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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 engaged 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.

1. Introduction

Public messaging in the US during the coronavirus pandemic has diverged sharply along partisan lines. President Trump and other Republican officials have sometimes downplayed the severity of the crisis, while Democratic leaders have given more emphasis to its dangers (Beauchamp, 2020; Stanley-Becker and Janes, 2020; Coppins, 2020; McCarthy, 2020). Similar divisions appear in partisan media (Aleem, 2020; Kantrowitz, 2020).

Nationwide surveys mirror the partisan divisions in elite messaging—with Democrats reporting more concern about COVID-19 and higher levels of social distancing than Republicans (see Fig. 1). 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. Furthermore, prior evidence shows that apparent partisan gaps in beliefs can shrink substantially when there are moderate incentives for accuracy (Bullock et al., 2015; Prior et al., 2015). Beliefs about the number of casualties in Iraq or the presidential approval rating have, for most people, few direct consequences. Beliefs about the severity of the pandemic and choosing whether to social distance, on the other hand, may be a matter of life or death. We ask whether partisan gaps persist in the face of these large incentives.

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 27, 2020 to July 12, 2020.

We 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

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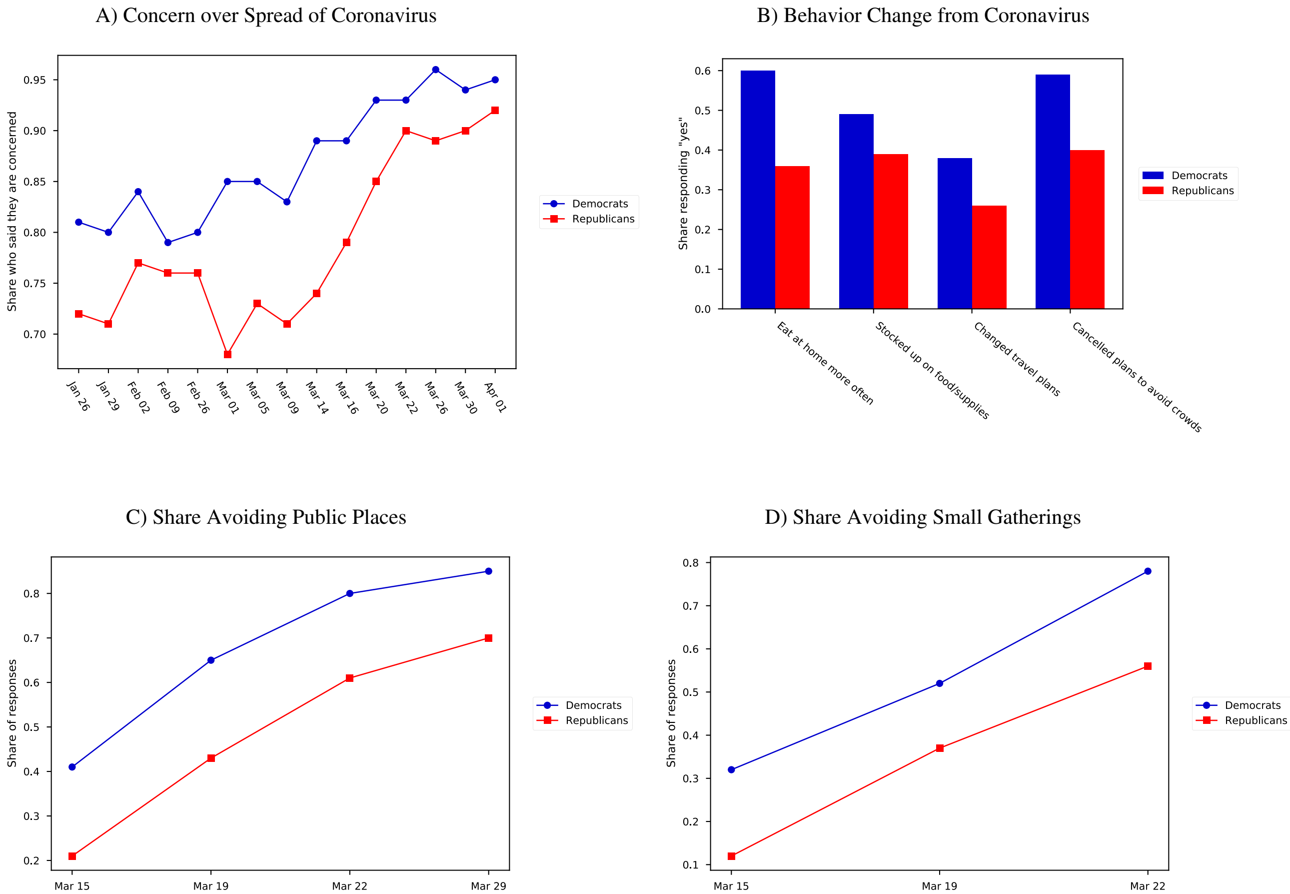

Fig. 1. Partisan differences in perceived risk and social distancing. Note: Figure shows responses to nationally representative polls by political affiliation. Panel A shows the share of people concerned about coronavirus spreading to the United States (Piacenza, 2020). Panel B shows self-reported behavior 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).

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). 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. Achieving a given level of social distancing in society will be more costly when otherwise similar agents have heterogeneous 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 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 11.5 and 15.2% increases in the number of POI visits during the weeks of April 6 and May 11, when social distancing and partisan gaps are at their respective peaks.

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 similar 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.

A number of contemporaneous studies also measure partisan differences in responses to COVID-19.[1] Gadarian et al. (2020), Makridis and Rothwell (2020), and Wu and Huber (2020) show that partisanship is a primary driver of attitudes about the pandemic and self-reported behaviors in surveys, and Druckman et al. (2020) show that affective polarization colors people's evaluations of the U.S.

[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. (Forthcoming) use transaction-level data and examine heterogeneity in consumption responses to COVID-19.

government response to the pandemic. Cornelson and Miloucheva (2020), Grossman et al. (2020), and Painter and Qiu (2020) demonstrate partisan differences in response to state-level stay-at-home orders. 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. Fan et al. (2020) find differences in risk perceptions and social distancing in GPS and survey data across political parties and other demographics. Our results are broadly consistent with these other studies, but we believe that our paper contributes to the discussion through a unique combination of observational data analysis, survey work, and a theoretical model that helps understand the economic implications of our results.

Ash et al. (2020), Bursztyn et al. (2020) and Simonov et al. (2020) find that people social distance less if quasi-randomly exposed to news sources that argue that COVID-19 is less risky, suggesting that media exposure is one possible driver for our results.[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). 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; Vaughan and Tinker, 2009). 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; 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, beliefs in the safety of vaccines, and hurricane evacuations (Hersh and Goldenberg, 2016; Lerman et al., 2017; Sances and Clinton, 2019; Trachtman, 2019; Krupenkin, 2018; Suryadevara et al., 2019; Long et al., 2019).

Finally, our work relates to broader literatures on partisan differences in trust and beliefs (e.g., Bartels, 2002; Gaines et al., 2007) and adds to the increasing number of papers using GPS or related data to study social interactions (e.g., Dubé et al., 2017; Chen and Rohla, 2018; Athey et al., 2019).

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

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 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 the 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:

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

The first-order condition for privately optimal risky behavior is

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

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?”

[2] Pastor and Veronesi (2020) also find that Democrats are more risk averse than Republicans. Differences in risk aversion would not explain the differences in beliefs we find in Section 5, but are a possible complementary explanation for the observed partisan gap in social distancing.

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}) and then 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 the externalities when choosing c_t^*.

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

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

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 $\mu_{t\theta} \coloneqq \beta i_t \delta(V_\theta(S) - V_\theta(I))$ 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 $\bar{\tilde{\mu}}_t \coloneqq \frac{1}{2}(\tilde{\mu}_{ta} + \tilde{\mu}_{tb})$ 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:

$$c^*_{tb} - c^*_{ta} = \frac{\tilde{\mu}_{ta} - \tilde{\mu}_{tb}}{-u''}. \tag{6}$$

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

$$\underbrace{\frac{\tilde{\mu}_{ta} - \tilde{\mu}_{tb}}{-u''}}_{\text{consumption difference}} \cdot \underbrace{\phi_t}_{\text{externality}}. \tag{7}$$

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:

$$\Delta W_t = \frac{s_t}{2} \cdot \frac{\left(\overbrace{\tilde{\mu}_{ta} - \bar{\tilde{\mu}}_t}^{\text{misperception}}\right)^2}{\underbrace{-u''}_{\text{slope of private marginal utility}}}. \tag{8}$$

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. Since the marginal cost of social distancing is increasing, 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. We use proxies to control for differences in actual risks and differences in the marginal costs of risk reduction—both of which 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) (SafeGraph, 2020). 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.

Our primary analysis uses data from a period of 24 weeks, from January 27 to July 12, 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, 2019 and updated regularly. We use data over the same 24 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 census block groups 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 the county level.[3] We add weather statistics on temperature and precipitation from gridMET (Abatzoglou, 2011), aggregated to the county-level.[4] 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).[5]

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, 2020 with Prime Panels from CloudResearch, a market research firm with access to 50 million participants. We recruited 2000 participants to complete the study. Participants are broadly representative of U.S. adults in terms of party affiliation, age, gender, and race. In addition, we weighted observations so that age, gender, and race distributions match 2010 Census data and party affiliation matches recent Gallup polling data (Gallup, 2020).

Participants were asked for their party affiliation on a seven-point scale, ranging from "Strongly Democratic" to "Strongly Republican." We transform the seven-point party affiliation scale to range between 0 (Strongly Democratic) and 1 (Strongly Republican), with intermediate values equally spaced.

The survey asked for demographic information (zip code, age, race, gender, income, education, number of children, and health characteristics). 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 US in April 2020, with 1013 subjects (51%) being financially incentivized for predictions that are closer to the correct answer.[6] The remaining 987 (49%) of subjects were not incentivized.

The primary four outcome variables are participants' answers to the three social-distancing questions and the one prediction question. These analyses correspond to the "main analyses" in our pre-analysis plan (AEA RCT Registry 5632). In the interest of space, we do not discuss the plan's "exploratory analyses" in this paper.

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

[4] We thank Jude Bayham for sharing aggregated versions of this dataset with the SafeGraph COVID-19 response community, originally constructed for Burkhardt et al. (2019).

[5] We combine policy data from: Keystone Strategy; a crowdsourcing effort from Stanford University and the University of Virginia; Hikma Health; and The New York Times (Athey et al., 2020; Ritchie et al., 2020; Noah et al., 2020; Mervosh et al., 2020).

[6] Participants who made financially incentivized predictions were told that we would randomly select 10 participants who would receive a payment of ($100 − Δ), where Δ is the percentage point difference between their answer and the true value.

4. SafeGraph empirical specification and results

Fig. 2 presents geographic variation in social distancing, partisanship, COVID-19 incidence, and stay-at-home orders. Panels A and B illustrate a strong geographic correlation between the counties with weaker social distancing responses during the week of peak social distancing (April 6–12, 2020) and those with higher Republican vote shares. However, partisanship is also strongly correlated with COVID-19 incidence (Panel C) and earlier stay-at-home orders (Panel D).

Fig. 3 reports trends in social distancing and COVID-19 incidence separately for Republican and Democratic counties. Panel A shows that the overall number of POI visits was relatively constant until COVID-19 cases begin emerging in the United States in March. Mobility levels then fell until reaching a minimum during the week of April 6–12, 2020, followed by a gradual recovery that remained below pre-pandemic levels as of July 6–12, 2020. Throughout this pandemic period, Democratic counties exhibited a larger drop in weekly POI visits than their Republican counterparts with this partisan gap generally growing over time. However, as Panel B demonstrates, Democratic counties also exhibited a larger rise in COVID-19 cases and deaths. Appendix Fig. A1 shows that, over the same time period in 2019, POI visits displayed a noticeable but smaller partisan gap.

Our main empirical specification takes the following form

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

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, μ_i and ζ_t represent county and week fixed effects respectively, X_{it} are non-parametric and time-varying controls, and ε_{it} is the county-specific error term.[7] We chose our covariates X_{it} to flexibly control for the four channels of divergent behavior highlighted in Eq. (2). Standard errors are clustered at the state-level throughout unless specified otherwise.

Fig. 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 channels. Throughout February, there are no significant partisan differences in POI visits relative to the January 27 week baseline. However, as COVID-19 begins to emerge in the United States, partisan differences arise and grow throughout the weeks of March and persist at least through early July.

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 only slightly.[8]

In Panel C, we flexibly control for various health,[9] economic,[10] and weather[11] characteristics of the county. We view the health controls

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

[8] State-time fixed effects also control for the partisan alignment between the governor and the state population, which may impact responses to social distancing orders (see, e.g., Painter and Qiu, 2020).

[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 ≥$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 averaged across days within a week.

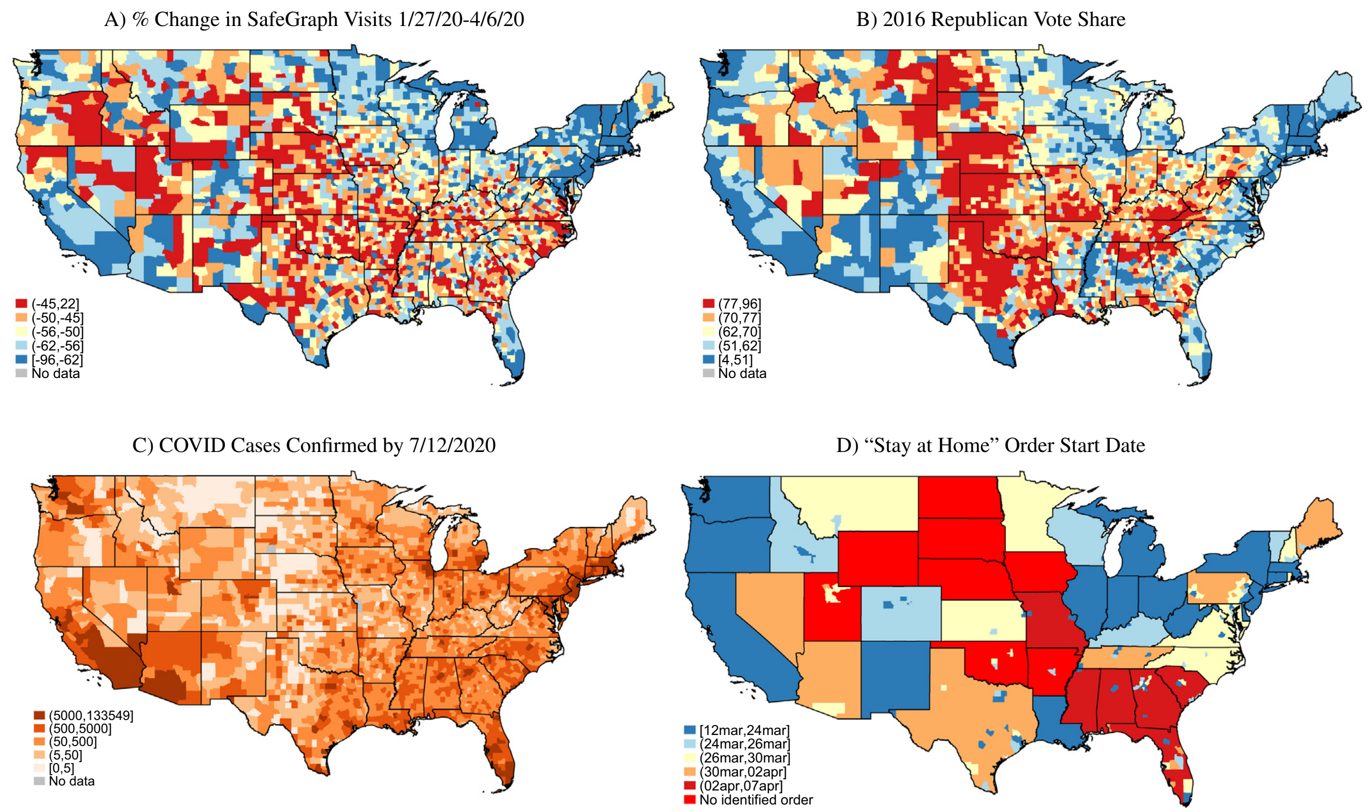

Fig. 2. Geographic variation in social distancing, partisanship, COVID-19, and public policy. Note: Figure shows the U.S. geographic distribution of social distancing, political affiliation, COVID-19, and public policy responses. Panel A shows, for each county, the percent change in aggregate visits between the week beginning January 27, 2020 and the week beginning April 6, 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 Republican presidential vote shares in the 2016 election. Red shading in this panel indicates more Republican counties, and blue shading indicates more Democratic counties. Panel C shows for each county the number of COVID-19 cases confirmed by July 12, 2020 (sourced from The New York Times). Panel D shades US 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.

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, which we interact with time fixed effects in order to allow the coefficients on these indicators to vary flexibly across time. Although these controls attenuate partisan differences, they remain economically and statistically significant. Appendix Fig. 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 relative to January. The estimate of our partisan gap coefficient α_t is 0.292 by the week starting April 6 (the week with the fewest number of visits) and 0.386 in the week starting May 11 (the week with the largest partisan gap). These estimates imply that going from a county with the 10th to the 90th percentile in Republican vote share is associated with 11.5 and 15.2% increases in the number of POI visits during these two weeks respectively.[12] The 11.5% gap during the week of April 6 corresponds to 6.5% of the total change in POI visits between the weeks of January 27 and April 6, and the partisan gap during the week of May 11 is comparable in size to 15.0% of the total change in POI visits between the weeks of January 27 and May 11.[13] The partisan gap in social distancing between very Republican and very Democratic counties is economically meaningful but only accounts for a limited portion of overall social distancing.

In Appendix Fig. 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 that are very small (less than 3000 people), very large (greater than 500,000 people), or are in 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 July.

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

13 Between the weeks of January 27 and April 6 (May 11), POI visits decreased by 64.0 (50.3) percent. We compare the fraction of this overall change equivalent to our 90th vs. 10th percentile partisan gap: $\frac{(0.115 \times visits_{Apr6})}{(visits_{Jan27} - visits_{Apr6})} = 0.115 \times \frac{(visits_{Apr6}/visits_{Jan27})}{(visits_{Jan27} - visits_{Apr6})/visits_{Jan27}} = 0.115 \times \frac{0.360}{0.640} = 0.065$. The fraction of social distancing during the week of May 11 is similarly derived.

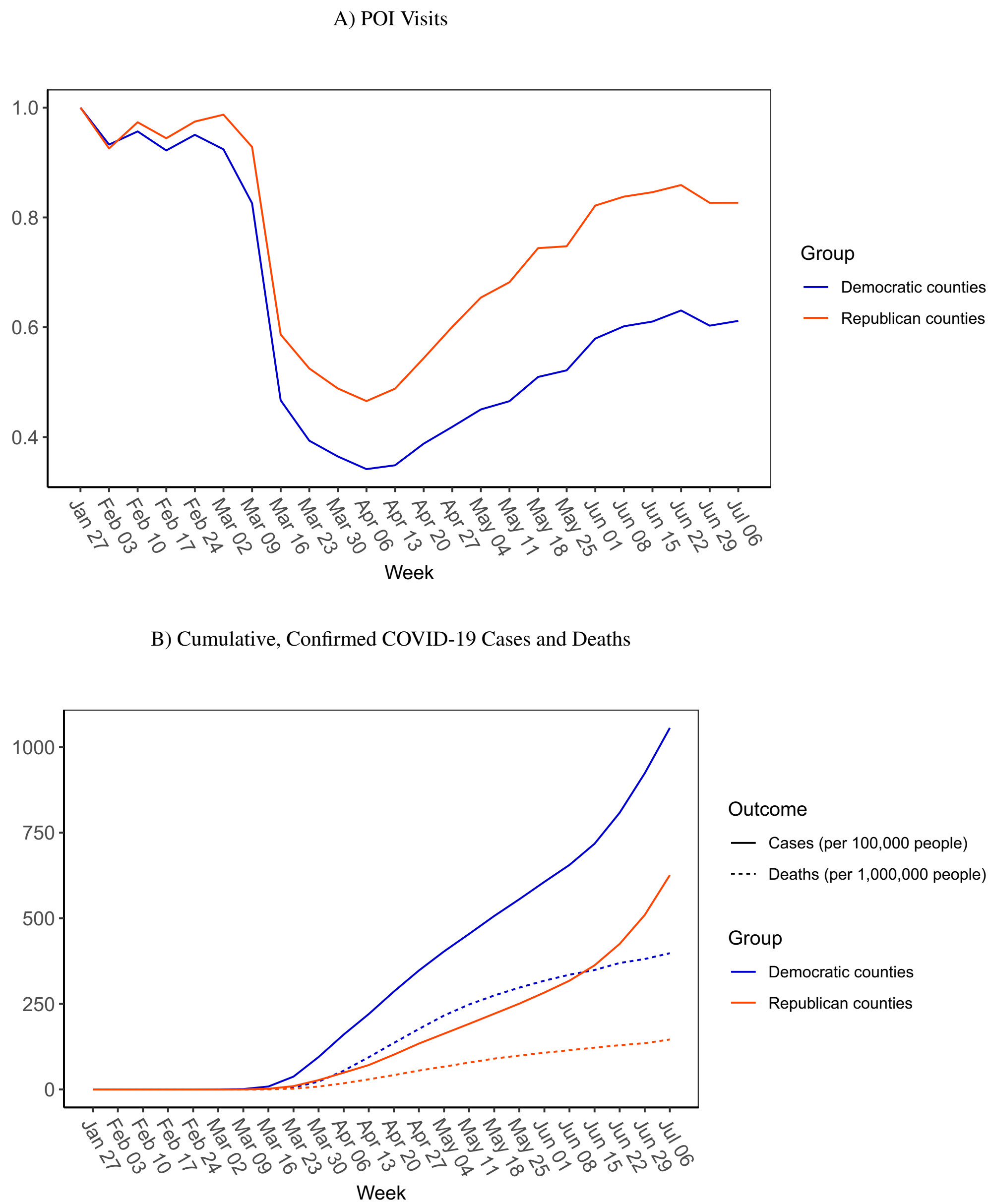

Fig. 3. Social distancing and COVID-19 incidence. Note: Panel A shows the number of visits (normalized to one) to SafeGraph POIs for each week since January 27, 2020 for Republican counties and Democratic counties separately. Panel B is analogous but plots cumulative, end-of-week values for confirmed COVID-19 cases (per 100,000 people) and confirmed COVID-19 deaths (per 1,000,000 people). Republican counties are defined to be those whose 2016 Republican vote share is greater than the median vote share (66.4%) 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.

Appendix Fig. A4 aggregates the number of POI visits at the electoral precinct level and shows similar partisan gaps, even when including county-time fixed effects. Again, these patterns are not present in 2019 (Appendix Fig. A5). Precinct-level analysis faces several limitations that lead us to prefer our county-level specification.[14]

[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 42 states (see Appendix A.1.2). 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.1.2, 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.

Appendix Fig. A6 examines heterogeneity across industries by 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. The partisan differences in visits to health care POIs are generally smaller and are statistically significant in fewer weeks.

Appendix Fig. A7 repeats Panel C of Fig. 4, but uses POI visits aggregated at the day level. The partisan differences emerge for both weekdays and weekends, suggesting these differences are not driven solely by differences in work-from-home policies.

Appendix Fig. A8 considers alternative measures of social distancing derived from SafeGraph's Social Distancing data. Statistically significant partisan differences emerge in March through at least early July 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

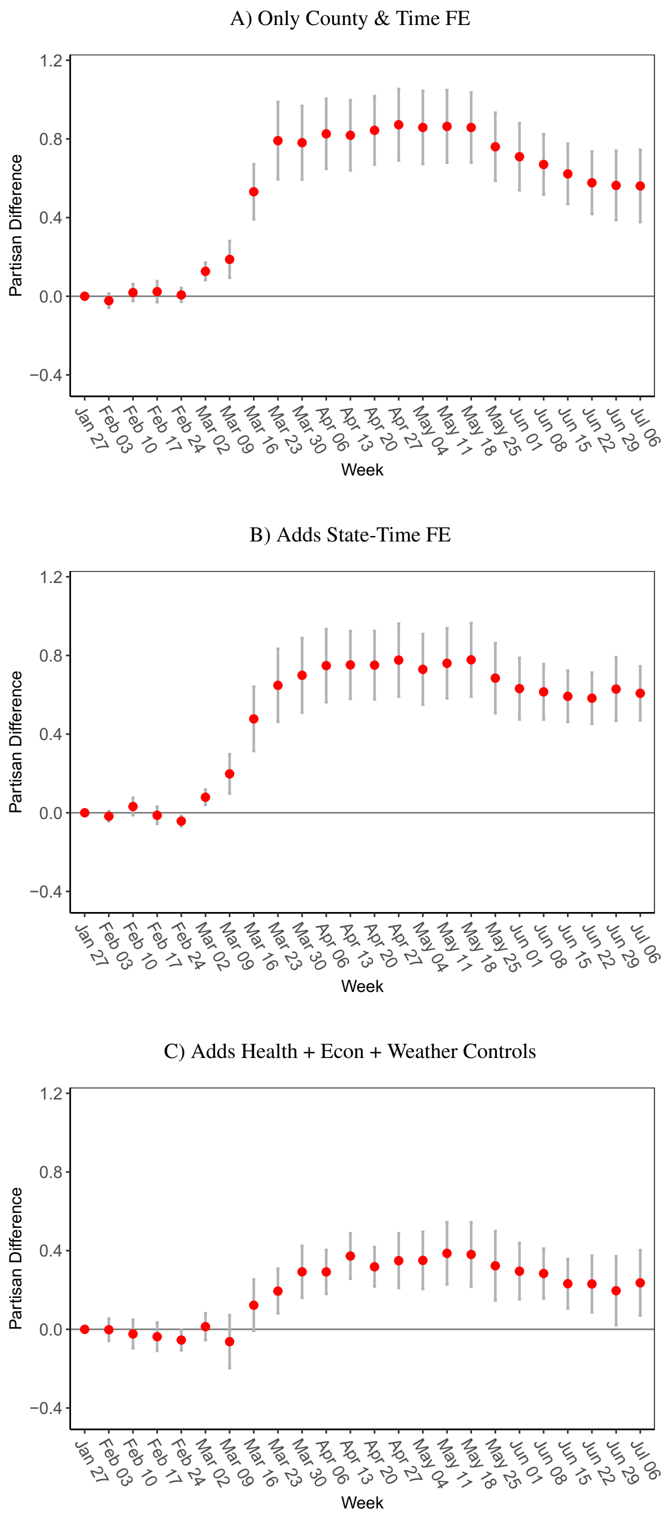

Fig. 4. Partisan differences in social distancing. Note: Figure shows the estimated coefficients for county Republican vote share ρ_i on the log number of POI visits in the county. For Panel A, only county and time fixed effects are included as controls. Panel B is the same as Panel A except state-time 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% confidence intervals constructed using standard errors clustered at the state-level.

home (Panel A), and the share of devices leaving home (Panel B).[15] 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 the log number of stops made in non-home census block groups, we find an economically and statistically significant partisan gap emerge starting in April and persisting through early July (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 individuals' beliefs related to COVID-19 are strongly associated with their social distancing behaviors. We find that a one standard deviation (SD) increase in beliefs about the efficacy of social distancing, as described below, is associated with a 0.323 SD increase in self-reported social distancing (SE 0.022; $p < 0.001$), controlling for demographic characteristics and state fixed effects. Similarly, a one SD increase in beliefs about the number of future cases in the US is associated with a 0.066 SD increase in self-reported social distancing (SE 0.023; $p = 0.004$).

Next, we show that there exist individual-level partisan differences in (self-reported) social distancing behaviors and attitudes, consistent with the GPS analysis 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.

Fig. 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%, with a SD of 24.5%. After including controls, strong Democrats report engaging in 0.18 SD more contact reduction than strong Republicans. This corresponds to a gap in contact reduction of 72.1% for strong Democrats versus 67.8% 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 partisan differences in underlying beliefs regarding COVID-19 severity and efficacy of social distancing. We find that Democrats' belief regarding the probability of catching COVID-19 without any social distancing is higher than the analogous belief held by Republicans. On average, participants assess this probability to be 55.0% (SD 31.9%). Strong Democrats believe this probability is 60.5%, which is 0.34 SD larger than the 49.6% belief held by strong Republicans.

We next consider beliefs about future COVID-19 cases in the entire US. 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 231,129 future cases on

[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 Appendix Fig. A8 footnotes for correction).

[16] These differences are also present when we do not weight observations for national representativeness, as shown in Appendix Fig. A9. For detail on observation weights, see Appendix A.2.1.

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

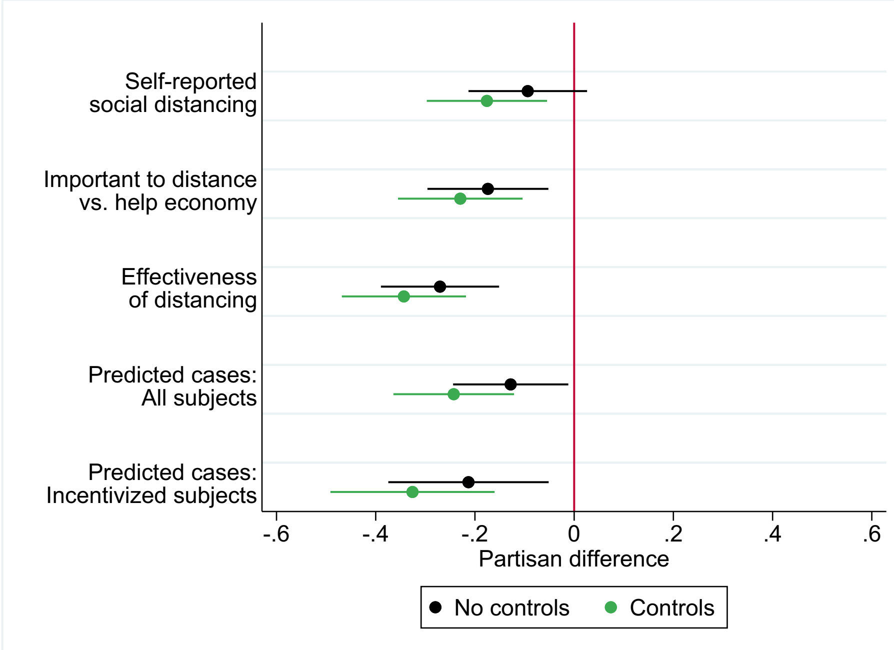

Fig. 5. Partisan differences in beliefs and actions. Note: Figure shows coefficient plots from regressing normalized measures of beliefs and actions on our seven-point measure of partisan affiliation which ranges between 0 (Strongly Democratic) and 1 (Strongly Republican). Negative estimates indicate less concern about COVID-19 or social distancing. Demographic controls are age, race, income, education, number of children, log population at the ZIP code level, county-level deaths and cases, and state fixed effects. 2% of observations are set to the mean due to an invalid ZIP code. 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; predicted cases are predictions about the number of new COVID-19 cases in the US in April; incentivized subjects restrict to the subsample whose answers are incentivized. Observations are weighted to mimic a representative sample as described in the text. Error bars represent 95% confidence intervals.

average, which is 0.24 SD more than the 174,491 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. When 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 Fig. A10 shows that on an explicitly political question, incentives do significantly reduce the partisan gap, consistent with previous findings.

Appendix Fig. A11 shows that comparing individuals within the same county produces qualitatively similar results, complementing the county-level partisan gap observed in the GPS analysis. However, since 21.5% of participants are the only participant from their county, statistical precision is lower and low-population counties are underweighted.

Finally, we do a back-of-the-envelope estimation of the deadweight loss from Eq. (8). We assume that agents have the same quadratic flow utility functions $u(c) = \frac{\nu}{2}c^2 + \eta c + k$ and normalize parameters so that $c^* = 1$ is the amount of risky behavior chosen in the absence of the coronavirus. (Formally, if $\beta = 0$, all agents choose $c^*(0) = 1$, i.e., $\nu = -\eta \le 0$.) We then consider what happens when partisan perceptions differ about infectiousness β. From our survey, we find that the median participant's willingness-to-accept for "cutting off all in-person contact with people outside your household for one month" versus "following your normal routine" (i.e., one month of $c = 0$ instead of $c = 1$) is \$1500. From the survey data above, we approximate that Democrats reduce consumption by 72.1% and Republicans reduce by 67.8%. This difference implies that, after controlling for observables that measure private costs and benefits of social distancing, Democrats perceive that the expected utility loss from following normal routines instead of cutting off all contact is $\tilde{\mu}_{tR} - \tilde{\mu}_{tD} = 129$ per month higher than what Republicans perceive.[20]

Plugging the perceived utility loss estimates into Eq. (8), 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 US and 99% of the country being susceptible, we estimate that partisan differences in risk misperceptions generate a deadweight loss of approximately $\Delta W = \$8.24$ per person per year, or \$2.7 billion for the US per year.

6. Conclusion

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

[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 misunderstanding of exponential growth, generic overoptimism, anchoring (177,226 was given as the reference number for cases by March 31), or to some other factor.

[19] The gap slightly increases, though the effect is statistically insignificant. Regressing predictions on the interaction between party and incentives corresponds to the specification in our pre-analysis plan.

[20] We use the willingness-to-accept data to say that $u(1) - u(0) = \frac{1}{2}\eta = 1500$, so that $\eta = \$3000$. Then, using that Republicans choose consumption $c^*_{tR} = 1 - 0.678 = 0.322$ and Democrats choose $c^*_{tD} = 1 - 0.721 = 0.279$, we have from Eq. (6) that $0.322 - 0.279 = \frac{\tilde{\mu}_{tR} - \tilde{\mu}_{tD}}{3000}$, so that $\tilde{\mu}_{tR} - \tilde{\mu}_{tD} = 129$.

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.

One explanation for these results is that media sources have sent divergent messages about the coronavirus Appendix Fig. A12 shows that the partisan gaps in the survey data are smaller when the partisanship of news consumption is controlled for, and that news partisanship is statistically significantly correlated with beliefs even when party is controlled for. While our evidence does not permit us to pin down the ultimate causes of partisan divergence, these patterns are consistent with divergent messaging playing an important role in driving differences in beliefs and behavior.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jpubeco.2020.104254.

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