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

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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 public policies, population density, and local COVID cases and deaths. We then present new survey evidence of significant gaps at the individual level between Republicans and Democrats in self-reported social distancing, beliefs about personal COVID risk, and beliefs about the future severity of the pandemic.

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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 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 May 9, 2020.

We begin with two motivating facts shown in Figure 1. First, nationwide surveys have shown that Democrats are more concerned about the spread of COVID-19 than Republicans (Panel A). Second, Democrats report taking more steps to avoid infection than Republicans (Panels B, C, and D). However, Democratic areas have also 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) or because their benefits of distancing are smaller (e.g., they are at lower risk of infection). How-

ever, 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. Compared to a society where agents have the same beliefs, the same level of social distancing will have a higher cost.

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 public 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 local policy, health, weather, 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 14.0 percent increase in the number of POI visits during the week of April 12, when social distancing is at its peak.

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 conditional on the same set of controls. We find mixed evidence of a partisan gap at the voting precinct level, but focus on county level analyses due to limitations facing the precinct specification (see footnote 14).

To complement the data showing county-level differences in behavior, we use a nationally-representative survey to show that individual behavior and beliefs about social distancing are partisan. 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. We 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. These partisan gaps in survey responses emerge even when comparing respondents within the same county.

Several contemporaneous studies also measure partisan differences in responses to COVID-19.[1] 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. Painter and Qiu (2020) examine partisan heterogeneity in response to state-level, stay-at-home orders. Bursztyn et al. (2020) and Simonov et al. (2020) find that individuals social distance less if quasi-randomly exposed to less concerned news, suggesting a possible driver for our result.[2]

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.

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

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[1]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.

[2]Pastor and Veronesi (2019) also find that Democrats are more risk averse than Republicans. Differences in risk aversion wouldn't explain the differences in beliefs we find in Section 5, but are a possible complementary explanation for the observed partisan gap in social distancing.

2 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. We consider how heterogeneity in perceived risks of not social distancing affects aggregate welfare.

2.1 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 β 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 ψ or Recovered with probability $(1 - \psi)$. Both D and R are absorbing states.

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

2.2 Individual Decisions

People of type θ earn flow utility $u_\theta(c_t; \sigma_t)$, which depends on their risky behavior c_t and their state σ_t. People discount the future at rate δ 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 σ; note that this also implicitly depends on current and future population states $\omega_{\theta \sigma t}$. Being infected reduces utility, so we assume $V_\theta(S) > V_\theta(I)$ for any given current population state.

We focus on Susceptible people, as they comprise most of the population during the period we study and are the people who face a trade-off between the benefit of consumption and the risk of becoming infected. 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:

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

The first-order condition for privately optimal risky behavior is

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

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.

2.3 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:

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

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 λ 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 ϕ_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:

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

People who are not Susceptible do not account for transition risks. In the constrained social optimum, they set $0 = u'_\theta + \phi_t + \lambda$.

2.4 Heterogeneous Risk Misperceptions

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

$$u'_\theta = \tilde{\mu}_{t\theta}, \tag{5}$$

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

For illustrative purposes, imagine 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 type a perceives greater risk, so $\tilde{\mu}_{a\theta} > \tilde{\mu}_{b\theta}$. Our survey data show Democrats perceive greater risk, so one can think of Democrats

as type *a*.

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

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

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:

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

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 Sections 4 and 5, 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. In Section 5, we ask if Democrats and Republicans have different risk *perceptions*, which would generate the transfers and efficiency costs described above. In these analyses, we control for factors such as population density, health risks, and local coronavirus cases that could generate difference in actual risks across types. We also give a back-of-the-envelope estimate for the efficiency cost of heterogeneous misperceptions.

3   Data

3.1   SafeGraph Mobile GPS Location Data

Our analysis uses data from SafeGraph, aggregating GPS pings from about 45 million mobile devices and numerous 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.[3]

Our primary analysis uses data from a period of fifteen weeks, from January 26 to May 9, 2020. We aggregate visits across all POIs in a given county and 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 fifteen 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, the number of other CBGs visited, or the median time spent away from home across devices.

We supplement the SafeGraph data with various other sources of county and census block group data. For demographic information on age, race, education, income, occupation, and poverty status at the county-level, we aggregate census block group data from SafeGraph Open Census to

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[3]SafeGraph removes POIs with fewer than five visitors in a given month for data through February 2020. Starting with 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.

the county level.[4] We add weather statistics on temperature and precipitation from gridMET (Abatzoglou 2011), aggregated to the county-level.[5] 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). We also add data on county or state stay-at-home policies from a variety of sources (as in Allcott et al. 2020).[6]

3.2 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 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.[7]

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 1 represents "Strongly Republican."

The survey asked for demographic information (zip code, 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. 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 − Δ) where Δ is the percentage point

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[4]The SafeGraph Open Census data is derived from the 2016 5-year ACS at the census block group level.

[5]We thank Jude Bayham for sharing aggregated versions of this dataset with the SafeGraph COVID-19 response community.

[6]We combine policy data from: Keystone Strategy; a crowdsourcing effort from Stanford and University of Virginia; Hikma Health; and the New York Times.

[7]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).

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.

4 SafeGraph Empirical Specification and Results

Figure 2 presents county-level variation in social distancing, partisanship, COVID-19 prevalence, and stay-at-home orders. Panels A and B exhibit a strong, geographic correlation between the counties with weaker social distancing responses and those with higher Republican vote shares. However, partisanship is also strongly correlated with COVID-19 case prevalence (Panel C) and earlier stay-at-home orders (Panel D).

Figure 3 reports trends in social distancing and COVID-19 prevalence separately for Republican and Democratic counties. 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 period, Democratic counties exhibited a larger drop in weekly POI visits than their Republican counterparts. However, as Panel B demonstrates, Democratic counties also exhibited a larger rise in COVID-19 cases and deaths—accounting for nearly all verified COVID-19 cases and deaths through May 9. Appendix Figure A1 shows that, over the same time period in 2019, POI visits are rising with a noticeable but smaller partisan gap.

Our main empirical specification takes the following form

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

where c_{it} is the number of POI visits in county i during week t, α_t are the time-varying coefficients on county partisanship ρ_i, X_{it} are non-parametric and time-varying controls, and ε_{it} is the county-specific error term.[8] We chose our covariates X_{it} to flexibly control for the four channels of divergent behavior highlighted in equation (2). Standard errors are clustered at the state-level throughout unless specified otherwise.

Figure 4 reports our estimates of α_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

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[8]We normalize α_t relative to the first week.

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 and extend at least through early May.

These results do not control for differences in public 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,[9] economic,[10] and weather[11] 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 include these controls nonparametrically via indicators for decile bins within a week, and allow the coefficient on these indicators γ_t to vary flexibly across time. Although these controls attenuate partisan differences to some degree, they remain economically and statistically significant. Appendix Figure A2 shows that these strong partisan differences do not appear over the same time period in 2019 conditional on the same controls. These results are consistent with behavioral differences driven by partisan misperceptions of risks at the group-level.

To better understand the magnitudes of this partisan gap, we compare the difference between very Republican and very Democratic counties to contemporaneous mobility levels and to overall social distancing. The estimate of our partisan gap coefficient α_t is 0.357 by the week starting April 12 (the week with the fewest number of visits) and 0.364 in the week starting May 3 (the last week of our sample). This implies that going from a county with the 10th to the 90th percentile in Republican vote share is associated with 14.0 and 14.3 percent increases in the number of POI visits during these two weeks respectively.[12] This 14.0 percent gap during the week of April 12 corresponds to 8.3 percent of the total drop in visits during this week relative to the baseline

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[9]Health controls include: an indicator for whether a county has been under a stay-at-home order; log of one plus the number of confirmed COVID-19 cases in the county; log of one plus the number of COVID-19 deaths in the county; log of one plus the county population density (individuals per square kilometer); and share of the population age 65+.

[10]Economic controls include: share of the population with at least a bachelor's degree; share in poverty; share with household income $\geq \$100,000$; shares white, black, and asian; share commuting by public transportation; share currently enrolled in undergraduate study; and shares of occupations in various categories (management, business, science, and art; services; sales and office occupations; natural resources, construction, and maintenance).

[11]Weather controls include daily high temperature, daily low temperature, and amount of precipitation.

[12]The difference between the 90th and 10th percentile of Republican vote share is 0.807 - 0.413 = 0.394.

week (starting January 26). The partisan gap during the week of May 3 is comparable in size to 16.3 percent of the total social distancing occurring in this week (relative to January 26).[13] These magnitudes show that the partisan gap in social distancing between very Republican and very Democratic counties is economically meaningful but that it accounts for only a limited portion of overall social distancing.

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 Republican vote share distribution. Panel F weights observations by the county's population, uses standard errors clustered at the county-level, and examines sensitivity to the start date. Except when restricting to counties in the top half of the Republican vote share, none of the alternative specifications change the central conclusion regarding partisan differences in social distancing in March through at least early May.

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 still holds, even when including county-time fixed effects. Again, these patterns are not present in 2019 (Appendix Figure A5). Precinct-level analysis faces several limitations that lead us to prefer our county-level specification.[14]

Appendix Figure A6 examines heterogeneity across industries by re-aggregating POI visits to the county level after restricting to certain 2-digit 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

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[13]There are 37.1 percent as many visits during the week of April 12 as there are in the week of January 26 in our sample, a drop of 62.9 percent. We compare the fraction of this drop equivalent to our 90th vs. 10th percentile partisan gap: $\frac{(0.140 \times visits_{Apr12})}{(visits_{Jan26} - visits_{Apr12})} = 0.140 \times \frac{(visits_{Apr12}/visits_{Jan26})}{(visits_{Jan26} - visits_{Apr12})/visits_{Jan26}} = 0.140 \times \frac{0.371}{0.629} = 0.083$. The fraction of social distancing during the week of May 3 is similarly derived given a 46.4 percent drop in visits.

[14]We note several limitations of our precinct-level analysis. Due to the limited availability of 2016 precinct-level shapefiles, our precinct-level analysis includes only 37 states (see Appendix A.1.3). Partisanship is measured at the precinct-level, while social distancing and our health, weather, and economic controls are generally measured at the census block group level. The latter set of variables are then mapped to precincts based on geographic overlap using the procedure described in Appendix A.1.3, potentially introducing correlated measurement error between our outcome and non-partisanship controls. Finally, POI visits are allocated to geographies by merchant location whereas partisanship is measured among residents. With smaller geographies, it becomes increasingly likely that visitors to a POI come from a different home geography, resulting in mismatch between visits and partisanship.

in visits to health care POIs.

Figure A7 repeats Panel C of Figure 4, 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 A8 considers alternative measures of social distancing derived from SafeGraph's Social Distancing data. Statistically significant partisan differences emerge in March through May for the log number of devices leaving home, the log number of stops made in non-home census block groups, the log of the median time away from home, and for our preferred measure of the share of devices leaving home adjusted for sample attrition.[15] We see mixed evidence of a partisan gap for alternative constructions of this share in Panel B of Figure A8. In Panel C, we conduct our alternative social distancing analysis at the precinct level while including county-time fixed effects. For the log number of devices leaving home and for the log number of stops made in non-home census block groups, we find an economically and statistically significant partisan gap only in the most recent weeks (though see footnote 14 for limitations of the precinct-level analysis).

5   Survey Results

Turning to the results of our survey, we first confirm that there exist individual-level partisan differences in (self-reported) social distancing behaviors and attitudes, consistent with the POI visits results presented above. We then show that beliefs about the effectiveness of social distancing and predictions of the spread of COVID-19 follow the same partisan patterns.

Our main empirical specification regresses normalized responses 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, ρ_i is the continuous measure of Republican party lean from 0 to 1, X_i are demographic and location controls, and ε_i is an error term.

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[15]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 A8 footnotes for correction).

Figure 5 shows consistent evidence for partisan differences in social distancing, both with and without control variables.[16] 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 72.1 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 partisan differences in social distancing attitudes could be attributed to underlying beliefs regarding COVID-19 severity and efficacy of social distancing. First, we find 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 believe this probability is 60.5 percent, which is 0.34 SD larger than the 49.6 percent belief held by 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.On average, participants predict 202,810 new cases in April 2020 (SD 233,343 cases, due to a long right tail).[17] Strong Democrats predict 231,283 future cases on average, which is 0.24 SD more than the 174,495 predicted by strong Republicans.[18] Bullock et al. (2015) and Prior et al. (2015) show that partisan differences on factual questions often shrink under incentives due to "partisan cheerleading" rather than differences in true beliefs. As such, we randomize whether subjects' predictions are incentivized for accuracy; we do not find evidence that the partisan gap decreases.[19] This supports the view that Democrats and Republicans genuinely differ in their beliefs about the severity of COVID-19.

Appendix Figure A11 shows that comparing individuals within the same county produces qualitatively similar results, although statistical precision is weaker. This sub-county survey analysis complements the county-level partisan gap observed in SafeGraph social distancing data.

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[16]These effects are not due to observation weighting, as shown in Appendix Figure A9.

[17]These averages are calculated after winsorizing at the 5-percent level to account for outliers.

[18]The actual number of confirmed April COVID cases was 901,670 (https://www.worldometers.info/coronavirus/country/us/). Subjects' underprediction might be due to overoptimism, anchoring (177,226 was given as the reference number for cases by March 31), or to some other factor.

[19]Appendix Figure A10 shows that on an explicitly political question, incentives do significantly reduce the partisan gap, consistent with previous findings.

Differences in beliefs and news may help explain differences in behavior. In Appendix Figure A12, 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, and that there is no gap when controlling for beliefs and respondents' news sources. While suggestive, we note that controlling for beliefs and news sources do not cleanly separate the causal role of these versus other factors.

Finally, we do a back-of-the-envelope estimation of the deadweight loss from Equation 7. We assume that agents have the same flow utility functions $u(c) = \frac{v}{2}c^2 + \eta c + k$ and normalize: if $\beta = 0$, all agents choose to consume $c^*(0) = 1$, so $-v = \eta \geq 0$. We then consider what happens when partisan perceptions differ about β. From our survey, we find that the median participant's willingness-to-accept for a month of consuming 1 instead of 0 is \$1500, so $\eta = 3000$. From the survey data above, we approximate that Democrats reduce consumption by 72.1% and Republicans reduce by 67.8%. Therefore, Democrats and Republicans differ in perceived risks by $\tilde{\mu}_{tR} - \tilde{\mu}_{tD} =$ \$129 per month.

Plugging this into Equation 7, we compare the deadweight loss if partisans have different perceived risks (μ_{tD}^*, μ_{tR}^*) compared to if they have the same perceived risk $(\mu_{tD}^* + \mu_{tR}^*)/2$. Using an estimate of 330 million people in the U.S. and 99% of the country being susceptible, we estimate that the partisan inefficiency costs approximately $\Delta W = \$8.24$ per person per year, or \$2.7 billion for the U.S. per year.

6 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 significant 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.
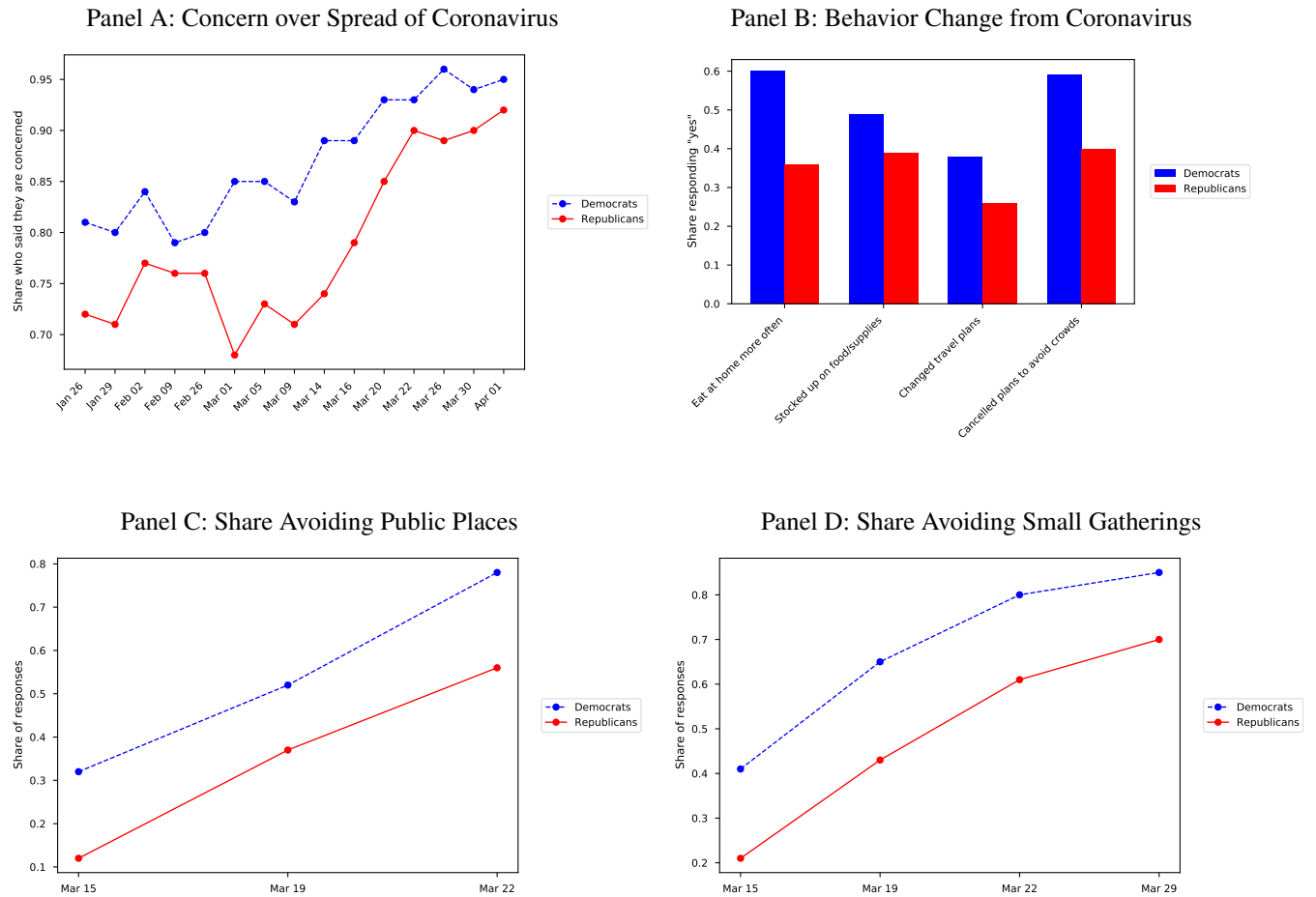
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Figure 1: Partisan Differences in Perceived Risk and Social Distancing

Panel A: Concern over Spread of Coronavirus

Panel B: Behavior Change from Coronavirus

Panel C: Share Avoiding Public Places

Panel D: Share Avoiding Small Gatherings

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

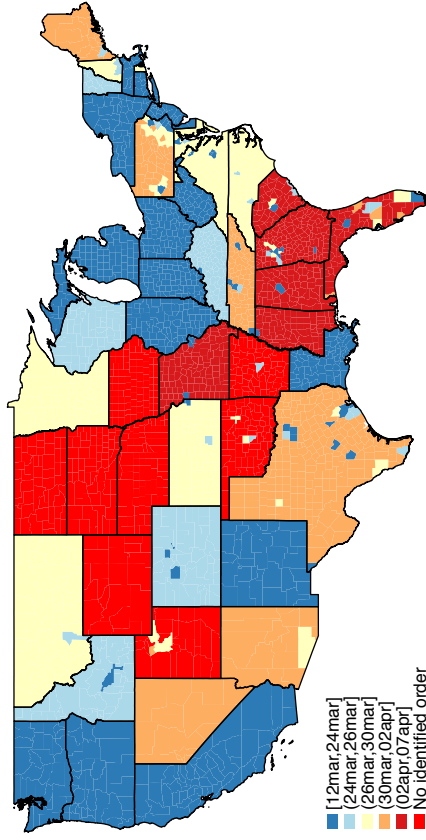Panel A: % Change in SafeGraph Visits
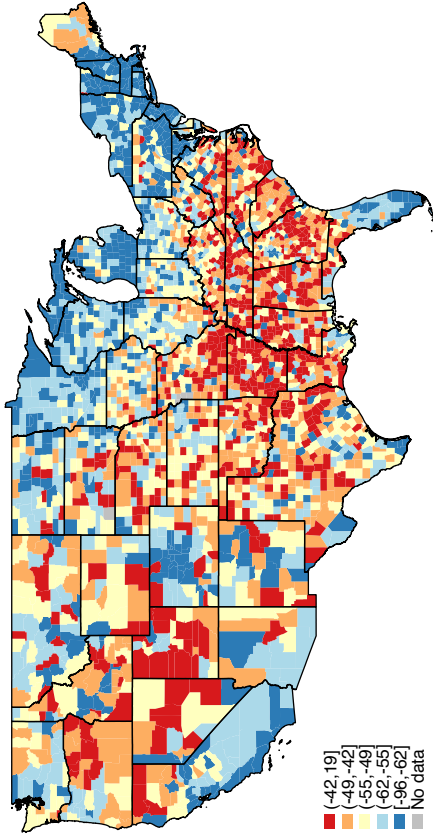
Panel B: 2016 Republican Vote Share
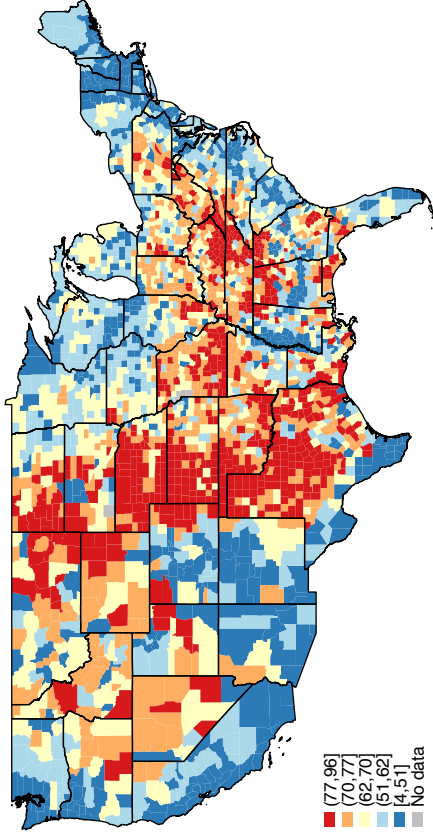
Panel C: COVID Cases Confirmed by 5/9/2020
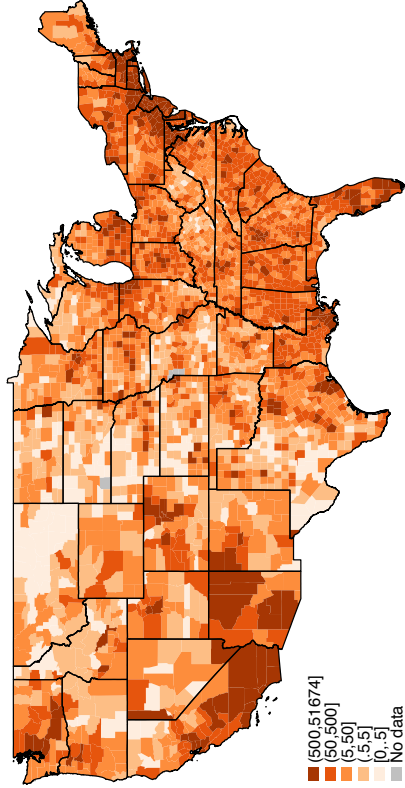
Panel D: "Stay at Home" Order Start Date

Note: This figure shows the U.S. geographic distribution of social distancing, political affiliation, COVID-19, and public policy re-sponses. Panel A shows for each county the percent change in aggregate visits between the week beginning January 26, 2020 and the week beginning April 12, 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). Panel C shows for each county the number of COVID-19 cases confirmed by May 9, 2020 (sourced from the New York Times). Panel D shades U.S. counties by the effective start date for the earliest "stay-at-home" order issued (see Section 3 for sources). Blue shading indicates an earlier order, while red shading indicates that an order was issued later or was never issued.
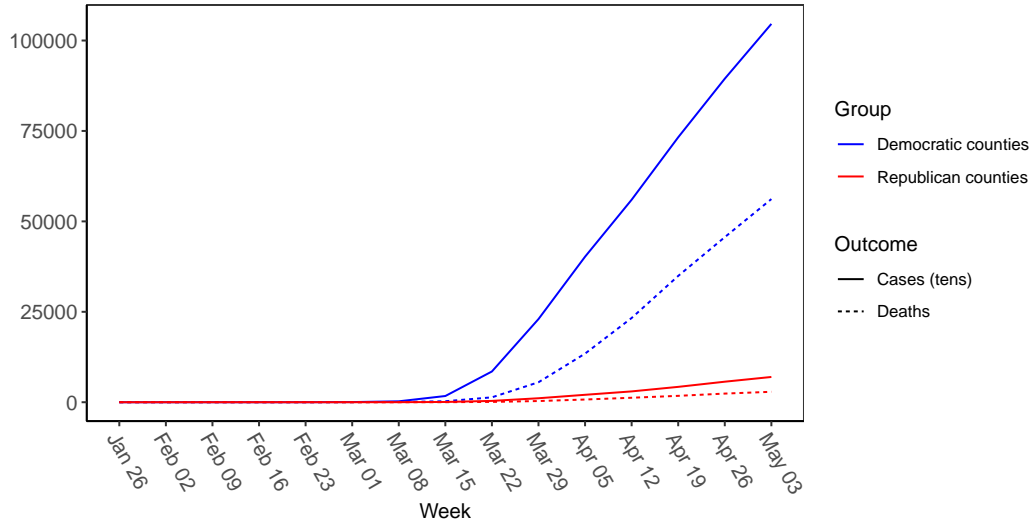
Figure 3: Social Distancing and COVID-19 Prevalence
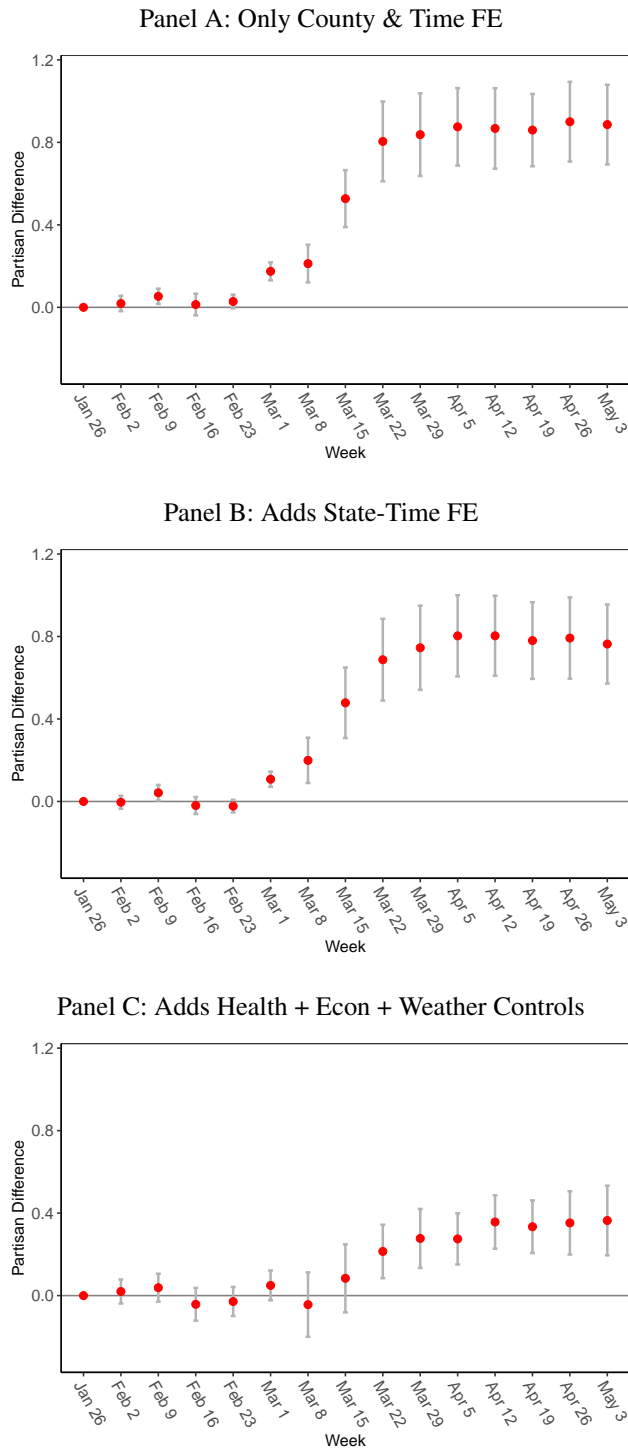
Panel A: POI Visits
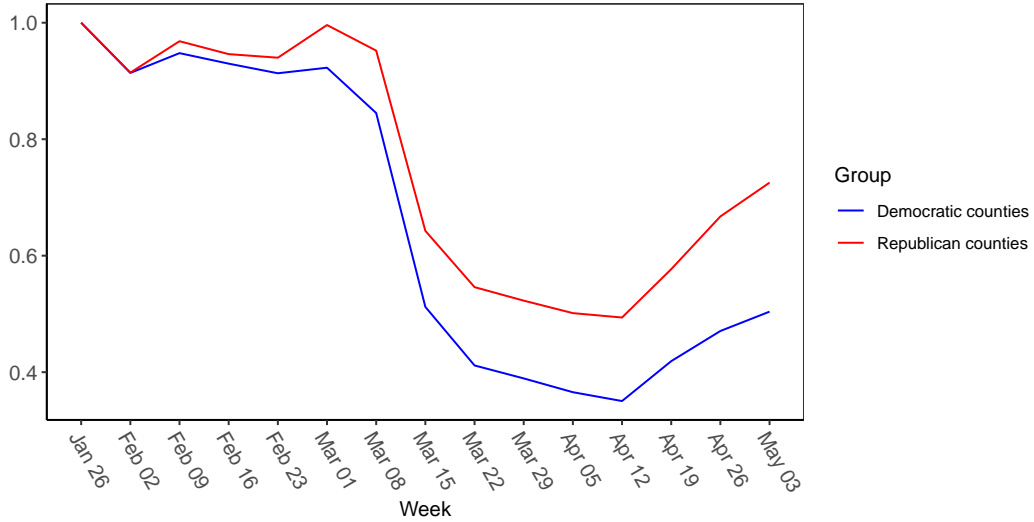


Panel B: COVID-19 Cases and Deaths

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. Counties covering New York City, Kansas City, and Alaska are excluded from these counts, as noted in Appendix A.1.1.

Figure 4: Partisan Differences in Social Distancing

Panel A: Only County & Time FE

Panel B: Adds State-Time FE

Panel C: Adds Health + Econ + Weather Controls

Note: Figure shows the estimated coefficients for county Republican vote share ρ_i on the log number of POI visits in the county. 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 that health, economic, and weather covariates are included (flexibly), as described in the main text. The grey error bars indicate 95 percent confidence intervals constructed using standard errors clustered at the state-level.

Figure 5: Partisan Differences in Beliefs and Actions
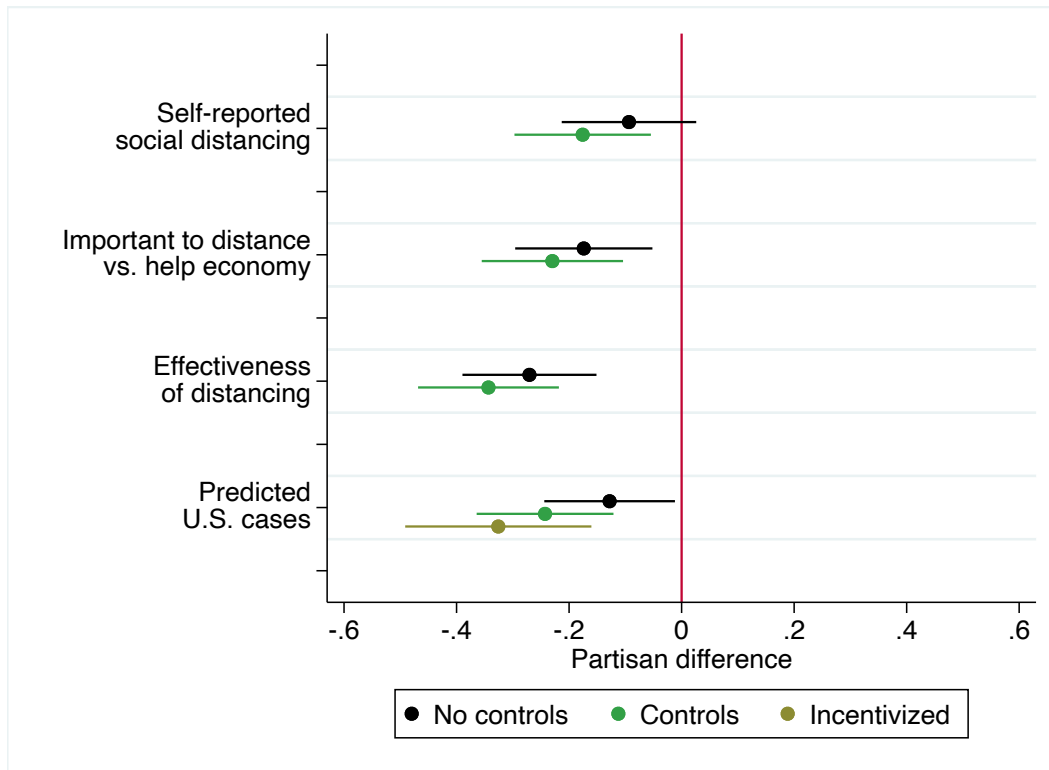
Note: This figure shows coefficient plots from regressing normalized measures of beliefs and actions on Republican party lean. Negative values indicate less concern about COVID-19 or social distancing. Demographic controls are age, race, income, education, number of children, ZIP code logged population density, state, county-level deaths and cases. 2 percent of observations are set to the mean due to an invalid ZIP code. Incentivized includes controls and restricts sample to subjects given accuracy incentives. 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.

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.[20] 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 May 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 gridMET weather data onto the output from (4). Precipitation and temperature means for a given county day or week are taken first as a mean across grid cell points that lie within a county boundary, and then across days within a week if needed prior to the merge with (4)'s output. Weather data was not available for Hawaii, so this particular state is dropped in regressions including weather controls.

6. We then merge a dataset of county-level shelter-in-place order start dates onto the output from (5). This dataset of shelter-in-place orders is the same as in Allcott et al. (2020), where its construction is described in detail. It is ultimately sourced from Keystone Strategy, a crowdsourcing effort from Stanford and University of Virginia, Hikma Health, and the New York Times.

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[20]Downloaded from https://www.census.gov/geo/maps-data/data/cbf/cbf_counties.html on July 24, 2018.

7. We then merge The New York Times COVID-19 tracking data onto our output from (6). 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:

1. We use the Daily Social Distancing SafeGraph data with observations at the census block group-day level for January 26 through May 9. 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)-(7) 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). 57 of these POIs (0.001%) are matched to two precincts. We then drop Alaska to match our county-level specification.

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.[21] 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 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. We then construct weather data by precinct day as a land area weighted average of gridMET weather data for overlapping census block groups. Census block group centroids were first associated with the nearest grid cell centroid in gridMET. We then average within a precinct across days in a week if needed, and merge the result onto our output from (4). Weather data was not available for Hawaii, so this particular state is dropped in regressions including weather controls.

6. As in Section A.1.1 steps (6) and (7), we then merge the county-level shelter-in-place policy data and the New York Times COVID-19 tracking data onto our output from (5).

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 emailled 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.

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[21]Downloaded from ftp://ftp2.census.gov/geo/tiger/TIGER2019/BG/ on April 1, 2020.

3. We merge ZIP code data with 2010 U.S. Census data and match ZIP codes to states and get population density.

4. We match ZIP codes to counties and use the week of March 29-April 4 and get county-level COVID cases and deaths via the New York Times. All ZIP codes in New York City are matched to the city-level cases and deaths since county-level data is unavailable from the New York Times. For analyses, we control for log(county cases + 1) and log(county deaths + 1).

5. 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.

6. 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. For analyses, we average consumption of news about politics and current events, trust in news about politics and current events, consumption of news about the coronavirus, and trust in news about the coronavirus.

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 <u>politics and current events</u> 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** from each of the following sources **<u>about politics and current events</u>** 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 <u>the coronavirus</u> 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** from each of the following sources **<u>about the coronavirus</u>** 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.

- <u>As of two weeks ago</u>, 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.

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 <u>additional</u> 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 <u>approve</u> of Trump's handling of the coronavirus outbreak on the latest poll that ends before April 30?

Appendix Figure A1: POI Visits in 2019
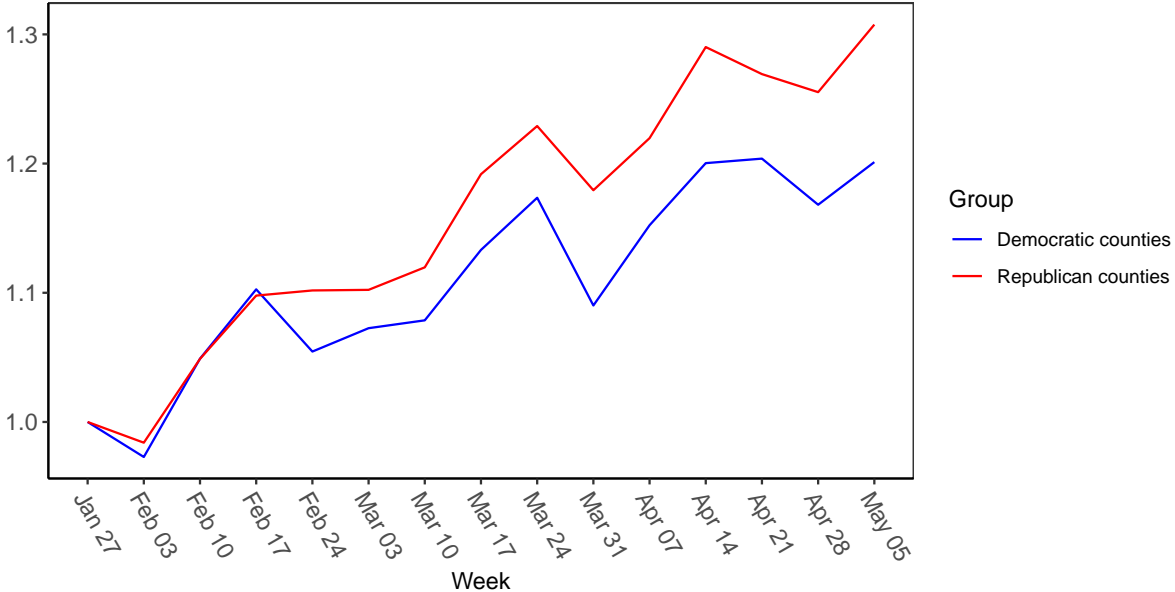
Note: Figure shows the aggregate number of POI visits (normalized to one) for fifteen weeks starting on January 27, 2019 for Republican counties and Democratic counties. Republican counties are defined to be those whose 2016 Republican vote share is greater than the median vote share across the counties in our sample. Counties covering New York City, Kansas City, and Alaska are excluded from these counts, as in Figure 3 and as noted in Appendix A.1.1.

Appendix Figure A2: Partisan Differences in Social Distancing, 2019
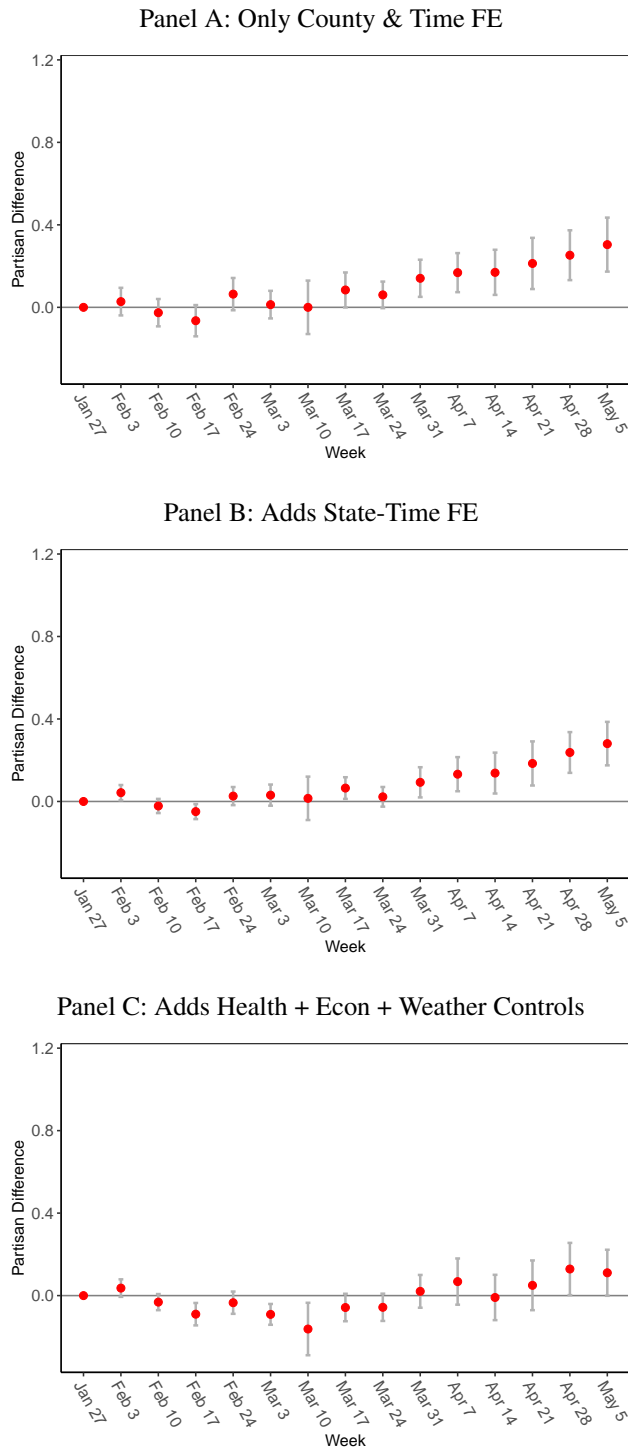
Panel A: Only County & Time FE

Panel B: Adds State-Time FE

Panel C: Adds Health + Econ + Weather Controls

Note: Figure shows the estimated coefficients for county Republican vote share ρ_i on the log number of POI visits in the county as in Figure 4, except that fifteen 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 that health, economic, and weather covariates are included (flexibly), as described in the main text. The grey error bars indicate 95 percent confidence intervals constructed using standard errors clustered at the state-level.

Appendix Figure A3: Partisan Differences in Social Distancing, Robustness

Panel A: Dropping Controls
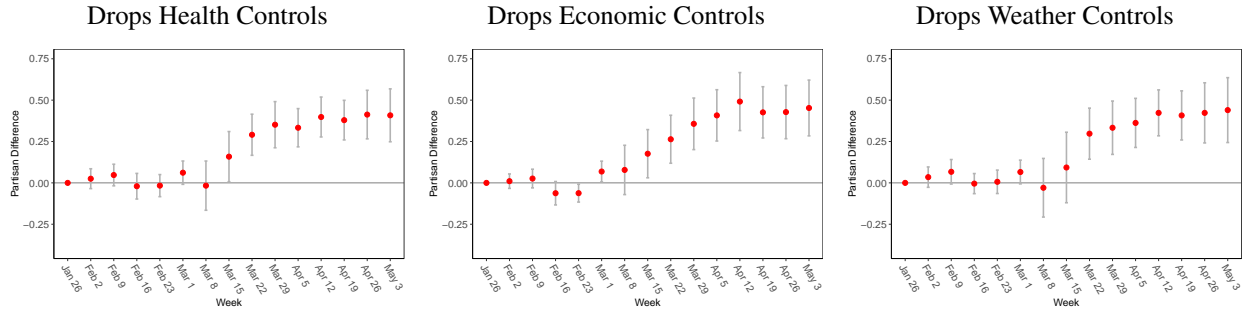
Panel B: Additional Specifications
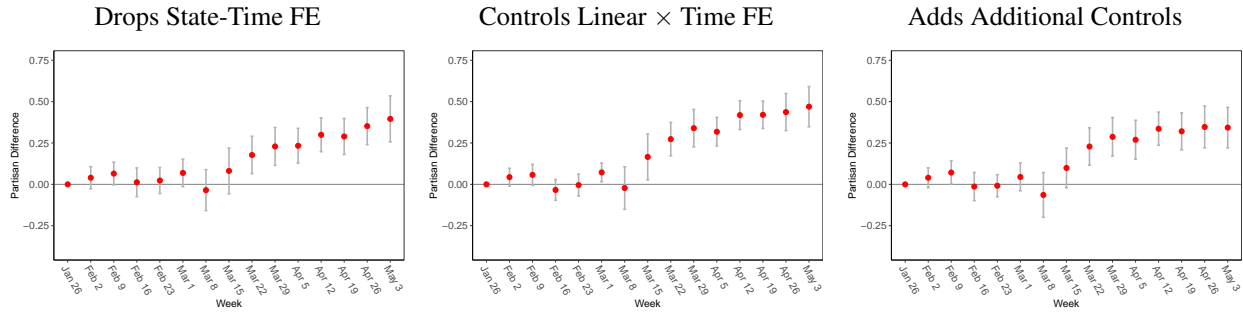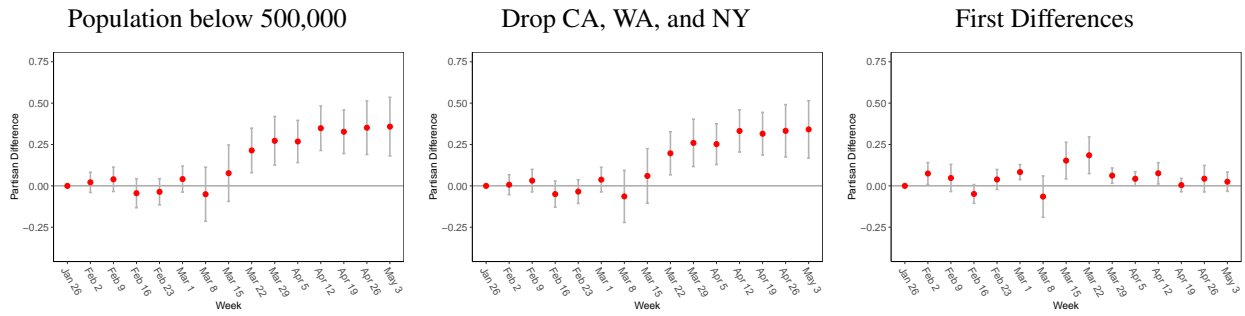

Panel C: Partisanship Indicators
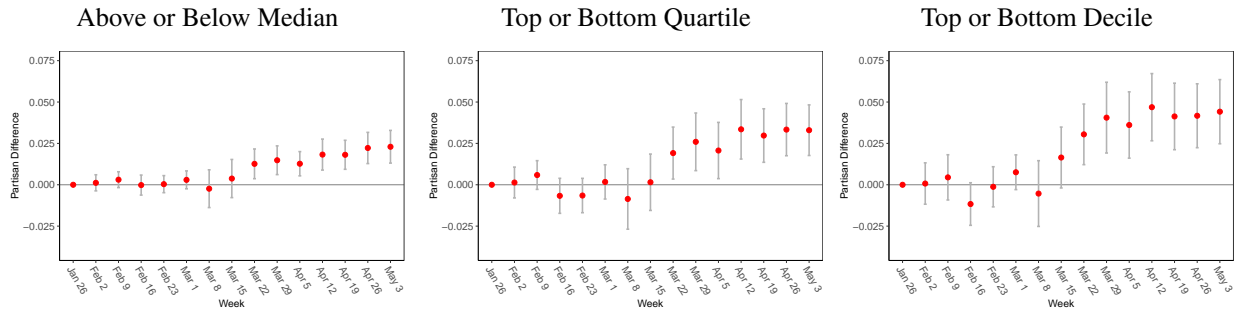
Note: Figure shows the estimated coefficients for county Republican vote share ρ_i on the log number of POI visits in the county. The specifications are analogous to our baseline in Panel C of Figure 4 except for the following deviations.
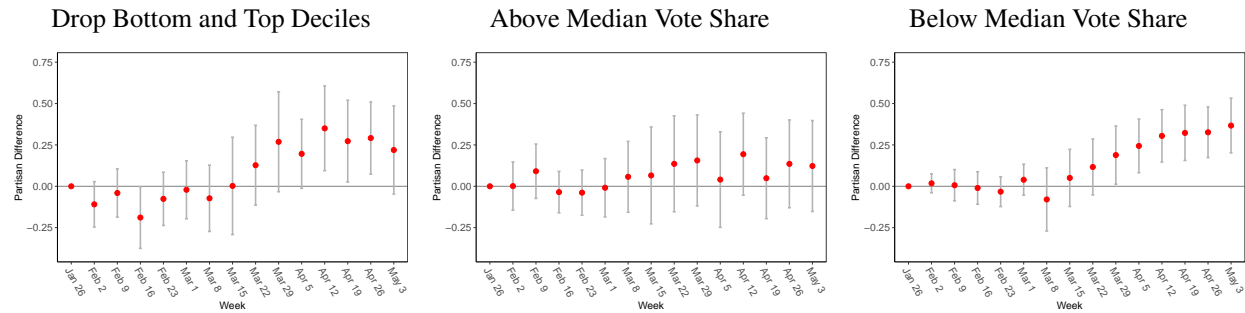
- Panel A: The first plot drops the health controls; the second plot drops the economic controls; and the third plot drops the weather controls.

- Panel B: The first plot drops state-time fixed effects (keeping county fixed effects and time fixed effects); the second plot interacts time fixed effects with linear versions of all controls, rather than with decile indicators; the third plot adds the following controls, each with time-varying decile indicators: share under age 18; shares with degrees in science+engineering, business, or arts+humanities; share of households with at least one vehicle; share of homes rented; share speaking only English at home; share with health insurance; shares commuting by auto, taxi, cycle, walking, or without commute; share enrolled in grad+professional school; share citizens; share married; shared of households with age 60+ occupant; shares of households of size 1, 2, or 3-5; share of households which are a family.

- Panel C: The first plot defines partisanship ρ_i to be 1 if Trump's vote share is greater than the median and -1 otherwise; the second plot defines partisanship ρ_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 ρ_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.
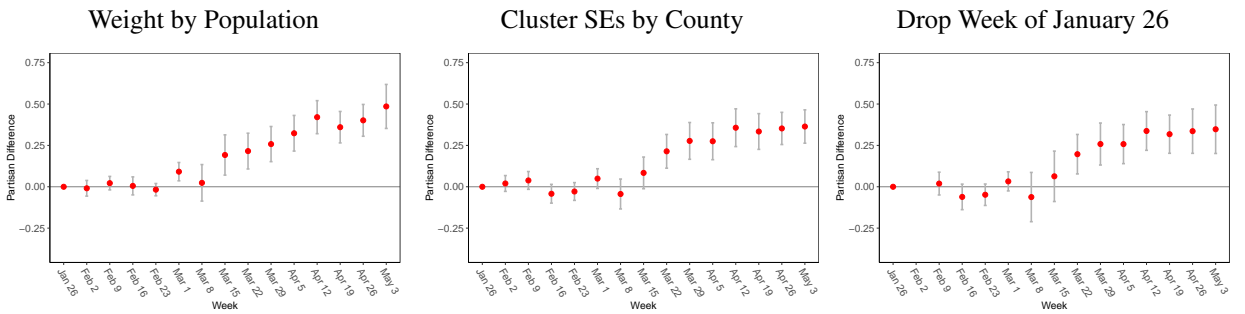
Panel D: Sample Restrictions and First Differences

Population below 500,000   Drop CA, WA, and NY   First Differences

Panel E: Sample Restrictions by Vote Shares

Drop Bottom and Top Deciles   Above Median Vote Share   Below Median Vote Share

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

Weight by Population   Cluster SEs by County   Drop Week of January 26

Note: Figure shows the estimated coefficients for county Republican vote share ρ_i on the log number of POI visits in the county. The specifications are analogous to our baseline in Panel C of Figure 4 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 ρ_i on the *change* in the log number of POI visits in the county.

- Panel E: The first plot drops counties for which Trump's vote share was in the bottom or top decile; the second plot keeps counties for which Trump's vote share is greater than the median; and the third plot keeps counties for which Trump's vote share is less than or equal to the median.

- Panel F: The first plot weights observations by the county's population. The second plot clusters standard errors at the county-level. The third plot drops the week of January 26 and normalizes the estimates relative to the week of February 2.

Appendix Figure A4: Partisan Differences in Social Distancing, Precinct
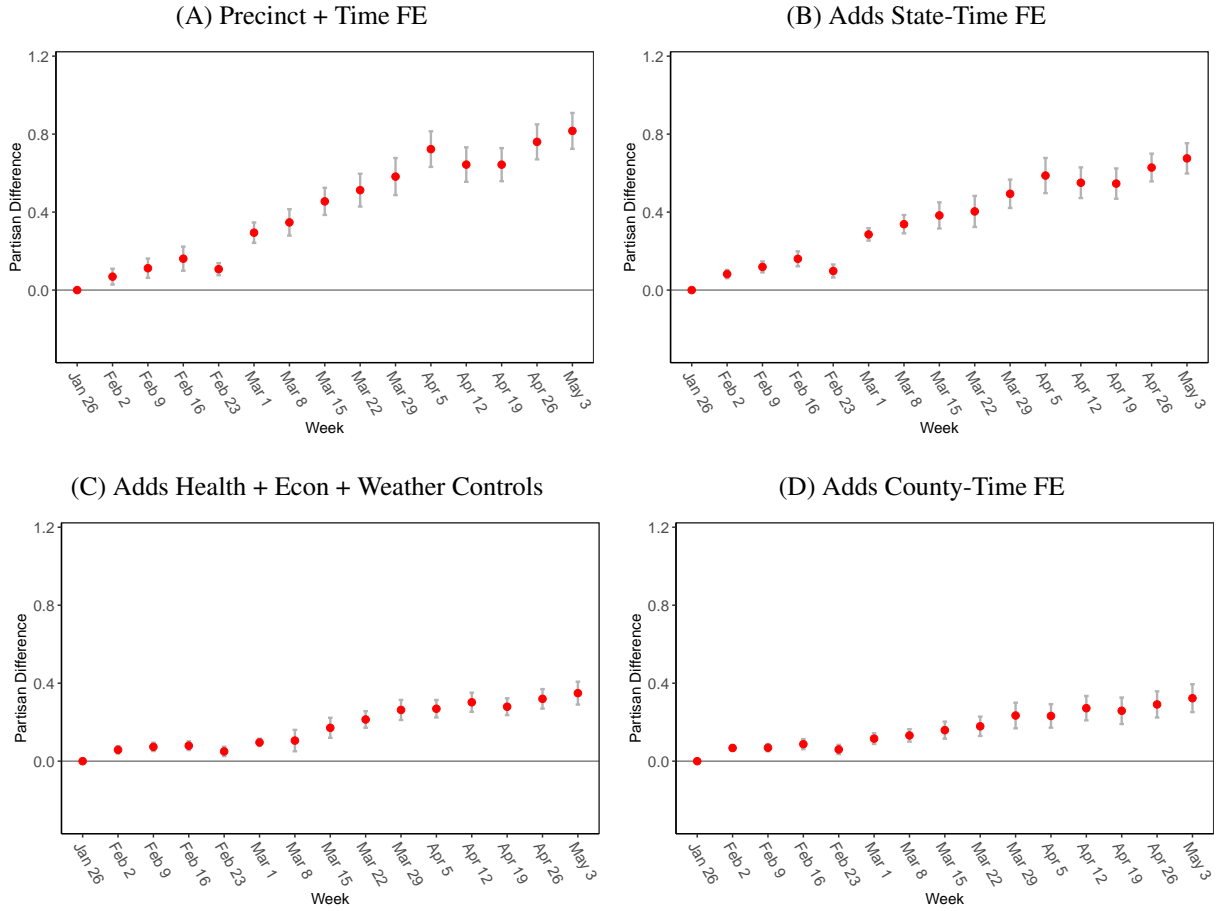
(A) Precinct + Time FE

(B) Adds State-Time FE

### (C) Adds Health + Econ + Weather Controls

(D) Adds County-Time FE

Note: Figure shows the estimated coefficients for precinct partisanship ρ_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 that health, economic, and weather covariates are included (flexibly), as described in the main text. 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 subsumed in this specification. The grey error bars indicate 95 percent confidence intervals constructed using standard errors clustered at the state-level. See footnote 14 for limitations regarding this precinct-level analysis.

Appendix Figure A5: Partisan Differences in Social Distancing, Precinct 2019
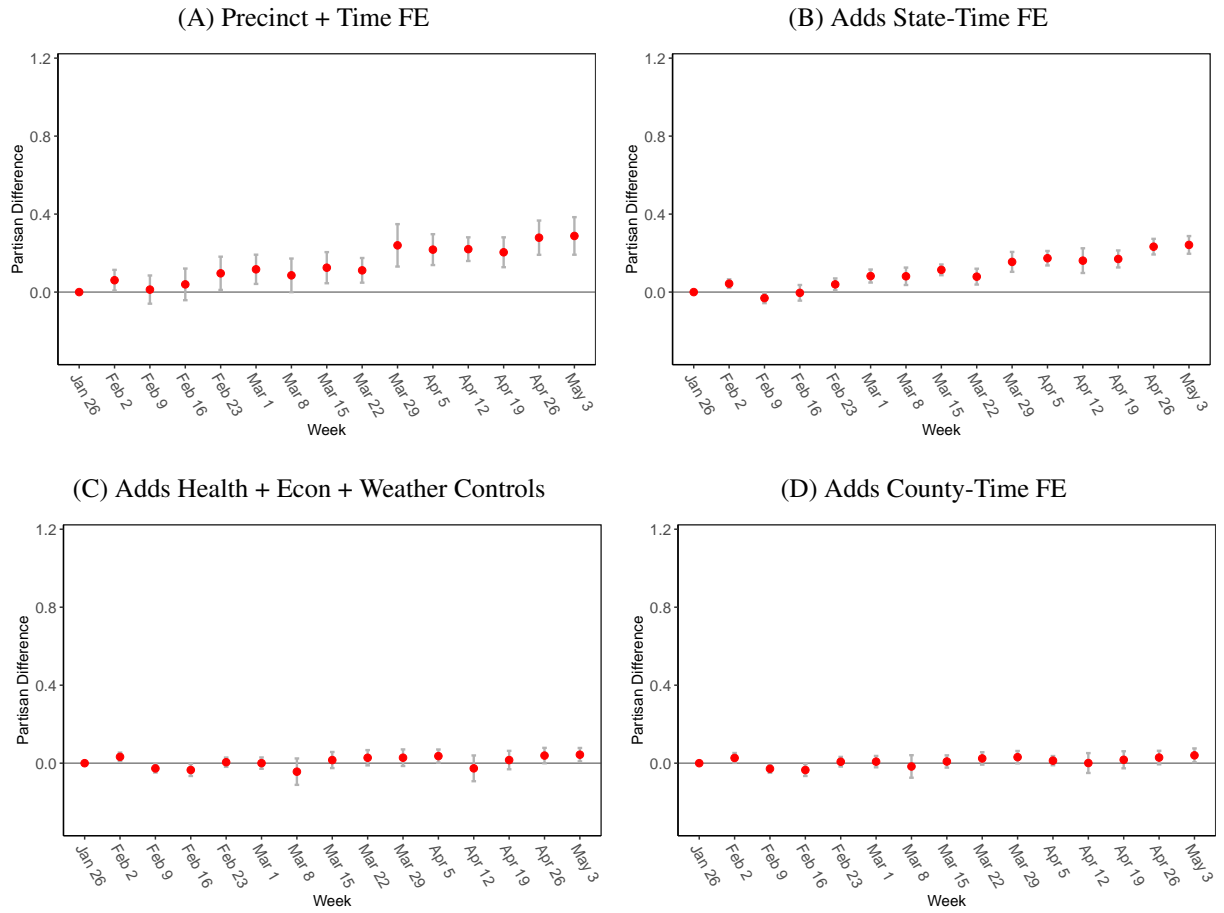
(A) Precinct + Time FE

(B) Adds State-Time FE

### (C) Adds Health + Econ + Weather Controls

(D) Adds County-Time FE

Note: Figure shows the estimated coefficients for precinct partisanship ρ_i on the log number of POI visits in the precinct. The figure mirrors Appendix Figure A4, except that fifteen 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 that health, economic, and weather covariates are included (flexibly), as described in the main text. 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 state-level. See footnote 14 for limitations regarding this precinct-level analysis.

Appendix Figure A6: Partisan Differences in Social Distancing by 2-Digit NAICS Code Industry
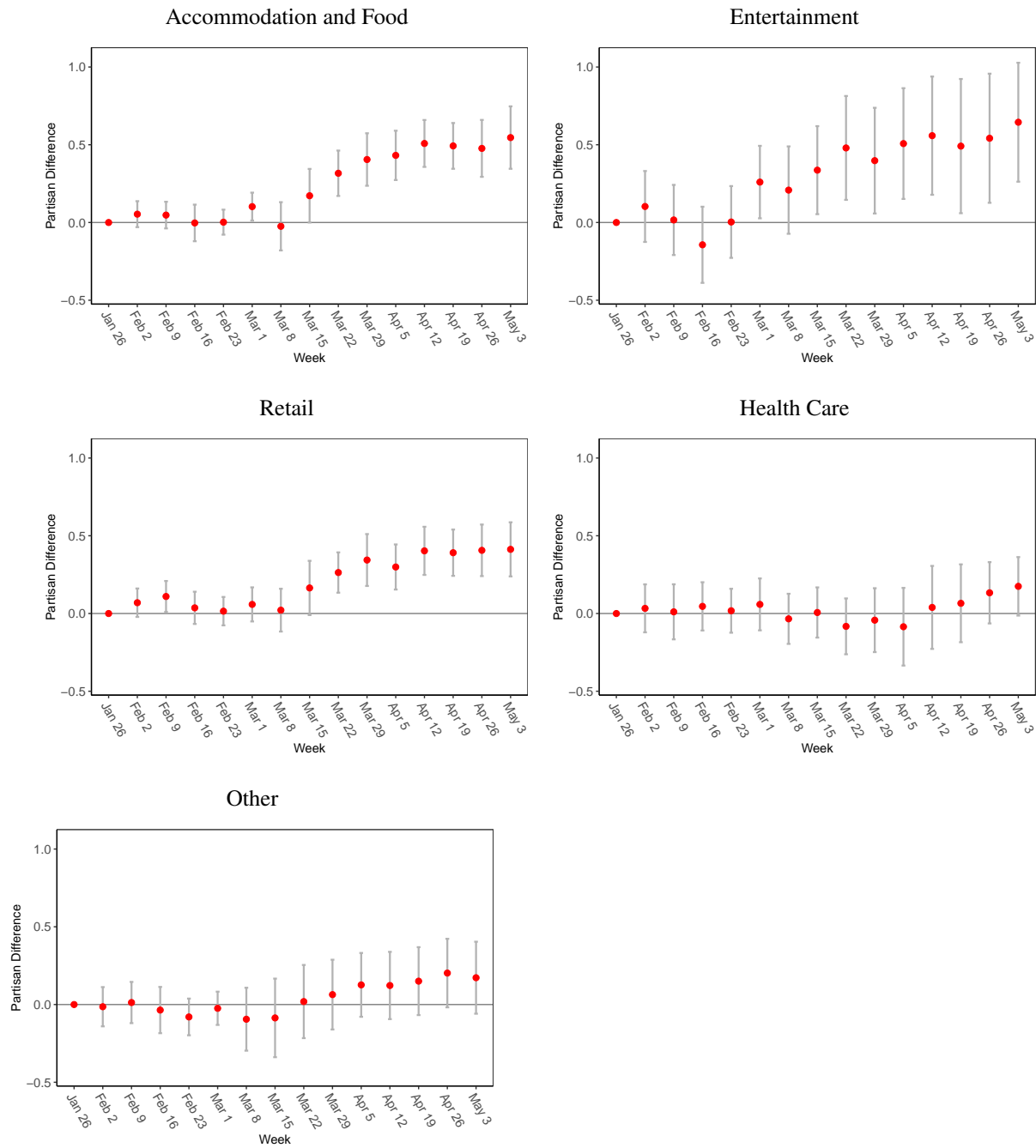
Note: Figure shows the estimated coefficients for county Republican vote share ρ_i on the log number of POI visits in the county after restricting POI visits to various 2-digit NAICS codes. The NAICS code groups are: Accommodation and Food (NAICS 72), Entertainment (NAICS 71), Retail Trade (NAICS 44 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 4. The grey error bars indicate 95 percent confidence intervals constructed using standard errors clustered at the state-level.

Appendix Figure A7: Partisan Differences in Social Distancing, Daily
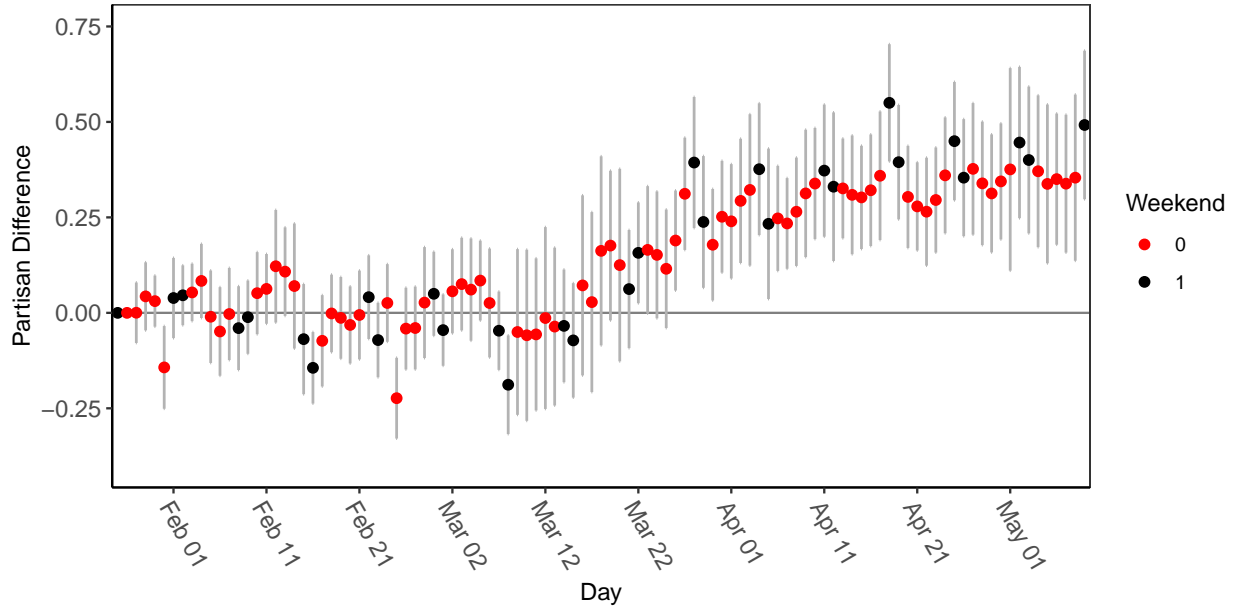
Note: Figure shows the estimated coefficients for county Republican vote share ρ_i on the log number of POI visits in the county. The same controls as in Panel C of Figure 4 are used except that state-time fixed effects occur at the day level, we add separate county fixed effects for weekdays vs. weekends, 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 state-level.

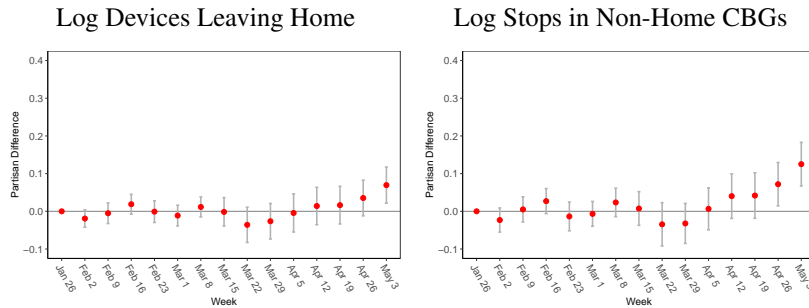# Appendix Figure A8: Partisan Differences in Social Distancing, Alternative Measures by Home Geography

Panel A: Alternative Measures by County
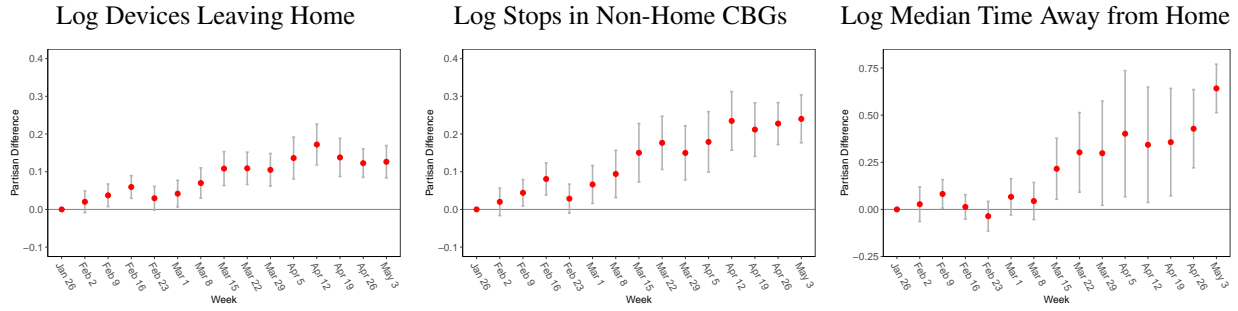
## *Panel B: Shares Devices Leaving Home by County*
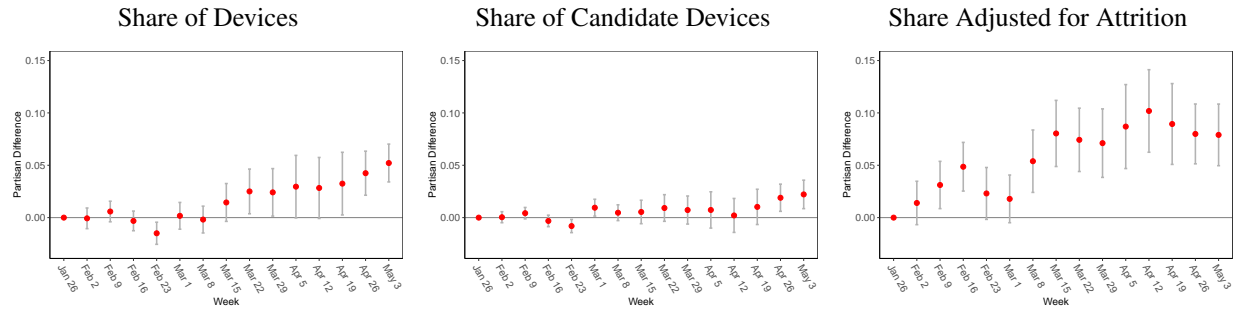
Panel C: Alternative Measures by Precinct

Note: Figure shows the estimated coefficients for Republican vote share ρ_i on alternative social distancing measures. The specifications are analogous to our baseline in Panel C of Figure 4 or Panel D of Figure A4 for county- and precinct-level regressions respectively, except that we replace log visits with the following alternative outcomes:

- Panel A: '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. 'Log Stops in Non-Home CBGs' counts, by home county, the number of devices which stop in a given non-home census block group. We then sum across non-home CBGs and days to form our county-week outcome. 'Log Median Time Away from Home' calculates the median time a device is observed outside its geohash-7 home, by home CBG. We then take a device-weighted average across CBGs and days to form our county-week measure, and then take the log of this value.

- Panel B: This panel shows the share of devices which are observed outside their geohash-7 home, making different assumptions about attrition observed in the data. 'Share of Devices' is defined to be $1 - \frac{\text{home devices}}{\text{current device count}}$, where 'home devices' are active devices never observed leaving their geohash-7 home and 'current device count' is the number of active devices for the current week. 'Share of Candidate Devices' is similarly defined as $1 - \frac{\text{home devices}}{\text{candidate device count}}$, where 'candidate device count' is the number of devices regardless of activity. 'Share Adjusted for Attrition' is defined to be $1 - \frac{\max\{0, \text{home devices} + (\text{initial device count} - \text{current device count})\}}{\text{initial device count}}$, where 'initial device count' is the number of active devices for the week of February 1.

- Panel C: This panel produces precinct-level analogues of the first two plots in Panel A. Our specification matches Panel D of Figure A4 (including county-time fixed effects), and we map our original CBG-level social distancing measures to precincts using the method described in Appendix A.1.3. See footnote 14 for limitations regarding this precinct-level analysis.

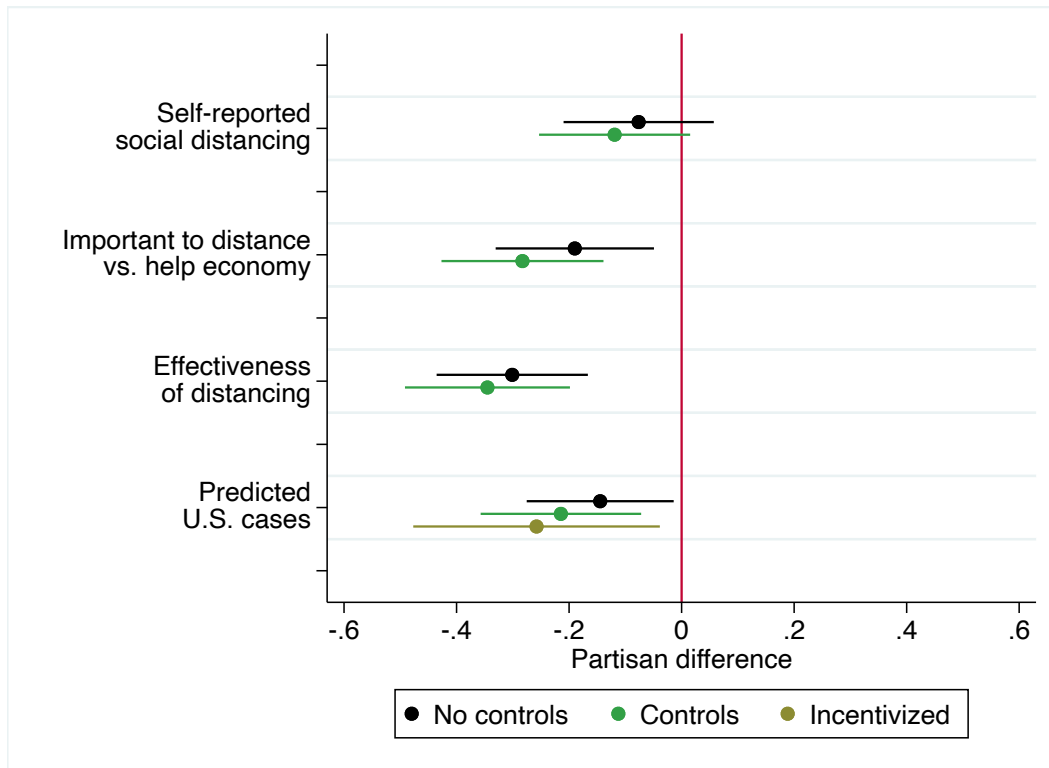Appendix Figure A9: Partisan Differences in Beliefs and Actions: Unweighted
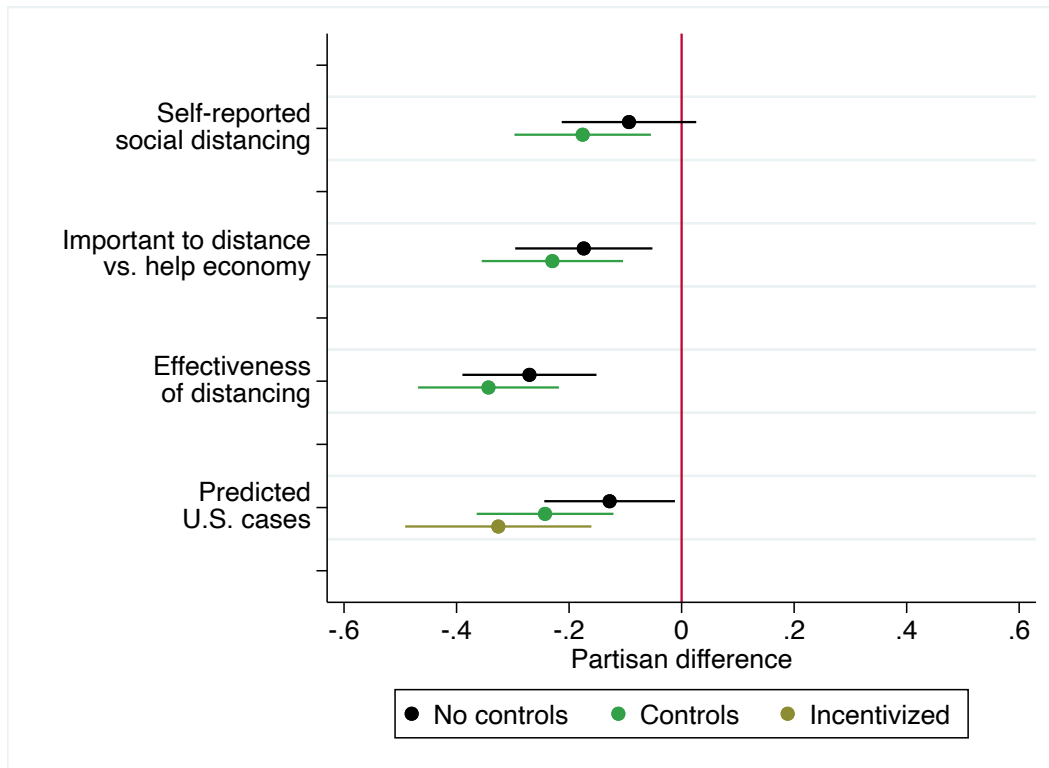
Note: This figure shows coefficient plots of regressing normalized measures of beliefs and actions on Republican party lean, without weighting observations. Negative values indicate less concern about COVID-19 or social distancing. Demographic controls are age, race, income, education, number of children, ZIP code logged population density, state, county-level deaths and cases. 2 percent of observations are set to the mean due to an invalid ZIP code. Incentivized includes controls and restricts sample to subjects given accuracy incentives. 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.

Appendix Figure A10: Effect of Incentives on Beliefs
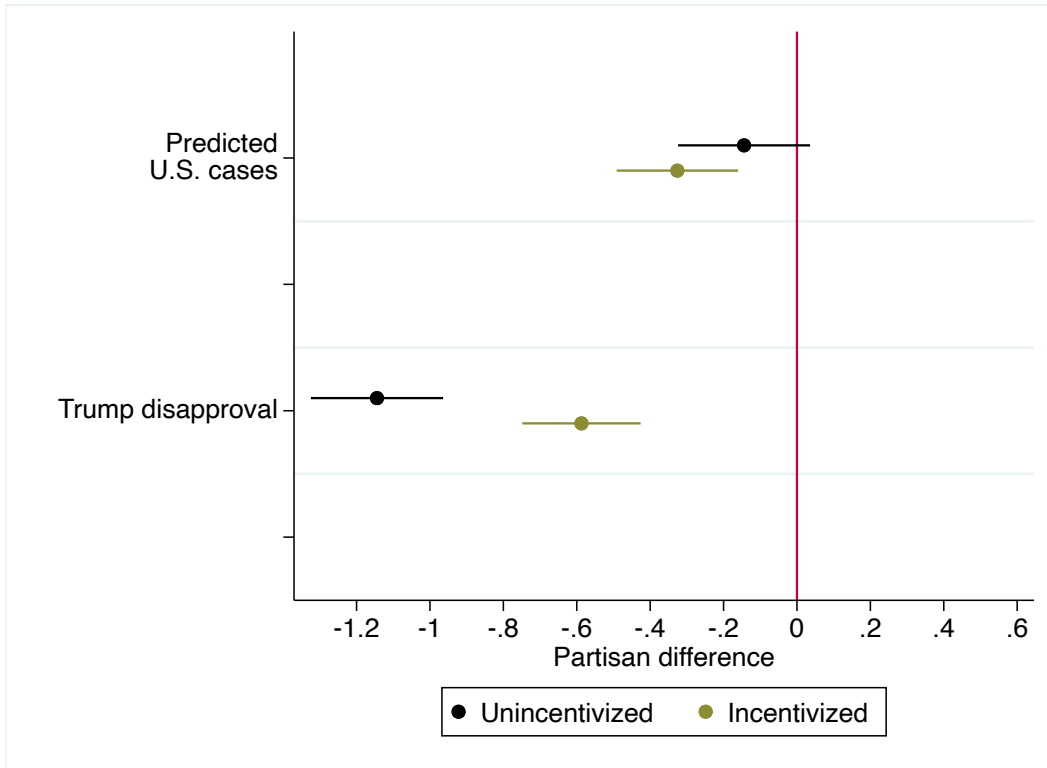
Note: This plot shows coefficient plots of regressing beliefs on Republican party lean, with and without incentives for getting close to the correct answer. Trump disapproval is a low-stakes question that is susceptible to partisan cheerleading (Bullock et al. 2015; Prior et al. 2015). These results 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.

Appendix Figure A11: Partisan Differences in Beliefs and Actions: County Fixed Effects

Note: This figure shows coefficient plots of regressing normalized measures of beliefs and actions on Republican party lean. Negative 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, county. 21.5 percent of observations are dropped due to an invalid ZIP code or unique county. Observations weighted to mimic a representative sample as described in the text. Incentivized includes controls and restricts sample to subjects given accuracy incentives. 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.

Appendix Figure A12: Partisan Differences in Social Distancing with Controls for Beliefs and News
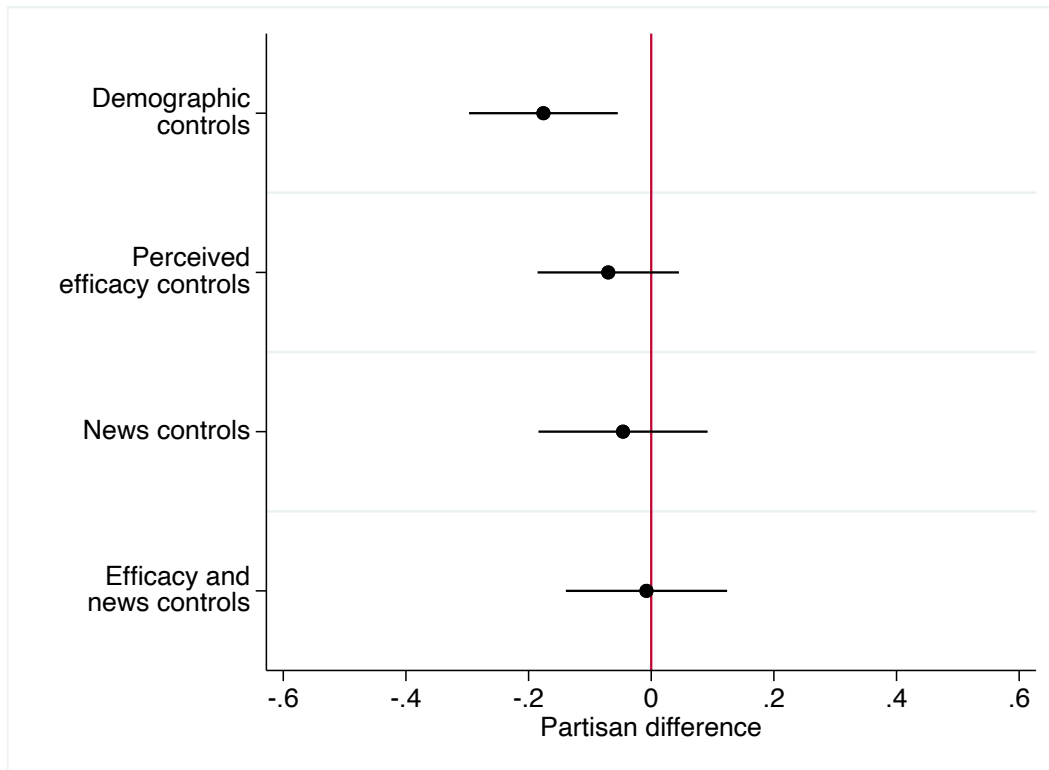
Note: This plot shows coefficient plots of regressing self-reported social distancing on Republican party lean, with and without controls for beliefs and news. Self-reported social distancing is the percent reduction in contact with others over one month. The first row includes only demographic control variables; the second additionally controls for subjects' normalized beliefs about the estimated likelihood of catching COVID-19 in one month without social distancing; the third controls for the partisanship in subjects' news habits; and the fourth controls for both. News habits average the partisanship of news consumption about politics and current events, news consumption about the coronavirus, trust in news about politics and current events, and trust in news about the coronavirus. 2 percent of observations are set to the mean due to an invalid ZIP code. Observations weighted to mimic a representative sample as described in the text. Error bars represent 95 percent confidence intervals.