

The Real Cost of Political Polarization: Evidence from the COVID-19 Pandemic

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Abstract

This paper examines the role of political factors in mediating the formation of beliefs among individuals and the adoption of regional policies in the United States. First, using comprehensive and nationally representative data on over 47,000 individuals available from March to July, we document that heterogeneity in beliefs about the SARS-CoV-2 pandemic and social distancing behaviors is driven primarily by political affiliation, mattering even more than factors directly connected to the disease, such as individual age and county infections. Second, we examine how political partisanship arising from these differences in beliefs about the virus propagate into the adoption of state policies. The adoption of these nonessential business closures and stay-at-home orders are associated with declines in retail visits, credit card spending, and small business revenue growth, relative to the pre-pandemic trend. In contrast, mask mandates reduce the spread of the virus at least as much and have none of the adverse economic effects. Our results provide evidence in favor of Majoritarian Electoral Democracy theories by showing that the average voter matters, countering the view that politics is driven purely by interest groups and elites.

Keywords: Beliefs, Coronavirus and COVID-19, Economic Disruption, Expectations, Partisanship, Political Affiliation, Social Distancing.

JEL Codes: E66, E71, I12, I31

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I. Introduction

There is now a large literature examining the effects of the COVID-19 pandemic, especially the resulting state and national quarantines, on employment (Coibion et al., 2020a; Cajner et al., 2020), consumption (Baker et al., 2020; Chetty et al., 2020), and real output (Guerrieri et al., 2020; Makridis and Hartley, 2020). Although national guidelines had an effect, states hold considerably more power in the United States than the Federal government in terms of setting and enforcing public health regulations. For example, there is already evidence that state policymaking has had a substantial effect on household expectations (Coibion et al., 2020b) and the supply of certain jobs (Ali et al., 2020). Along these lines, several papers have found that state health policies have had real effects on social-distancing behaviors and slowing the growth rate of infections (Sears et al 2020; Courtmanche et al. 2020; David et al 2020; Lyu et al ,2020). However, there is still an ongoing debate about the economic consequences of these policies, including Chetty et al. (2020) arguing that health concerns were more important than state policies in affecting consumption expenditures.

Using the most comprehensive and nationally representative panel data available to date in the United States from March to July 2020, this paper investigates how households form beliefs about the coronavirus pandemic and the resulting effects on economic activity. Motivated by a large literature about the sources of inattention (Gabaix, 2019), coupled with evidence about the role of politics (Allcott et al., 2020; Bursztyrn et al., 2020), we focus on political affiliation as a mediating factor and how it may have prompted states to adopt suboptimal policies. For example, according to Gallup in late May 2020, 79% of Republicans reported that the coronavirus situation was getting better, compared to only 22% of Democrats.² Moreover, these individual partisan differences have real economic effects: they correspond with meaningful institutional differences across states. For example, Figure 1 shows that political affiliation is closely tied with policy decisions: there is a 20

² <https://news.gallup.com/poll/312014/optimism-pandemic-less-duration.aspx>

percentage point (pp) difference in the probability that a state adopts a state shut down order and a 40pp difference in the probability that a state adopts a mandatory mask-wearing policy based on the winner of the 2016 election.³ These differences in state policies are also associated with large differences in economic outcomes, including: retail visits, small business growth, and consumption.

[INSERT FIGURE 1 HERE]

The first part of the paper introduces our data from Gallup between March 13th and July 26th. We document substantial differences in attitudes about the pandemic and economic disruption across party lines and over time since the declaration of a national emergency by President Trump on March 13. These differences are not explained by local exposure to the virus, population density, or other observable factors. We show that our data is nationally representative, in relation with the Current Population Survey, with the advantage of having daily variation and county identifiers.

The second part of the paper quantifies the quantitative importance of political affiliation of typical determinants of beliefs about the pandemic and the economy. In contrast with the large literature on the role of personal experience (Malmendier and Nagel, 2011; 2016), even among firms (Coibion et al., 2018), we find that local fluctuations in new infections and unemployment insurance claims have very weak predictive power over our measures of beliefs. Moreover, we also find that measures of infections mediated through social networks also play less of a role, in contrast to Makridis and Wang (2020). This makes sense since people are not interacting as much with one another, meaning that there is less margin for personal encounters and information gathering through observation of the local environment to inform beliefs—and greater reliance on media sources, which are heavily filtered by partisanship (Gallup and Knight Foundation 2018). Instead, political affiliation remains the most important predictor—even more significant than, for example, age, gender, race, college attainment, or even whether the person has a serious medical condition.

³ Figure A.1 in the Online Appendix shows that the 2016 Trump vote share is representative of current attitudes.

The third part of the paper investigates whether political affiliation also plays a mediating role on real economic outcomes. After controlling semi-parametrically for the age, education, race, and even industry distribution, we show that a 1 percentage point (pp) increase in the vote share for Trump in 2016 is associated with a 1.86pp and 1.82pp decrease in the probability of a state passing a stay-at-home order (SAHO) and a nonessential business closure. Our data also enables us to provide direct microeconomic evidence in favor of Majoritarian Electoral Democracy theories with the presence of polarization. For example, Republicans *or* Democrats, relative to Independents, are 9-13pp less likely to approve of the state government policy response to the pandemic on average, but they are 26-28pp more likely to approve if their governor is of the same party. Moreover, we do not find that different interest groups, which we proxy using occupation, or that elites, which we proxy using income, drive approval of state policy responses. Motivated by the evidence, we find that states that adopted stricter policies also exhibited sharper declines in economic activity. For example, the adoption of a SAHO and nonessential business closure is associated with a sharp decline in retail visits and more modest 1-4% declines in credit card spending and small business revenue growth, relative to the January baseline. Importantly, the adoption of mask policies is not statistically related with declines in credit card spending or small business revenue growth.

Furthermore, we show that, while nonessential business closures are not associated with declines in the spread of the virus, SAHOs and mask requirements in public were associated with a 0.7% and a 1% decline in infections, respectively. Given that mask requirements are not associated with declines in economic activity, and are associated with even greater reductions in the spread of the virus, we interpret these middle-of-the-road policies as pareto improving, consistent with the view from Acemoglu et al (2020) that the optimal disease-suppression policy balances economic concerns with minimizing mortality through lockdown requirements. Given the wide variation in risk by age, they conclude that targeted lockdowns could limit mortality with only modest economic

losses. These targeted interventions have been implemented in Hong Kong, Taiwan, Japan, South Korea, and Iceland, while simultaneously deploying mask-wearing, contact tracing, quarantine, and testing to various degrees not observed in the United States (Cheng et al 2020; Rothwell, 2020).

Our paper contributes closely to a literature on political polarization, including how different news outlets can provide very different coverage on the same topic (Benkler et al., 2018), how selective exposure to information affects attitudes and behaviors (Martin and Yurukoglu 2017; Durante et al., 2019), and the role of the media has played towards these patterns (Gentzkow et al., 2014). However, there is still debate about the causes and consequences of political polarization. We add to the available evidence using data on individuals between March and July exploiting variation over the pandemic to trace out the response of beliefs about the coronavirus and social distancing behaviors. We provide microeconomic support for Majoritarian Electoral Democracy theories of politics (Gilens and Page, 2014), showing that political affiliation, and whether the respondent is the same party as their governor, is the most important predictor of their approval about state policies. Moreover, we build on Allcott et al. (2020) and Bursztyn et al. (2020) by showing how political affiliation not only affects beliefs, but also influences the adoption of state policies that affects economic activity. We are not aware of prior literature that has been able to cleanly quantify the factors behind these differences in state policies from the perspective of the pandemic.

We also build on several other surveys eliciting beliefs. Wozniak (2020) developed the COVID Impact Survey (CIS) to track well-being and physical health at a high frequency, finding large declines in self-reported well-being across space and demographic brackets. Our results are also consistent with Papageorge et al. (2020) who use the large-scale survey effort from Belot et al. (2020) to study the correlation between attitudes about the pandemic and socio-economic characteristics. They find that individuals with lower income and less flexible income arrangements are less likely to engage in social distancing behaviors. Fetzer et al. (2020) investigate a global dataset of internet

searches and cross-sectional data from the United States, finding that beliefs about the pandemic are associated with beliefs about economic anxiety and that the framing of information by the media exerts a large effect on beliefs. Binder (2020) also shows that beliefs about the pandemic are associated with measures of economic confidence, such as unemployment and inflation. We extend these results to additional measures, including beliefs about economic disruption, mask-usage, visiting work, and worrying about the virus, explain the dispersion in these beliefs, and quantify their effects on realized economic activity using new and nationally representative panel data.

The second is a separate macroeconomic literature about the effects of beliefs on real economic activity. While Mian et al. (2018) argue that that political partisanship affects economic sentiment, but sentiment does not affect consumption, an ongoing debate remains. For example, using the University of Michigan Survey of Consumer Sentiment, Benhabib and Spiegel (2019) provide state-level evidence that changes in economic activity are correlated with changes in sentiment about national conditions. Moreover, Gillitzer and Prasad (2018) exploit changes in the government party in power to identify the effects of expectations on an intent to spend more in the future. Makridis (2020) uses data from Gallup to quantify the effects of economic sentiment on non-durables consumption, exploiting plausibly exogenous variation in exposure to different social networks. Kamdar and Ray (2020) build a model where disagreement about macroeconomic fundamentals leads to changes in consumption and Bianchi et al. (2020) show how distortions in beliefs can create over-optimism that leads to systematic changes in aggregate productivity.

The structure of the paper is as follows. Section II summarizes our data and measurement strategy focusing on the new facts from the Gallup micro-data. Section III quantifies the factors that affect beliefs and predicts the adoption of state disease-suppression policies. Section IV estimates how these policies affect health outcomes and economic outcomes and how politics mediates these

outcomes. Section V evaluates the public health effects of these state policies and pairs these with the costs. Section VI discusses the implications for macroeconomic models. Section VII concludes.

II. Data and Measurement

Our individual survey-based data are from Gallup's COVID Tracking Survey. Gallup fielded the survey on March 13, 2020 and collected roughly 1000 responses per day until April 26th when the sample declined to roughly 500 responses per day. The survey remains in the field, but we restrict our analysis to July 26th as the cutoff date. Our sample is a subset of the Gallup panel, which is representative of the U.S. population with approximately 100,000 members contacted via random-digit dialing. Our sample has 102,750 responses from 47,536 unique individuals who completed the survey online or using a smartphone after receiving an emailed invitation. While no one in the sample has more than three responses, the presence of at least some longitudinal variation is a substantial advantage over traditional surveys in this literature because it allows us to trace out how a given individual has adjusted their expectations over the duration of the pandemic, rather than relying on repeated cross-sections based on limited observable characteristics. Nonetheless, we use weights based on age, gender, education, region, race, and Hispanic ethnicity to ensure the sample is nationally representative. Out of an abundance of caution, we benchmark the sample with the Current Population Survey between March and April in Table A.1 of the Online Appendix.

Our Gallup data has contains the zip code for every respondent, allowing us to match confirmed COVID-19 cases and deaths from USA Facts at the county-level, together with county unemployment insurance (UI) claims from various state agencies and demographic characteristics from the Census Bureau's American Community Survey (ACS).

We focus on six major outcome variables, which we detail in Table 1. We have a mix of economic sentiment and pandemic response variables. For example, our measure of expected disruption captures the degree of economic impact from COVID-19 on business and organizational

closures. We also have several variables measuring expectations about the severity of the virus and individual responses to these concerns. Individuals report their degree of social distancing, self-isolation, and wearing a mask. Broadly speaking, these variables reflect expectations about the pandemic, rather than specifically about the economy as in Coibion et al. (2020).

[INSERT TABLE 1 HERE]

Figure 2 documents significant cross-sectional and time series variation in these attitudes. For example, in early April, roughly 32% of Republicans were visiting the workplace, whereas only 20% of Democrats were. By late July, the share among Republicans climbed to nearly 40%, whereas the share among Democrats remained roughly the same, although it had climbed to 25% by late June. We also see an even larger gap in the share of respondents who are very worried about COVID-19. On average, roughly 20% of Democrats were very worried in April, but it grew to 25% in June before it fell back to 20% in late July. However, the share fell among Republicans from 8% in April to roughly zero by late July, highlighting a substantial wedge. The wedge is even greater when focusing on the share of respondents participating explicitly in social distancing behaviors.

Even though Republicans and Democrats were equally participating in social distancing almost always as of April, the share fell to 40% by late July for Republicans, although it has increased slightly to 100% among Democrats. Self-isolation exhibits a similar wedge, but it fell even more for Republicans from 65% in early April to 30% in late July for Republicans (versus 80% to 60% for Democrats). Nonetheless, we see greater convergence among the share of Republicans and Democrats wearing a mask (80% and nearly 100%, respectively, as of late July), as well as expectations about a significant economic disruption lasting until at least the end of the year (60% for Republicans and 100% for Democrats, respectively, as of late July).

[INSERT FIGURE 2 HERE]

To understand how beliefs translate into differences in state policies, we obtain the start and end dates of state stay-at-home-orders and closures of non-essential businesses from Institute for Health Metrics and Evaluation (IHME). Using data current to the end of July, we construct indicators for each state policy. We have also examined other policies (e.g. bans on social gatherings and school closures), but, because there is much less within-state variation, we focus on important policies with greater variation. We follow Lyu et al (2020) and use Boston University School of Public Health's COVID-19 policy database to measure variation in the start-date of mask policies. This database includes the start-date of policies that require face masks to be worn in public and those that require workers to wear them in public-facing businesses (e.g., grocery stores).

Our daily data on positive tests confirming COVID-19 cases and deaths are from USAFacts, which pulls the original data from state health departments. We have these data through the end of July, 2020. We also pull state and county demographic data from the U.S. Census Bureau, land area data from the Missouri Census Data Center's geographic correspondence engine, the U.S. Department of Labor on state unemployment insurance claims, and the Opportunity Insights Project for other county-level economic outcomes. Data on 2016 Presidential election results by county are from Tony McGovern who created the database from news sources.

III. Evaluating the Determinants of Household Expectations and Behaviors

To estimate the determinants of household expectations about the pandemic and degree of economic disruption, we consider regressions of the following form:

$$y_{ict} = \gamma P_{ict} + \zeta COVID_{ct} + \phi D_{ict} + \eta_c + \lambda_t + \epsilon_{ict} \quad (1)$$

where y denote individual i 's outcome in county c and day-of-the-year t , P denotes indicators for Republican and Democrat political affiliation (normalized to moderates), $COVID$ denotes the logged number of new COVID-19 cases per capita, and D denotes a vector of

individual demographic characteristics, and η and λ denote fixed effects on county and day-of-the-year. We cluster standard errors at the county-level to allow for arbitrary degrees of autocorrelation (Bertrand et al., 2004). We focus on the six major outcome variables from Section II, which we bin as binary variables and estimate linear probability models so that we can easily include fixed effects. We also experimented with the number of unemployment insurance claims as a share of the county workforce and a proxy for exposure to COVID-19 from the respondent's social network from Makridis and Wang (2020), but we omit these from the main results because they are insignificant.

Table 2 documents these results. Measured by the t -statistic, we find that political affiliation is the most important predictor of expectations of economic disruption and mask-usage, and second-only to either educational attainment or the existence of a medical condition on other outcomes regarding fear, social-distancing, and visits to work. For example, Republicans are 18% less likely to believe that the COVID-19 disruption will last until the end of the year, whereas Democrats are 11% more likely, relative to independents or those who prefer an "other" party. To put that in perspective with other correlates, we see that a 10% rise in the number of new infections per capita is associated with a 0.1% increase in the probability of expected disruption, which is only significant at the 10% level. Moreover, political affiliation is statistically and economically even more predictive of beliefs of severe economic disruption from coronavirus than employment status (they are 8% less likely to expect significant disruption) and even more predictive than having a medical condition (they are 5% more likely to expect significant disruption). Gender, age, education, and race all rank less statistically and economically important as well.⁴

⁴ We do not believe that these trends can be explained by partisan differences in the levels of trust in government. In separate surveys, Democrats and Republicans have similar levels of trust in local or state government, and Republicans report far higher levels of trust in the current Executive Branch and slightly higher levels of trust for the legislative and judicial branch than Democrats. <https://news.gallup.com/poll/243563/americans-trusting-local-state-government.aspx> and <https://news.gallup.com/poll/243293/trust-legislative-branch-highest-nine-years.aspx>

In unreported results, we find that the unemployment rate—the number of UI claims divided by the employment level in 2018—and the SCI-weighted infections per capita are uncorrelated with these attitudes about the pandemic with the exception of economic disruption as an outcome variable. But, even here the magnitude of these two factors is economically insignificant. The fact that unemployment is not correlated with beliefs about the pandemic and disruption suggests that local factors and personal experience are dwarfed in significance by the role of political affiliation, which influences the way people process and attend to different information.

We see similar patterns when we look at other outcome variables. For example, Republicans are 4% less likely to report being somewhat or very worried about getting the illness, Democrats are 6% more likely, relative to moderates. As expected, increases in actual local infections raises concerns about contracting the virus. Here, employment status matters at least as much as political affiliation: those employed in a job are 6% less likely to worry about getting sick, perhaps reflecting that many are working remotely (Brynjolfsson et al., 2020). Likewise, we see that those with serious medical problems are 8% more likely to worry about getting sick, which reflects not only a potential selection effect, but also the possible heightened exposure to coronavirus.

Turning to our remaining attitudinal outcomes, we see that Republicans are 7% less likely to social distance very often or always, 8% less likely to self-isolate mostly or completely, and 10% less likely to wear a mask, relative to moderates, whereas Democrats are 7%, 6%, and 9% more likely, respectively. Interestingly, increases in infections per capita are not statistically or economically associated with attitudes or behaviors around social distancing and self-isolation. We also find that Republicans are 5% more likely to visit work at least once in the past day, whereas Democrats are 4% less likely. Compliance with public health guidelines is increasing in educational attainment and, in unreported regressions, we find omission of political affiliation further raises its *t*-statistic. Future

work could explore to what extent this is related to being more informed about those guidelines and their value, including remote work (Gallipoli and Makridis, 2020; Dingel and Nieman (2020).

[INSERT TABLE 2 HERE]

These results about the correlation between political affiliation and beliefs are consistent with several recent contributions. For example, Barrios and Hochberg (2020) use county data to show that the share of Trump voters is associated with lower search intensity for information about the pandemic, but these areas nonetheless experience an uptick following public statements from the White House and other federal social distancing guidelines. Bursztyn et al. (2020) also show that exposure to different types of information affect social distancing behaviors.

The inclusion of individual political affiliation represents a major advantage in our data. Because political affiliation is correlated with both demographic characteristics, failing to control for it may lead to biased estimates of how these demographic factors correlate with behavior and attitudes during the pandemic. For example, we find that African Americans are 9% more likely to anticipate that economic disruption will last at least until the end of the year when we fail to control for political affiliation. However, after adding these controls, we find that the magnitude drops to 3% and becomes less statistically significant. Similarly, those with a bachelor's degree and those with a post-graduate degree are 6% and 8% more likely to anticipate economic disruption that will last at least until the end of the year, but the coefficients drop to 2% (not statistically significant) and 3% (significant at the 1% level) once political affiliation is included. We find similar patterns in our estimated coefficients for our other outcomes measures of social distancing and wearing masks.

One shocking result is that age becomes almost insignificant in predicting fear of contracting the virus after we control for political affiliation, despite the striking relationship between age and mortality-risk documented by the CDC.⁵ Indeed, age is much less powerful than political affiliation

⁵ <https://data.cdc.gov/NCHS/Provisional-COVID-19-Death-Counts-by-Sex-Age-and-S/9bhg-hcku>

in explaining all of our attitudes and behaviors. This explains the contrasting result from Wozniak (2020) or Papageorge et al. (2020) who find statistically significant correlations between age and race, for example, and beliefs about the pandemic. However, like them, we continue to find that those with medical conditions are more likely to self-isolate, social distance, and avoid the workplace.

IV. State Policymaking and Political Polarization

Our results thus far show that beliefs about the pandemic are heavily influenced by political affiliation even after controlling for a wide array of demographic characteristics and local factors that may influence expectations about the economy or the spread of the virus. We now examine whether political affiliation influences the type of state policy that is used to counter the spread of the virus:

$$STPOL_{st} = \zeta TRUMP_s + \zeta COV_s + g(D_{st}, \theta) + \epsilon_{st} \quad (2)$$

where *STPOL* denotes an indicator for the adoption of a specific state policy, *TRUMP* denotes the 2016 share of voters within a state that voted for Trump, *COV* denotes the logged number of new infections over the past 7 days, $g(D, \theta)$ denotes a semi-parametric function of demographic to control for a wide array of differences across states.⁶ Our baseline controls include the age distribution (under age 18, age 18-24, age 25-34, age 35-64, age 65+), the education distribution (less than high school, high school, some college, college, more than college), and the race distribution (white, black). Our industry controls include the full industry distribution, especially the share of workers in retail trade and food and hospitality. These controls help mitigate against concerns about the cross-sectional variation, but we nonetheless caution against a causal interpretation: our goal is simply to quantify the relation between political affiliation and state policy.

⁶ We use the 2016 share of voters for Trump as a proxy for contemporaneous political affiliation because it is a salient, well-defined, and comprehensive measurement. However, Figure A.1 in the Online Appendix plots the degree of persistence between these two terms at the state-level using more recent data from Gallup.

Table 3 documents these results. We find that a 1pp rise in the Trump share in 2016 is associated with a 0.69pp (1.14pp) decline in the probability that the state adopts a nonessential business closure (stay-at-home order, SAHO). While the former is only statistically significant at the 10% level, the latter is at the 1% level. Moreover, even though increases in infections are positively associated with the adoption of nonessential business closures—which is not surprising—they are not statistically related with the adoption of SAHOs or mask-wearing mandates.

On top of our existing controls (e.g., population density and cases), we introduce additional controls in the even-numbered columns to address concerns about differences in industry composition. For example, since areas with a higher share of jobs in professional services are much less likely to have voted for Trump (correlation is -0.78), but could work from home easier than jobs in mining. Following the introduction of these controls in columns (2) and (4), we find that a 1pp rise in the share of people who voted for Trump in 2016 is associated with a 1.86pp (1.82pp) decline in the probability that a state adopts a nonessential business closure law and a SAHO.

We also consider health policies with no clear economic externalities: testing and face-covering requirements. For example, states with greater testing capacity may have felt less need to implement shutdowns. Public health leaders have said that a high positive test rate indicates low testing capacity because it suggests that only the most vulnerable people are getting tested, despite the large threat of asymptomatic transmission (Collins, 2020). However, we find no significant relationship between the testing rate and party orientation. Moreover, we also find no statistically significant association between the number of infections and the probability of adopting a mask-wearing policy—nearly all of the variation here (upwards of 60%) is explained by demographics.

[INSERT TABLE 3 HERE]

However, simply showing that political affiliation predicts the adoption of state policies does not allow us to fully test specific theories of policymaking (Gilens and Page, 2014). Motivated by a

large literature, we now turn to our individual-level data where we observe respondents' approval of their state policy responses to the pandemic. We regress approval on political affiliation (normalized to Independents), its interaction with whether the respondent is the same party as the governor, an indicator for whether the respondent is a small business owner, income bins (normalized to under \$60,000 in annual household income), and a vector of individual demographics, as well as both state and time fixed effects. Our identification strategy exploits the fact that we observe observationally equivalent people in the same state, but some are Republican and others are Democrat.

Table 4 documents these results. While Republicans and Democrats are 9pp and 13pp less likely, relative to Independents, to approve of their state's policy response, the interactions with the indicator for holding the same party affiliation as their governor is over twice as large and positive.⁷ We subsequently examine whether interest groups potentially explain differences in state policy (column 2), which we proxy using occupation fixed effects, specifically an indicator for being a small business owner. However, we obtain a statistically and economically insignificant point estimate. We also add in income bins, normalized to those earning under \$60,000/year in household income, to proxy for whether elites potentially drive policy (column 3). Again, we find insignificant results. In sum, these results are consistent with a Majoritarian Electoral Democracy theory of politics where the average voter influences policy, but where there is intense polarization.

[INSERT TABLE 4 HERE]

Given that we have documented the quantitative significance of political affiliation as a determinant of beliefs about the pandemic and its severity, together with the effects of political affiliation on the adoption of different state policies, we now investigate whether differences in political affiliation also mediate the effects of state policies on realized economic outcomes.

⁷ None of the demographics were statistically significant: employment status, and race. Males were 3-5% less likely to approve of state policies, but age was positively correlated with approval. The only statistically significant race categories were Native Hawaiian and Other Race who were 18-21% and 24-25% more and less likely to approve, respectively.

Drawing on measures of economic activity, namely retail sales, small business revenue growth, and consumer spending from Chetty et al. (2020), we estimate regressions of the form:

$$y_{ct} = \phi STPOL_{st} + \zeta COV_{ct} + \xi_s + \lambda_t + \epsilon_{ct} \quad (3)$$

where y denotes our outcome variable of interest, $STPOL$ is an indicator for whether the state policy (e.g., business closure law) has passed, COV again denotes the logged number of new infections per capita, and ξ and λ denote our usual fixed effects. Our identifying variation in estimation Equation (3) comes from the fact that counties within the same state vary in their political ideology, which influences the adoption of different policies and potentially mediates the effects on outcomes. Our estimates here resemble those from some related literature, i.e., Andersen et al. (2020), who explore the effects of national policies on economic outcomes in Scandinavia.

Table 5 documents these results. We begin by examining the effects of SAHOs and nonessential business closures on retail visits, credit card spending, and small business revenue growth with state and week fixed effects in columns (1), (4), and (7). We find statistically negative effects on retail visits and small business revenue growth. While declines in retail visits are almost mechanical, the result for small businesses is unique: the introduction of a SAHO and nonessential business closure is associated with a 4% decline in revenue growth for small businesses ($p < 0.01$) and a 1% decline in credit card spending ($p < 0.10$), relative to the January baseline.

We subsequently explore the robustness of these results by introducing county fixed effects in columns (2), (5), and (8). Our results are unchanged. We finally add an indicator for whether masks are required in businesses. Importantly, we find no statistically significant effect of these policies on small business revenue growth and the effect on credit card spending is a zero, whereas the effects of nonessential business closure on credit card spending are negative, albeit statistically

insignificant. This suggests that mask wearing policies may have little effect on economic activity, so if they are effective for combating the spread of the disease, they are an optimal policy.

[INSERT TABLE 5 HERE]

While county-level data on unemployment rates are not yet available for most states, we present additional results in Table A.2 of the Online Appendix showing that the adoption of these SAHOs and nonessential business closures are associated with a 1.4-1.6 percentage point increase in the state unemployment rate. However, the adoption of masks in public or in businesses are not statistically related with increases in the unemployment rate, except in one specification that is significant at the 10% level. We interpret these results as consistent with those from Table 4.

V. Discussion and Health Consequences of State Policies

Our results suggest that beliefs about the pandemic and its economic effects are largely driven by political affiliation, rather than realized infections or even local economic activity, and that these political differences may have influenced the adoption of more extreme or relaxed state policies. We now explore whether these policies may have had benefits beyond the adverse costs that they imposed on economic activity and use these to put our estimates in perspective.

There is already a large literature on the potentially beneficial effects of SAHOs and nonessential business closure laws on infections. For example, Courtmanche et al. (2020) show that the adoption of social distancing measures reduced the daily growth rate of infections by 5.4pp after 1-5 days, which may have grown even larger over time (e.g., up to 9.1pp after 16-20 days). Similarly, Sears et al. (2020) show that the introduction of these SAHOs led to a substantial decline in average distance traveled and human encounters and a reduction in the number of infections and deaths.

How do we make sense of these competing costs and benefits? Even without empirical evidence, we are not surprised that limiting human encounters will reduce the transmission of the virus. Cross-country evidence from Scandinavia suggests as much since Sweden, which did not close

down its economy, has seen many more deaths per capita than Denmark, which did (Juranek and Zoutman 2020). Yet, the constellation of policies that work optimally in practice remains empirically ambiguous. Japan appears to have limited both economic damage and the virus's spread with light social-distancing and testing, instead relying mask-wearing, quarantine, and contact tracing.⁸

Though still unclear how much to attribute to policies compared to avoidance behaviors, it seems clear that shut-down policies will raise unemployment and depress consumer demand, which not only affects economic activity, but also affects mortality (Sullivan and von Wachter, 2009), long-run earnings (Jacobsen et al., 1993), and mental health (Paul and Moser, 2009; Kuhn et al., 2009). As far as we can tell at the time of our writing, current analyses have not distinguished between the lives saved due to social distancing and the harm due to economic malaise. Using more comprehensive data that spans until the end of July and adding face-covering mandates, we follow Courtmanche et al. (2020) and assess the potential benefits of state mitigation policies. We adopt a difference-in-differences event-study framework with the following form:

$$COV_{ct} = \rho COV_{c,t-1} + \phi STPOL_{s,w+1} + \phi STPOL_{s,w-1} + \phi STPOL_{s,w-2} + \xi_c + \lambda_t + \epsilon_{st} \quad (4)$$

where COV represents the confirmed cases or deaths from COVID-19 in log form plus one to allow for county-days with zero cases to be included in the model. The time-periods for the state policies are grouped into weekly bins for reasons we explain below, denoted as w to distinguish from daily changes. Our preferred specification predicts the log of cumulative cases (deaths) after controlling for the log cumulative number the day before. We also tried using one week before and found very similar results. Mathematically, subtracting the lagged log from both sides of the equation, yields the growth rate on the left-hand side, and only the policies and fixed effects on the right-hand-side. This makes the regression equivalent to predicting growth: future cases, given the

⁸ <https://www.wsj.com/articles/japan-declares-coronavirus-under-control-lifts-state-of-emergency-11590413785>

starting point. As in the macroeconomic literature on convergence, there is good reason to believe that the starting point matters, since new infections comes from those previous infected.

Nonetheless, in Table A.4 of the Online Appendix, we report regressions that use the pure growth rate (subtracting logs) on the left-hand side without including the lagged variable as a control. The results are similar and, if anything, more suggestive that mask policies are effective.

Coronavirus-suppression policies are not exogenously determined—they could be endogenously a function of a dynamic bargaining game. To account for the fact that anticipated outbreaks prompt state policy makers to adopt stricter requirements, we control for the forward and lagged effects of policy and compare both to cases during the week preceding the present. Given the lag between infection and the revelation of a positive test or death, we think that the comparison to the week preceding the present is the right one. To address this concern, our preferred coefficients predict the effects of a policy 7 to 13 days later and 14 to 20 days later, with the latter being especially relevant for deaths. Deaths may be more relevant than cases for two reasons: given early limits in testing capacity, many symptomatic people could not be tested in March and even April. Second, we know from serology data and other studies that most people who become infected are asymptomatic and are never revealed as a positive confirmed case, because they are not tested.

Table 6 documents these results. Not surprisingly, much of the variation is explained by the previous day's cases (deaths), but we focus on the coefficients associated with state policies. Broadly speaking, we find evidence for significant health benefits from stay-at-home orders and especially masks, but not the closure of non-essential businesses. Stay-at-home orders predict 0.8% fewer cases 14 to 20 days later and predict 0.5% fewer deaths per day. Nonessential business closures do not predict any declines in the number of infections or deaths. However, mask requirements in public have a larger effect than either mask requirements in businesses or SAHOs: the adoption of these requirements is associated with a 1% decline in infections 14-20 days later, although the estimates

are not statistically significant for deaths. When both sets of mask requirements are included simultaneously, we find some evidence of complementarity, but we cannot rule out that we simply observe both happening jointly in both states, so we caution against a causal interpretation.⁹

[INSERT TABLE 6 HERE]

Given our findings that Republicans are less likely to wear-masks or practice social-distancing, we would expect that mask-policies would be less effective in Republican-controlled areas. Indeed, Texas offers an interesting example. The county judge of Harris County, which encompasses Houston, Texas, is a Democrat named Linda Hidalgo. She imposed a mask-order on April 27th.¹⁰ Yet, in the same metropolitan area, the Republican judge of Galveston County, Mark Henry, publicly stated that he thought mask ordinances were an infringement of liberty, and he would not require them in his jurisdiction.¹¹ The views of these politicians are likely to be reflected in their constituents, with similar debates playing out around the country. If compliance is greater (less) in Democrat (Republican) counties, then we should see that state mask ordinances are more (less) effective in Democrat (Republican) counties. We document results consistent with this hypothesis in Table A.4 of the Online Appendix. For example, daily growth in cases and deaths are 1.5% to 2% higher in counties where Trump won with a margin of 75% of the vote relative to counties in which he received just 25% of the vote. These results are statistically significant for growth in cases and deaths across both ways of measuring growth. The interaction effect is particularly strong for mask-requirements focused on private individuals wearing masks in public.

Moreover, our Gallup micro-data allow us to check whether Republicans respond differently than Democrats when living under the same stay-at-home-order or mask-orders. We find that they

⁹ Table A.3 of the Online Appendix shows that these results are robust to working with the growth rates. Masks are at least as effective at reducing the growth in infections as stay-at-home-orders, although the effects on death rates are less statistically significant. Using 7-day growth rates instead of single day rates did not meaningfully change these results.

¹⁰ <https://www.readyharris.org/Newsroom/ReadyHarris-Alerts/All-Previous-Alerts/mandatory-face-coverings-required-starting-42720>

¹¹ https://www.galvnews.com/opinion/guest_columns/article_3b5c58bb-6029-594a-bcd6-c66b129715f1.html

do. We estimate our regression models from Table 2, but add SAHOs and mask requirements and interact them with Republicans-party identification. In Table A.5 of the Online Appendix, we see that Republicans are significantly less likely to wear masks than Democrats generally and that gap persists even when they live in the same county with the same state policy. The regression-adjusted gap in mask-wearing is 29pp between Republicans and Democrats when they are not living in a state that requires masks. Mask-wearing rises for both Democrats and Republicans by 5pp when they live in a state that requires mask-usage, and the gap closes to 20pp, because Republicans respond even more. Yet, a 20pp gap in compliance with a public health mandate has meaningful consequences to the economy and public health. Social-distancing is also higher in states with stay-at-home-orders and mask-orders, but again, this does not eliminate the partisan gap. This is the first evidence that clearly links the probability of compliance with public health mandates to partisan politics.

VI. Conclusion

The coronavirus has had a profound effect on public health and the economy. Yet, as we show, neither the health nor economic consequences can be explained without understanding how partisan politics has shaped the adoption of disease-suppressing policies and behaviors. Using a uniquely high-quality longitudinal sample, consisting of a large representative daily survey of U.S. adults, we find that fear, economic expectations, workplace visits, social-distancing, and mask-wearing are all driven largely by party-identification to a much greater extent than local public-health conditions, state economic conditions, or state public health policies. Partisanship is also more important in explaining disease-mitigation behaviors than actual individual risk of death (measured by age or self-reported risk), as well as other demographic factors, such as gender, race, or education. In terms of predicting these outcomes, party affiliation is roughly as powerful as employment status and the presence of pre-existing medical conditions—and, in some cases, more powerful.

This finding alone has enormous implications since it suggests that behavioral factors, like rational inattention, may exert especially large effects in mediating the effects of public health campaigns, the accuracy of epidemiological models, and the realities of compliance. We also examine how partisanship affects the adoption of state policies, showing a clear and robust negative relationship between disease-suppression policies and the share of votes won by President Trump that cannot be explained by the local disease burden. Governors and state legislatures, therefore, are responding in much the same way as individuals: according to their partisan inclinations.

In the final section of the paper, we show how these partisan differences play out with respect to economic and health outcomes. Even Trump-dominated states have experienced a sharp rise in unemployment and Trump-dominated counties have seen large losses in small business revenue and consumer spending. This suggests that the disease itself largely explains most of the economic damage the country has experienced. Still, state and counties oriented more strongly to the Republican Party have seen significantly less economic damage than those oriented toward the Democratic Party. This result cannot be explained by different rates of exposure to COVID-19, but rather the result of stricter controls and restrictions on business put in place in Democratic areas and stricter compliance with social-distancing measures by individual Democrats in these areas.

The relaxed policies and relaxed compliance found in Republican areas has meant less economic damage, but potentially at the cost of higher infections and deaths. These joint results suggest that Republicans and Democrats can learn from one another. Disease suppression efforts are crucial to saving lives and the economy is unlikely to recover while the disease is out of control. Yet, some of the more extreme policies—shutting down non-essential businesses—seem to create economic damage without bending the curve, while others (like mask-wearing) are almost costless to the economy but effective at slowing growth in mortality. In any case, the fact that policies and individual attitudes and behaviors are predicted by party identification more than actual conditions is

strong evidence that the many Americans are not pursuing a disease-suppression strategy that balances concerns about infection with concerns about economic livelihood. In this sense, our results are consistent with the recommendations from Acemoglu et al. (2020) for targeted lockdowns, rather than uniform lockdowns of economic sectors and individuals.

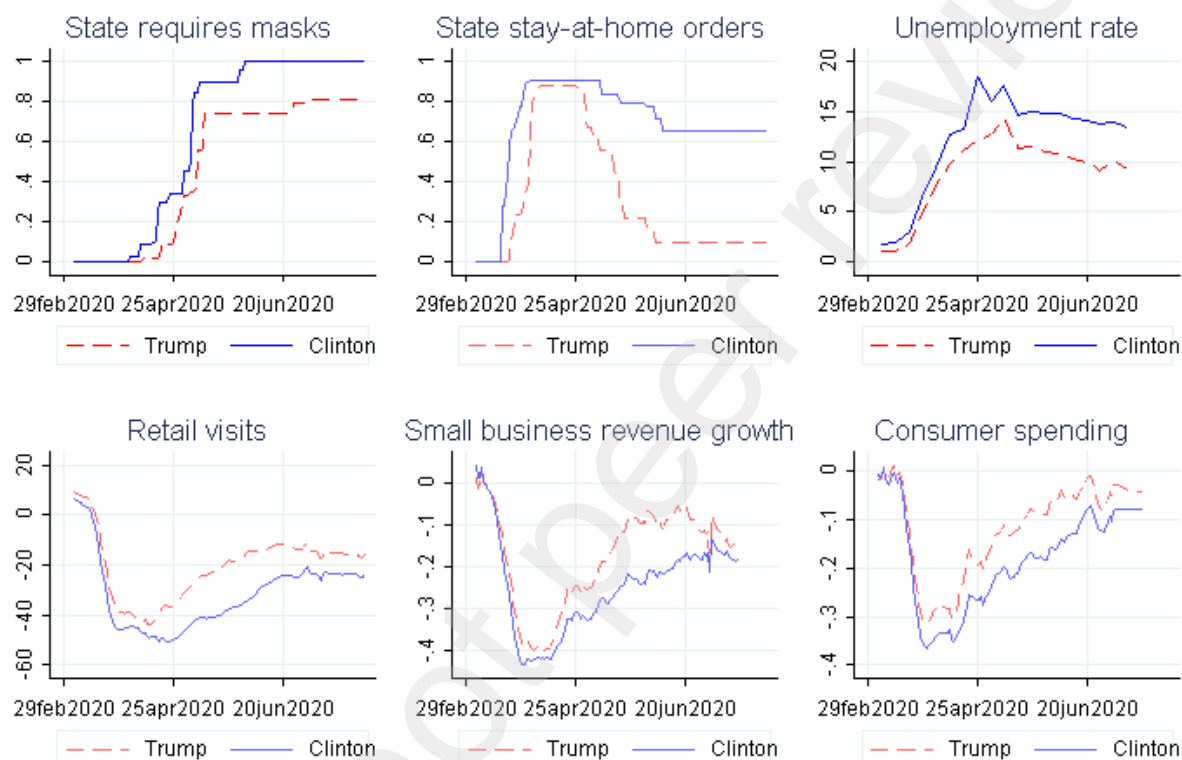
We suggest that our research could be improved with comprehensive county or local data on public health policies that would uncover even greater variation within states. We would also like to see work that further explains the sources of geographic vulnerability to infection, beyond population density. At this stage, it remains unclear why areas like New York City faced an infection and mortality rate so much greater than any other major city. Moreover, given the international variation, there are still many unanswered questions about which disease-suppression strategies are most effective and best balance individual liberty and economic necessity, with health and safety.

Tables and Figures

Table 1: Definition of Economic and Pandemic Expectation Variables

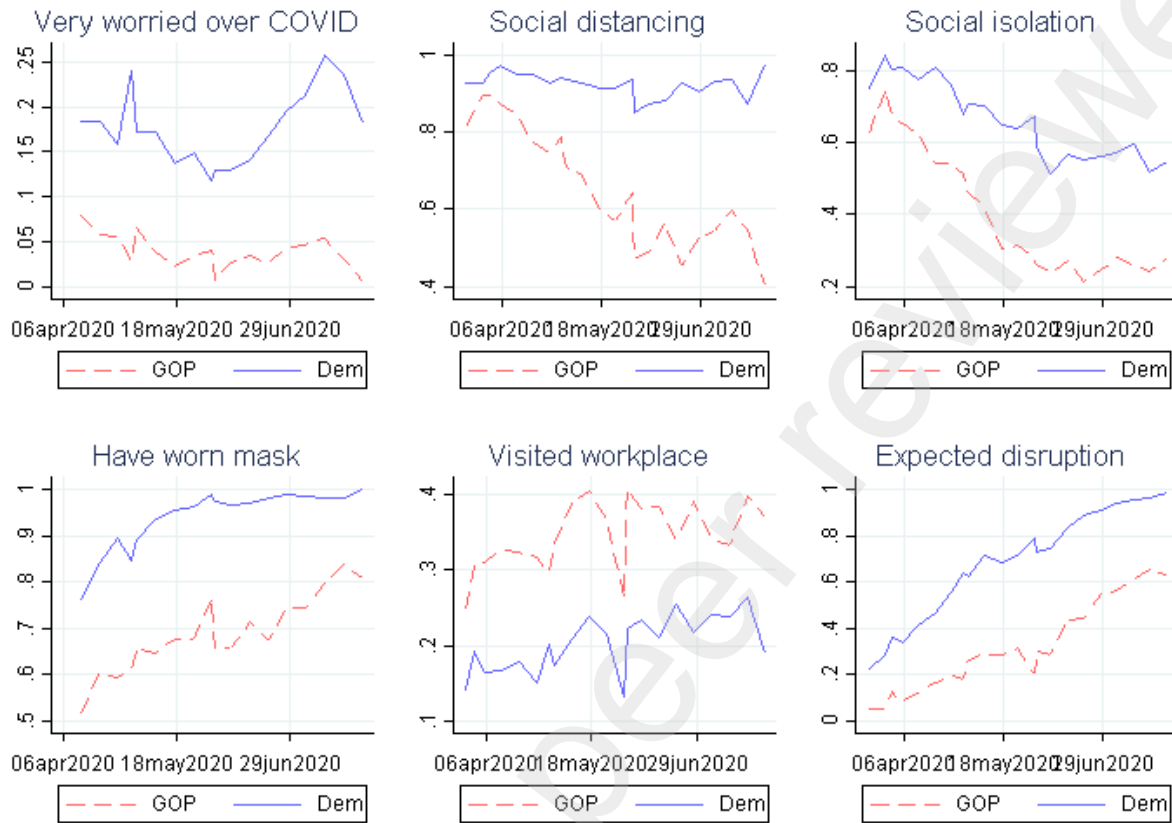
Variable	Survey Question	Categorical Values
Expected Disruption	How long do you think the level of disruption occurring to travel, school, work and public events in the U.S. will continue before it starts to improve?	<ol style="list-style-type: none"> 1. A few more weeks 2. A few more months 3. For the rest of the year 4. Longer than this year
Worried About Illness	How worried are you that you will get the coronavirus (COVID-19)?	<ol style="list-style-type: none"> 1. Not worried at all 2. Not too worried 3. Somewhat worried 4. Very worried
Social Distancing	Over the past 24 hours, how often have you been practicing social distancing?	<ol style="list-style-type: none"> 1. Always 2. Very often 3. Sometimes 4. Rarely 5. Never
Self Isolation	Next, thinking about everything you've done in the past 24 hours, which of the following comes closest to describing your in-person contact with people outside your household?	<ol style="list-style-type: none"> 1. Completely isolated yourself, having no contact with people outside your household 2. Mostly isolated yourself, having very little contact with people outside your household 3. Partially isolated yourself, having some contact with people outside your household 4. Isolated yourself a little, still having a fair amount of contact with people outside your household 5. Did not make any attempt to isolate yourself from people outside your household.
Wearing Masks	There are some things people may do because of their concern about the coronavirus. For each one of the following, please indicate if this is something you have done, are considering doing or have not considered in the past 7 days. Worn a mask on your face when outside your home?	<ol style="list-style-type: none"> 1. Have done 2. Considering doing 3. Have not considered
Visited Work	In the past 24 hours have you visited your place of work?	Binary

Figure 1: State Policy Decisions and Economic Outcomes by Winner of 2016 Election



Note: Weighted by state population. Sources: U.S. DOL; IHME; Boston University; Google, 7-day mean; Federal Elections data. Opportunity Insights: Affinity for consumer spending; Womply for revenue

Figure 2: Evolution of Beliefs About the Pandemic and Economy, by Political Affiliation



Notes.—Sources: Gallup Panel. The figure plots the share of respondents reporting that they are very worried about COVID-19, that they social distance very often or always, that they have mostly or always self-isolate, that they are wearing a mask, that they have visited the workplace in the past 24 hours, and that they expect the economic disruption to last at least till the end of the year.

Table 2: Baseline Determinants of Individual Beliefs about the Pandemic

	Expected disruption	Worry about illness	Social distancing	Self- Isolating	Wearing mask	Visited work
	(1)	(2)	(3)	(4)	(5)	(6)
log(New Infections)	0.01*	0.01***	0.01	0.01	0.02***	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Republican	-0.18***	-0.04***	-0.08***	-0.08***	-0.10***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Democrat	0.11***	0.06***	0.07***	0.06***	0.09***	-0.04***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Employed	-0.08***	-0.06***	-0.05***	-0.16***	0.01	0.37***
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
Out of workforce	-0.04*	-0.07***	0.00	0.04**	0.03	-0.07***
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)
Male	-0.01	-0.03***	-0.04***	-0.06***	-0.04***	0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Age/10	-0.01***	-0.00*	0.01***	-0.01***	0.02***	0.01*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Some College	0.04***	0.01	0.03***	0.04***	0.05***	-0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Bachelors degree	0.02	0.00	0.08***	0.15***	0.08***	-0.16***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Graduate degree	0.03***	0.01	0.09***	0.17***	0.09***	-0.19***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Hispanic	0.01	0.02*	0.01	-0.00	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Black	0.03**	-0.01	-0.01	-0.06***	0.02	0.02
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Asian	0.03	0.06	0.04**	0.04	-0.01	-0.08***
	(0.03)	(0.04)	(0.02)	(0.03)	(0.03)	(0.03)
American Indian	0.03	0.01	0.02	0.00	0.01	0.02
	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Native Hawaiian	0.08	0.15**	-0.03	-0.01	-0.03	0.06
	(0.07)	(0.07)	(0.06)	(0.09)	(0.05)	(0.07)
Other Race	0.05	0.00	-0.01	-0.06**	-0.03	0.06*
	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.04)

Has medical condition	0.05*** (0.01)	0.08*** (0.01)	0.04*** (0.01)	0.06*** (0.01)	0.05*** (0.01)	-0.02** (0.01)
Lives with children	0.00 (0.01)	0.01 (0.01)	-0.01 (0.01)	-0.02* (0.01)	-0.02* (0.01)	0.00 (0.01)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R2	0.28	0.14	0.23	0.24	0.31	0.39
Sample Size	67,859	44,655	67,800	67,814	48,369	59,497

Notes.—Sources: Gallup Panel. The table reports the coefficients associated with regressions of indicators for different beliefs about the pandemic and its economic implications on the logged number of new infections averaged over the past seven days, political affiliation, and demographic controls, including age: race, employment status, living with children, having a medical condition from March 13-July 26. Standard errors are clustered by county and observations are weighted by the sample weights.

Table 3: Predicting the Adoption of State Pandemic Policy Responses

	Nonessential Businesses Closure		Stay-at-Home Order		Positive Test Ratio		Masks Required in Businesses	
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Trump 2016 Vote, %	-0.69*	-1.86***	-1.14***	-1.82***	0.09	0.06	-0.67	-0.57
	(0.41)	(0.38)	(0.41)	(0.60)	(0.08)	(0.09)	(0.55)	(0.54)
log(New Infections)	0.09***	0.10***	0.00	0.01	0.04***	0.03***	-0.00	0.00
	(0.03)	(0.02)	(0.03)	(0.03)	(0.01)	(0.01)	(0.03)	(0.03)
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Controls	No	Yes	No	Yes	No	Yes	No	Yes
Adj. R2	9,600	9,600	9,600	9,600	7,372	7,372	9,600	9,600
Sample Size	0.49	0.53	0.49	0.54	0.40	0.42	0.63	0.66

Notes.—Sources: IHME, Chetty et al. (2020), Census 2014-2018, USA Facts, Boston University School of Public Health (2020). The table reports the coefficients associated with state regressions of indicators for nonessential business closures and stay-at-home orders and the positive test ratio for COVID-19 on the 2016 share of votes for Trump, conditional on the logged number of new infections per capita over the past 7 days and a function of demographic controls from March 13-July 26. Baseline controls include: population density, the age distribution (under age 18, age 18-24, age 25-34, age 35-64, age 65+), the education distribution (some college, college, more than college), and the race distribution (white, black). Our industry controls include the share working in agriculture, mining, and forestry, in construction, in manufacturing, in wholesale trade, in retail trade, in transportation and utilities, in information services, in finance, insurance, and real estate (FIRE), in education and healthcare, in arts, services, and food/accommodation, and in other services. Standard errors are clustered at the state-level and observations are unweighted since we have the whole population

Table 4: Predicting Approval of State Government Coronavirus Policy Responses

Approves of State Government Policy Response			
	(1)	(2)	(3)
Republican	0.26***	0.26***	0.26***
× Republican Governor	(0.06)	(0.06)	(0.06)
Democrat	0.28***	0.28***	0.28***
× Democrat Governor	(0.05)	(0.06)	(0.06)
Republican	-0.09***	-0.10***	-0.10***
	(0.03)	(0.03)	(0.04)
Democrat	-0.13***	-0.14***	-0.13**
	(0.05)	(0.05)	(0.05)
Small business owner		0.00	0.01
		(0.03)	(0.03)
Household income \$60,000 to \$179,000			-0.01
			(0.02)
Household income at least \$180,000			-0.03
			(0.03)
Observations	8,914	7,230	6,904
State FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Adj. R2	0.13	0.14	0.14

Notes.—Sources: Party of governor data are from the National Conference of State Legislatures. Other data is from Gallup Panel. The table reports the coefficients associated with regressions of an indicator for whether the individual approves of the state government's policy response on an indicator for whether an individual is Republican or Democrat (normalized to independents), their interactions with an indicator for whether the respondent is the same party as the state's governor, an indicator for whether an individual is a small business owner, income bin indicators, and a vector of demographic characteristics, including: employment status indicators (employed, out of the labor force), male, age, education (some college, college, more than college), race (Hispanic, Black, Asian, American Indian, Native Hawaiian, Other), has a medical condition, and lives with children. The survey question is: "Do you approve or disapprove of the way each of the following is handling the response to the coronavirus in the U.S.? A. Your state government." Observations are weighted by the sample weights and standard errors are clustered at the state-level.

Table 5: State Policies and Realized Economic Outcomes Mediated by Political Affiliation

	Retail Visits			Credit Card Spending			Small Business Revenue Growth		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Stay-at-home-order	-4.49**	-4.28**	-4.20**	-0.01*	-0.01*	-0.01*	-0.04***	-0.04***	-0.04***
	(1.75)	(1.81)	(1.77)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Nonessential Business Closure	-5.99**	-5.66**	-5.49**	-0.02*	-0.02*	-0.02*	-0.03*	-0.03*	-0.03**
	(2.19)	(2.04)	(2.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Masks Required in Businesses			-1.53			0.01			-0.01
			(1.70)			(0.01)			(0.02)
log(New Infections)	-1.10***	-1.18***	-1.16***	-0.00**	-0.00***	-0.00***	-0.00	-0.00	-0.00
	(0.35)	(0.34)	(0.33)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	No	No	Yes	No	No	Yes	No	No
County FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Adj. R2	0.75	0.82	0.82	0.43	0.63	0.63	0.26	0.55	0.55
Sample Size	89,790	89,789	89,789	312,534	316,293	316,293	375,307	376,893	376,893

Notes.—Sources: IHME, Chetty et al. (2020), Census Bureau 2014-2018, USA Facts, Boston University School of Public Health (2020). The table reports the coefficients associated with county regressions of indicators for economic outcomes from March 2020 to June 2020 on state public health policies, conditional on the logged number of new infections per capita over the past 7 days and a flexible function of demographic controls from March 13-July 26. Our controls include all those in Table 2: population density, the age distribution (under age 18, age 18-24, age 25-34, age 35-64, age 65+), the education distribution (some college, college, more than college), and the race distribution (white, black). Our industry controls include the share working in agriculture, mining, and forestry, in construction, in manufacturing, in wholesale trade, in retail trade, in transportation and utilities, in information services, in finance, insurance, and real estate (FIRE), in education and healthcare, in arts, services, and food/accommodation, and in other services. We also add controls for the percent of households with various levels of income. Standard errors are clustered at the state-level and observations are unweighted since we have the whole population.

Table 6: COVID-19 Confirmed Cases and Deaths Regressed on State Policies with County and Time Fixed Effects

	log(Cumulative COVID-19 Cases)			log(Cumulative COVID-19 Deaths)		
	(1)	(2)	(3)	(4)	(5)	(6)
log(COVID-19 Cases), $t - 1$ day	0.991*** (0.000)	0.991*** (0.000)	0.991*** (0.000)			
log(COVID-19 Deaths), $t - 1$ day				0.995*** (0.000)	0.995*** (0.000)	0.995*** (0.000)
Stay-at-home-order, $t + 1$ -7 days	0.009* (0.005)	0.009* (0.005)	0.009* (0.005)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)
Stay-at-home-order, $t - 7$ -13 days	-0.004 (0.004)	-0.004 (0.004)	-0.005 (0.004)	0.005*** (0.002)	0.004** (0.002)	0.005*** (0.002)
Stay-at-home-order, $t - 14$ -20 days	-0.008*** (0.003)	-0.007** (0.003)	-0.007** (0.003)	-0.005*** (0.002)	-0.004*** (0.001)	-0.005*** (0.001)
Nonessential businesses closed, $t + 1$ -7 days	0.016** (0.008)	0.015* (0.008)	0.015** (0.008)	0.005** (0.003)	0.006* (0.003)	0.005* (0.003)
Nonessential businesses closed, $t - 7$ -13 days	-0.001 (0.005)	-0.002 (0.005)	-0.001 (0.005)	0.004** (0.002)	0.004** (0.002)	0.004** (0.002)
Nonessential businesses	-0.001 (0.005)	-0.002 (0.005)	-0.002 (0.005)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)

closed, $t - 14-20$ <i>days</i>						
	(0.004)	(0.004)	(0.004)	(0.001)	(0.002)	(0.001)
Masks required in businesses, $t +$ $1-7$ <i>days</i>	-0.003		-0.005*	0.008***		0.008***
	(0.003)		(0.003)	(0.003)		(0.002)
Masks required in businesses, $t -$ $7-13$ <i>days</i>	-0.005*		-0.005*	-0.005***		-0.007***
	(0.003)		(0.003)	(0.002)		(0.002)
Masks required in businesses, $t -$ $14-20$ <i>days</i>	-0.004		-0.001	-0.002		-0.001
	(0.003)		(0.003)	(0.001)		(0.001)
Masks required in public, $t + 1-7$ <i>days</i>		0.002	0.005		0.002	-0.001
		(0.004)	(0.004)		(0.002)	(0.002)
Masks required in public, $t - 7-13$ <i>days</i>		-0.002	-0.000		0.000	0.003
		(0.002)	(0.003)		(0.002)	(0.002)
Masks required in public, $t - 14-$ 20 <i>days</i>		-0.010***	-0.010**		-0.003	-0.002
		(0.003)	(0.004)		(0.002)	(0.003)
Adj. R2	0.999	0.999	0.999	0.998	0.998	0.998
Sample Size	559,988	559,988	559,988	559,988	559,988	559,988

Notes.—Sources: IHME, USA Facts, Boston University School of Public Health (2020). The table reports the coefficients associated with county-level regressions of public health policies on COVID-19 confirmed cases and deaths. The policies are set equal to one if implemented or zero otherwise and averaged over various time periods from March 2020 to June 2020. Standard errors are clustered on state. All models include county and time fixed effects.

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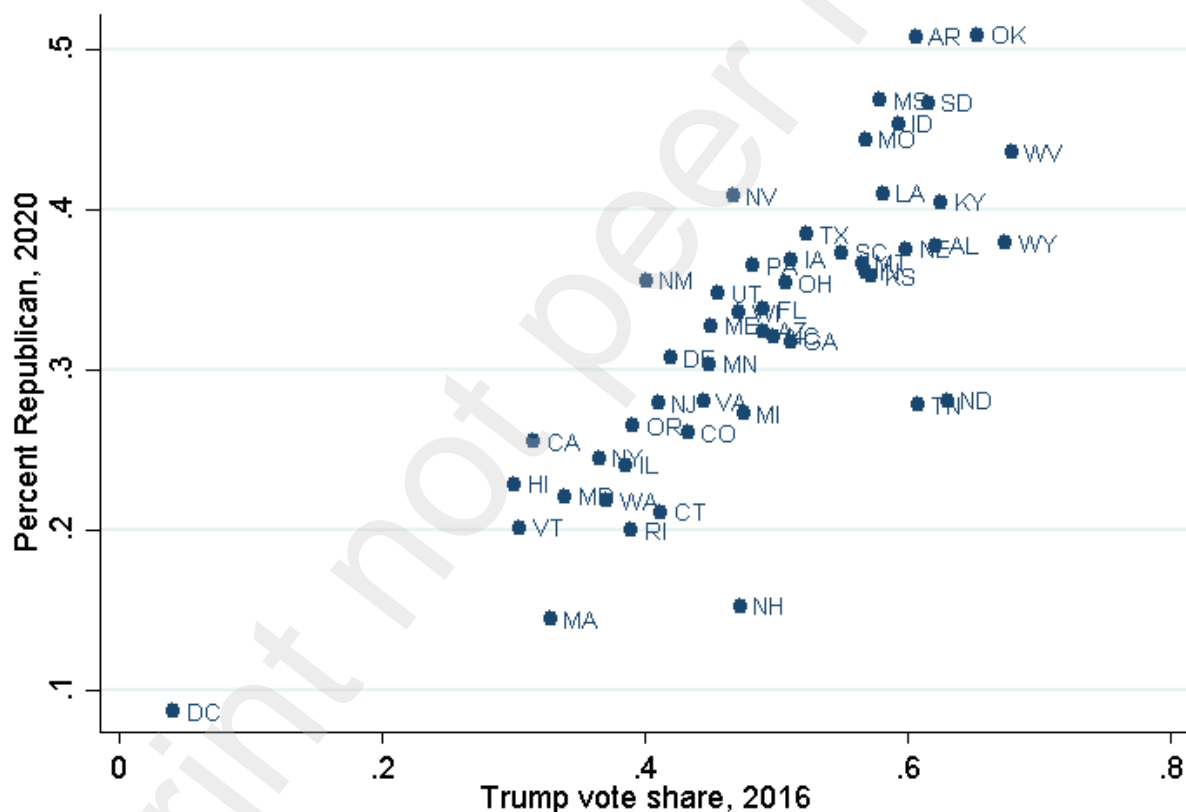
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Online Appendix

Election Vote Shares in 2016 Are Correlated With Contemporaneous Political Affiliation

One concern with our use of the 2016 Trump vote share is that it is an imperfect proxy for current political attitudes. For example, attitudes may have grown closer or further away in ways that are correlated with location characteristics. Figure A.1 shows that there is a strong correlation of 0.78 between the share of 2016 election votes going towards Donald J. Trump and the share of adults identifying as members of the Republican Party in During COVID-19 Pandemic, March-June, 2020.

Appendix Figure A.1: Correlation Between 2016 Voting and 2020 Self-Reported Political Affiliation



Source: Gallup COVID Tracking Panel and Tony McGovern's election database

The Gallup Panel Resembles the Distribution of the Current Population Survey

We benchmark the Gallup panel with the Current Population Survey (CPS) over March to May 2020. Although there is a minor difference among the share of respondents with a bachelor's degree—that is, the Gallup Panel has a higher share of college-educated workers than the CPS—the remainder of the demographic characteristics exhibit strong balancing.

Appendix Table A.1: Comparison of the Current Population Survey and Gallup Panel

	Current Population Survey		Gallup Panel	
	Mean	Std. Dev.	Mean	Std. Dev.
Average Age	44.73	17.61	49.54	16.55
Share Age 19-29	0.21	0.40	0.11	0.31
Share Age 30-44	0.33	0.47	0.32	0.47
Share Age 45-64	0.28	0.45	0.35	0.48
Share Age 65+	0.17	0.37	0.22	0.42
Share Male	0.48	0.50	0.49	0.50
Share White	0.84	0.37	0.85	0.36
Share Black	0.12	0.32	0.13	0.33
Share Married	0.58	0.49	0.63	0.48
Share Hispanic	0.11	0.31	0.15	0.36
Share Employed	0.61	0.49	0.59	0.49
Share Some college, no degree	0.26	0.44	0.30	0.46
Share Bachelor's or higher	0.23	0.42	0.34	0.47
Observations	6925293	6925293	80,491	80,491

Notes.—Sources: Current Population Survey (March to May 2020) and Gallup Panel (March to June). The table reports the means and standard deviations of various demographic characteristics.

Similar Results of State Policies on State Unemployment Rates

We present additional evidence on the effects of different state policies on the state unemployment rate. We find strong effects of SAHOs and nonessential business closures on the unemployment rate, even after we control for state and time fixed effects. However, we find little effects of mask wearing policies, particularly masks in public, on state unemployment. For example, the adoption of nonessential business closures and SAHOs are associated with a 0.94-1.4 (1.55-1.62) percentage point increase in the state unemployment rate, which are generally significant at the 1% level. However, mask wearing policies are not statistically related with increases in unemployment, except masks required in businesses, which is significant at the 10% level when introducing fixed effects.

Appendix Table A.2: State Policies and Unemployment Rates

	(1)	(2)
Masks Required in Public	0.815 (1.049)	0.633 (1.082)
Masks Required in Businesses	1.200 (0.831)	1.470* (0.780)
Stay-at-home-order	1.551*** (0.578)	1.620*** (0.592)
Nonessential Businesses Closure	1.403** (0.639)	0.940 (0.607)
log(New Infections, 7-day Avg)	-0.469 (0.294)	-0.402 (0.308)
Time FE	Yes	Yes
State FE	No	Yes
Sample Size	969	969
Adj. R-squared	0.842	0.870

Notes.—Sources: IHME, Census Bureau 2014-2018, U.S. Department of Labor, USA Facts, Boston University School of Public Health (2020). The table reports the coefficients associated with state-level regressions of the insured unemployment rate on public health policies from March 2020 to June 2020, conditional on the logged number of new infections per capita over the past 7 days. Column one controls include all those in Table 2: population density, the age distribution (under age 18, age 18-24, age 25-34, age 35-64, age 65+), the education distribution (some college, college, more than college), and the race distribution (white, black). Our industry controls include the share working in agriculture, mining, and forestry, in construction, in manufacturing, in wholesale trade, in retail trade, in transportation and utilities, in information services, in finance, insurance, and real estate (FIRE), in education and healthcare, in arts, services, and food/accommodation, and in other services. Column one includes state fixed-effects. Column two uses county-fixed effects. Standard errors are clustered at the state-level and observations are unweighted since we have the whole population. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix Table A.3: COVID-19 Confirmed Cases and Deaths Regressed on State Policies with County and Time Fixed Effects

	100 X Log cases (t) - log cases (t-1)			100 X Log deaths (t) - log deaths (t-1)		
	(1)	(2)	(3)	(4)	(5)	(6)
Masks required in businesses, future 1-7 days	0.934*** (0.298)	-	1.064*** (0.349)	0.622** (0.275)	-	0.561** (0.266)
Masks required in businesses, lag 7-13 days	-0.460* (0.246)	-	-0.328 (0.317)	0.710*** (0.225)	-	0.818*** (0.214)
Masks required in businesses, lag 14-20 days	-0.520** (0.257)	-	-0.177 (0.233)	-0.388** (0.152)	-	-0.0502 (0.137)
Stay-at-home-order, future 1-7 days	0.785* (0.445)	0.743 (0.458)	0.851* (0.438)	0.173 (0.243)	0.207 (0.224)	0.205 (0.231)
Stay-at-home-order, lag 7-13 days	-0.606 (0.452)	-0.577 (0.441)	-0.595 (0.452)	0.419** (0.176)	0.376** (0.166)	0.419** (0.180)
Stay-at-home-order, lag 14-20 days	0.895*** (0.285)	0.887** (0.345)	-0.790** (0.299)	-0.383** (0.157)	-0.321** (0.155)	-0.328** (0.151)
Nonessential businesses closed, future 1-7 days	1.219* (0.677)	1.178* (0.679)	1.129* (0.643)	0.487* (0.261)	0.462* (0.250)	0.451* (0.251)
Nonessential businesses closed, lag 7-13 days	-0.356 (0.508)	-0.379 (0.511)	-0.385 (0.513)	0.352** (0.171)	0.345* (0.176)	0.359** (0.167)
Nonessential businesses closed, lag 14-20 days	-0.506 (0.367)	-0.517 (0.430)	-0.542 (0.371)	-0.175 (0.177)	-0.219 (0.185)	-0.227 (0.179)
Masks required in public, future 1-7 days	-	-0.449 (0.490)	0.232 (0.505)	-	0.609 (0.410)	0.124 (0.408)
Masks required in public, lag 7-13 days	-	-0.574* (0.308)	-0.394 (0.415)	-	-0.453 (0.416)	0.259 (0.382)
Masks required in public, lag 14-20 days	-	0.804** (0.367)	-0.936** (0.376)	-	0.864*** (0.267)	0.925*** (0.304)
Sample Size	434,148	434,148	434,148	434,148	434,148	434,148
Adj. R-squared	0.086	0.085	0.086	0.044	0.044	0.044

Notes.—Sources: IHME, USA Facts, Boston University School of Public Health (2020). The table reports the coefficients associated with county-level regressions of public health policies on COVID-19 confirmed cases and deaths. All models include county and time fixed effects. The policies are set equal to one if implemented or zero otherwise and averaged over various time periods from March 2020 to June 2020. Standard errors are clustered on state. All models include county and time fixed effects. *** p<0.01, ** p<0.05, * p<0.1

Appendix Table A.4. COVID-19 County-Level Growth in COVID-19 Cases and Deaths on State Policies interacted with Presidential Voting with County and Time Fixed Effects

	100 X Log cases (t) - log cases (t-1)	100 X Log deaths (t) - log deaths (t-1)	Log of cumulative COVID-19 cases	Log of cumulative COVID-19 deaths
	1	2	3	4
Log of cumulative COVID-19 cases, lag 1 day			0.993*** (0.000601)	
Log of cumulative COVID-19 deaths, lag 1 day				0.997*** (0.000397)
Stay-at-home-order, future 1-7 days	0.842* (0.442)	0.192 (0.236)	0.00979** (0.00481)	0.00193 (0.00242)
Stay-at-home-order, lag 14-20 days	-0.589 (0.460)	0.424** (0.180)	-0.00472 (0.00446)	0.00444** (0.00180)
Stay-at-home-order, lag 14-20 days	-0.624* (0.311)	-0.292* (0.155)	-0.00511* (0.00296)	-0.00260* (0.00145)
Nonessential businesses closed, future 1-7 days	1.331** (0.646)	0.448* (0.256)	0.0131* (0.00697)	0.00418 (0.00263)
Nonessential businesses closed, lag 7-13 days	-0.435 (0.517)	0.435** (0.177)	-0.00290 (0.00508)	0.00462** (0.00177)
Nonessential businesses closed, lag 14-20 days	-0.425 (0.384)	-0.174 (0.157)	-0.00327 (0.00369)	-0.00141 (0.00156)
Masks required in public, future 1-7 days	-0.495 (1.702)	1.042 (1.400)	0.00314 (0.0144)	0.0133 (0.0140)
Masks required in public, lag 7-13 days	-2.037** (0.995)	-1.069 (1.258)	-0.0172* (0.00886)	-0.00985 (0.0124)
Masks required in public, lag 14-20 days	-3.320*** (0.984)	-3.144*** (0.745)	-0.0293*** (0.00874)	-0.0279*** (0.00733)
Masks required in businesses, future 1-7 days	-6.222*** (1.016)	0.476 (0.792)	-0.0431*** (0.00930)	0.0105 (0.00766)
Masks required in businesses, lag 7-13 days	1.143 (0.711)	-2.266*** (0.660)	0.00687 (0.00670)	-0.0232*** (0.00653)
Masks required in businesses, lag 14-20 days	-0.428 (0.504)	-0.356 (0.403)	-0.00405 (0.00457)	-0.00274 (0.00391)
Trump share of vote X Masks required in public, future 1-7 days	1.926 (2.734)	-1.575 (2.025)	0.00458 (0.0233)	-0.0209 (0.0200)
Trump share of vote X Masks required in public, lag 7-13 days	2.515 (1.596)	2.496 (1.811)	0.0221 (0.0146)	0.0240 (0.0180)

Trump share of vote X Masks required in public, lag 14-20 days	4.227*** (1.526)	3.885*** (1.169)	0.0358** (0.0141)	0.0340*** (0.0117)
Trump share of vote X Masks required in businesses, future 1-7 days	8.134*** (1.644)	0.146 (1.024)	0.0569*** (0.0143)	-0.00633 (0.00992)
Trump share of vote X Masks required in businesses, lag 7-13 days	-2.247* (1.237)	2.252** (1.010)	-0.0160 (0.0122)	0.0236** (0.0100)
Trump share of vote X Masks required in businesses, lag 14-20 days	0.354 (0.749)	0.561 (0.566)	0.00344 (0.00682)	0.00488 (0.00547)
County Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes
Observations	429,456	429,456	429,456	429,456
Adjusted R-squared	0.091	0.046	0.998	0.997

Notes.—Sources: IHME, USA Facts, Boston University School of Public Health (2020). The table reports the coefficients associated with county-level regressions of public health policies on COVID-19 confirmed cases and deaths. All models include county and time fixed effects. The policies are set equal to one if implemented or zero otherwise and averaged over various time periods from March 2020 to June 2020. Standard errors are clustered on state. All models include county and time fixed effects. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix Table A.5: Regression of Attitudes and Behaviors on Local Infection Risk and Party Identification with County and Time Fixed Effects

	Expected disruption	Expected disruption	Worry about illness	Worry about illness	Social distancing	Social distancing	Isolating	Isolating	Wearing mask	Wearing mask	Visited work	Visited work
Republican w/ mask req.		-0.09*** (0.02)		0.03** (0.02)		-0.05** (0.02)		-0.06** (0.03)		0.10*** (0.02)		-0.01 (0.02)
Republican w/ SAHO		0.02 (0.01)		0.01 (0.01)		0.03* (0.02)		-0.03 (0.02)		0.05*** (0.02)		0.01 (0.02)
Republican	-0.18*** (0.01)	-0.18*** (0.01)	-0.04*** (0.01)	-0.06*** (0.01)	-0.07*** (0.01)	-0.08*** (0.02)	-0.08*** (0.01)	-0.06*** (0.02)	-0.10*** (0.01)	-0.16*** (0.02)	0.06*** (0.01)	0.05*** (0.01)
Democrat	0.11*** (0.01)	0.11*** (0.01)	0.06*** (0.01)	0.06*** (0.01)	0.06*** (0.01)	0.06*** (0.01)	0.06*** (0.01)	0.06*** (0.01)	0.08*** (0.01)	0.09*** (0.01)	0.02*** (0.01)	-0.02*** (0.01)
log(New Infections, 7- day)	0.02** (0.01)	0.02*** (0.01)	0.01* (0.01)	0.01* (0.01)	0.00 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.03*** (0.01)	0.03*** (0.01)	-0.00 (0.01)	-0.00 (0.01)
Stay-at-home-order	0.01 (0.01)	0.00 (0.01)	-0.01 (0.01)	-0.01 (0.01)	0.02* (0.01)	0.01 (0.01)	0.03** (0.01)	0.04*** (0.01)	0.00 (0.01)	-0.02 (0.01)	0.02* (0.01)	0.02 (0.01)
Masks required in public	0.03* (0.01)	0.05*** (0.02)	0.00 (0.01)	-0.00 (0.02)	0.03** (0.01)	0.04*** (0.01)	-0.01 (0.01)	0.00 (0.02)	0.06*** (0.02)	0.03* (0.02)	0.02 (0.01)	0.02* (0.01)
Employed last week	-0.08*** (0.02)	-0.08*** (0.02)	-0.06*** (0.02)	-0.06*** (0.02)	-0.05*** (0.01)	-0.05*** (0.01)	-0.15*** (0.02)	-0.15*** (0.02)	0.02 (0.02)	0.02 (0.02)	0.28*** (0.01)	0.28*** (0.01)
Out of workforce	-0.05** (0.02)	-0.04** (0.02)	-0.07*** (0.02)	-0.07*** (0.02)	0.00 (0.01)	0.01 (0.01)	0.05** (0.02)	0.05** (0.02)	0.03 (0.02)	0.03 (0.02)	0.07*** (0.01)	-0.07*** (0.01)
Male	-0.00 (0.01)	-0.00 (0.01)	-0.03*** (0.01)	-0.03*** (0.01)	-0.04*** (0.01)	-0.04*** (0.01)	-0.06*** (0.01)	-0.06*** (0.01)	-0.05*** (0.01)	-0.05*** (0.01)	0.07*** (0.01)	0.07*** (0.01)
Age divided by 10	-0.01*** (0.00)	-0.01*** (0.00)	-0.01* (0.00)	-0.01* (0.00)	0.01*** (0.00)	0.01*** (0.00)	-0.01*** (0.00)	-0.01*** (0.00)	0.02*** (0.00)	0.02*** (0.00)	0.00 (0.00)	0.00 (0.00)
Some college no degree	0.04*** (0.01)	0.04*** (0.01)	0.01 (0.01)	0.01 (0.01)	0.02** (0.01)	0.02** (0.01)	0.03*** (0.01)	0.03** (0.01)	0.05*** (0.01)	0.05*** (0.01)	-0.02** (0.01)	-0.02** (0.01)
Bachelors degree	0.01 (0.01)	0.01 (0.01)	0.00 (0.01)	0.00 (0.01)	0.07*** (0.01)	0.07*** (0.01)	0.15*** (0.02)	0.14*** (0.02)	0.08*** (0.01)	0.08*** (0.01)	0.13*** (0.01)	-0.13*** (0.01)
Graduate degree	0.03** (0.01)	0.03** (0.01)	0.01 (0.01)	0.01 (0.01)	0.09*** (0.01)	0.09*** (0.01)	0.17*** (0.01)	0.17*** (0.01)	0.08*** (0.01)	0.08*** (0.01)	0.15*** (0.01)	-0.15*** (0.01)

Hispanic	0.00 (0.01)	0.00 (0.01)	0.02 (0.01)	0.02 (0.01)	0.01 (0.01)	0.01 (0.01)	-0.00 (0.02)	-0.00 (0.02)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)	0.01 (0.01)
Black	0.04** (0.01)	0.04** (0.01)	-0.00 (0.01)	-0.00 (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.06*** (0.02)	-0.06*** (0.02)	0.02 (0.01)	0.02 (0.01)	0.02** (0.01)	0.02** (0.01)
Asian	0.02 (0.04)	0.02 (0.04)	0.06 (0.04)	0.06 (0.04)	0.04*** (0.02)	0.04*** (0.02)	0.03 (0.04)	0.03 (0.04)	-0.00 (0.03)	-0.01 (0.03)	0.07*** (0.02)	-0.07*** (0.02)
American Indian	0.02 (0.03)	0.02 (0.03)	0.00 (0.02)	-0.00 (0.02)	0.01 (0.02)	0.01 (0.02)	0.01 (0.03)	0.01 (0.03)	0.01 (0.03)	0.01 (0.03)	0.02 (0.02)	0.02 (0.02)
Native Hawaiian	0.06 (0.07)	0.06 (0.08)	0.16* (0.08)	0.16* (0.08)	-0.04 (0.07)	-0.04 (0.06)	-0.03 (0.09)	-0.03 (0.09)	-0.03 (0.06)	-0.03 (0.06)	0.05 (0.06)	0.05 (0.06)
Other Race	0.04 (0.03)	0.04 (0.03)	0.02 (0.03)	0.02 (0.03)	-0.01 (0.03)	-0.01 (0.03)	-0.06* (0.03)	-0.06* (0.03)	-0.02 (0.03)	-0.02 (0.03)	0.06* (0.03)	0.06* (0.03)
Has medical condition	0.05*** (0.01)	0.05*** (0.01)	0.08*** (0.01)	0.08*** (0.01)	0.04*** (0.01)	0.04*** (0.01)	0.05*** (0.01)	0.05*** (0.01)	0.05*** (0.01)	0.05*** (0.01)	-0.02** (0.01)	-0.02** (0.01)
Lives with children	-0.00 (0.01)	-0.00 (0.01)	0.01 (0.01)	0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.01 (0.01)	-0.02* (0.01)	-0.02* (0.01)	0.00 (0.01)	0.00 (0.01)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R-Square	0.26	0.26	0.14	0.14	0.23	0.23	0.23	0.23	0.31	0.32	0.36	0.36
Sample Size	61687	61687	38423	38423	61625	61625	61646	61646	42139	42139	53294	53294

Notes.—Source: Gallup Panel. Demographic controls included in the model but not shown: binary variables for the following: being employed last week, being out of the labor force last week; male; having some college but no degree, holding a bachelor's degree, holding a graduate degree; being Black, Asian, American Indian, Native Hawaiian, another non-White race, or Hispanic; you or household member having a medical condition that puts them at risk for COVID-19; living with a child. Standard errors are clustered at the county-level.