow utility functions  $u(c) = \frac{\nu}{2}c^2 + \eta c + k$ , but differ by partisanship in their beliefs about  $\beta$ . In particular, we assume when  $\beta = 0$ , all agents choose to consume  $c^*(0)$ , which we normalize to 1, so that  $-\nu = \eta \geq 0$ ; we consider what happens when  $\beta > 0$  and perceptions of  $\beta$  differ:  $\tilde{\beta}_D \neq \tilde{\beta}_R$ .

From our survey, we find that the median participants’ willingness-to-accept for a month of consuming 1 instead of 0 is \$1500, so  $u(1) - u(0) = 1500$  and  $\eta = 3000$ . From the data above, we suppose that Democrats reduce consumption by 72.2% and Republicans reduce by 67.8%. Therefore, Democrats and Republicans differ in perceived risks by  $\tilde{\mu}_{tR} - \tilde{\mu}_{tD} = -u'' \cdot (c_{tD}^* - c_{tR}^*) = \$132$  per month.

Plugging this into Equation 7 assuming that 99% of the country is currently susceptible, we compare the deadweight loss per person per year if partisans have perceived risks  $(\mu_{tD}^*, \mu_{tR}^*)$  compared to if they have the same perceived risk  $(\mu_{tD}^* + \mu_{tR}^*)/2$ , and find that  $\Delta W = \$8.62$  per person per year. That is, given the current U.S. population of about 330 million, we approximate that the partisan inefficiency costs approximately \$2.8 billion per year.

## 7 Conclusion

Messages from political leaders and media outlets about the severity of COVID-19 could substantially affect how Americans respond to the pandemic. If Republicans and Democrats disagree about the potential risks, they may also differ in how much they reduce the risk of disease transmission through social distancing and other actions. In this case, our model shows how society ends up with more disease transmission at higher economic cost than if people had the same beliefs.

Our empirical results show that partisan gaps in beliefs and behavior are real. GPS evidence reveals large partisan gaps in actual social distancing behaviors. Survey evidence shows substantial gaps between Republicans and Democrats in beliefs about the severity of COVID-19 and the importance of social distancing. The raw partisan differences partly reflect the fact that Democrats are more likely to live in the dense, urban areas hardest hit by the crisis, and to be subject to policy restrictions—in other words, to face stronger individual incentives for social distancing. Even after controlling carefully for such factors, however, the partisan gaps remain statistically and economically significant. While our evidence does not permit us to conclusively pin down the ultimate causes of partisan divergence, the patterns are consistent with the messaging from politicians and media having played an important role.

## References

- Aleem, Zeeshan. 2020. A new poll shows a startling partisan divide on the dangers of the coronavirus. *Vox*. March 15. <https://www.vox.com/2020/3/15/21180506/coronavirus-poll-democrats-republicans-trump>.
- Andersen, Martin. 2020. Early evidence on social distancing in response to COVID-19 in the United States. *Working Paper*.
- Athey, Susan, Billy Ferguson, Matthew Gentzkow, and Tobias Schmidt, 2019. Experienced Segregation. *Working Paper*.
- Baker, Scott R., R.A. Farrokhnia, Steffen Meyer, Michaela Pagel, Constantine Yannelis. 2020. How does household spending respond to an epidemic? Consumption during the COVID-19 pandemic. *Working Paper*.
- Barrios, John M. and Yael V. Hochberg. 2020. Risk perception through the lens of politics in the time of the COVID-19 pandemic. *Working Paper*.
- Bartels, Larry M. 2002. Beyond the running tally: Partisan bias in political perceptions. *Political Behavior*. 24(2): 117-150.
- Beauchamp, Zack. 2020. The stunning contrast between Biden and Trump on coronavirus. *Vox.com*. <https://www.vox.com/policy-and-politics/2020/3/12/21177135/coronavirus-covid-19-pandemic-trump-biden-speeches>.
- Benoit, Jean-Pierre, and Juan Dubra. 2014. A theory of rational attitude polarization. *Working Paper*.
- Bish, Alison, and Susan Michie. 2010. Demographic and attitudinal determinants of protective behaviours during a pandemic: A review. *British Journal of Health Psychology*. 15(4): 797-824.
- Blattman, Christopher, Donald Green, Daniel Ortega, and Santiago Tobón. 2017. Place-based interventions at scale: The direct and spillover effects of policing and city services on crime. *Working Paper*.
- Blendon, Robert J., Lisa M. Koonin, John M. Benson, Martin S. Cetron, William E. Pollard, Elizabeth W. Mitchell, Kathleen J. Weldon, and Melissa J. Herrmann. 2008. Public response to community mitigation measures for pandemic influenza. *Emerging Infectious Diseases*. 14(5): 778.
- Bullock, John G., Alan S. Gerber, Seth J. Hill, and Gregory A. Huber. 2015. Partisan bias in factual beliefs about politics. *Quarterly Journal of Political Science*. 10(4): 519-578.
- Bults, Marloes, Desirée JMA Beaujean, Onno de Zwart, Gerjo Kok, Pepijn van Empelen, Jim E van Steenbergen, Jan Hendrik Richardus, and Hélène ACM Voeten. 2011. Perceived risk, anxiety, and behavioural responses of the general public during the early phase of the In-

- influenza A (H1N1) pandemic in the Netherlands: results of three consecutive online surveys. *BMC Public Health*. 11(1): 2.
- Campante, Filipe R., and Daniel A. Hojman. 2013. Media and polarization: Evidence from the introduction of broadcast TV in the United States. *Journal of Public Economics*. 100: 79-92.
- Chen, M. Keith, and Ryne Rohla. 2018. Politics Gets Personal: Effects of Political Partisanship and Advertising on Family Ties. *Science*. 360: 1020-1024.
- Chuang, Ying-Chih, Ya-Li Huang, Kuo-Chien Tseng, Chia-Hsin Yen, and Lin-hui Yang. 2015. Social capital and health-protective behavior intentions in an influenza pandemic. *PloS One*. 10(4).
- Coppins, McKay. 2020. Trump's Dangerously Effective Coronavirus Propaganda. *TheAtlantic.com*. <https://www.theatlantic.com/politics/archive/2020/03/trump-coronavirus-threat/607825/>.
- Davis, Donald R., Jonathan I. Dingel, Joan Monras, and Eduardo Morales. 2019. How segregated is urban consumption? *Journal of Political Economy*. 127(4): 1684-1738.
- Dixit, Avinash K., and Jörgen W. Weibull. 2007. Political polarization. *Proceedings of the National Academy of Sciences*. 104(28): 7351-7356.
- Dubé, Jean-Pierre, Zheng Fang, Nathan Fong, and Xueming Luo. 2017. Competitive price targeting with smartphone coupons. *Marketing Science*. 36(6): 944-975.
- Economist. 2020. Democrats seem to take social distancing more seriously than Republicans. *Economist.com* April 4. <https://www.economist.com/united-states/2020/04/04/democrats-seem-to-take-social-distancing-more-seriously-than-republicans>.
- Fineberg, Harvey V. 2014. Pandemic preparedness and response—lessons from the H1N1 influenza of 2009. *New England Journal of Medicine*. 370(14), 1335-1342.
- Fryer Jr, Roland G., Philipp Harms, and Matthew O. Jackson. 2019. Updating beliefs when evidence is open to interpretation: Implications for bias and polarization. *Journal of the European Economic Association*. 17(5): 1470-1501.
- Gadarian, Shana Kushner, Sara Wallace Goodman, and Thomas B. Pepinsky. 2020. Partisanship, health behavior, and policy attitudes in the early stages of the COVID-19 pandemic. *Working Paper*.
- Gaines, Brian J., James H. Kuklinski, Paul J. Quirk, Buddy Peyton, and Jay Verkuilen. 2007. Same facts, different interpretations: Partisan motivation and opinion on Iraq. *The Journal of Politics*. 69(4): 957-974.
- Gallup. 2020. Party Affiliation. *Gallup*. <https://news.gallup.com/poll/15370/party-affiliation.aspx>.
- Gamma, Anna E., Jurgita Slekiene, Gregor von Medeazza, Fredrik Asplund, Placido Cardoso, and Hans-Joachim Mosler. 2017. Contextual and psychosocial factors predicting Ebola prevention behaviours using the RANAS approach to behaviour change in Guinea-Bissau. *BMC Public Health*. 17(1): 446.

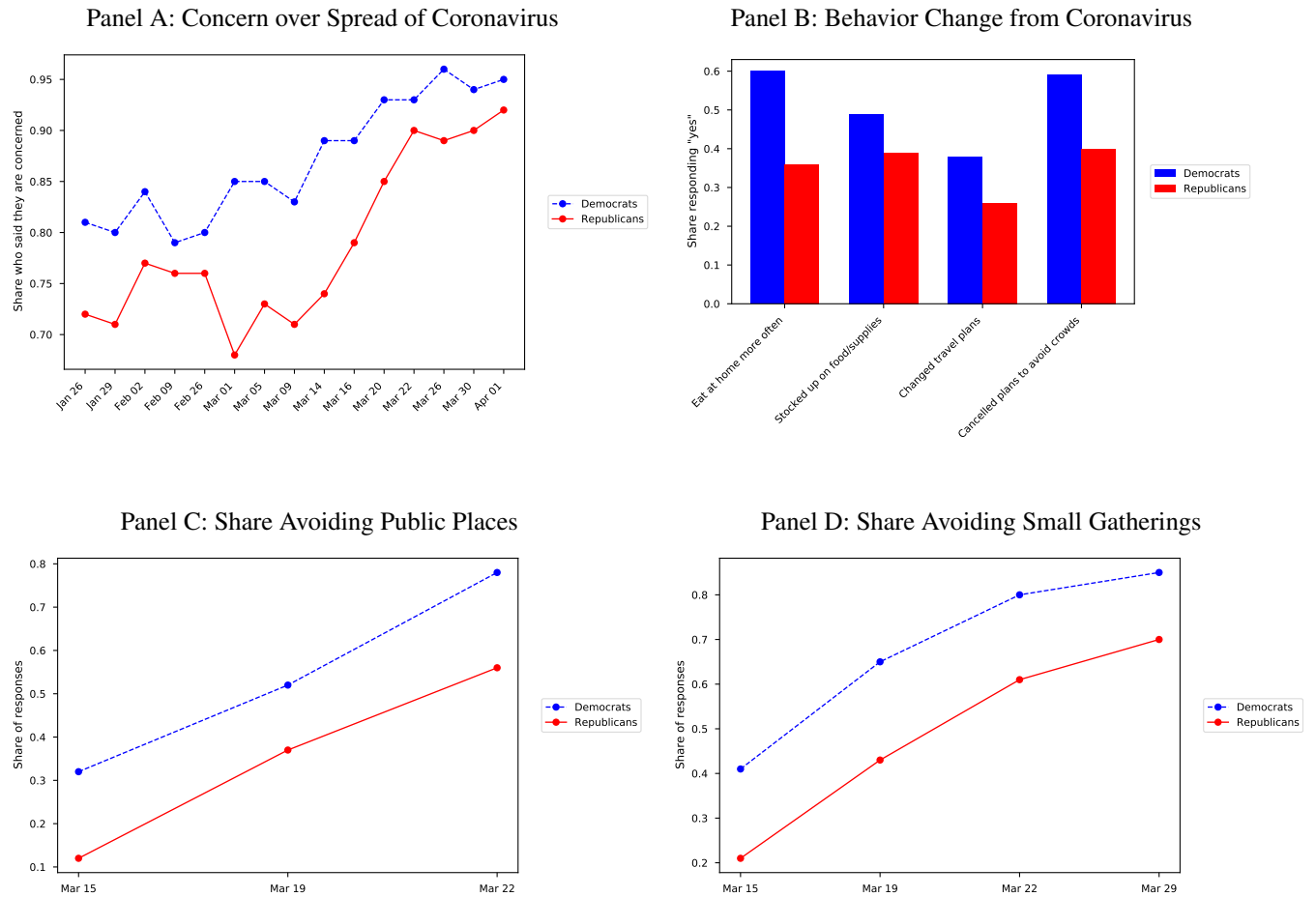


- Glaeser, Edward L., and Bryce A. Ward. 2006. Myths and realities of American political geography. *Journal of Economic Perspectives*. 20(2): 119-144.
- Hanna, Rema, Gabriel Kreindler, and Benjamin A. Olken. 2017. Citywide effects of high-occupancy vehicle restrictions: Evidence from “three-in-one” in Jakarta. *Science*. 357(6346): 89-93.
- Hersh, Eitan D. and Matthew N Goldenberg. 2016. Democratic and Republican physicians provide different care on politicized health issues. *Proceedings of the National Academy of Sciences*. 113(42): 11811–11816.
- Holmes, Bev J. 2008. Communicating about emerging infectious disease: The importance of research. *Health, Risk & Society*. 10(4): 349-360.
- Ibuka, Yoko, Gretchen B. Chapman, Lauren A. Meyers, Meng Li, and Alison P. Galvani. 2010. The dynamics of risk perceptions and precautionary behavior in response to 2009 (H1N1) pandemic influenza. *BMC Infectious Diseases*. 10(1): 296.
- Iyengar, Shanto, Yphtach Lelkes, Matthew Levendusky, Neil Malhotra, and Sean J. Westwood. 2019. The origins and consequences of affective polarization in the United States. *Annual Review of Political Science*. 22: 129-146.
- Kantrowitz, Alex. 2020. Conservative media still isn’t sure what to think about the coronavirus. *Buzzfeed News*. March 18. <https://www.buzzfeednews.com/article/alexkantrowitz/conservative-media-still-isnt-sure-coronavirus>
- Kermack, William Ogilvy, and Anderson G. McKendrick. 1927. A contribution to the mathematical theory of epidemics. *Proceedings of the Royal Society of London. Series A, Containing Papers of a Mathematical and Physical Character*. 115(772): 700-721.
- Krupenkin, Masha. 2018. Does partisanship affect compliance with government recommendations? *Working Paper*.
- Lee, Alicia. 2020. These states have implemented stay-at-home orders. Here’s what that means for you. *CNN*. <https://www.cnn.com/2020/03/23/us/coronavirus-which-states-stay-at-home-order-trnd/index.html>. Accessed on April 10, 2020.
- Lerman, Amy E., Meredith L. Sadin, and Samuel Trachtman. 2017. Policy uptake as political behavior: Evidence from the Affordable Care Act. *American Political Science Review*. 111(4): 755–770.
- Marist. 2020. March 13th and 14th survey of American adults. [http://maristpoll.marist.edu/wp-content/uploads/2020/03/NPR\\_PBS-NewsHour\\_Marist-Poll\\_USA-NOS-and-Tables\\_2003151338.pdf](http://maristpoll.marist.edu/wp-content/uploads/2020/03/NPR_PBS-NewsHour_Marist-Poll_USA-NOS-and-Tables_2003151338.pdf).
- McCarthy, Tom. 2020. Disunited states of America: Responses to coronavirus shaped by hyper-partisan politics. *The Guardian*. Mar 29. <https://www.theguardian.com/us-news/2020/mar/29/america-states-coronavirus-red-blue-different-approaches>.
- McCarty, Nolan, Keith T. Poole, and Howard Rosenthal. 2006. *Polarized America: The Dance of*

- Political Ideology and Unequal Riches*. MIT Press: Cambridge, MA.
- MIT Election Data and Science Lab. 2018. County Presidential Election Returns 2000-2016. *Harvard Dataverse*. <https://doi.org/10.7910/DVN/VOQCHQ>.
- Montoya-Williams, Diana and Elena Fuentes-Afflick. 2019. Political determinants of population health. *JAMA Network Open*. 2(7): e197063.
- Ortoleva, Pietro, and Erik Snowberg. 2015. Overconfidence in political behavior. *American Economic Review*. 105(2): 504-35.
- Piacenza, Joanna. 2020. Tracking public opinion on the coronavirus. *Morning Consult*. <https://morningconsult.com/public-opinion-on-the-coronavirus/>.
- Prior, Markus. 2013. Media and political polarization. *Annual Review of Political Science*. 16: 101-127.
- Prior, Markus, Gaurav Sood, and Kabir Khanna. 2015. You cannot be serious. The impact of accuracy incentives on partisan bias in reports of economic perceptions. *Quarterly Journal of Political Science*. 10(4): 489–518.
- Saad, Lydia. 2020. Americans step up their social distancing even further. *Gallup*. <https://news.gallup.com/opinion/step-social-distancing-even-further.aspx>.
- Sances, Michael W. and Joshua D. Clinton. 2019. Who participated in the ACA? Gains in insurance coverage by political partisanship. *Journal of Health Politics, Policy and Law*. 44(3): 349–379.
- Shultz, James M., Janice L. Cooper, Florence Baingana, Maria A. Oquendo, Zelde Espinel, Benjamin M. Althouse, Louis Herns Marcelin et al. 2016. The role of fear-related behaviors in the 2013–2016 West Africa Ebola virus disease outbreak. *Current Psychiatry Reports*. 18(11): 104.
- Stanley-Becker, Isaac and Chelsea Janes. 2020. As virus takes hold, resistance to stay-at-home orders remains widespread – exposing political and social rifts. *Washington Post*. April 2. [https://www.washingtonpost.com/politics/as-virus-takes-hold-resistance-to-stay-at-home-orders-remains-widespread-exposing-political-and-social-rifts/2020/04/02/d87314e0-7436-11ea-85cb-8670579b863d\\_story.html](https://www.washingtonpost.com/politics/as-virus-takes-hold-resistance-to-stay-at-home-orders-remains-widespread-exposing-political-and-social-rifts/2020/04/02/d87314e0-7436-11ea-85cb-8670579b863d_story.html)
- Suryadevara, Manika, Cynthia A. Bonville, Donald A. Cibula, Joseph B. Domachowske, and Amar C. Suryadevara. 2019. Associations between population based voting trends during the 2016 US presidential election and adolescent vaccination rates. *Vaccine*. 37(9): 1160–1167.
- Taylor, Melanie, Beverley Raphael, Margo Barr, Kingsley Agho, Garry Stevens, and Louisa Jorm. 2009. Public health measures during an anticipated influenza pandemic: factors influencing willingness to comply. *Risk Management and Healthcare Policy*. 2: 9.
- The New York Times. 2020. Coronavirus (Covid-19) Data in the United States. <https://github.com/nytimes/covid-19-data>. Accessed on April 2, 2020.

- Trachtman, Samuel. 2019. Polarization, participation, and premiums: How political behavior helps explain where the ACA works, and where it doesn't. *Journal of Health Politics, Policy and Law*. 44(6): 855–884.
- van der Weerd, Willemien, Daniëlle RM Timmermans, Desirée JMA Beaujean, Jurriaan Oudhoff, and Jim E. van Steenbergen. 2011. Monitoring the level of government trust, risk perception and intention of the general public to adopt protective measures during the influenza A (H1N1) pandemic in the Netherlands. *BMC Public Health*. 11(1): 575.
- Vaughan, Elaine, and Timothy Tinker. 2009. Effective health risk communication about pandemic influenza for vulnerable populations. *American Journal of Public Health*. 99(S2): S324-S332.
- Voting and Election Science Team. 2018. 2016 Precinct-Level Election Results. *Harvard Data-verse*. V37. <https://doi.org/10.7910/DVN/NH5S2I>.

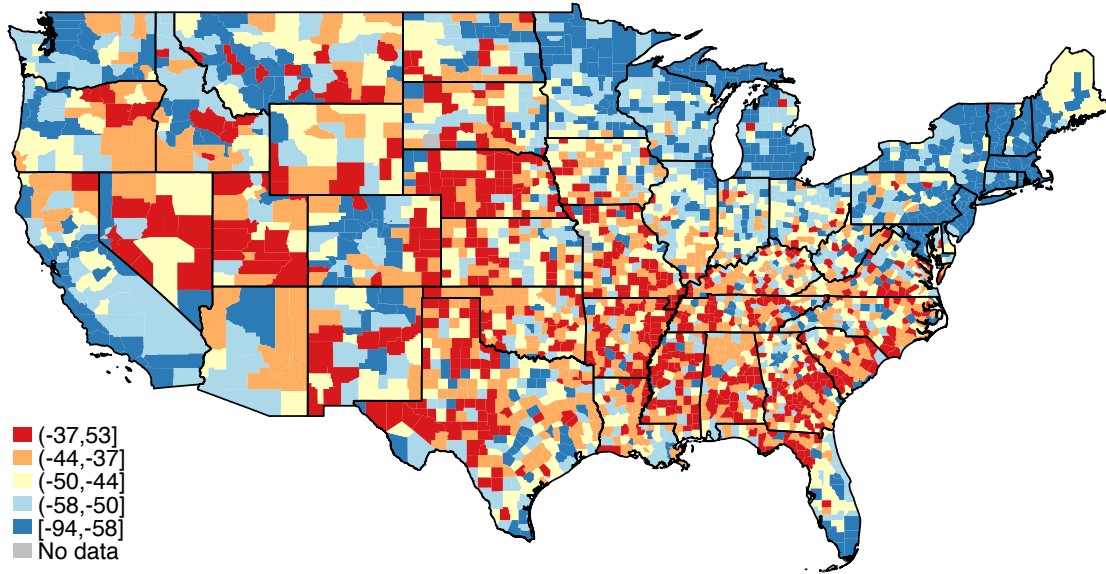
Figure 1: Partisan Differences in Perceived Risk and Social Distancing



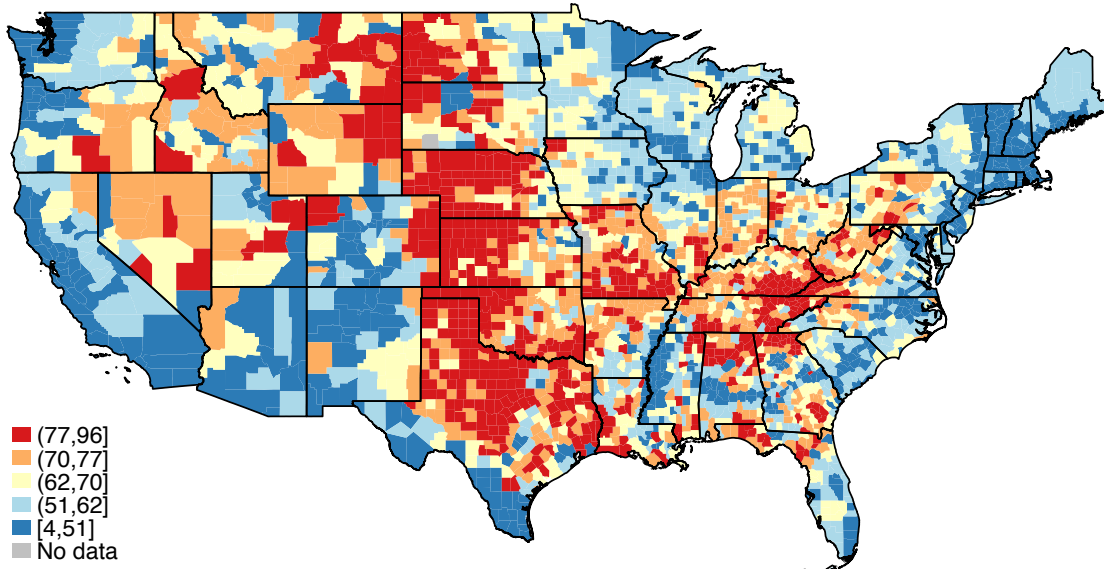
Note: This figure shows responses to nationally representative polls by political affiliation. Panel A shows the share of people concerned about coronavirus spreading to the United States (Piacenza 2020). Panel B shows self-reported behavior change as of March 13-14 (Marist 2020). Panel C shows the share of people avoiding public places, such as stores and restaurants (Saad 2020). Panel D shows that share of people avoiding small gatherings, such as with friends and family (Saad 2020).

Figure 2: Geographic Variation in Social Distancing, Partisanship, COVID-19, and Public Policy

Panel A: % Change in SafeGraph Visits



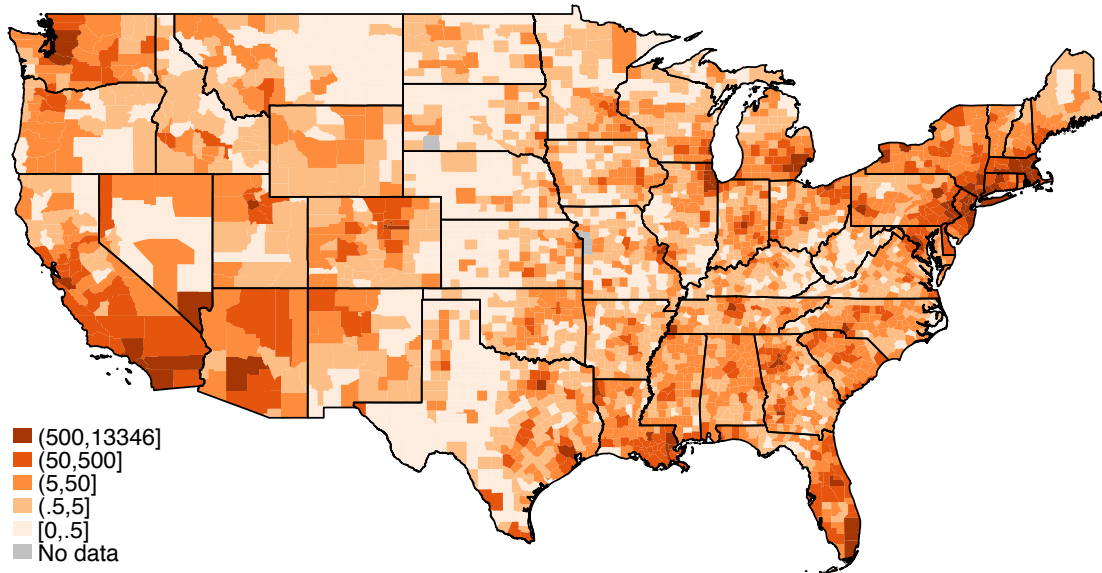
Panel B: 2016 Republican Vote Share



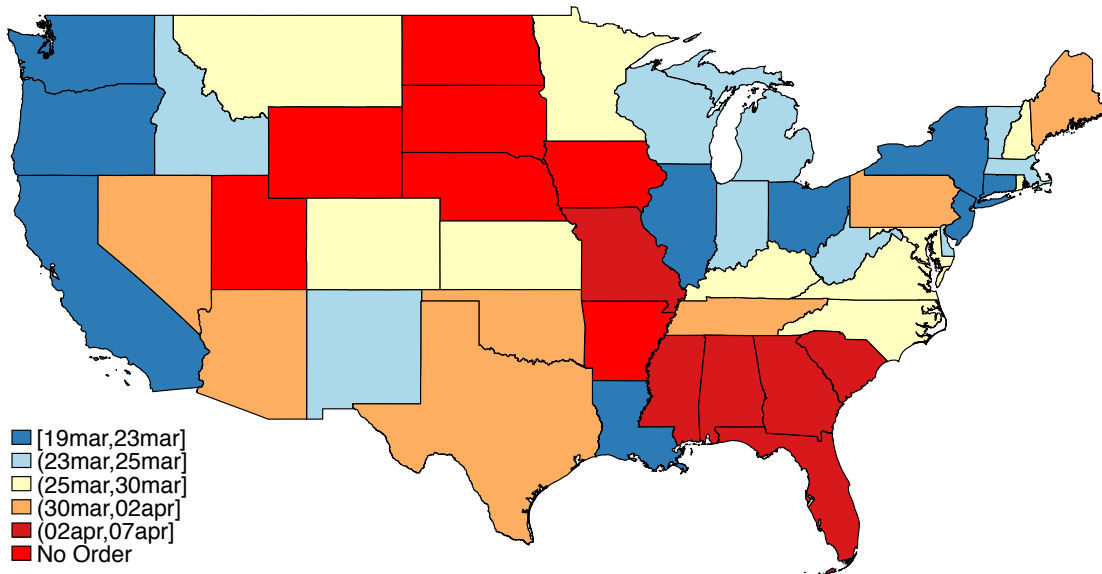
Note: This figure shows the U.S. geographic distribution of social distancing, political affiliation, COVID-19, and public policy responses. Panel A shows for each county the percent change in aggregate visits between the week beginning January 26, 2020 and the week beginning March 29, 2020. Blue shading denotes a more negative percent change in visits during the latter week relative to the former. Red shading indicates an increase or a smaller decrease in visits. These visits are sourced from SafeGraph’s mobile device location data. Panel B maps counties by the percentage of votes Donald Trump received in the 2016 presidential election. Red shading in this panel indicates more Republican counties (higher Trump vote share), and blue shading indicates more Democratic counties (lower Trump vote share).

Figure 3: Geographic Variation in Social Distancing, Partisanship, COVID-19, and Public Policy cont.

Panel C: COVID Cases Confirmed by 4/4/2020



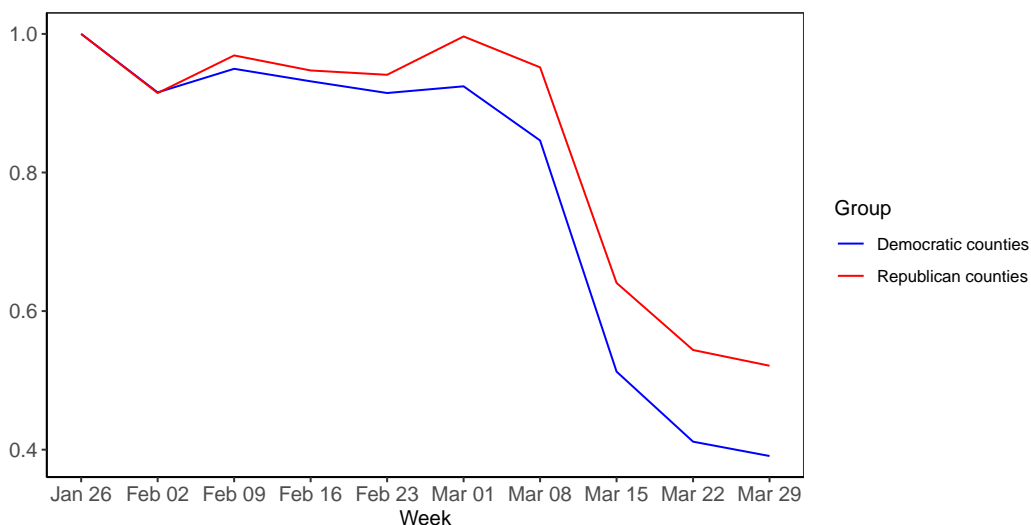
Panel D: State “Stay at Home” Order Start Date



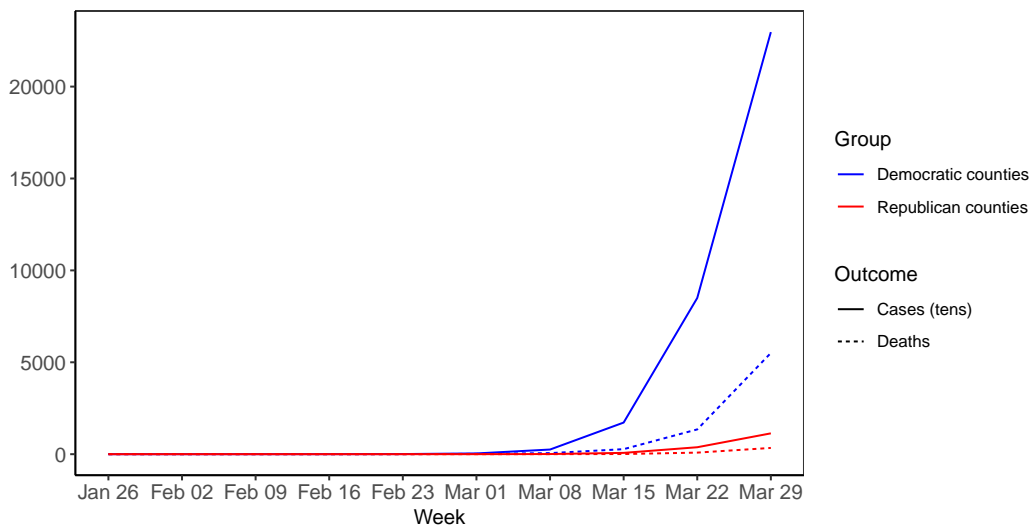
Note: This figure shows the U.S. geographic distribution of social distancing, political affiliation, COVID-19, and public policy responses. Panel C shows for each county the number of COVID-19 cases confirmed by April 4, 2020 (sourced from the New York Times). Panel D shades U.S. states by the effective start date for the earliest statewide “stay-at-home” order issued (Lee 2020). Blue shading indicates an earlier order, while red shading indicates that an order was issued later or was never issued.

Figure 4: Social Distancing and COVID-19 Prevalence

*Panel A: POI Visits*

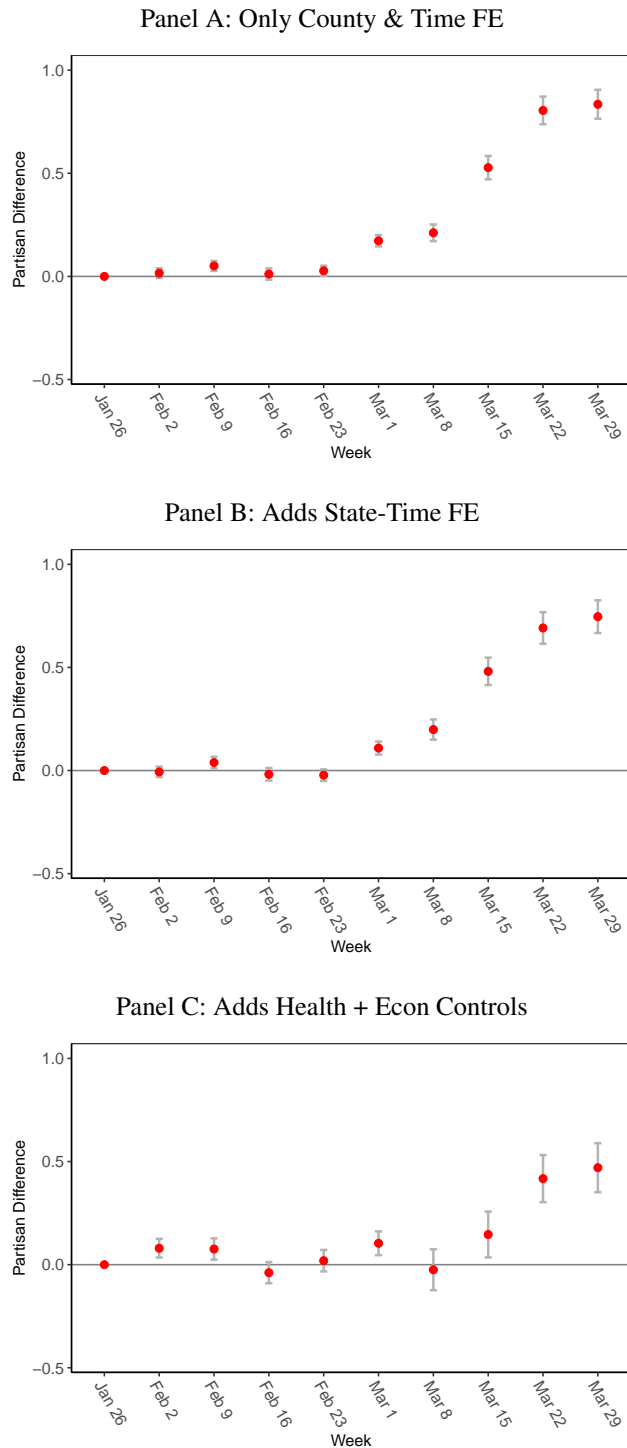


*Panel B: COVID-19 Cases and Deaths*



Note: Panel A shows the number of visits (normalized to one) to SafeGraph POIs for each week since January 26, 2020 for Republican counties and Democratic counties separately. Panel B is analogous but plots COVID-19 cases (in tens) and COVID-19 deaths. Republican counties are defined to be those whose 2016 Republican vote share is greater than the median vote share across the counties in our sample.

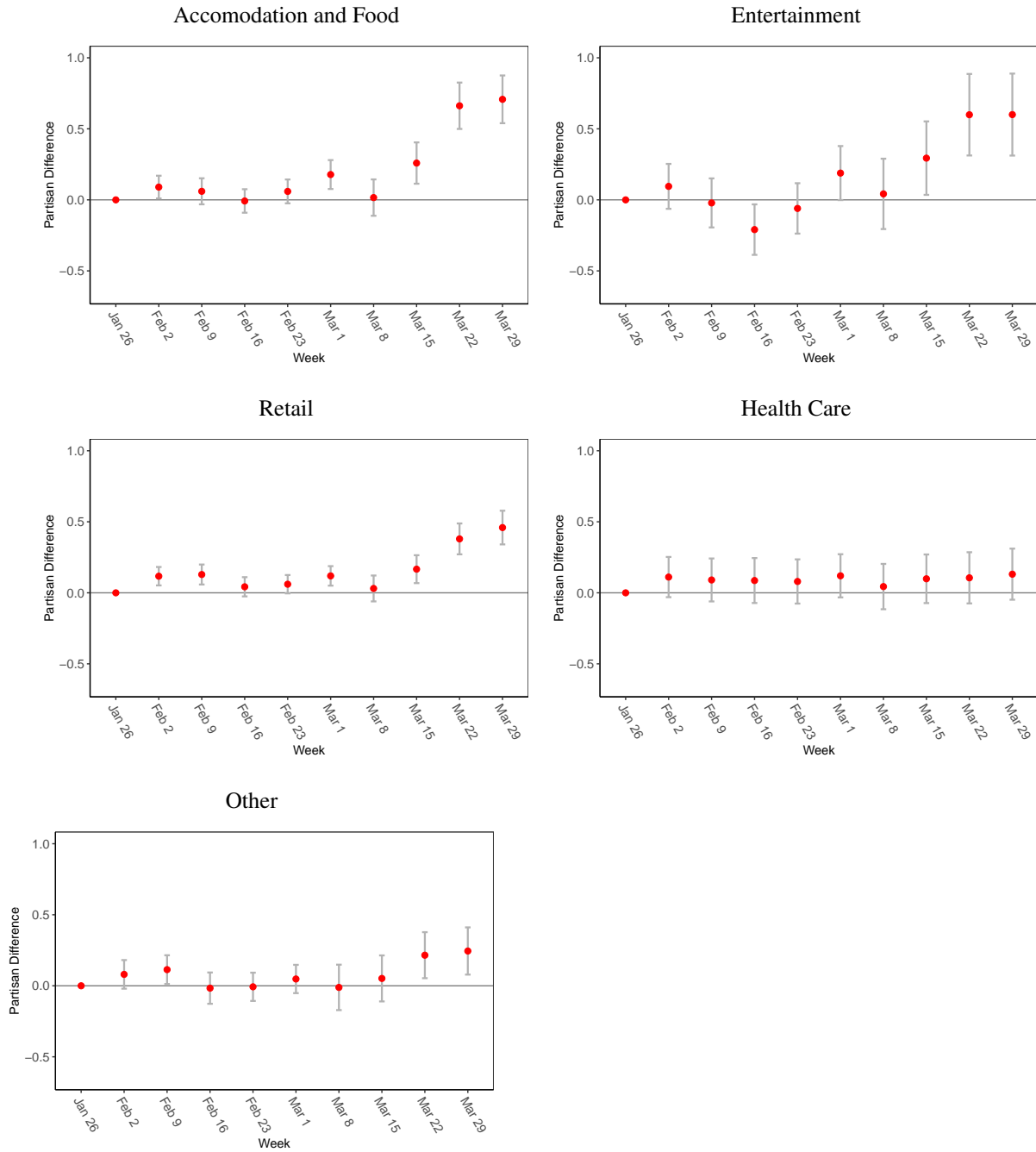
Figure 5: Partisan Differences in Social Distancing



Note: Figure shows the estimated coefficients for county partisanship  $\rho_i$  on the log number of POI visits in the county using the specification outlined in the main text. For Panel A, only county and time fixed effects are included as controls. Panel B is the same as Panel A except state-time fixed effects replace the time fixed effects. Panel C is the same as Panel B except the health and economic covariates are included. The grey error bars indicate 95 percent confidence intervals constructed using standard errors clustered at the county-level.

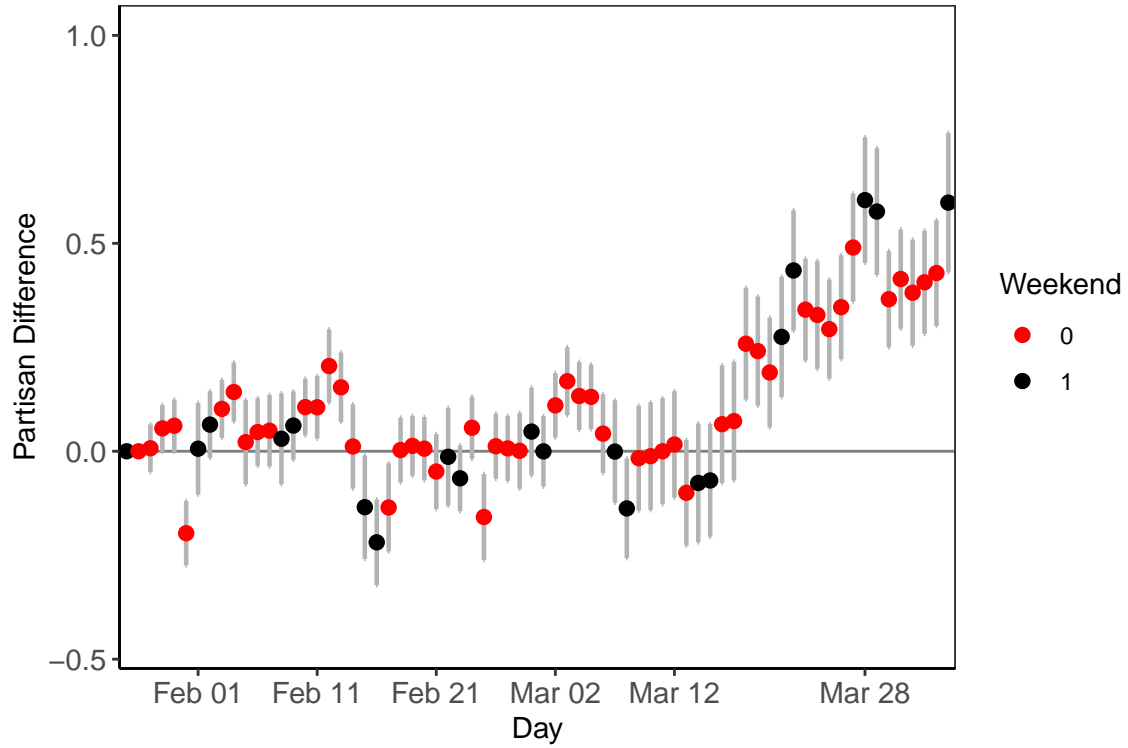


Figure 6: Partisan Differences in Social Distancing by 2-Digit NAICS Code Industry



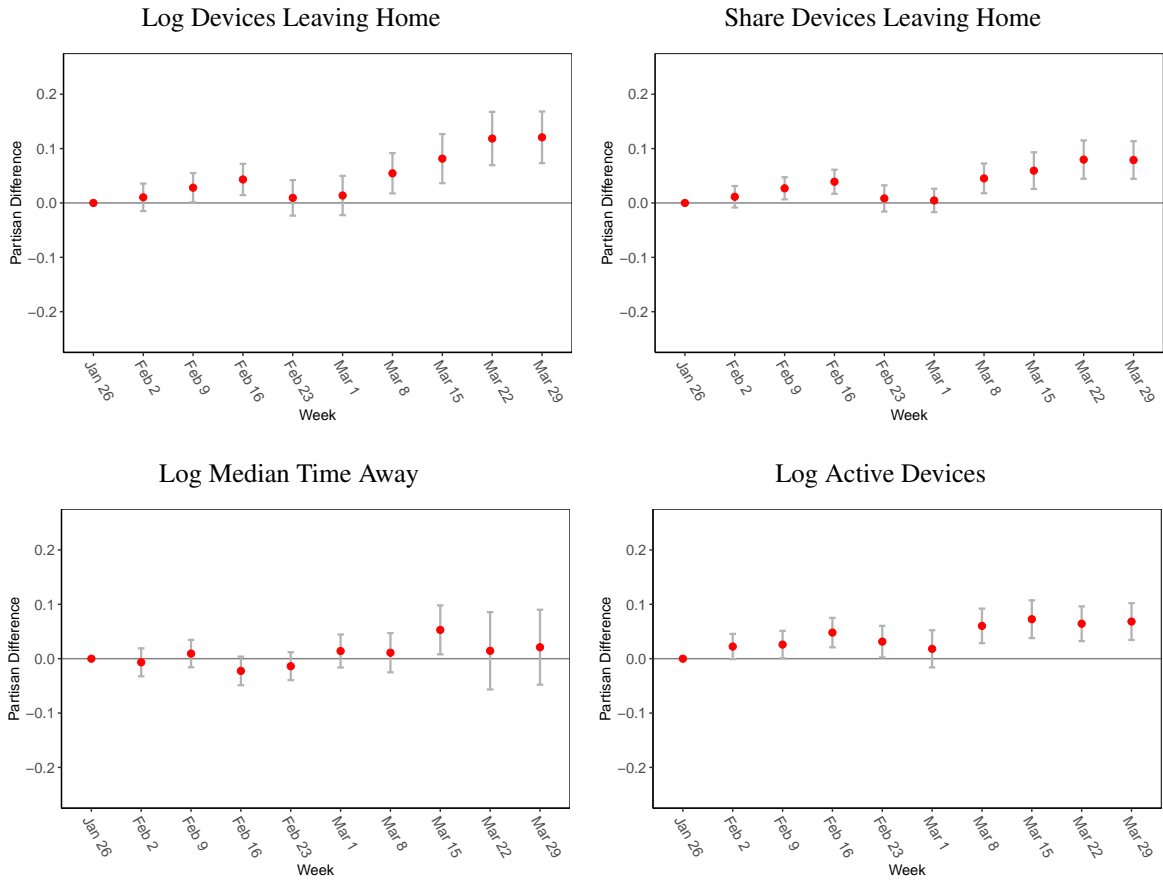
Note: Figure shows the estimated coefficients for county partisanship  $\rho_i$  on the log number of POI visits in the county after restricting POI visits to various 2-digit NAICS codes. The NAICS code groups are: Accomodation and Food (NAICS 72), Entertainment (NAICS 71), Retail Trade (NAICS 44 and 45), Health Care (NAICS 62), and Other Industries (All NAICS codes not previously used). The same controls are used as in Panel C of Figure 5. The grey error bars indicate 95 percent confidence intervals constructed using standard errors clustered at the county-level.

Figure 7: Partisan Differences in Social Distancing, Daily



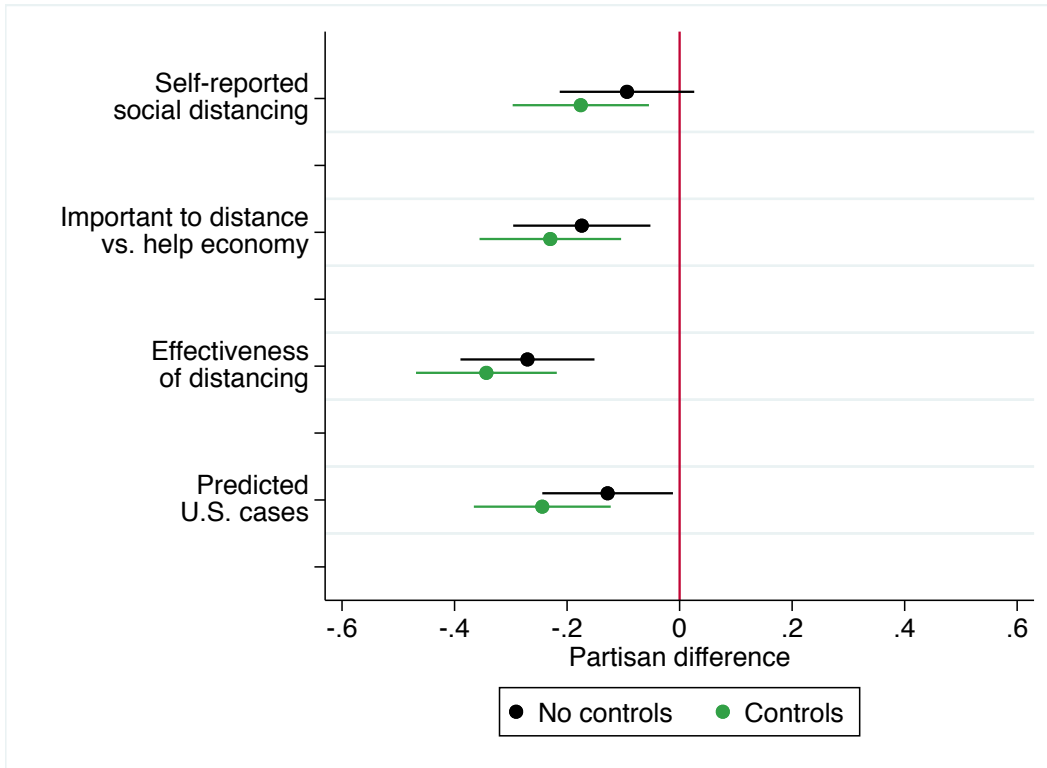
Note: Figure shows the estimated coefficients for county partisanship  $\rho_i$  on the log number of POI visits in the county. The same controls as in Panel C of Figure 5 are used except that state-time fixed effects occur at the day level and the weekday and weekend series are normalized separately. The grey error bars indicate 95 percent confidence intervals constructed using standard errors clustered at the county-level.

Figure 8: Partisan Differences in Social Distancing, Alternative Measures



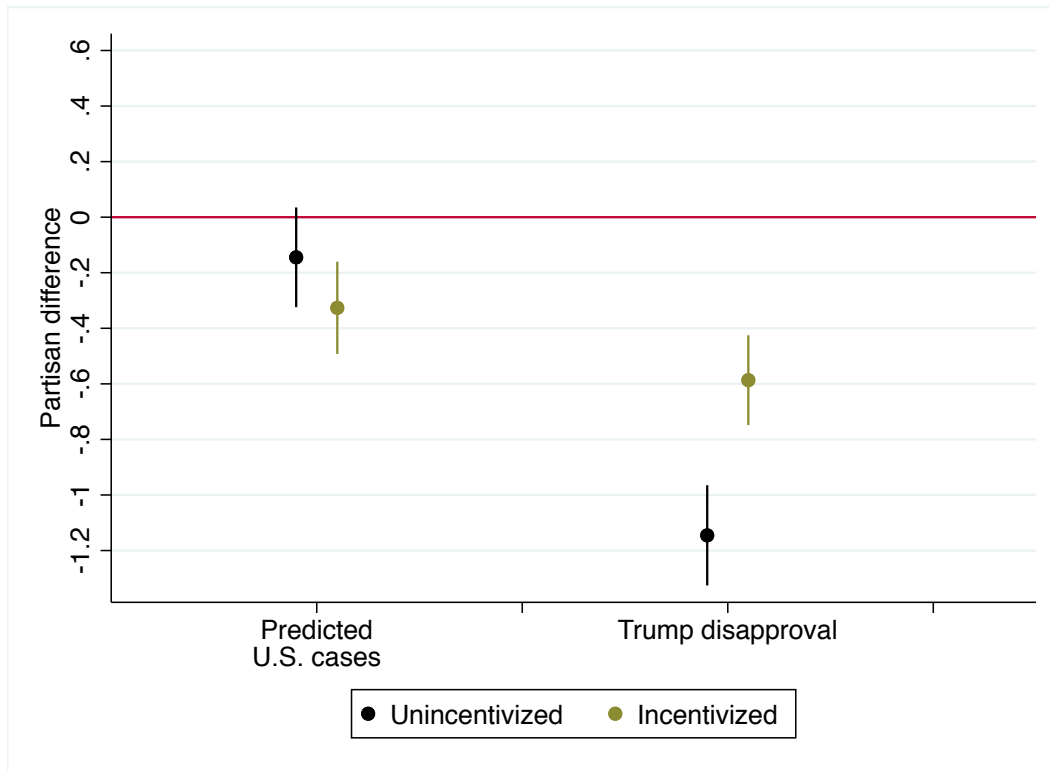
Note: Figure shows the estimated coefficients for county partisanship  $\rho_i$  on various alternative outcomes constructed from the Daily Social Distancing dataset from SafeGraph. ‘Log Devices Leaving Home’ is the log of one plus the number of active devices in the panel minus the active devices never observed leaving their geohash-7 home. ‘Share Devices Leaving Home’ is defined to be  $1 - \frac{\max\{0, \text{home devices} + (\text{initial device count} - \text{current device count})\}}{\text{initial device count}}$ , where ‘home devices’ are active devices never observed leaving their geohash-7 home, ‘initial device count’ is the number of active devices for the week of February 1, and ‘current device count’ is the number of active devices for the current week. ‘Log Median Time Away’ is  $\log(1 + 1440 - \text{time home})$  where ‘time home’ is the median observed time at home across devices. ‘Log Active Devices’ is the log of one plus the number of active devices in the panel. The same controls are used as in Panel C of Figure 5. The grey error bars indicate 95 percent confidence intervals constructed using standard errors clustered at the county-level.

Figure 9: Partisan Differences in Beliefs and Actions



Note: This figure shows coefficient plots of regressing normalized measures of beliefs and actions on party. Positive values indicate less concern about COVID-19 or social distancing. Demographic controls are age, race, income, education, number of children, ZIP code logged population density, state. 2 percent of observations are dropped for not including a valid ZIP code. Predicted U.S. cases are predictions about the number of new COVID-19 cases in the U.S. in April; self-reported social distancing is the percent reduction in contact with others over one month; effectiveness of distancing is the estimated likelihood of catching COVID-19 in one month without social distancing; importance of distancing vs. economy is subjects' perception of whether it is more important to go out and stimulate the economy versus staying in and preventing the spread of COVID-19. Observations weighted to mimic a representative sample as described in the text. Error bars represent 95 percent confidence intervals.

Figure 10: Effect of Incentives on Beliefs



Note: This plot shows coefficient plots of regressing beliefs on party, with and without incentives for getting close to the correct answer. Trump disapproval is a low-stakes question that is susceptible to partisan cheerleading (Bullock et al. 2015; Prior et al. 2015). These results show that predicting COVID-19 cases does not appear susceptible to the same behavior. Observations weighted to mimic a representative sample as described in the text. Error bars represent 95 percent confidence intervals.

## A Appendix

### A.1 Data Details

#### A.1.1 County-Level Data Build (POI and Visits)

To construct the county-level POI dataset used in the analysis, we proceeded as follows:

1. We use county data on 2016 Presidential votes shares (MIT Election Data and Science Lab 2018). We define the Republican vote share to be the share of votes received by the Republican candidate over the sum of votes across all candidates. We exclude Alaska, and merge with the 2010 TIGER county shapefile.<sup>13</sup> Two counties in the shapefile do not have valid vote data (FIPS: 15005, 51515).
2. We then use the latitude and longitude in the the April 2020 Core POI dataset from SafeGraph to match POIs to counties. We successfully assign more than 99.9 percent of the POIs to a county.
3. We merge the output from (2) with the Patterns dataset from SafeGraph using the safegraph-place-id variable. We sum visits by county for a given day or week, aggregating across POI. We drop all county observations with invalid vote shares at this stage.
4. We use the Open Census data from SafeGraph to construct a county-level dataset of demographic information. We do this by aggregating up the data given at the census block group level to the county level. We then merge the county demographic information with the output from (3).
5. We then merge The New York Times COVID-19 tracking data onto our output from (4). We assume zero cases and deaths for the observations not observed in The New York Times data. We drop the five counties associated with New York City and the four counties which overlap with Kansas City (MO), because The New York Times lists these as geographic exceptions where it either does not assign cases to these counties or excludes cases occurring within the city.

#### A.1.2 County-Level Data Build (Social Distancing)

To construct the county-level social distancing dataset used in this analysis, we proceeded as follows:

---

<sup>13</sup>Downloaded from [https://www.census.gov/geo/maps-data/data/cbf/cbf\\_counties.html](https://www.census.gov/geo/maps-data/data/cbf/cbf_counties.html) on July 24, 2018.

1. We use the Daily Social Distancing SafeGraph data with observations at the census block group-day level for January 26 through April 4. We drop duplicate observations and exclude Alaska. We restrict our sample to census block groups with active devices throughout the entire time period. We also drop one census block group with anomalous behavior as notified by SafeGraph (FIPS: 190570010001).
2. We then aggregate to the county level. For the ‘device count’ and ‘completely home device count’ variables, we take the sum. For the ‘median home dwell time’ variable we take the mean weighted by ‘the device count’ in the census block group.
3. We then follow steps (4) and (5) described in Section A.1.1.
4. Lastly, we merge on 2016 Presidential vote shares, only keeping observations with valid vote shares.

### A.1.3 Precinct-Level Data Build (POI and Visits)

1. We use 2016 precinct-level shapefiles and presidential election votes (Voting and Election Science Team 2018). We define the Republican vote share as in Section A.1.1 step (1). This data covers the following 38 states: AK, AR, AZ, CA, CO, DE, FL, GA, HI, IA, IL, KS, LA, MA, MD, ME, MI, MN, MO, MT, NC, ND, NE, NH, NM, NV, OK, OR, RI, SC, TN, TX, UT, VA, VT, WA, WI, WY
2. Using the set of POIs matched to county in Section A.1.1 step (2), we then use the latitude and longitude of these POIs and the precinct shapefiles from (1) to identify the precinct containing a given POI. We are able to match 100 percent of the POIs from Section A.1.1 step (2). 55 of these POIs (0.001%) are matched to two precincts.
3. As in Section A.1.1 step (3), we merge the output from (2) with the Patterns dataset from SafeGraph using the safegraph-place-id variable. We sum visits by precinct, aggregating across POIs.
4. We use the Open Census data from SafeGraph to construct a precinct-level dataset of demographic information. We do this by first constructing the geographic intersections formed by our precinct shapefiles and 2019 Tiger census block group shapefiles.<sup>14</sup> Let  $a_p$ ,  $a_b$ , and  $a_{cp}$  denote the area of precinct  $p$ , census block group  $b$ , and of their intersection respectively. For a given count variable  $x_b$  given at the block group level in SafeGraph’s Open Census data, we construct a precinct-level estimate as:  $\hat{x}_p := \sum_b \frac{a_{bp}}{a_b} x_b$ . This estimate is exactly correct if

<sup>14</sup>Downloaded from <ftp://ftp2.census.gov/geo/tiger/TIGER2019/BG/> on April 1, 2020.

a given demographic  $x_b$  is evenly distributed across a census block group's area. We then form ratios (e.g., population density or share hispanic) using these summed precinct-level estimates. We merge the precinct demographic information with the output from (3).

5. As in Section A.1.1 step (5), we then merge the New York Times COVID-19 tracking data onto our output from (4).

## A.2 Survey Details

### A.2.1 Data

We clean the survey data from Qualtrics as follows:

1. We match participant IDs from Qualtrics with a list of emailed IDs from CloudResearch and drop observations that do not match to remove test subjects. There is one exception, where the ID on Qualtrics did not correctly generate. We find exactly one remaining participant with the same demographics in the CloudResearch, so we keep this participant.
2. We change one miscoded age from .23 to 23 and one miscoded ZIP code from ,43011 to 43011.
3. We merge ZIP code data with 2010 U.S. Census data and match ZIP codes to states and get population density.
4. We weight observations across age category, gender, race/ethnicity, and party affiliation using the stata ebalance command. Weights are prespecified in the pre-analysis plan.
5. News sources are numbered in the data in the following order: (1) Network news; (2) Breitbart; (3) CNN; (4) Facebook; (5) Fox News; (6) MSNBC; (7) New York Times; (8) Wall Street Journal; (9) Twitter; (10) Wikipedia; (11) CDC; (12) WHO.

We have the following demographic groups prior to weighting:

- Age: 45.7% 18-39, 33.8% 40-59, 20.5% 60+
- Gender: 51.9% Female, 47.75% Male, 0.35% Other / Non-binary
- Race: 66.6% White (Not Hispanic or Latinx), 15.25% Hispanic or Latinx, 11.2% Black or African American (Not Hispanic or Latinx), 4.95% Asian or Pacific Islander, 2.0% Other.
- Party: 34.65% Democratic, 31.25% Republican, 32.8% Independent, 1.3% Other



## A.2.2 Survey Questions

### Screening

- What is your gender? [Male; Female; Other / Non-binary]
- What race/ethnicity best describes you? [American Indian or Alaska Native; Asian or Pacific Islander; Black or African American (Not Hispanic or Latinx); Hispanic or Latinx; White (Not Hispanic or Latinx); Other]
- Do you consider yourself a Republican, a Democrat, or an Independent? [Democrat (Strongly Democratic); Democrat (Weakly Democratic); Independent (Lean toward the Democratic Party); Independent (Do not lean towards either party); Independent (Lean toward the Republican Party); Republican (Weakly Republican); Republican (Strongly Republican); Other / prefer not to say]
- What is your age?
- Do you currently live in the United States? [Yes; No]

### Consent

[Page seen if age > 18, United States = Yes, and not screened out due to demographic quotas.]

**Congratulations! You are eligible to participate. Please read the consent form below:**

**DESCRIPTION:** You are invited to participate in an online research study on your views about the news and predictions of what will happen in the future. This is a research project being conducted by researchers at Harvard University and New York University.

**TIME INVOLVEMENT:** Your participation will take approximately 20 minutes, and the entire study will take place online.

**RISKS AND BENEFITS:** We will ensure that your individual responses are strictly confidential, and research results will only be presented in the aggregate. Your responses will not be shared with government officials or any 3rd party. We hope that the knowledge gained from this study will benefit society in general. **We cannot and do not guarantee or promise that you will receive any direct benefits from this study.**

**PAYMENTS:** If you are eligible for the study, and once you complete the study, you will receive a participation fee. You may also earn a bonus payment of up to \$100 via an Amazon gift card. All payments will be through your research provider.

**PARTICIPANT'S RIGHTS:** If you have read this form and have decided to participate in this project, please understand your **participation is voluntary** and you have the **right to withdraw your consent or discontinue participation at any time without penalty or loss of benefits**

**to which you are otherwise entitled. The alternative is not to participate.** You have the right to refuse to answer particular questions. The results of this research study may be presented at scientific or professional meetings or published in scientific journals.

**CONTACT INFORMATION:**

**Questions:** If you have any questions, concerns or complaints about this research, its procedures, risks and benefits, contact the researchers at rb4337@nyu.edu.

**Independent Contact:** If you are not satisfied with how this study is being conducted, or if you have any concerns, complaints, or general questions about the research or your rights as a participant, please contact the Harvard University Area Institutional Review Board (IRB) to speak to someone independent of the research team at cuhs@harvard.edu, (617)-496-2847. You can also write to the Committee on the Use of Human Subjects, Harvard University, 44-R Brattle Street, Suite 200, Cambridge, MA 02138.

**Please retain a copy of this form for your records.**

If you wish to participate in this study, please click “I consent” to proceed. This serves as an electronic signature indicating your consent to participate in the study.

[I consent; I do not consent]

[Only consenting subjects proceed]

*Demographics*

- How many children under the age of 18 do you have? [0; 1; 2; 3; 4; 5 or more]
- What is the highest degree or level of schooling that you have completed? [Less than a high school diploma; High school diploma or equivalent (for example: GED); Some college but no degree; Associate’s degree; Bachelor’s degree; Graduate degree (for example: MA, MBA, JD, PhD)]
- What was your total income in 2019? Please include only employment income (wages, salary, bonuses, tips, and any income from your own businesses). [I did not earn income in 2019; \$1 to \$9,999; ...; \$50,000 to \$59,999; \$60,000 to \$74,999; \$75,000 to \$99,999; \$100,000 to \$124,999; \$125,000 to \$149,999; \$150,000 or more] [Coded as midpoint of range in thousands of dollars except for top bracket, who is coded at 200. Log(income + 1) is used as the control.]
- In what ZIP Code do you currently live? Please enter your 5-digit ZIP Code.
- In general, how would you rate your OVERALL health? [Excellent / Very good / Good / Fair / Poor]

- Has a doctor ever told you that you had the following conditions? [Yes / No]
  - Diabetes or high blood sugar
  - Lung disease such as chronic bronchitis or emphysema
  - A heart attack, coronary heart disease, angina, congestive heart failure, or other heart problems
- Please answer the following yes/no questions:
  - In the past week, have you had to go to a work environment in which you were within six feet of others?
  - Have you smoked at least 100 cigarettes in your entire life?
  - Have you smoked at least 10 cigarettes in the past week?

*Information sources*

- All of the following questions were asked about the following 12 news sources: Network news (ABC, CBS, NBC); Breitbart; CNN; Facebook; Fox News; MSNBC; The New York Times; The Wall Street Journal, Twitter, Wikipedia, The Centers for Disease Control (CDC); The World Health Organization (WHO).
- **Last year, how much trust and confidence** did you have in each of the following sources when it comes to **reporting about politics and current events fully, accurately, and fairly?** [A great deal / A fair amount / Not very much / None at all / Not familiar with this outlet]
- **Last year, how frequently did you get news and information** did you have in each of the following sources about **politics and current events** through any medium (including reading online, watching on TV, etc.)? [Often / Sometimes / Rarely / Never / Not familiar with this outlet]
- How much **trust and confidence** do you have in each of the following sources when it comes to **reporting about the coronavirus fully, accurately, and fairly?** [A great deal / A fair amount / Not very much / None at all / Not familiar with this outlet]
- How **frequently are you getting news and information** did you have in each of the following sources about **the coronavirus** through any medium (including reading online, watching on TV, etc.)? [Often / Sometimes / Rarely / Never / Not familiar with this outlet]

*Changes in behavior and effects of social distancing*

- Think about the ways you may have changed your daily routine in the past two weeks specifically because of the coronavirus. For example, you may be washing your hands more, avoiding restaurants and other public places, and/or reducing interactions with friends and family.
- By what percent have you reduced your overall contact with other people as a result of the coronavirus outbreak? Please enter a percentage from 0 to 100.
- Think back to two weeks ago.
- As of two weeks ago, by what percent had you reduced your overall contact with other people as a result of the coronavirus outbreak? Please enter a percentage from 0 to 100.
- Imagine that starting today and for the rest of the month, you went back to your **normal daily routine from before the coronavirus**. What do you think is the probability that you would catch the coronavirus in the next month? Please enter a percentage from 0 to 100. [Subjects who answer 0 for the percent reduction question see “continued with” instead of “went back to.”]
- Imagine that starting today and for the next month, **you cut off all in-person contact with people outside your household**. What do you think is the probability that you would catch the coronavirus in the next month? Please enter a percentage from 0 to 100.
- We’d like to quantify the overall costs (in terms of time, money, and inconvenience) that social distancing imposes on you. Consider a hypothetical situation in **a normal month in the future, after the coronavirus outbreak is completely over**.

Imagine you had a choice between:

(A) following your normal routine for one month,

OR

(B) cutting off all in-person contact with people outside your household for one month, AND receiving \$X cash.

Presumably if you were offered a large amount of cash (\$X is large), you’d be willing to cut off all social contact. If you weren’t offered any cash (\$X is 0), you’d prefer to stick with your normal routine. What value of X would make you equally happy with these two options? Please answer in dollars.

### *Factual questions*

- How did the coronavirus originate? [It came about naturally; It was developed intentionally in a lab; It was made accidentally in a lab]
- Has President Trump taken a coronavirus test? [Yes, and he tested positive; Yes, and he tested negative; No, he has not taken a test]

Subjects are told the correct answers to these (It came about naturally; Yes, and he tested negative) at the end of the survey.

### *Economic trade-offs*

- When there was no “stay-at-home” order for your area, what did you think was the best way to help the country in this time of crisis? [7-point scale from “Go out more to help the economy” to “Go out less to avoid spreading the coronavirus”]

### *Predictions*

[If unincentivized:]

- You will now be asked to make a few predictions.

[If incentivized:]

- You will now be asked to make a few predictions. Think carefully! We’ll randomly select 10 participants for an accuracy reward. If you’re selected, we’ll pay you up to \$100 depending on how accurate your prediction was. For example:
  - If your answer is exactly right, we’ll give you \$100
  - If your answer is 1% off, we’ll give you \$99
  - If your answer is 2% off, we’ll give you \$98
  - ...
  - If your answer is 50% off, we’ll give you \$50
  - etc.

All subjects see:

- We want to know how well you think the U.S. will limit the spread of the coronavirus in the next month. There had been 177,226 known cases of coronavirus in the U.S. by March 31. How many additional known cases will there be in the U.S. in the month of April?

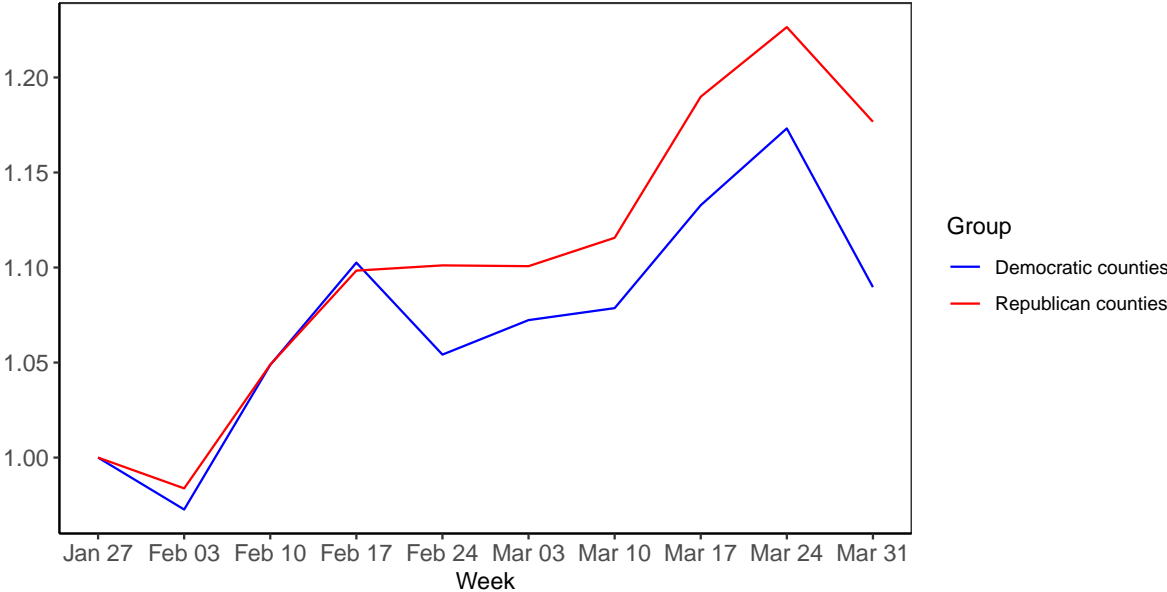
- RealClearPolitics reports polling data on public approval of President Trump's handling of the coronavirus outbreak. What percent of people will say they approve of Trump's handling of the coronavirus outbreak on the latest poll that ends before April 30?

*Motivated Reasoning*

Only for the unincentivized group:

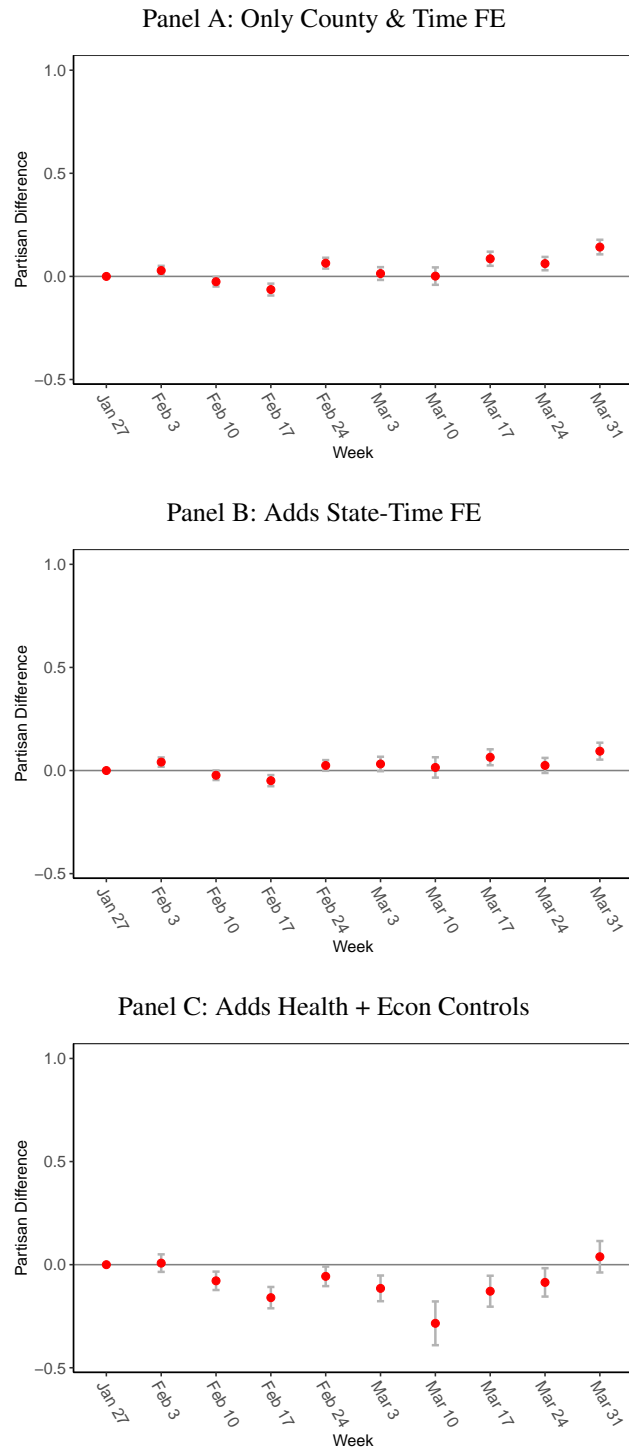
- Now suppose that in May, you were given information that was randomly selected to be from either a True News source (one that always reports the truth) or a Fake News source (one that always reports the opposite of the truth). The information will say either that the number of additional known coronavirus cases in the U.S. in the month of April was **greater than** [previous answer] or that it was **less than** [previous answer].
- Suppose the information says that the number of additional known cases in the U.S. in April was **greater than** [previous answer]. Would you think that the source was: [True News / Fake News / Equally likely to be both]
- Suppose the information says that the number of additional known cases in the U.S. in April was **less than** [previous answer]. Would you think that the source was: [True News / Fake News / Equally likely to be both]

Appendix Figure A1: POI Visits in 2019



Note: Figure shows the aggregate number of POI visits (normalized to one) for ten weeks starting on January 27, 2019 for Republican counties and Democratic counties. Republican counties are defined to be those whose 2016 Republican vote share is greater than the median vote share across the counties in our sample.

Appendix Figure A2: Partisan Differences in Social Distancing, 2019

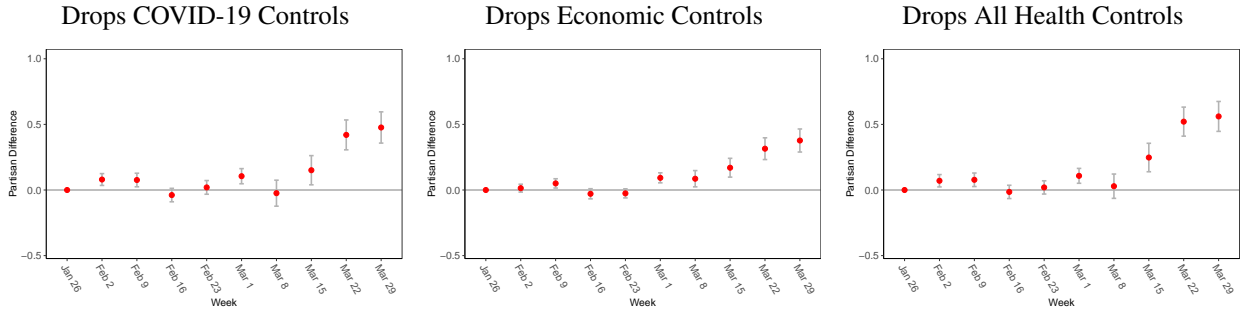


Note: Figure shows the estimated coefficients for county partisanship  $\rho_i$  on the log number of POI visits in the county as in Figure 5, except that ten weeks of data from January 27, 2019 are used instead of January 26, 2020. For Panel A, only county and time fixed effects are included as controls. Panel B is the same as Panel A except state-time fixed effects replace the time fixed effects. Panel C is the same as Panel B except the health and economic covariates are included. The grey error bars indicate 95 percent confidence intervals constructed using standard errors clustered at the county-level.

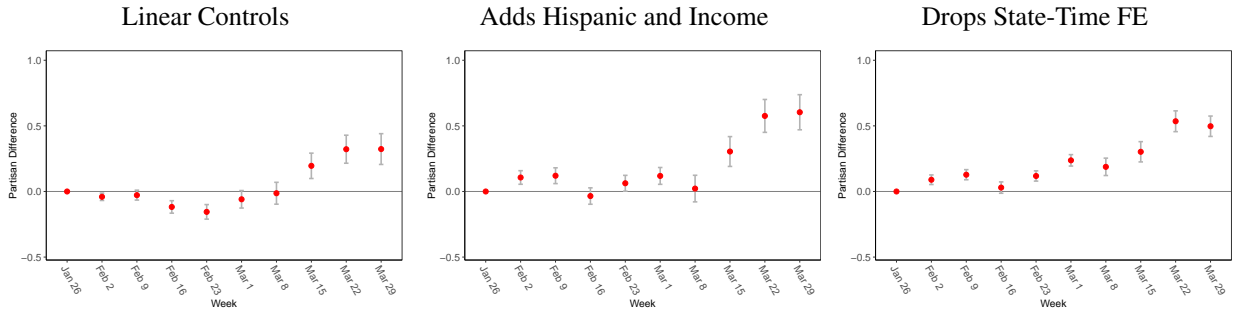


## Appendix Figure A3: Partisan Differences in Social Distancing, Robustness

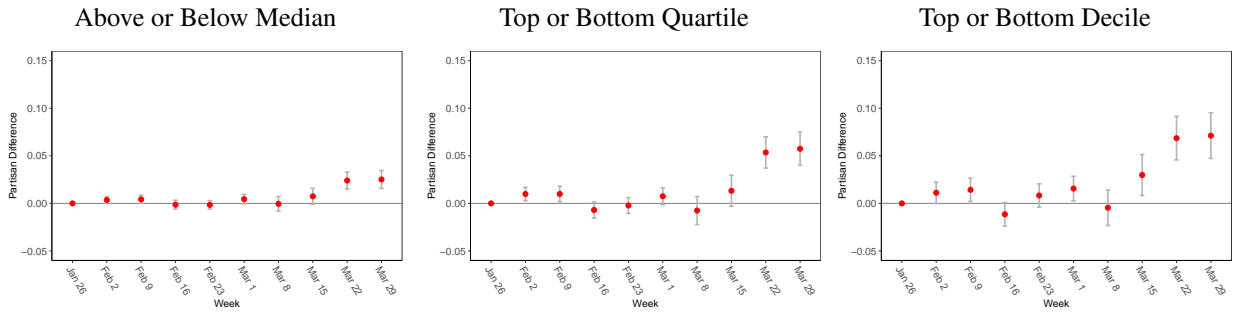
### Panel A: Dropping Controls



### Panel B: Additional Specifications



### Panel C: Partisanship Indicators

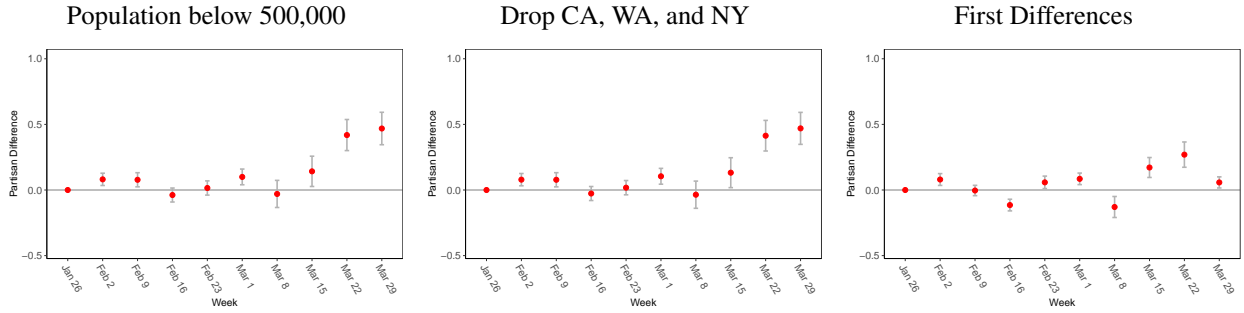


Note: Figure shows the estimated coefficients for county partisanship  $\rho_i$  on the log number of POI visits in the county. The specifications are analogous to our baseline in Panel C of Figure 5 except with the following deviations.

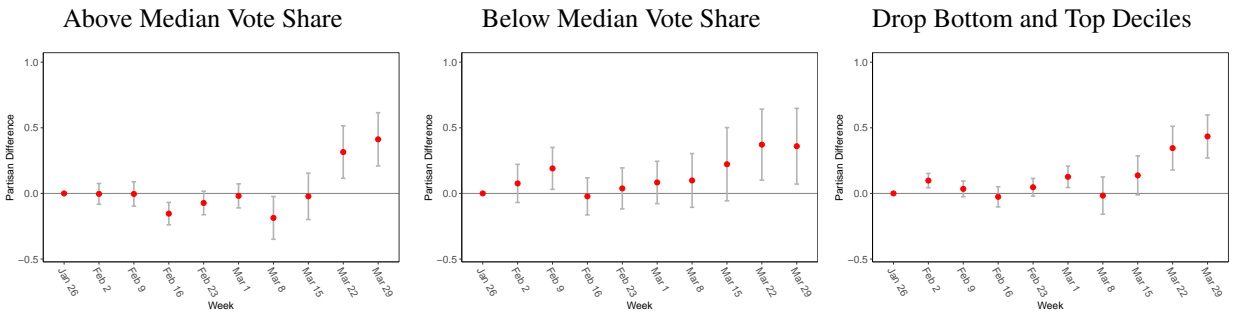
- Panel A: The first plot drops the COVID-19 cases and deaths controls; the second plot drops the economic controls; and the third plot drops all of the health controls, including the COVID-19 ones.
- Panel B: The first plot does not allow the coefficients on the controls to vary over time and interacts time-invariant controls with a linear time trend; the second plot adds the share Hispanic and the share with income less than 60k with time-varying coefficients; and the third plot drops the state-time fixed effects.
- Panel C: The first plot defines partisanship  $\rho_i$  to be 1 if Trump's vote share is greater than the median and -1 otherwise; the second plot defines partisanship  $\rho_i$  to be 1 if Trump's vote share is in the top quartile, -1 if in the bottom quartile, and 0 otherwise; and the third plot defines partisanship  $\rho_i$  to be 1 if Trump's vote share is in the top decile, -1 if in the bottom decile, and 0 otherwise.

Appendix Figure A3: Partisan Differences in Social Distancing, Robustness cont.

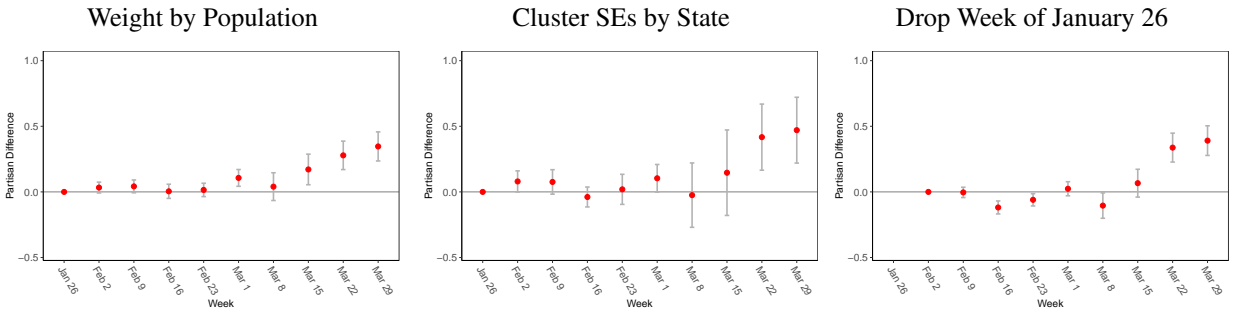
Panel D: Sample Restrictions and First Differences



Panel E: Sample Restrictions by Vote Shares



Panel F: Weighting, State Clustering, and Alternative Start Date



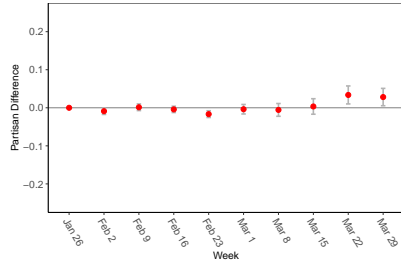
Note: Figure shows the estimated coefficients for county partisanship  $\rho_i$  on the log number of POI visits in the county. The specifications are analogous to our baseline in Panel C of Figure 5 except with the following deviations.

- Panel D: The first plot only keeps counties with a population below 500,000; the second plot drops California, Washington, and New York; and the third plot shows the estimated coefficients for county partisanship  $\rho_i$  on the *change* in the log number of POI visits in the county while dropping county fixed effects.
- Panel E: The first plot keeps counties for which Trump's vote share is greater than the median; the second plot keeps counties for which Trump's vote share is less than or equal to the median; and the third plot drops counties for which Trump's vote share was in the bottom or top decile.
- Panel F: The first plot weights observations by the county's population. The second plot clusters standard errors at the state-level. The third plot drops the week of January 26 and normalizes the estimates relative to the week of February 2.

Appendix Figure A3: Partisan Differences in Social Distancing, Robustness cont.

*Panel G: Alternative Measures*

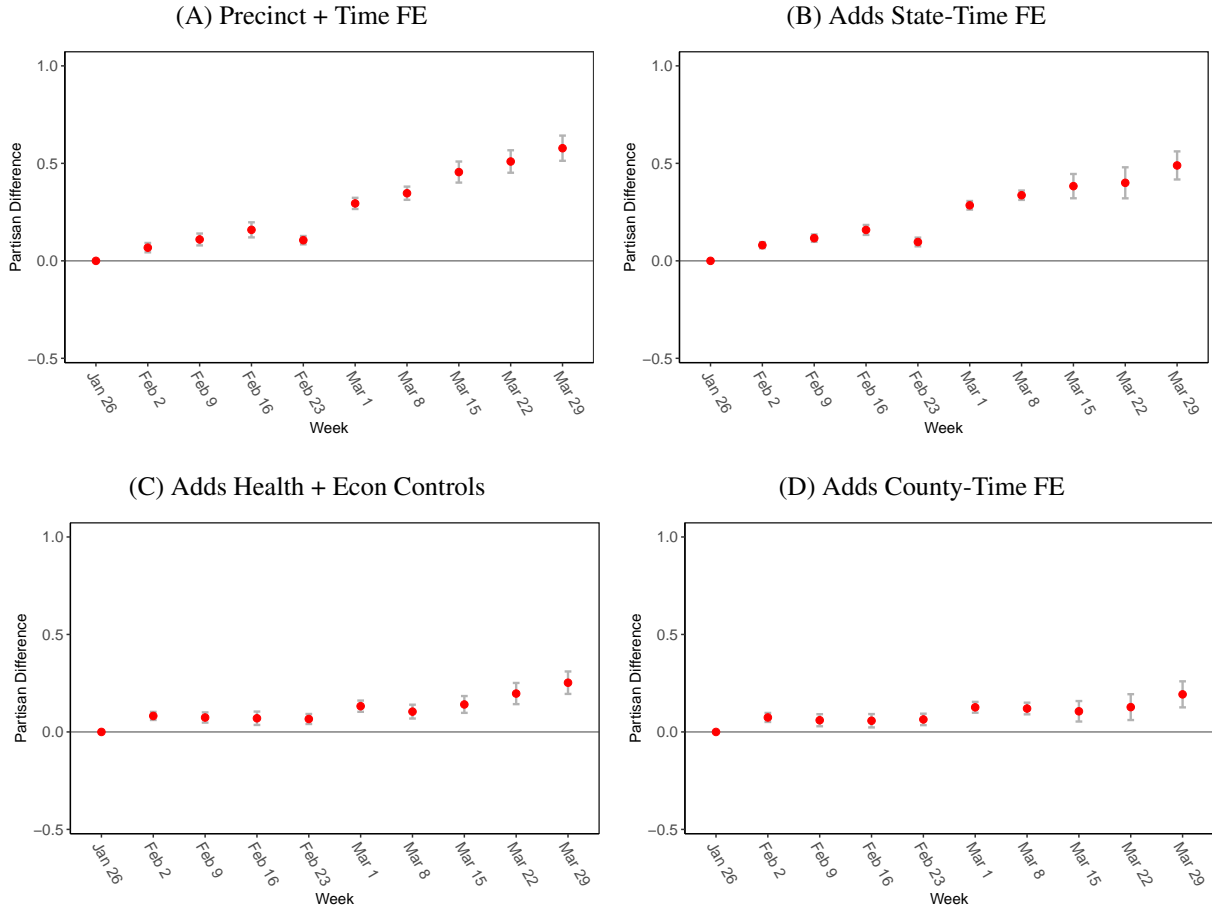
Share Devices Leaving Home, No Correction



Note: Figure shows the estimated coefficients for county partisanship  $\rho_i$  on the log number of POI visits in the county. The specifications are analogous to our baseline in Panel C of Figure 5 except with the following deviations.

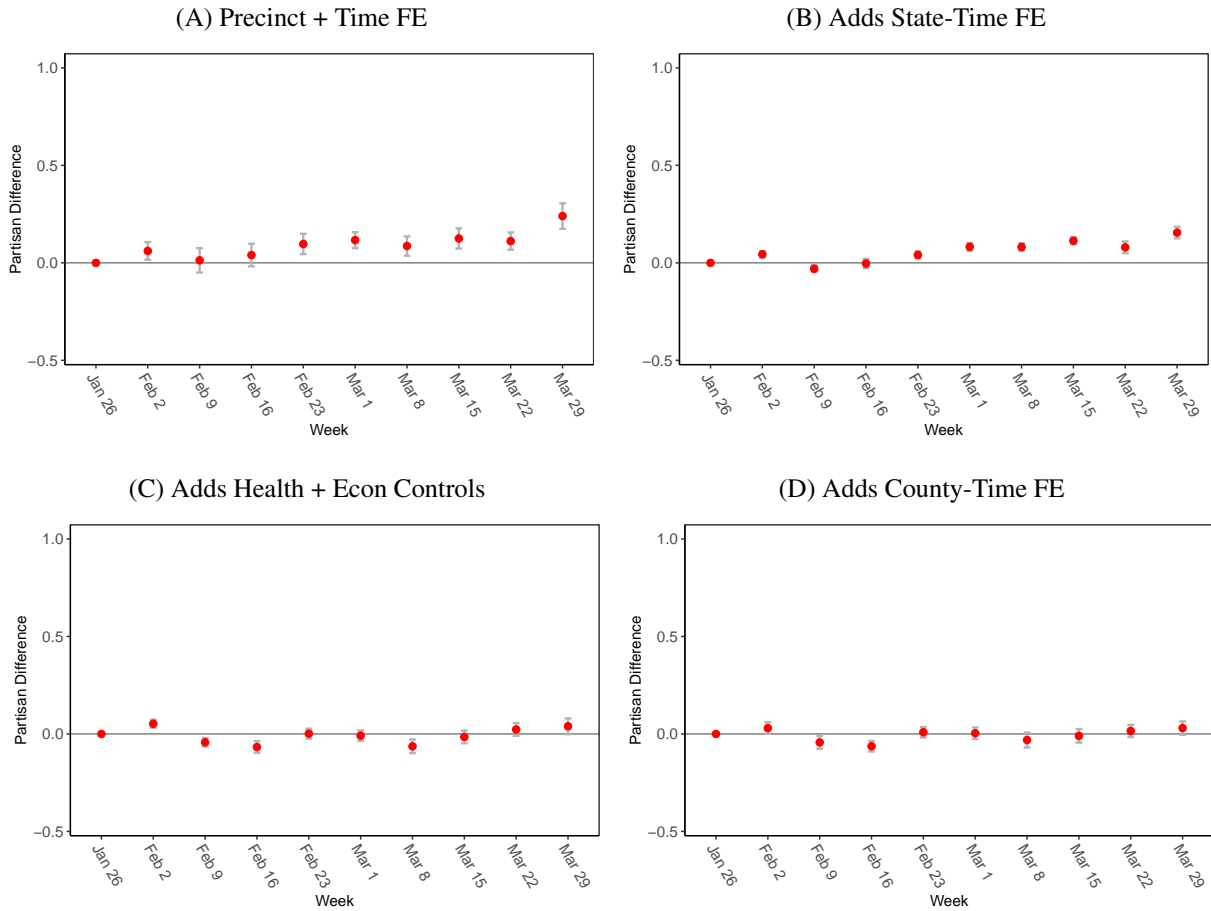
- Panel G: The first plot is analogous to 'Share Devices Leaving Home' in Figure 8, except that it does not account for differential sample attrition. Specifically, the outcome is defined to be number of devices observed leaving home divided by the share of devices in the panel for the same period.

Appendix Figure A4: Partisan Differences in Social Distancing, Precinct



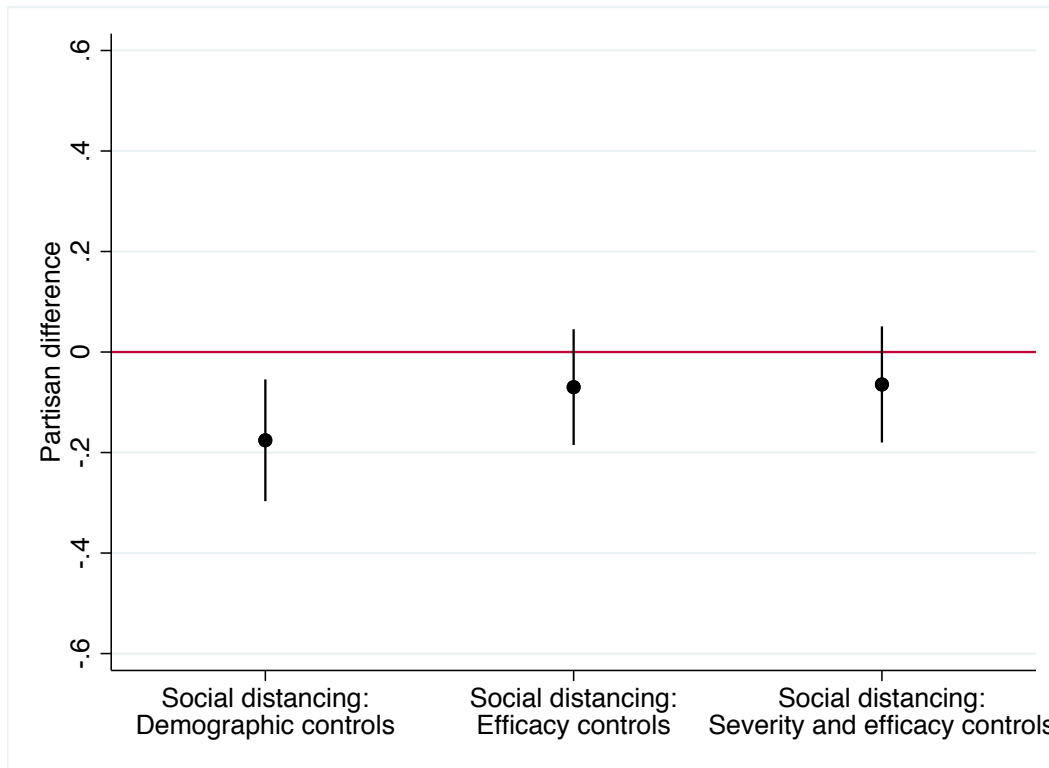
Note: Figure shows the estimated coefficients for precinct partisanship  $\rho_i$  on the log number of POI visits in the precinct using the specification outlined in the main text. For Panel A, only precinct and time fixed effects are included as controls. Panel B is the same as Panel A except state-time fixed effects replace the time fixed effects. Panel C is the same as Panel B except the health and economic covariates are included. Panel D is the same as panel C except that county-time fixed effects replace the state-time fixed effects, the county-level COVID-19 controls are also dropped in this specification. The grey error bars indicate 95 percent confidence intervals constructed using standard errors clustered at the county-level.

Appendix Figure A5: Partisan Differences in Social Distancing, Precinct 2019



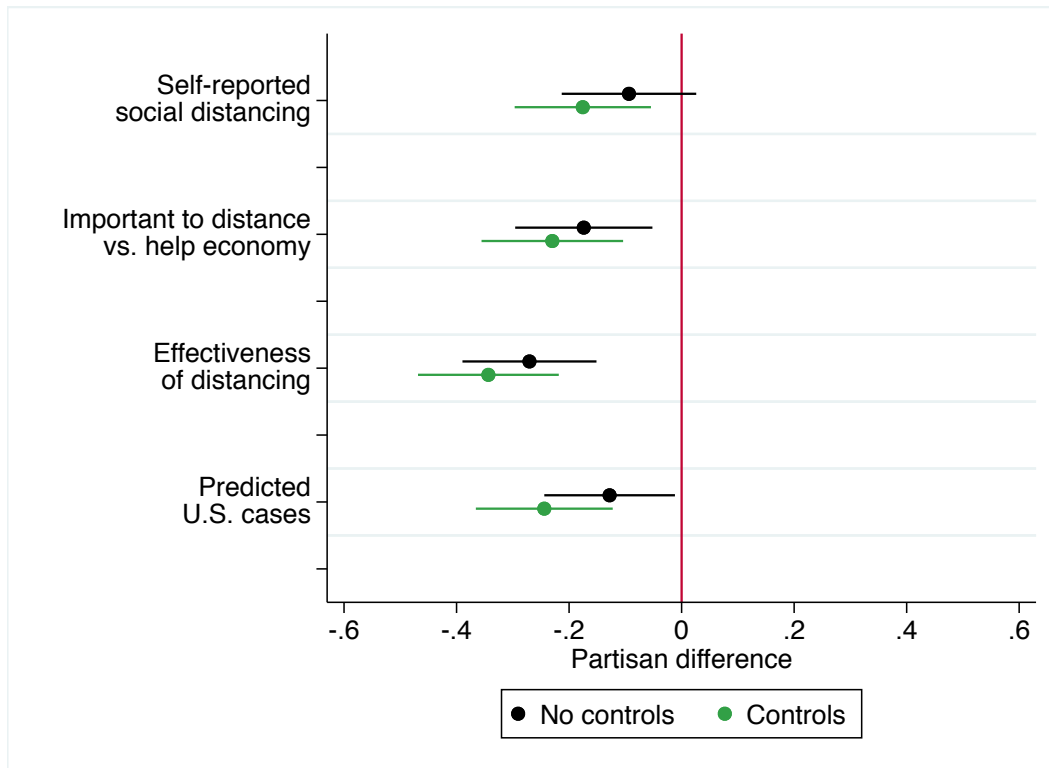
Note: Figure shows the estimated coefficients for precinct partisanship  $\rho_i$  on the log number of POI visits in the precinct. The figure mirrors Appendix Figure A4, except that ten weeks of data from January 27, 2019 are used instead of January 26, 2020. For Panel A, only precinct and time fixed effects are included as controls. Panel B is the same as Panel A except state-time fixed effects replace the time fixed effects. Panel C is the same as Panel B except the health and economic covariates are included. Panel D is the same as panel C except that county-time fixed effects replace the state-time fixed effects, the county-level COVID-19 controls are also dropped in this specification. The grey error bars indicate 95 percent confidence intervals constructed using standard errors clustered at the county-level.

Appendix Figure A6: Partisan Differences in Social Distancing with Controls for Beliefs



Note: This plot shows coefficient plots of regressing self-reported social distancing on party, with and without controls for various beliefs. Self-reported social distancing is the percent reduction in contact with others over one month. The first column includes only demographic control variables; the second additionally controls for subjects' normalized beliefs about the estimated likelihood of catching COVID-19 in one month without social distancing; and the third column additionally controls for subjects' normalized predictions about the number of new COVID-19 cases in the U.S. in April. Observations weighted to mimic a representative sample as described in the text. Error bars represent 95 percent confidence intervals.

Appendix Figure A7: Partisan Differences in Beliefs and Actions: Unweighted



Note: This figure shows coefficient plots of regressing normalized measures of beliefs and actions on party, without weighting observations. Positive values indicate less concern about COVID-19 or social distancing. Demographic controls are age, race, income, education, number of children, ZIP code logged population density, state. 2 percent of observations are dropped for not including a valid ZIP code. Predicted U.S. cases are predictions about the number of new COVID-19 cases in the U.S. in April; self-reported social distancing is the percent reduction in contact with others over one month; effectiveness of distancing is the estimated likelihood of catching COVID-19 in one month without social distancing; importance of distancing vs. economy is subjects' perception of whether it is more important to go out and stimulate the economy versus staying in and preventing the spread of COVID-19. Error bars represent 95 percent confidence intervals.