Economics affects mobility, and ideology affects mask-wearing: How COVID-19 drifted to the red areas within the USA in 2020

Zhihan Cui*, Sherry Wu*, Lu Liu*, Jeffrey Shrader, Alex English, Yu Ding, Daniel Molden, Michael W. Morris, Thomas Talhelm, Eileen Wu, Yi Yang, Ziqi Zhao and Geoffrey Heal

Abstract

The US experienced multiple, sustained outbreaks of COVID-19 in 2020. From March to November, the spread of the disease in the US showed puzzling patterns: the epicenter of the outbreak drifted from large urban Democractic centers to sparsely populated Republican and rural areas. Denser regions that were initially badly hit did comparatively better. This paper explains such a paradoxical diffusion of COVID-19 across US states and counties by pinning it down to the failure of two typical measures: social distancing and mask wearing. We build a behavioral model incorporating extrinsic incentives and intrinsic motivations to analyze the determinants of these two behaviors. We hypothesize that economic vulnerability (e.g., the risk that a country or an individual could be damaged by repeated financial shocks and instabilities), should be the key predictors of failure of social distancing. On the other hand, given the low cost of mask wearing, Conservatism and Trump-support should instead be the dominant predictors of this measure. We use county-level and state-level data to test these hypotheses. Using Standardized Seemingly Unrelated Regression and coefficient tests, we show that economic vulnerability largely predicts mobility, and ideology largely predicts mask wearing and does less for mobility. Also, we analyze the effect of these factors over time and find that for many indicators, Conservatism and Trump-support had a larger effect after August. This finding is strengthened by an increasing trend of correlation coefficients between Trump vote share and total cases per capita. These results, together, suggest that states and counties with lower economic vulnerability and Conservatism were likely to have better responses to COVID-19, and the effect of the latter was increasing in Fall, 2020.

Introduction

The management of COVID-19 in the United States has been poor. It has had nearly twice as many cases and deaths as any other country. As of December 15, 2020, confirmed cases and deaths per 1M people have respectively reached over 60,000 and 1,000, both among the highest in the world (1); and from December to January 2021, the pandemic has been widespread and uncontrolled, with nearly all states experiencing high infection and death rates. The COVID-19 response puts into the question the reasonable presumption of America's public health competence (2) and calls for an investigation of their failure. Specifically, in the 8 months from when the first local cases were identified in March, to November—which also coincided with the US Presidential election—the US was unable to prevent the most severe outbreak of COVID-19. What hindered the country from controlling the disease?

The spread of COVID-19 in the US was distinctive in three ways before the nationwide catastrophe in December. First, the United States has left the power to individual states (See Fig. 1 and SM) to start and end COVID-related policies[1] (3). The lack of a coordinated response is associated with a range of problems and has possibly made social and behavioral factors more important in determining the COVID-19 response in the USA (4).

Second, unlike its European counterparts, the US has failed to control the pandemic at any point since late March. The 14-day average daily infection rate has stayed above 20,000, or 0.005% per capita. In the United States, there are two dominant distinctions that correspond with states being labeled as either "red" or "blue." A red state (Republican state) is definied as a state that lean towards Trump and the Republicans (3). Particularly, red states are larger contributors to this per capita pattern than the blue states.

Third, the epicenters of the US pandemic have drifted away from large urban centers (The NY-NJ-CT Tristate area) to less urbanized areas (the Sun Belt and the Midwest; see SM). For instance, at the US State level, the initial infection rate (as of Apr 30) is not correlated with the total infection rate, which is a relatively unique pattern in the US, deviant from almost any other developed country in the world[2]. In addition, the drift has been heading to less urbanized areas, despite much lower population densities.

These atypical "American" patterns, as mentioned above, did not take place in some states. In April (5), the seven initially heavily attacked Northeastern States (NY, NJ, CT, MA, RI, DE and

[1] Belgium, which has an even higher death/100M than the US, has a similar type of problem. The three major regions (Flanders, Wallonia, and Brussels, have distinctive culture and health policies). This is suggestive evidence that supports our hypothesis. Detailed information can be retrieved at https://foreignpolicy.com/2020/11/26/why-does-belgium-have-the-worlds-highest-covid-19-death-rate/

[2] The state (province/region for other countries)-level Pearson bivariate correlation (same for all correlations in the remainder of this paper) between the per capita infection from the initial outbreak (cases up to Apr 30, 2020) and the per capita infection till Nov 30 is -0.041 (95%CI: -0.319 to 0.243), while this number is 0.71 (95% CI: 0.16 to 0.93) across 10 Canadian provinces and generally larger than 0.8 within European countries. If we consider that the US is largely heterogeneous and diverse across states, we might want to compare with the European Union rather than single countries. However, the within-EU correlation is still 0.57 (95%CI: 0.25 to 0.78), showing that the drifting of epicenter in the US is a highly exceptional phenomenon. (See SM Figure S3 for map demonstration)

PA) formed a coalition promoting collaborative coping and smart reopening. These states launched longer stay-at-home orders in comparison to other states (see Fig. 1 and SM) and kept COVID-19 numbers in control from May to October (See Fig. 1B). In other words, there were sizeable within-US differences in COVID-19 control throughout 2020. This motivates us to investigate potential mechanisms behind the abovementioned distinctive patterns empirically with state level and county level administrative and behavioral data.

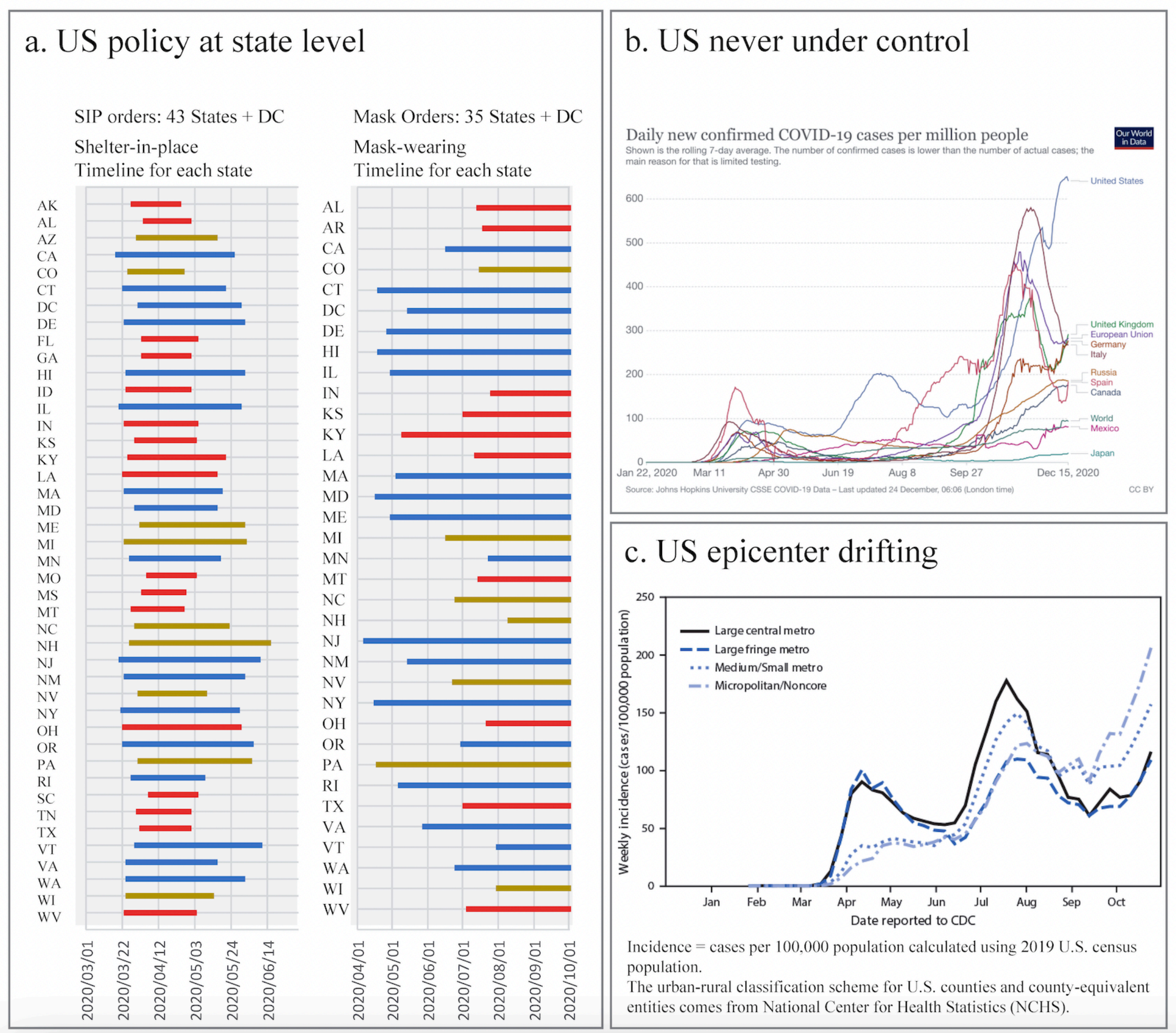


Figure 1A: COVID Response and Spread in the USA

Figure 1 shows the timelines of statewide Shelter-in-place/Stay-at-home order and mask mandates up to Oct 1. If a state had never had such a policy, it is not included in the bar-plot. The list is here:

No-SIP states: AR, IA, ND, NE, OK, SD, UT and WY.

No-mask-order states: AK, AZ, FL, GA, ID, ND, NE, MO, MS, OK, SC, SD, TN, UT and WY. (IA starting in Nov., thus not shown in the graph)

Figure 1b shows the daily new confirmed COVID-19 cases per million people across the United States, the EU, the world and some major countries from Jan 22, 2020 to Dec 15, 2020. Figure 1c shows the dynamics of daily new cases per 100k population in four types of areas in the United States. In SM Figure S1A S1B and S2, a more detailed demonstration is available.

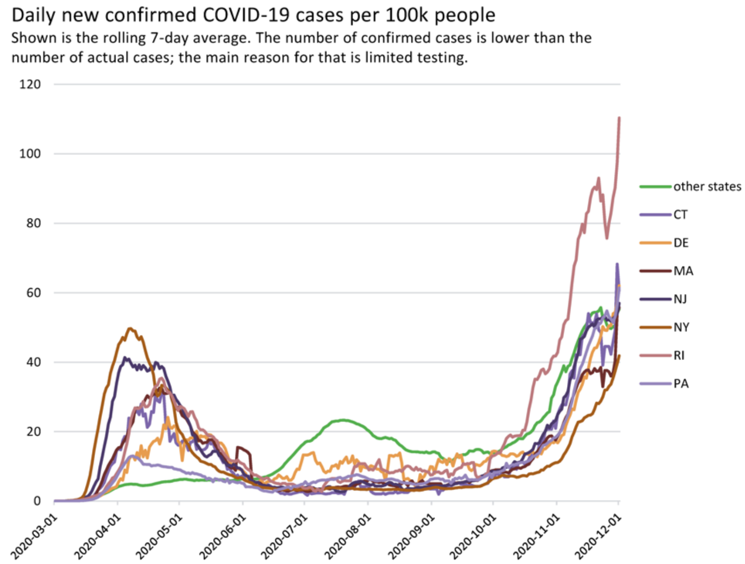


Figure 1B: Pandemic Curves of the Northeastern Coalition States vs the Rest of the Country– Daily New Confirmed COVID-19 Cases per 100k People

Theory and Research Hypotheses

Epidemiologists suggests three fundamental ways of dealing with a pandemic: source control, cutting off transmission routes and protecting susceptible hosts (6). From March to November 2020, when vaccines were unavailable and contact tracing was scarce, America's solutions to COVID-19 had been social distancing (cutting off transmission routes) and mask wearing (both for source control and protection of susceptible hosts). Thus, the effectiveness of these two measures is fundamental to preventing the spread of COVID-19. Numerous studies have documented that socially distancing and mask wearing *causally* impact COVID-19 outcomes (Social Distancing, 7-11; Masks, 12-15). Therefore, studying the underlying behavioral mechanisms of COVID-19 outbreaks requires studying the failure of social distancing and mask coverage—specifically, factors closely related to the adherence of these two measures.

From a behavioral science perspective (3), social distancing (SD) and mask coverage draw adherence from multiple factors. First, the major deterrent for shelter-in-place is that most people have to work away from home[3](16). Going out to work during the pandemic is associated with two positive incentives and one cost. The extrinsic incentive is to make money -- and during a pandemic, people usually work away from home only when their need for money is intense. The intrinsic incentive is to demonstrate political stances and build reputation in their communities. The cost with working away from home is associated with the perception of being exposed to COVID-19. These three dimensions are likely to be impacted by unique factors. The extrinsic incentives are impacted by financial status (17-18). During the pandemic, essential workers may still work away from home. However, they only compose a small proportion of population. Most non-essential workers are unable to telecommute (16, 19). Therefore, if the government were to keep shutting down non-essential sectors, these people, without sufficient

[3] At the county level, the Pearson correlation coefficient between time spent at home and workplaces is -0.84 (95%CI: -0.85 to -0.83), while the same coefficient former and other constructs are much lower. And the work-from-home ratio is <40% for almost all states in the US.

social safety nets, would face severe financial difficulties. Thus, as shelter-in-place orders are introduced, urgent economic needs surge and this makes it difficult for the local governments to maintain social distancing policies. For the intrinsic incentives, researchers have found that Republicans and Democrats may have different reputation and value concerns on social distancing (20-23). Democrats and Independents view social distancing as a public good that promotes reputation, while (firm) Republicans, in contrast, may believe *working* outside during COVID-19 shows solid support of conservative values and President Trump (24-26). Thus, firm Republicans might find that working—and not social distancing—enhance their reputation in a conservative community. Numerous studies have shown the highly negative impact of Republican partisanship and American Conservatism in the risk perception of COVID-19 (21-22, 27-28), and thereby social distancing (20-26) and virus spread (20, 29).

Theories (30) predict that the relative strength of partial effects of the different types of incentives vary when their values are different. As we observe and hypothesize, only firm Republicans will promote non-compliance of social distancing and mask wearing as a good that promotes reputation. When economic incentives are low, they can more easily show their identity by working away from home to win the support of their conservative communities. In this case, the reputational motivations are high, and the partial effects of economic incentives are lower. However, when economic need is high, the incentives may be either a result of urgency to work, or Republican values. In this case, reputational concerns are lower, and the relative effect of economic incentives will be higher. A detailed theory model is in the Methods section.

IConsequently, people with a high vulnerability to economic shocks from COVID-19 are more susceptible. Magnifying this to the regional level, we establish a family of factors that is hypothesized to predict social distancing failure: *Economic Vulnerability (EV)*. Higher economic vulnerability comes from many sources. In the United States, red states in the South are the most economically vulnerable in multiple dimensions (See SM Fig. S4). Southern red states have higher poverty rates (31-32), less coverage of insurances (33), less protection for unemployment (34), and lower intellectual human capital (35). They are considered high in economic vulnerability compared with the country average, which is already more vulnerable than other developed countries (See SM Fig. S5). To validate this point, many Southern states had a high level of unemployment filings during the first two months of the COVID-19 outbreak (36). Southern conservatives also save less than residents of other states and other high-income countries (37-38). Moreover, although the United States ranks among the countries with the highest work-from-home potential, most red states do not share this privilege (16, 19). All of these features strengthen the economic pressure that pulls people to work away from home during the pandemic.

The theoretical discussion and the empirical facts indicate that at least for some places, economic vulnerability is likely high enough to be the major determinant of social distancing. Accordingly, we have the first hypothesis:

H1: The likelihood of an individual social distancing and staying home is negatively predicted by both economic vulnerability and American Conservatism, but the former should have a stronger effect at least when the region-level economic vulnerability is higher.

Unlike social distancing, mask wearing is less affected by economic incentives. For most families, regular masks are affordable, and self-made masks are also an available option (39). Thus, the economic incentives to refuse a mask are low. As the current literature and polls show (40-42), masks have been highly politicized during the pandemic. Almost all Democrats endorse masks, but the proportion is much lower among Republicans, since many extreme Republicans refuse to do so to show their values and support of Trump. Also, they may do so to show their religious values or attitudes against large governments. Refusal of mask wearing is mainly promoted by ideological and political factors[4], as conservatives tend to have a lower perception of risk of COVID-19 infection and death (27), and they simultaneously tend to refuse a mask to demonstrate their values and political stance (39, 43). Consequently, we establish our second hypothesis:

H2: Mask wearing is strongly negatively predicted by Republican partisanship and American Conservatism, but much less (or even not) by economic vulnerability.

Despite the rich literature on related topics, this paper has its unique contributions in three aspects: 1) Using interdisciplinary datasets, we holistically review the determinants of social distancing and mask wearing in the United States, and find that economic vulnerability and Conservatism (Trump support) are two dominant predictors; 2) with the cross-validation of a theoretical model and econometric analysis, we unmask the heterogeneity of the effects of economic and ideological factors on COVID-19 response in terms of different measures and time periods, and 3) on a theoretical basis, we offer a large-scale real-world test of how people deal with extrinsic incentives and intrinsic motivations, and show that their partial effects on behaviors can depend on their magnitudes, improving our understanding of the motivation theories.

Results

Dependent variables.

We rely on three categories of dependent variables in this paper: mobility change (time spent at different locations), mask wearing, and COVID-19 cases (mainly in state-level results). Based on our hypothesis H1, we are interested in time spent at homes and workplaces. We thus use the Google Mobility Trend (44) dataset as the baseline data. Based on data availability and our hypotheses, we choose two sets of masks wearing data: the New York Times-Dynata Survey (45) that covers >2,000 counties and 250,000 respondents from July 2-July 17, and Carnegie Mellon University's COVIDCast dataset (46) that covers fewer counties (~600) from September to November. For COVID-19 cases and deaths, we obtain the data from the CDC official reports.

Independent variables.

[4] A national map (state level) is available in SM Fig S6.

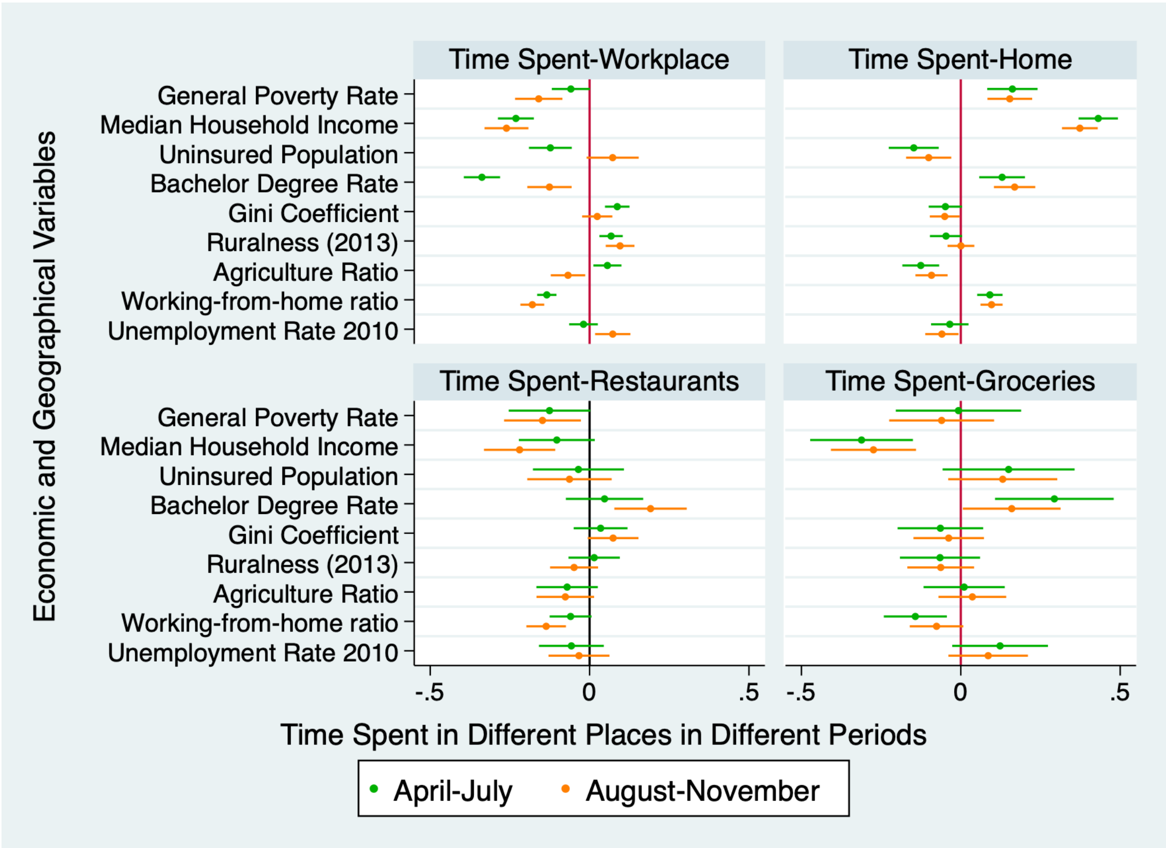
Our independent variables mainly fall into two categories: economic vulnerability and ideology. For economic vulnerability, we focus on two classes of indicators: social safety net (the capacity of the local economy to cope with negative economic shocks), and industry structures that do not allow telecommuting. Both of them may impact people's choice on the tradeoff between telecommuting or working away from home. For ideological variables, we utilized four different, but correlated, dimensions of American Conservatism that have important influences on behaviors that lead to further COVID-19 outbreaks: religiosity, support for limited government, skepticism of media and science, and Trump-support. Each of these variables may have important effects on COVID-19 spread. Detailed measures and explanations of these variables are shown in the Methods section. In county-level analysis we also control for state fixed effects and local culture (47).

County-level analysis.

The current paper focuses on the quantification of county-level economic vulnerability and ideological effects on social distancing and mask coverage. Our main indicator for social distancing includes four measures of where people spend their time (home, workplaces, restaurants and grocery stores), from April to November, 2020. Since the economic incentives are mainly associated with working, we would expect that the time spent in workplaces should be most impacted by economic vulnerability, and the time spent in restaurants and grocery stores should be more impacted by ideological and political indicators. Finally, time spent at home should be mainly determined by going out to work.

In the main results, we separate the timeline into two periods: First, from April to July, during which many parts of the country were under a shelter-in-place order, or at least some restrictive orders about enforcing social distancing. Secondly, from August to November, during which most places reopened (but certain places returned to stronger measures) and the only remaining order for many states became mask mandates. We argue that when stay-at-home orders were (fully or partially) prevalent, the incentive structures of going out might differ. For instance, the EV incentive might be lower in the second period because the economy was reopened and booming again after the historic downfall in April-June. Also, the elections campaigns began in August, leading to a higher level of politicization of COVID-19, and many Trump-supporters were protesting against masks and social distancing to show their loyalty. This actually mirrors the completely contrasting reputation motivations of Democrats and Republicans.

The following two figures show the determinants of mobility. We use a standardized regression setup, allowing us to compare the relative contributions of the variables of interest to our dependent variable. We controlled total cases till the time of interest, population density, age and gender structures, temperature and other key variables that may impact mobility but not belong to either of our main category.


Time Spent-Workplace
Time Spent-Home
Time Spent-Restaurants
Time Spent-Groceries
General Poverty Rate
Median Household Income
Uninsured Population
Bachelor Degree Rate
Gini Coefficient
Ruralness (2013)
Agriculture Ratio
Working-from-home ratio
Unemployment Rate 2010
Economic and Geographical Variables
-.5
0
.5
Time Spent in Different Places in Different Periods
April-July
August-November

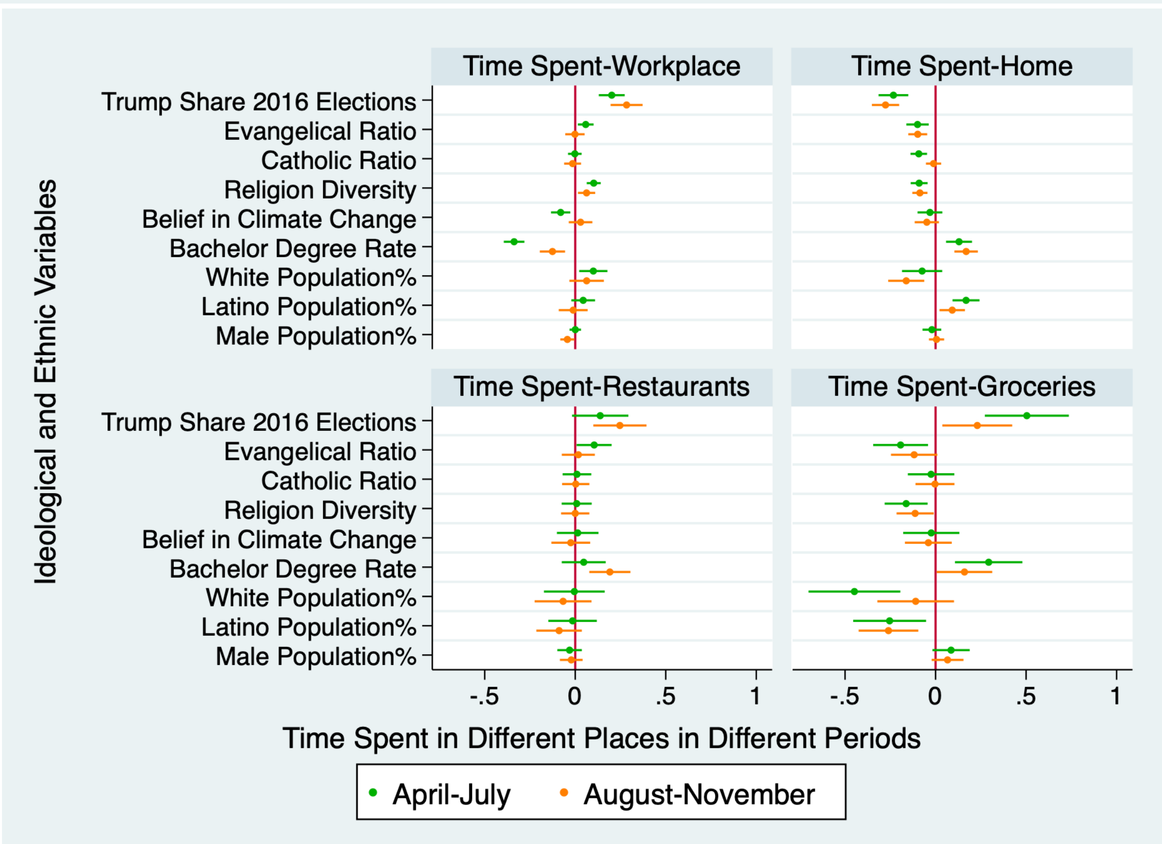

Time Spent-Workplace
Time Spent-Home
Time Spent-Restaurants
Time Spent-Groceries
Trump Share 2016 Elections
Evangelical Ratio
Catholic Ratio
Religion Diversity
Belief in Climate Change
Bachelor Degree Rate
White Population%
Latino Population%
Male Population%
Ideological and Ethnic Variables
-.5
0
.5
1
Time Spent in Different Places in Different Periods
April-July
August-November

Figure 2A and 2B. Regression coefficient plot for economic variables and social distancing.
The left-hand side is a certain response of COVID-19 (time spent in different places). The right-hand side includes lagged cases per capita, recent speed of infection, state*culture interaction terms, and ideological variables. Models are conducted with Ordinary Least Squares (OLS). The round point is the point estimate value, while the lines are 95% CI.

First, we examined how economic vulnerability and ideology predict social distancing. Although coefficients may differ across time, the basic take-home message is clear. First, during a pandemic, the most indoor time that people spend away from home is in workplaces – when it is necessary, and other needs, such as dining in and shopping, are generally minimized and have a lower correlation with staying home (see page 4 footnote). As the county-level correlation between working and staying home is around -0.85, the two have similar predictive power. It is clear that both conservatism (measured by Trump vote shares, religiosity, ethnic structures, etc.) and economic vulnerability (Lower education, less income, low work-from-home ratio, etc.) are robust predictors for working outside more and therefore, staying home less. The time spent at restaurants and grocery stores are less impacted from economic vulnerability, and more by Republican partisanship. Detailed discussions are in SM.

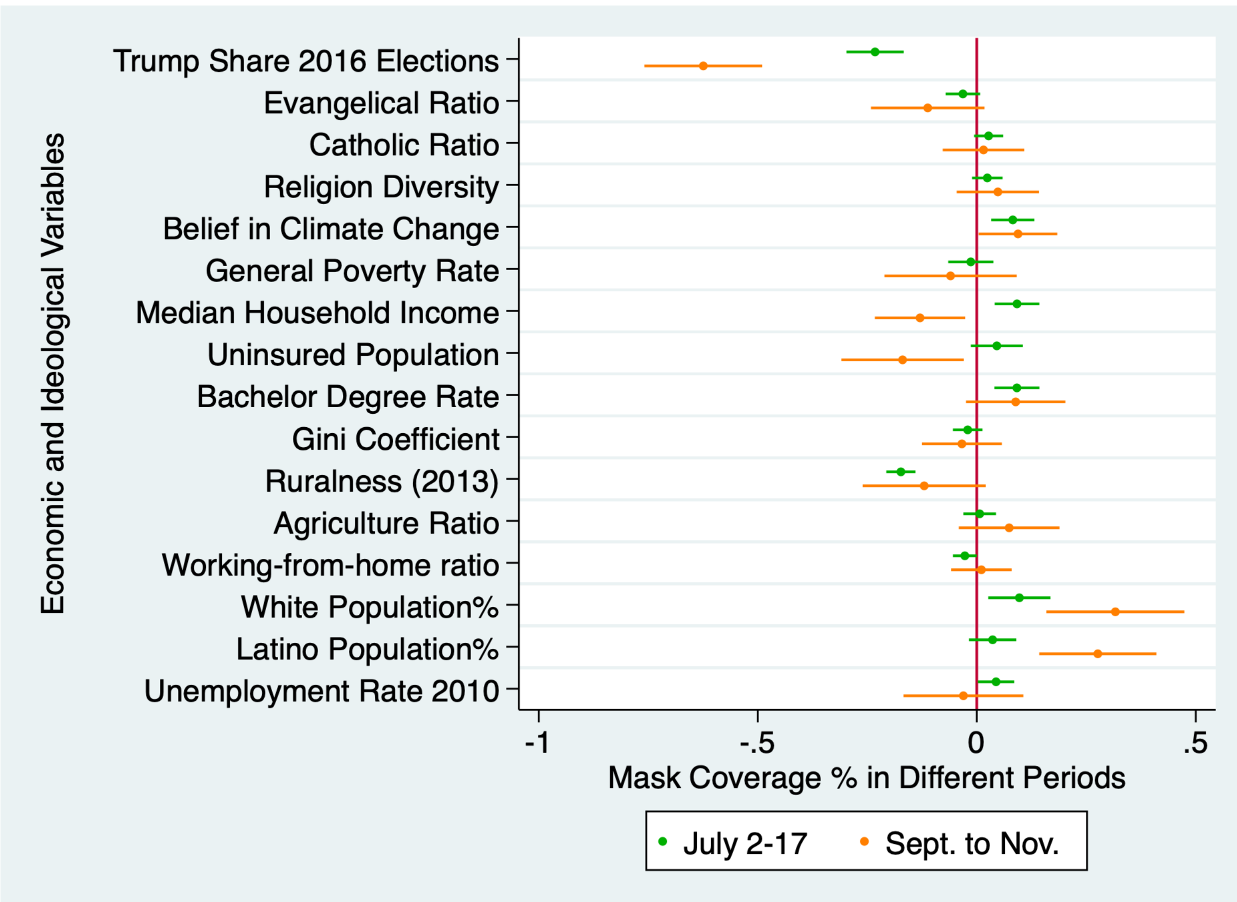


Figure 3. Regression coefficient plot for economic and ideological variables and mask coverage
The left-hand side is a certain response of COVID-19 (mask-wearing). The right-hand side includes lagged cases per capita, recent speed of infection, state*culture interaction terms, and ideological variables. Models are conducted with Ordinary Least Squares (OLS). The round point is the point estimate value, while the lines are 95% CI.

Next, we examined how economic vulnerability and ideology predict mask wearing. For mask wearing, results are slightly different in the second peak (July) and the third peak (October-November). In July and Fall (Sep-Nov), the best predictor of mask coverage is Trump support, but the coefficient for Fall is significantly more negative. In July, the partial correlation coefficient is -0.21 (95%CI -0.30 to -0.17) being a major but not dominant predictor. However, in October and November, other variables become statistically insignificant or only marginally significant, and the Trump share explains more than 1/3 (partial correlation 0.63, 95%CI 0.50 to 0.75) of the variation in our baseline regressions. This is coherent with our findings on the state-level correlations of Trump support and confirmed cases in the third peak.

Heterogeneity Analysis for Social Distancing and Masks
In this part, we report formal statistical tests and dynamics of how the marginal effect of economic vulnerability and conservative ideology correlates with social distancing and mask coverage. Our hypothesis and theory model (see Methods) will formally denote three dimensions of heterogeneities:

(1) If we compare time spent at the workplaces with mask coverage during similar time periods, the ideology effect should be larger with masks, and the economic effect should be larger with time spent at workplaces.
(2) If we compare within regressions of working-outside and masks, we should find evidence that working outside is explained better by EV measures and mask-wearing is explained better by ideology and Trump support.
(3) As time goes by, during which EV forces were (arguably) going down and the politicization of COVID-19 increased, for both social distancing and mask coverage, the effect of Republican orientation should be mostly increasing.

To formally test these assumptions, we examine if within a group of regressions, the regression coefficients are different. Since the two behaviors in one county may share similar unobserved factors, the pairwise correlations between error terms are not independent. Thus, we use a Seemingly Unrelated Regression (48-49) to estimate these models and thereby test our hypotheses. For each of the behaviors (working, stay-at-home and mask wearing), here are three tables for the predictions (1) (2) and (3):

	Period 1		**Period 2**	
	Bachelor's	Earnings	Bachelor's	Earnings
	Working time: Republican			
Chi2	**5.3**	0.36	3.99(Rev)	0.15
P	0.0214	0.548	0.0457**	0.697
	Stay-at-home time: Republican			

Chi2	2.62	**13.4**	3.13(Rev)	**4.12**
P	0.105	0.000***	0.077*	0.042**
	Mask: Republican			
Chi2	8.49	15.38	30.44	102.26
P	0.000***	0.000***	0.000***	0.000***
	Working-Mask			
Chi2	37	11.53	0.26	33.74
P	0.000***	0.000***	0.6076	0.000***
	Working-Mask: Republican			
Chi2	0.34		16.4	
P	0.56		0.000***	

Table 1A: This first three rows of this table is the within-regression comparison of the standardized regression coefficients of conservatism (represented by Trump vote share in 2016), and economic vulnerability (represented by Bachelor's degree ratio and median earnings). We use a standard coefficient test from the *suest* command in Stata. The null hypothesis is that the two compared coefficients sum to zero (as income/education are the opposite side of EV). When there is a "Rev" inside the table, it means that for this result, the absolute value of the coefficient of the Republican partisanship is larger than that of education/earnings, which is actually the reversed result of the main hypothesis (that EV has an larger effect than Republican partisanship/Ideology).

Table 1A shows that when we compare SD and mask regressions during similar time periods, the ideology effect is larger with masks, and the economic effect is larger with time spent at workplaces. It also shows that in Period 1, when we compare ideological variables (the one with the highest coefficient is Trump share) with EV variables in social distancing regression, the latter is generally playing the leading role. But in Period 2, such advantage has significantly shrunk. Also, such comparison is reversed in the mask regression, and in Period 2 the effect of partisanship is dominating.

	Period1 vs Period2		
	Republican	Bachelor's	Earnings
	Working		
Chi2	**3.41**	**35.33**	0.89

P	0.065*	0.000***	0.345
		Stay-at-home	
Chi2	1.04	0.95	**3.22**
P	0.307	0.33	0.073*
		Mask	
Chi2	**30.68/24.17**	(coefficients insignificant)	
P	0***/0***		

Table 1B: This is a table that compares the standardized regression coefficients of the three representative variables on social distancing and mask wearing behaviors. We use a standard coefficient test from the *suest* command in Stata. The null hypothesis is that the two coefficients are equal across two periods (for Working and Stay-at-home, Period 1=Apr-Jul, Period 2=Aug-Nov; for mask coverage, Period 1=July 2-17, Period 2=Sep-Nov). The two values of mask wearing is because Period 2 has a much smaller sample size than Period 1 due to data availability. The left value is resulted from directly using SUR on two original regressions, and the right value is resulted from using SUR on the very same sample.

Table 1B shows the evidence that as time reached August (when shelter-in-place orders all ended and election campaigns began), the marginal effect of economic vulnerability goes down and that of political ideology goes up.

Next, here is a graph that shows the dynamics of the predictive power of some key variables of interest on Social Distancing (working and staying home) on a monthly scale. For masks, due to data availability we only have a two-point comparison, so that at both first-glance observation and rigorous hypothesis testing show good support of our heterogeneity story. As these results converge, we have more confidence that our hypotheses are well supported.

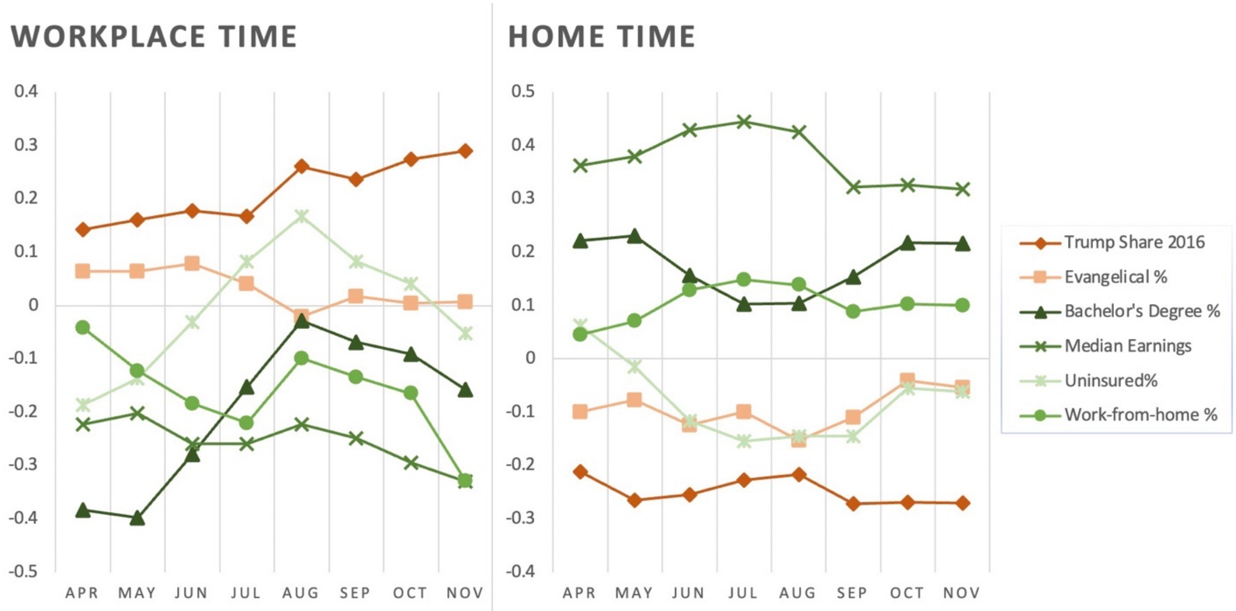


Figure 4: This is a time series plot for the standardized regression coefficients of two representative ideological and four representative economic variables. Each point is a regression coefficient of the result in certain time periods, in which the dependent variable is the mentioned social distancing variable on a monthly average.

Finally, there is extra evidence that suggests social distancing is less impacted by economic vulnerability, and that mask wearing behaviors are more politicized in Fall than in Spring/Summer. For instance, Pearson correlations between bachelor's coverage and working time was -0.67 from April to July, while it was only -0.51 from August to November, and The Pearson correlations between the Trump Voting Share in 2020 and 2016 elections (county level) are respectively -0.52 and -0.48 for July, -0.80 and -0.77 for October, and -0.74 and -0.72 in November. The highest salience of partisanship was around the election. The election days were witnessing more politicization of COVID response.

State-level correlations.

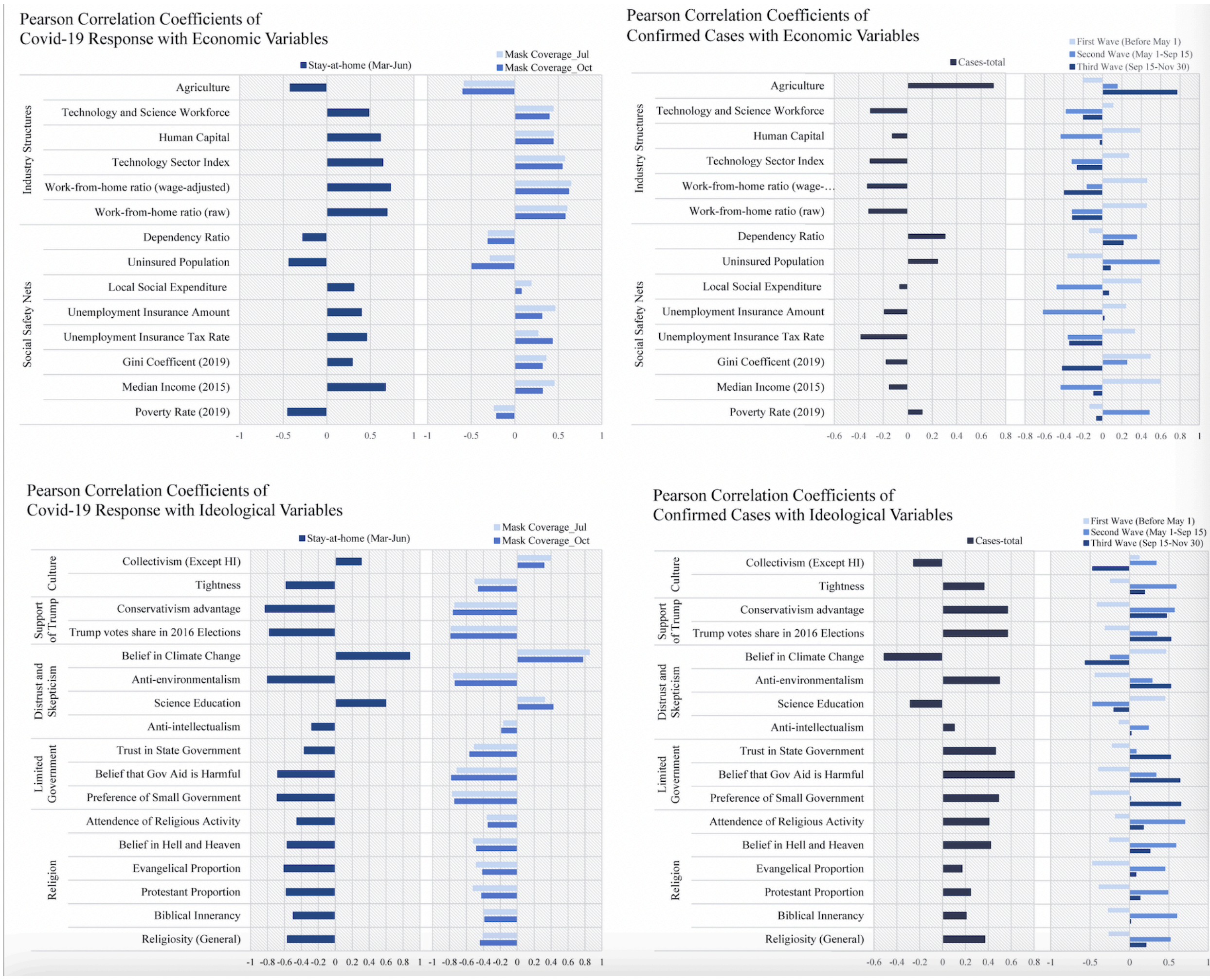


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Figure 5. Pearson Correlation Coefficients of COVID-19 Response and Confirmed Cases / 100K with Economic and Ideological Variables.

Consistent with our hypotheses, evidence from the aggregated state level shows that social distancing and staying home is largely predicted by economic vulnerability, while mask wearing is strongly predicted by ideology. The state level analyses further our understanding of interstate differences in COVID-19 spread. For Hypothesis 1, we find two important features: First, indicators of economic vulnerability are systematically positively correlated with fewer COVID-19 preventative measures, especially less social distancing. Human capital (*r*(50)=0.62, 95% CI 0.40-0.76), industrial sector distribution (Technology Sector Index: *r*(50)=0.64, 95% CI 0.44-0.78; Work-from-home ratio (wage-adjusted): *r*(50)=0.73, 95%CI 0.56-0.84, Work-from-home ratio: *r*(50)=0.69, 95%CI 0.51-0.82) and median income (in 2015, *r*(50)=0.67, 95%CI 0.48-0.80) are the strongest predictors for social distancing measures at the state level. On the aggregate level, social safety net is still a statistically significant predictor (*r*(50)<0.4). This is consistent with the fact that states with high economic vulnerability tend to have shorter or even no shelter-in-place orders (see SM), further supporting our hypotheses. Second, economic vulnerability has distinctive correlations with the three peaks of cases. In the first peak, economic vulnerability is negatively correlated with COVID cases, because in March, the first epicenters took place around NYC due to intensive international travel and high population mobility. In the second peak, social safety net variables are robustly crucial predictors (selected predictors: uninsured population, r=0.59, 95%CI 0.36-0.74; unemployment insurance amount, r=-0.61, 95%CI -0.40 to -0.76, and >0.4 for others) for the outbreak in Southern red states, which was the main reason why the US has never controlled COVID-19. In the third peak, industry structures are stronger predictors, with agricultural/GDP percentage (r=0.77, 95%CI 0.62-0.86) the dominant one. This might be due to the specialties of agriculture (such as the presence of meat processing plant, see Taylor and Almond (50)), or just a geographical coincidence. Further exploration at the county level is necessary. In SM, we also show partial correlations between economic and ideological variables with the state color (4) or Trump vote share controlled, which suggest that there are still many of them being statistically significant.

For Hypothesis 2, indicators of ideology are good predictors of less social distancing and mask wearing, and the effects for the latter are slightly larger. The strongest predictor for social distancing is the belief in climate change (r=0.88, 95%CI 0.79-0.93), which is a typical measure about belief in scientific consensus. Trump support (r=-0.77, 95%CI -0.63 to -0.87), conservatism advantage (r=-0.83, 95%CI -0.71 to -0.90) and anti-environmentalism (r=-0.80, 95%CI -0.67 to -0.88) are also strongly negative predictors for social distancing. Results are similar if we look at mask-wearing (detailed numbers in SM), and the predicting power of Trump support is among the highest. When we come to confirmed cases, in the first wave the patterns are again reversed, likely for similar reasons concerning the generally more liberal values of individuals in the predominant NYC epicenter. The second wave seems to be better explained by religious activities than pure Republican partisanship, and the religious activity participation (r=0.70, 95%CI 0.53-0.82) is a dominant predictor. This is a suggestive piece of evidence that religious activities, which include mass gatherings, might have been highly related to COVID-19 spread in summer. In the third wave, the national outbreak with the epicenter starting in Midwest states, the partisanship effect (r=0.53, 95%CI 0.29-0.72) seems larger, and the social safety net/religious activity effects are weaker (r<0.4). Among all ideological factors, preference for small government (r=0.65, 95%CI 0.45-0.79) and opposition to government aid (r=0.64, 95%CI 0.44-0.78) are dominant predictors. This offers suggestive evidence that the recent peak of COVID-19 is more associated with Republican partisanship than the first two peaks, and specifically the small-government preferences are associated with less COVID-19 response.

On the whole, the coalition states and some other Democratic states (such as VT, NH, ME, WA and OR) were more successful with their low economic vulnerability and less conservative culture. This is not necessarily causal, but it is a coherent explaining at the correlational level.

General Discussion

Heterogeneous effects in the first, second and the third peak.

In our analysis, we show clear time-varying effects in the predictive power of our target variables on COVID-19 related behaviors: in earlier times, economic vulnerability prevailed and after August, ideological ones. This drives us to look into the underlying reasons. The first peak, which mainly took place in Democratic and metropolitan areas from March to May, resembles the first outbreak in other Western countries. The outbreak in the Tri-State area is highly analogous to that in Lombardy, Italy and London, UK. However, the patterns start to be unique in the United States, especially in red states, after mid-May. The second peak mainly took place in the South and is mostly likely to be explained jointly by economic vulnerability and religiosity, while other dimensions of conservatism seem to have a lower direct influence at the state level. Our model shows a two-step story for these states: in late April, southern states reopened too early without suppressing the effective reproduction number (Rt) below 1, or at least, they bounced back over 1 quickly after radical reopenings designed for economic recovery (51). These premature reopening orders took place in Southern states with worse social safety nets (52-53), justifying the economic vulnerability story. Consequently, religious activities rebounded immediately with large gatherings and hardly any mask adherence. This lead to churches becoming a crucial source of COVID-19 spread (54). Such situations were not changed until mask orders started to cover these states in August and September (See the graph in Introduction). The third wave, starting from Midwest Republican States in October, however, was more politicized. Our evidence shows that Trump support and Republican partisanship are among the best predictors for not wearing masks and for large numbers of cases in this period. In addition, the epicenters in this peak were likely those states which have a large reliance on agriculture and preference towards limited government interference. The Midwest red states are different than the Southern red states and it was even harder to launch mask and lockdown orders in the Midwest states. Moreover, October was right before the elections, and campaign activities might have enhanced virus spread (55-56). More detailed data visualization and policy demonstration of these three peaks are qualitatively articulated in the supplementary materials. Note that all these findings are correlation-based, and there do exist alternative explanations that we are not able to rule out in this paper.

Interactive dynamics of economic vulnerability and ideological factors. In previous analyses, we tend to treat and construct these two dimensions of variables distinctively. Nevertheless, these two families of variables may have significant interactions, especially with regards to political stances. It has been noted that economic inequality may lead to political polarization, which naturally leads to politicization of crucial issues (57), from global warming (58), family relationships (59), to COVID-19 response (60). Economic inequality and wealth redistribution caused by globalization has significantly altered social thought processes (61-62). Cognitive biases provide a pathway from economic vulnerability to ideological change and politicization of, simply, everything. This is linked to the current literature on motivated reasoning. The model of "motivated denial of science", and specifically, the rational denial mentioned by Lewandowsky and Oberauer (63-65), in which the denial of science might be "an entirely rational operation that has clear political and economic goals". This is likely to match the COVID-19 response in red states: economically vulnerable states might appeal for the denial of scientific consensus of COVID-19 because they are economically more inclined to early reopening and less mask-wearing. In other words, denying COVID-19 is an endorsement of reopening the market, which is an urgent need from local economic vulnerability. Another possible cognitive way is scarcity thinking (66-67), which suggests that economic constraints may deplete cognitive resources and therefore drive them to think less even without a bias, which is also a studied reason for sciencitific denial (68). Economic vulnerable people may face this challenge and are therefore more inclined to rely on heuristics or traditions instead of science when facing COVID-19. Which mechanisms are prevalent? This is to be studied by future researchers.

Limitations and Future Perspectives. The limitations of this study lie in epidemiological modeling and causal identification. First, in our study, we use a linear dynamic model to show that different factors have highly variable impacts on anti-COVID measures and cases across time. However, the real effects may be nonlinear and may contain more complicated structures. Second, our findings are mainly partial correlations, which do not necessarily imply causality. To identify and quantify the underlying causal relationships between socioeconomic/ideological variables and COVID response, we need to pin them down in experiments. A natural thought is to reduce the macro-level analysis to the individual level. If we can observe laboratory evidence that these factors causally impact individual attitudes and behaviors, it will give more reliable justification for our whole project. Finally, we put relatively little emphasis on studying how these responses finally lead to COVID-19 spread. This is mostly because of the huge literature that has already explicitly established this causality. However, people may still want to fully establish the causal contributions of EV and conservatism to the spread of COVID-19 and find counterfactuals; and we suggest that future interdisciplinary research should investigate this.

Methods and Data

Behavioral Model.

In this model, we analyze the behaviors of non-essential workers who are not able to work from home. We generate our predictions by using a behavioral model derived from Bénabou and Tirole (30), in which we characterize the behaviors of staying home with different types of motivations. For a typical Republican to determine the time h allocated to work away from home ("outside") during the pandemic, we assume that they are influenced by four factors:

(1) Extrinsic incentives. The job generates an income that can cover their needs. We denote the financial urgency need that can be resolved from one hour's work as W, meaning that the more economically vulnerable they are, the higher W is.[5] W is publicly observable. For instance, when the macroeconomy faces a downfall, W goes up.

(2) Intrinsic motivations. We assume that a Republican may feel two types of satisfaction during working: First, as a job it satisifies their own values. This value per hour is denoted by $V_r > 0$; Second, it generates reputational gains G within the community, which are jointly determined by the payoff W and the hours h, i.e., $G_r = G_r(W, h)$. G should satisfy the following properties: $\partial G_r(W, h)/\partial h > 0$, as Republicans believe that working (instead of staying home) shows their support for Trump and for reopening; $\partial G_r(W, h)/\partial W < 0$ and $\partial^2 G_r(W, h)/\partial W \partial h < 0$, indicating the "crowding out" effect of Bénabou and Tirole: when the extrinsic incentive is higher, observers (community members) are less likely to interpret this behavior as a devotion to Trump, and more likely to see it as self-interested conduct.

(3) Cost. Working has a cost of time lost from other activities and a risk of infection, generating a total cost function $C = C(h)$. As usual, we assume that $C', C'' > 0$.

For a typical Democrat, however, motivation structures are different. We have many reasons to believe that they are not working outside for reputation concerns, as they usually had good

[5] Usually W is associated with lower but not higher wage. Low-wage workers tend to have less savings and social safety, which means that they tend to face severe economic problems in the pandemic. On the contrary, high-wage workers may already have a lot of savings and assets, so they do not need to take the risk working outside when the pandemic is intensive.

conformity with stay-at-home orders and did not challenge them from a politicized perspective. An easier setup is just to make the political factors $V_d = G_d = 0$.

How the Model Led to Our Hypotheses: Comparative Statistics and Theoretical Predictions. Without losing generality, we assume that for any *h* and *W*, $G_r \geq 0$, meaning that any time spent working outside will generate positive reputation for a Republican. We also put important boundary conditions for the reputation function G_r. For a Republican, $\partial G_r(0, h_r)/\partial h_r$ is bounded[6], and for any *h*, as $W \to \infty,\ G_r \to 0$.

Since we cannot spend negative time working, the optimization problem of a Democratic decision maker is:

$$MaxP(h_d) = Wh_d - C(h_d)\ s.t.\ h \geq 0$$

When $W \leq C'$, a Democrat will always stay from home, so $\frac{\partial h_d}{\partial W} = 0$. When $W \geq C'$, $\frac{\partial h_d}{\partial W} = \frac{1}{C''(h_d)}$. It is relatively straightforward.

And the optimization problem of a Republican agent will be:

$$\max\ P(h_r) = (W + V_r)h_r - C(h_r) + G_r(W, h_r)$$

Solving the first order condition we have:

$$W + V_r + \partial G_r(W, h)/\partial h_r = C'(h_r)$$

Using the implicit function theorem, we have the main condition for comparative statics:

$$\frac{\partial h_r}{\partial W} = \frac{1 + \partial G_r(W, h_r)/\partial W \partial h_r}{C''(h_r)}$$

The predictions of the model for Republicans are determined by the term $\partial G_r(W, h_r)/\partial W \partial h_r$ (denoted as G_{Wh_r} and its relationship with *W*. The total time h_r is determined by infection risks and the structures of G_{Wh_r}. For working outside, we talk about high-EV (*W* is large) and low-EV (*W* is small) cases. When *W* is large, the reputation motivations of Republicans is small or close to 0. In this case, the partial effect of *W* on *h* will be clearly positive. When *W* goes to infinity, $\frac{\partial h_r}{\partial W}$ will converge to $1/C''(h_r)$ for both partisans. This is the cases when *W* has the largest partial effect on social distancing. When *W* is small, however, for Republicans, G_{Wh} is large such that the partial effect of wage on social distancing is smaller, or even negative. And for Democrats, since $V_d = G_d = 0.$, there time spent on working away from home will be very low. When $W \leq C'$, $\frac{\partial h_d}{\partial W} = 0$, indicating that in this case, EV may have no positive partial effect on working outside. When $W \geq C'$, $\frac{\partial h_d}{\partial W} = \frac{1}{C''(h_d)}$, indicating that from here on, EV starts to have positive effects on working outside, but it is still below the maximum effect when *W* goes to infinity.

Our hypothesis takes a perspective from changing *W* in this model. It leads to the partial effect of EV on social distancing larger when EV is high (in the shelter-in-place period), smaller when EV is low (after July, as the economy began to reboom), and no effect when EV is 0 (mask

[6] This boundary condition rules out the possibility that when there is no EV, a Republican will work infinitive time to increase her reputation.

coverage). When aggregated to the county level, it generates our final hypothesis: economic vulnerability will have a larger partial effect on social distancing when county-level EV is higher.

A numerical example, which shows an easier understanding of this model, is available in SM.

Empirical Strategy.
Our main hypotheses have the following testable predictions as discussed in the result part. The basic setup of our paper is linear.

In this paper, we are using standardized regressions to make the coefficients comparable. First, in one regression on mask wearing and social distancing, we want to compare the standardized coefficients *within* this regression:

And also, we want to compare the coefficients *across* two types of regressions:

$$Social\ Distancing: Y_i = \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_n X_{ni} + r + \varepsilon_i$$

$$Masks: Y_1' = \beta_1' X'_{1i} + \beta_2' X'_{2i} + \cdots + \beta_n' X_{ni} + r' + \varepsilon_i'$$

In this way, we need to use the Seemingly Unrelated Regressions model on these two measures. Most β_1's are the same across the regressions, and we want to test whether the variables of interest have different coefficients that match our hypothesis. The Seemingly Unrelated Regression method is used to do coefficient comparisons across regressions that may have correlations in error terms, and it is a good fit for our paper.

Data.
Our research complies with all relevant ethical regulations. Since all data are publicly available from the Internet, these are categorized as exempt according to the UCLA Institutional Review Board. We are unaware of whether participants were compensated. Given the aggregated nature of these data, the sex, age and exact number of participants are unknown. No statistical methods were used to predetermine sample size (in terms of the number of included US counties), but we are covering most counties (3,088 counties) in our sample. Such a sample size allows us to detect and justify small-scale correlations between variables, and to compare the relative strengths of these relationships.

In our county-level regressions, we standardized all our variables by subtracting the mean and then dividing by the standard deviation, so that we can compare the relative predictive powers of different variables of interest.

Dependent variables
Our dependent variables fall into three categories: cases and deaths (per capita), social distancing and mask wearing. Here is a brief description.

Variable	**Level**	**Data Description**	**Source**
Cases and Deaths	County and State	Daily confirmed cases and deaths of COVID-19 at the county and state level from	CDC of the United States Downloadable at:

		Feb.15, 2020 to Nov. 30, 2020.	https://usafacts.org/visualizations/coronavirus-covid-19-spread-map/
Population	County and State	Population of the regions to be studied in 2019; used to compute per capita cases and deaths.	Same as above
Social Distancing I	County and State	A dataset that shows how visits to places, such as workplaces and homes, are changing in each geographic region. The numbers are the change from a baseline, the median value, for the corresponding day of the week, during the 5-week period Jan 3–Feb 6, 2020. Time Span: Mar-Nov 2020.	Google Mobility Trends (44) https://www.google.com/covid19/mobility/data_documentation.html?hl=en
Social Distancing II	County and State	A dataset that shows a 7-day trailing average of a fraction of people spending 3-6 hours and >6 hours between 8am-6pm, in one location away from their home, based on SafeGraph mobility data. Time Span: Oct-Nov 2020.	Safegraph (69), Downloaded from COVIDCast (46) https://delphi.cmu.edu/covidcast/
Mask Wearing I	County and State	The firm asked a question about mask use to obtain 250,000 survey responses between July 2 and July 14. Response is measured in a 5-item Likert scale, and then aggregated to the county level to compute the total frequency of mask wearing.	New York Times and Dynata https://www.nytimes.com/interactive/2020/07/17/upshot/coronavirus-face-mask-map.html
Mask Wearing II	County and State	Percentage of people who report wearing a mask most or all of the time while in public, based on surveys of Facebook users. Time Span: Oct-Nov 2020.	COVIDCast (Survey conducted on Facebook)

All state-level variables are aggregated from county-level variables. For the NYT Mask Wearing data, the aggregation is manual (weighted average by population); for others, the state-level data is directly available on the source websites.

Independent Variables -- Variable Selection

Economic vulnerability indicators capture the state in which local residents might face a cash shortage during the COVID outbreak so that they would oppose lockdown or stay-at-home orders. The state government facing such economic pressure might have to reopen prematurely to revive the economy while the basic reproduction number is still larger than 1. Low incomes and the lack of sufficient social safety nets will both contribute to economic precariousness. We have measures at the state and the county level from various data sources. Industry structures are also related to social distancing. For industry structures, we mainly follow the study by

Dingel and Neiman (16) to compute the work-from-home rate for different states and counties. We also look at the effect of certain sectors and ruralness as robustness checks.

We use partisanship and conservatism advantage as a baseline. Other than partisanship, we have chosen four dimensions of American Conservatism measures. Religiosity might lead to massive gatherings in churches, which were documented as a potentially major source of COVID-19 spread during the Summer (70). Furthermore, some denominations believe in Biblical Inerrancy (belief that the Bible should be interpreted literally) and that infection is purely decided by God (71). Such beliefs undermine communal actions against the pandemic. Support for limited government will drive the conservative agents to doubt and even protest against the legitimacy of stay-at-home and mask mandates, as they may be afraid the governments are illegally enhancing control or gaining authoritarian rule over the public through anti-COVID-19 measures (72). Skepticism and anti-intellectualism are associated with downplay of COVID-19 risks (8, 73-75), support for conspiracy theories (75-76), and many other irrational coping behaviors. These constructs are correlated with but still distinctive from Trump support and Republican partisanship.

Independent Variables -- County Level

In our main regressions, all variables are mean centered and divided by the standard deviation, so that coefficients are comparable in terms of magnitude of influence. At the county level, we are measuring the following variables: poverty rate below federal poverty line (in percentage point), median household income (in 2010 dollars), proportion of uninsured population (in percentage point), proportion of population with at least a bachelor's degree (in percentage point), degree of income inequality (Gini coefficient), ruralness (the level of being rural, in an index), proportion of agriculture (farming, fishing and forestry) as a part of the economy (%GDP), proportion of population able to work from home (non-adjusted and adjusted; derived from the employment population and wage from NAICS two-digit sectors), Trump share in the 2016 Elections (in percentage point), proportion of people identifying themselves as Evangelical and Catholic (in percentage point), religion diversity (computed from the population of different religious divisions, measured in entropy scores, and details can be seen in a working paper (77)), proportion of people believing in climate change (percentage point, 78), proportion of ethnic groups (in percentage point), and cultural zone affiliation (from Colin Woodard (47)).

Independent Variables -- State Level

At the state level, we are measuring the following variables: Poverty rate, median income, gini coefficient, unemployment tax, unemployment insurance amount (in dollars), local social expenditure (in dollars/year), proportion of uninsured population, nest egg index (38, an indicator for savings rate), dependency ratio (80, the ratio of working population vs. people below 18 or over 65), working-from-home proportion (same algorithm as above), workforce in technology sector (% labor force), human capital (in standardized index), proportion of agriculture as part of the economy (% GDP), general level of religiosity and skepticism of media (derived from factor analysis and item response theory models from World Value Survey Wave 7 (81)), proportion of people believing in Biblical Inerrancy, Evangelicalism, Protestantism, belief in Hell and Heaven, attendance of religious activity (% people who at least go to church once a week, 82), support of limited government (83), belief that that government aid is harmful (83), trust in the state government (84), science education level (scored index, 85), attitudes of environmental protection (86), belief in climate change (78), Trump share in the 2016 elections, advantage of Conservatism (% people identified as conservatives minus % people as liberals, 86), collectivism (87) and tightness (88).

Detailed notes for the sources of the data and their summary statistics can be found in our Supplementary Materials.

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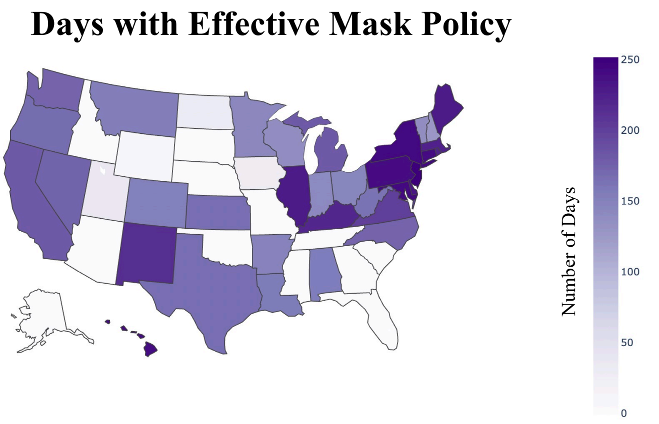
ProxySIFigure S1: Comparison of COVID-19 Policies Across Different Regions in the United States

Figure S1A – Stay-at-Home/Shelter-in-Place Order Timeline (Mar-Jul)

Note: The color of the state is based on the coding of Cui and colleagues (2020). A state is classified as Democratic (colored in blue), Republican (colored in red), or swing (colored in yellow): a state is Democratic (Republican) if it has two Democratic (Republican) senators at least 48% of the vote was for Clinton (Trump) in 2016, or if it has one Democratic (Republican) senator and at least 50% of the vote was for Clinton (Trump) in 2016. The remainder are swing states

Comment [TT1]: But what does it mean? This should be explained.

Figure S1B: Mask Mandates Timeline



Note: Mask mandate coverage time length as to December 15, 2020. (No states have yet revoked a mask mandate after launching one.)

More details: https://www.nytimes.com/interactive/2020/us/states-reopen-map-coronavirus.html

Figure S2: Regional Epicenter Dynamics of COVID-19 from March to November in the USA
(Unit: Confirmed Cases/100,000 Residents)

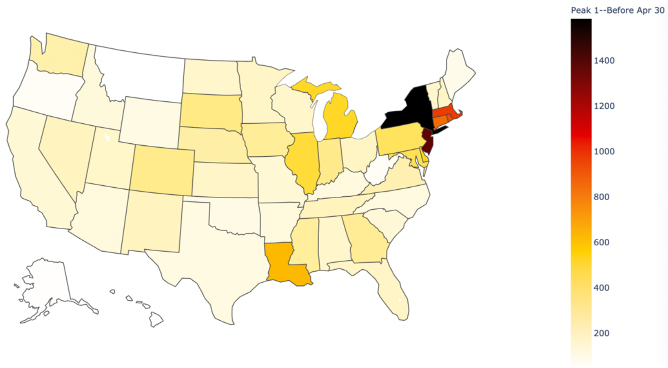


Figure S2A: First Peak – Cases/100,000 Residents, Before Apr 30

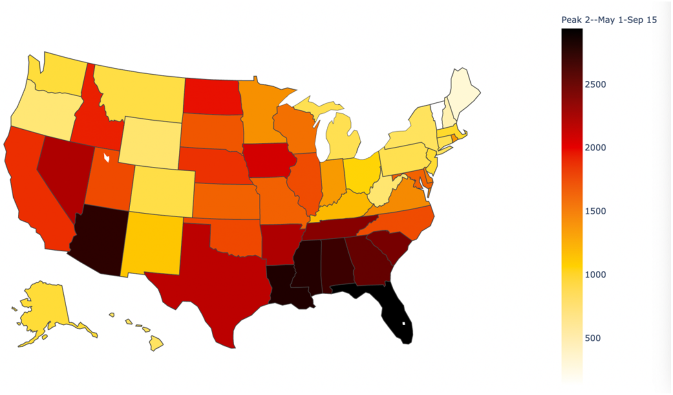


Figure S2B: Second Peak – Cases/100,000 Residents, May 1 – September 15

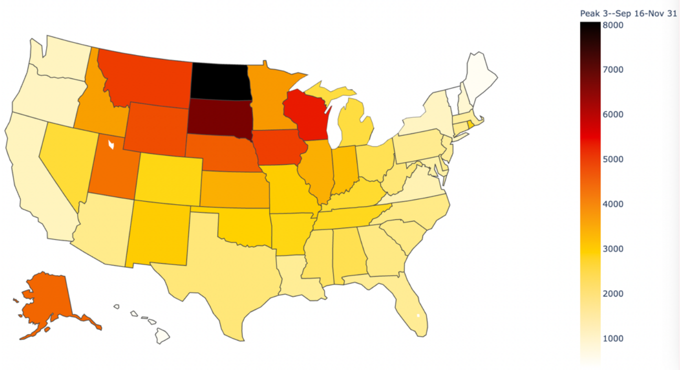
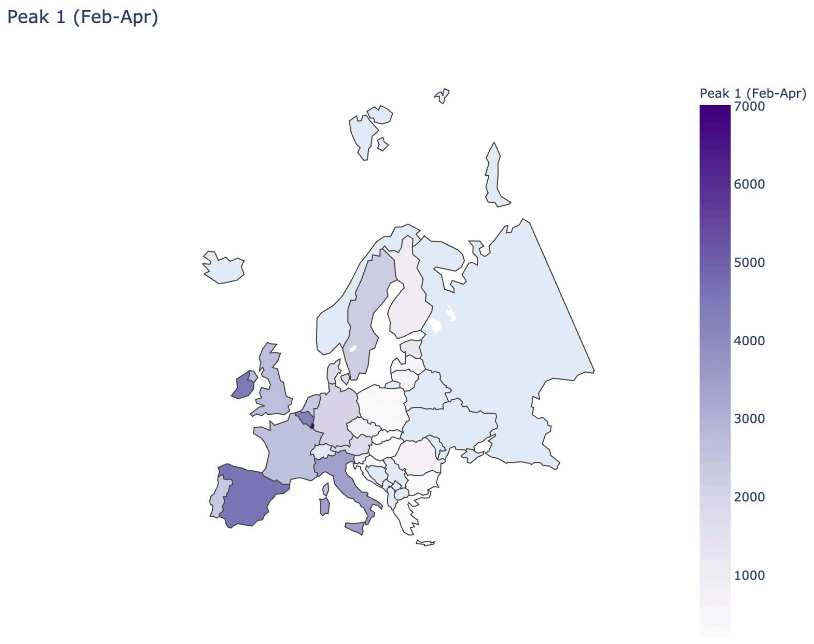


Figure S2C: Second Peak – Cases/100,000 Residents, September 16-November 31

Comment [TT2]:

Figure S3 Confirmed Cases Across the EU and UK through April 30th (top) and up November 30th (bottom)



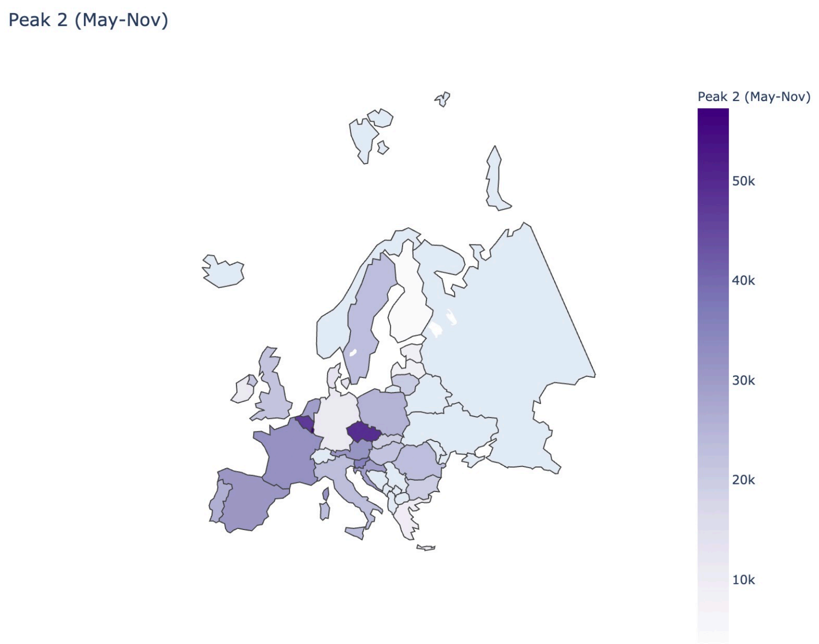
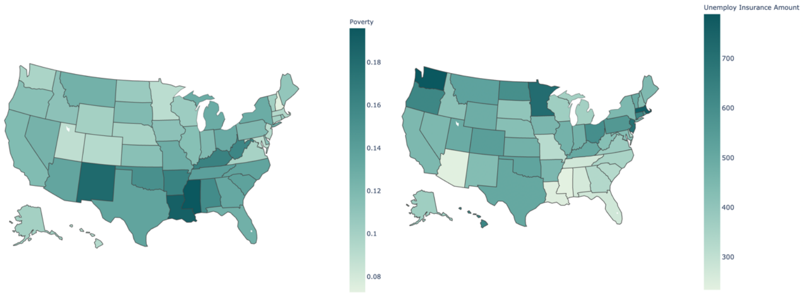
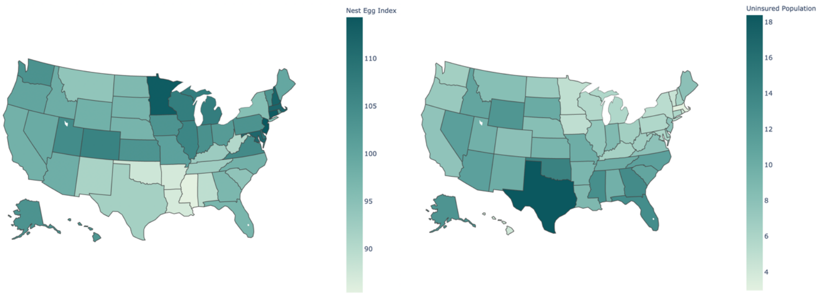


Figure S4 Geographical Distribution of Economic Vulnerability within the United State



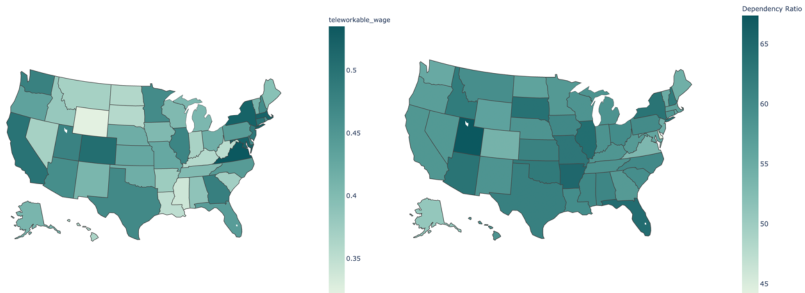
Figures S4A-S4B Poverty Rate and Unemployment Insurance Amount



Figures S4C-S4D Nest Egg Index and Uninsured Population

Comment [TT3]: You'll need to tell readers what the nest egg index is. Also, uninsured how? Health insurance?

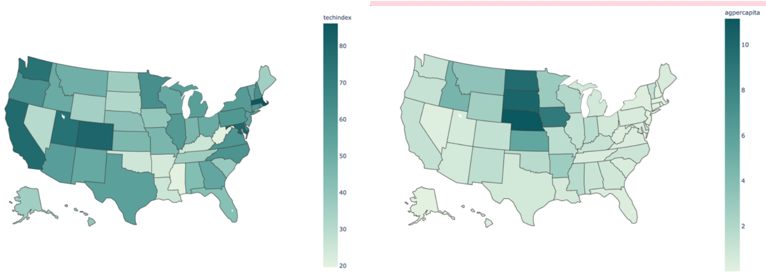
Comment [ou4R3]: Also explained in the body of the paper



Figures S4E-S4F Tele-workable Population (Wage Adjusted) and Dependency Ratio

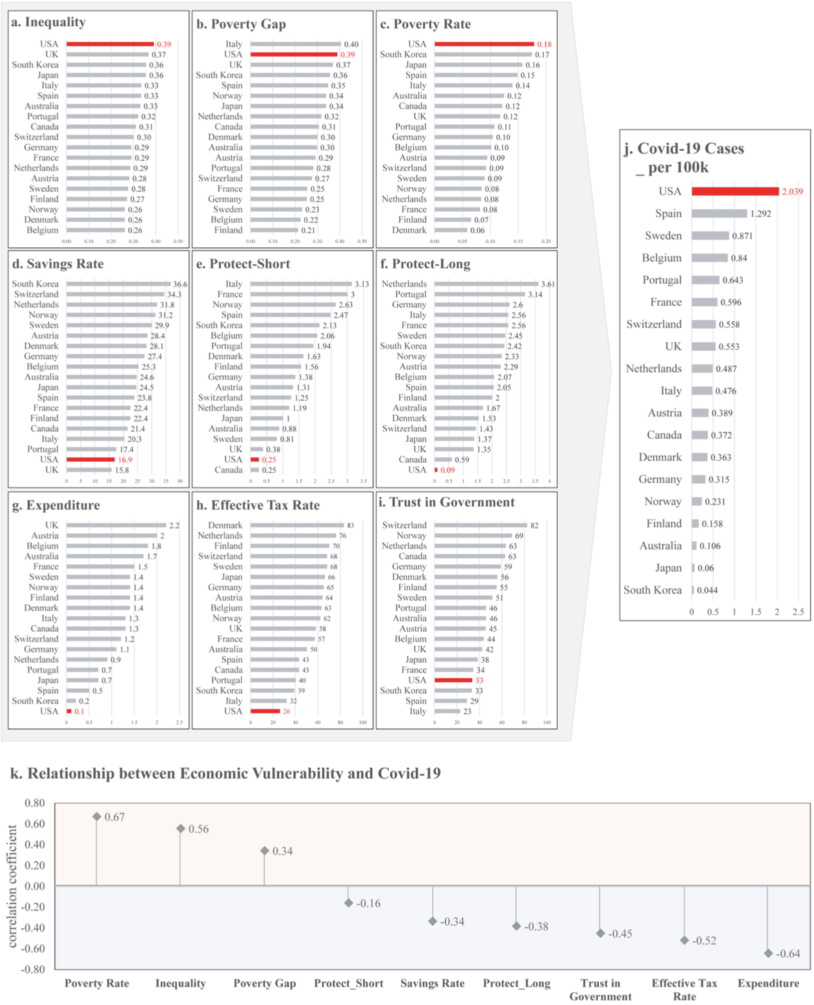
Comment [TT5]: What's a dependency ratio?

Comment [ou6R5]: It is mentioned in the main body of the paper, should I explain again here?



Figures S4G-S4H Technology Index and Agricultural Percentage of GDP

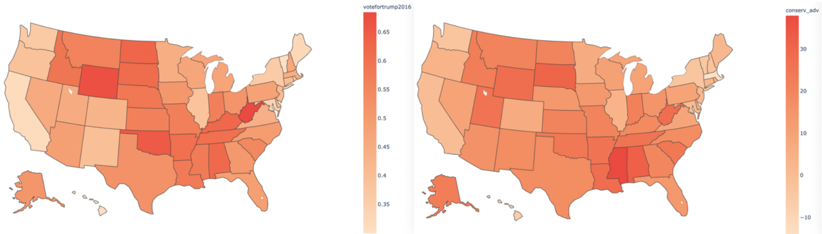
Figure S5 Important Economic Vulnerability Indicators across developed OECD Countries and their correlations with infections in the second period (May 1-Sep 15), which was the second peak in the United States but a relatively low-infection period in other developed countries



Note: Protect-short and Protect-long are protections for short-term and long-term unemployment. Expenditure is the government expenditure that are designed to use on social safety nets.

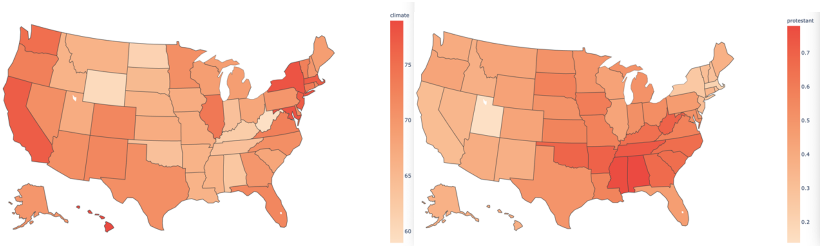
Comment [TT7]: This will need more explanation in the note. What are "protect-short" and long? What is "expenditure?"

Figure S6 Geographic Distribution of Ideological Dimensions within the United States

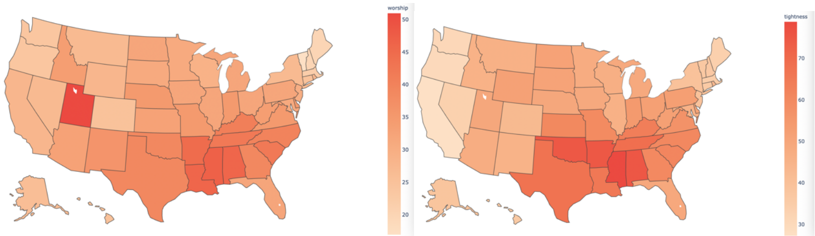


Figures S6A-S6B Trump Share in 2016 Elections and Conservative Advantage

Comment [TT8]: What's the conservative advantage? Needs to be defined in the note.



Figures S6C-S6D Belief in Climate Change and Protestant Population



Figures S6C-S6D Proportion of People Joining Religious Activities Weekly and Tightness-Looseness

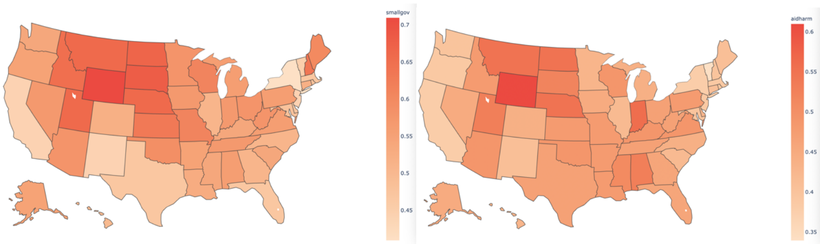
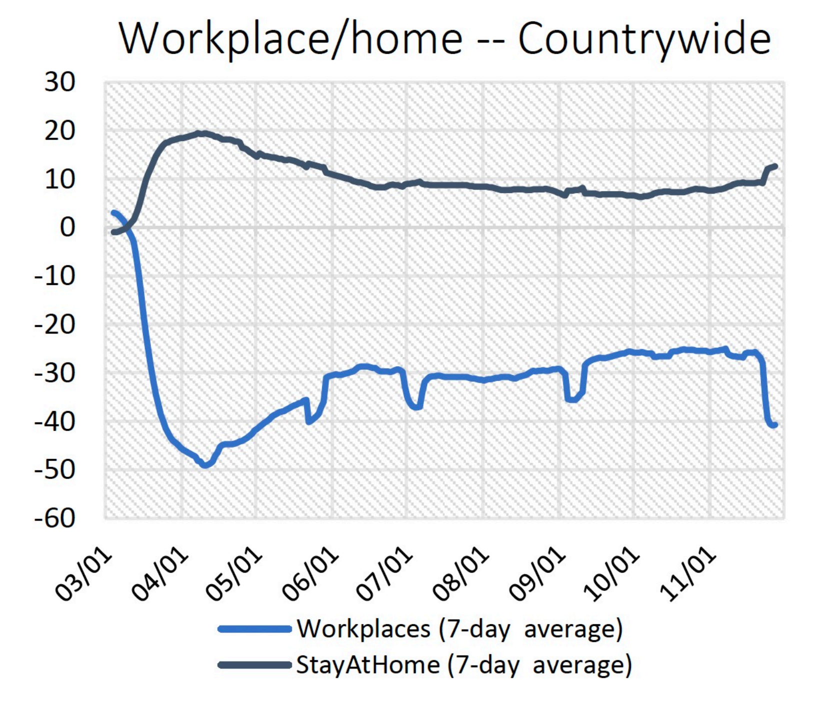


Figure S6G-S6H Preference for a Small Government and Belief that Government Aid is Harmful

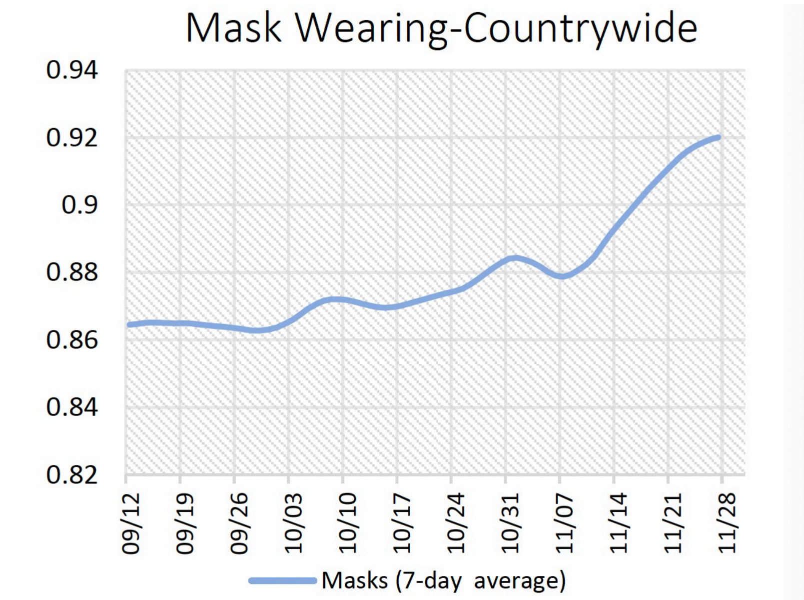
Table S1 Summary Statistics of Dependent Variables – State Level (at Timings of Interest)

Variable	Source	Obs	Mean	Std. Dev.	Min	Max
Dependent Variables						
Cases/100,000 First Peak	CDC	50	283.1	320.2	42.4	1584.9
Cases/100,000 Second Peak	CDC	50	1477.9	734.0	130.9	2942.8
Cases/100,000 Third Peak	CDC	50	2496.9	1609.4	351.2	8078.4
Total Cases/100,000 as to Nov 30	CDC	50	4257.9	1814.9	624.0	10161.0
Probability of everyone wearing a mask with 5 encounters (NYT), July	NYT/Dynata	50	0.4	0.2	0.1	0.7
Self-reported mask coverage, October	Covidcast/Delphi	50	0.9	0.1	0.6	0.9
Stay-at-home Time Change	Google Mobility	50	11.2	2.5	6.9	17.2

Figure S7 Mobility (Top) and Mask Wearing (Bottom) over Time across the US



Note: the unit of the Y-axis is the relative increase/decrease in comparison to the same time period in 2019.

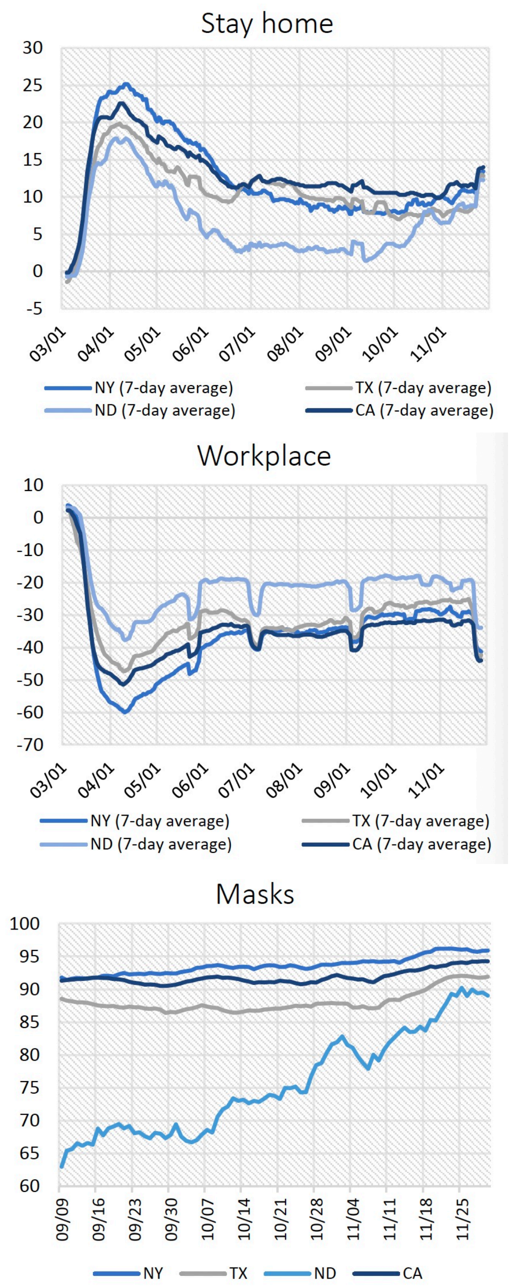


Note: The unit of the Y-axis is the proportion of people who self-report wearing a mask outside on Facebook (data from Delphi/CovidCast).

Comment [TT9]: I don't understand what the different blue lines are. This needs to be made clear.

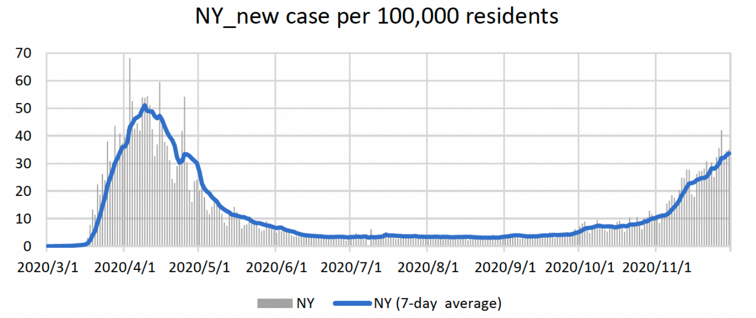
Comment [TT10]: It'd be better to put this in the figure itself (and make the y axis a percentage).

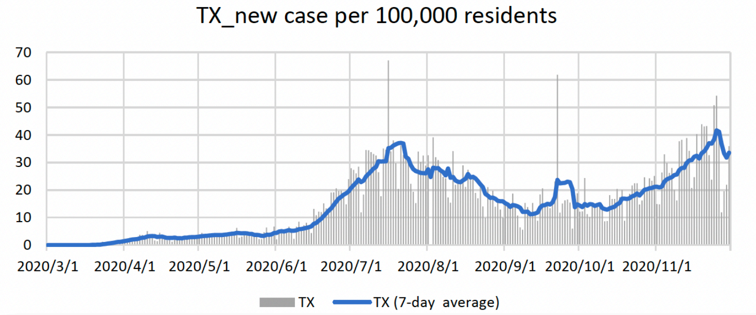
Figure S8 Time Dynamics of Mobility, Mask Wearing and Confirmed Cases/100,000 in Representative States of the Three Peaks: New York, Texas, North Dakota and California

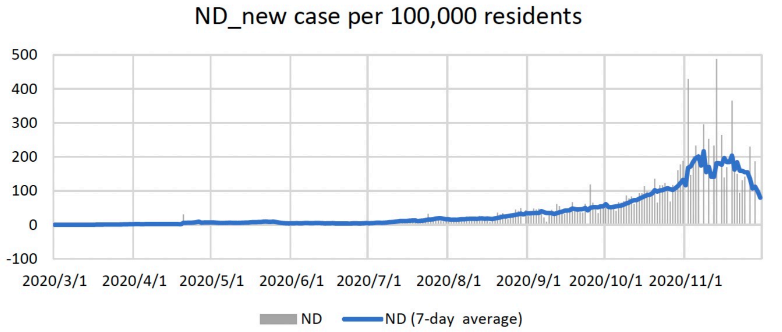


Comment [TT11]: Wait, what? I don't see mobility or masks here.

Comment [ou12R11]: Oh my bad that page was missing. Sorry here


NY_new case per 100,000 residents
70
60
50
40
30
20
10
0
2020/3/1 2020/4/1 2020/5/1 2020/6/1 2020/7/1 2020/8/1 2020/9/1 2020/10/1 2020/11/1
NY
NY (7-day average)


TX_new case per 100,000 residents
70
60
50
40
30
20
10
0
2020/3/1 2020/4/1 2020/5/1 2020/6/1 2020/7/1 2020/8/1 2020/9/1 2020/10/1 2020/11/1
TX
TX (7-day average)


ND_new case per 100,000 residents
500
400
300
200
100
0
-100
2020/3/1 2020/4/1 2020/5/1 2020/6/1 2020/7/1 2020/8/1 2020/9/1 2020/10/1 2020/11/1
ND
ND (7-day average)

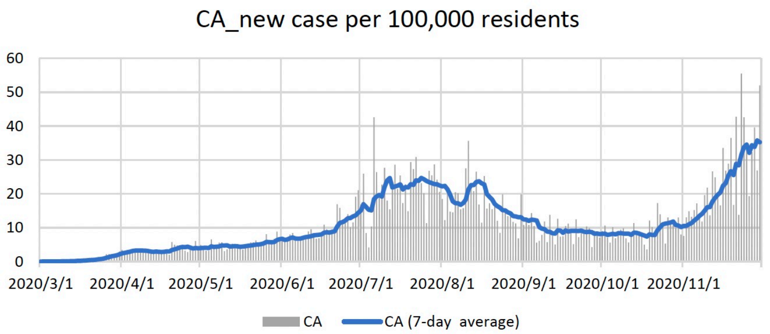

CA_new case per 100,000 residents
60
50
40
30
20
10
0
2020/3/1 2020/4/1 2020/5/1 2020/6/1 2020/7/1 2020/8/1 2020/9/1 2020/10/1 2020/11/1
CA
CA (7-day average)

Table S2 Summary Statistics of the State-level Economic and Ideological Variables

Table S2A Summary Statistics of the State-level Economic Variables

Variable	Source	Obs	Mean	Std. Dev.	Min	Max
Independent Variables -- Economics						
Poverty Rate (2019)	NBS	50	0.12	0.03	0.07	0.20
Median Income (2015)	NBS	50	46244	7013	35444	66972
Gini Coefficient (2019)	Census	50	0.46	0.02	0.41	0.51
Unemployment Insurance Tax Rate	Census	50	1.64	0.96	0.43	4.88
Unemployment Insurance Amount	Census	50	460.28	133.48	235.00	790.00
Local Social Expenditure $/year	Census	50	9330	1797	6766	15393
Uninsured Population	Wallethub	50	8.50	3.08	3.00	18.40
Nested Egg Index[1]	Wallethub	50	100.19	7.44	85.48	114.35
Dependency Ratio[2]	Census	50	58.74	3.90	44.20	67.40
Work-from-home ratio (raw)	Dingel and Neiman (2020)	50	0.35	0.03	0.30	0.42
Work-from-home ratio (wage-adjusted)	Dingel and Neiman (2020)	50	0.43	0.06	0.32	0.54
Technology Sector Index	State Technology and Science Index	50	49.72	16.46	19.78	86.25
Human Capital	State Technology and Science Index	50	51.10	15.16	22.48	81.62
Technology and Science Workforce	State Technology and Science Index	50	46.34	11.26	25.86	75.76
Agriculture (%GDP)	NBS	50	1.88	2.67	0.04	11.16

[1] An indicator for savings rate, focusing on assets that are saved for unexpected uses.
[2] The ratio of working population vs. people below 18 or over 65.

Table S2B Summary Statistics of the State-level Ideological Variables

Variable	Source	Obs	Mean	Std. Dev.	Min	Max
Independent Variables -- Ideology						
Religiosity (General)	World Value Survey Wave 7(WVS)	43	2.42	0.19	1.99	2.88
Biblical Inerrancy[3]	PEW Research (PEW)	50	0.30	0.10	0.14	0.56
Protestant Proportion	PEW	50	0.48	0.15	0.14	0.78
Evangelical Proportion	PEW	50	0.26	0.11	0.07	0.52
Belief in Hell and Heaven	PEW	50	0.65	0.09	0.45	0.83
Attendance of Religious Activity	Gallup Analytics (GAL)	50	0.33	0.07	0.17	0.51
Preference of Small Government	PEW	50	0.55	0.07	0.41	0.71
Belief that Gov Aid is Harmful	PEW	50	1.35	6.30	0.34	45.00
Trust in State Government	GAL	50	2.10	0.16	1.50	2.50
Skepticism of Public Sectors	WVS	43	3.35	0.10	3.09	3.57
Civil Responsibilism[4]	WVS	43	3.73	0.10	3.39	3.89
Anti-intellectualism	WVS	43	1.89	0.12	1.67	2.27
Science Education	Live Science	50	2.70	0.74	1.11	4.82
Anti-environmentalism	PEW	50	0.39	0.07	0.26	0.56
Belief in Climate Change	Yale Climate Opinion Survey	50	0.69	0.05	0.59	0.79
Trump vote share in 2016 Election	Wikipedia	50	0.49	0.10	0.30	0.69
Conservativism advantage	GAL	50	0.14	0.12	-0.14	0.38
Tightness	Harrington and Gelfand (2015)	50	50.14	12.60	27.37	78.86
Collectivism (Except HI)	Cohen (1999)	49	50.12	11.45	31.00	91.00

[3] Proportion of people who have a belief that the Bible should be interpreted literally.
[4] Belief that one should take her civil and public responsibilities.

Discussion S1 Construction of World Value Survey Indicators through Item Response Analysis

24 items on 4 dimensions (Religion, Skepticism of Public Sectors, Civil Responsibilism and Anti-intellectualism) were selected using multidimensional graded response model (GRM) with confirmatory full-information item factor analysis (CIFA). GRM is a multidimensional item response theory model for ordinal responses. CIFA applies to item response theory in a way that is analogous to confirmatory factor analysis for continuous variables. The Metropolis-Hastings Robbins-Monro (MH-RH) Algorithm was employed, which is a full-information algorithm. Both parameter estimation (item discrimination and difficulty parameters) and graphic visualization (item characteristic curve and item information curve) were examined. All discrimination estimates (a) are greater than 1.7. Item information curves suggest that these items are fairly informative. Response categories of each item are nearly equally spaced apart according to the item response category characteristic curves. Most RMSEA values are smaller than 0.05 thus we may conclude good model fit.

Dimension	**Item**	**a**	**b1**	**b2**	**b3**	**RMSEA**	***p***
Religion	Q6	4.445 (0.357)	-0.633 (0.065)	-0.072 (0.058)	0.584 (0.064)	0.046	0.000
	Q64	1.874 (0.150)	-1.765 (0.136)	-0.042 (0.076)	1.387 (0.113)	0.011	0.363
	Q94	-2.869 (0.246)	0.081 (0.065)	-0.555 (0.072)	N/A	0.000	0.832
	Q169	2.315 (0.183)	-1.816 (0.129)	-1.058 (0.089)	0.270 (0.072)	0.024	0.095
	Q171	2.808 (0.221)	-0.686 (0.075)	-0.118 (0.065)	0.346 (0.068)	0.008	0.419
	Q172	3.886 (0.349)	0.049 (0.060)	0.217 (0.061)	0.573 (0.065)	0.047	0.000
	Q173	3.249 (0.288)	-0.042 (0.063)	1.218 (0.086)	N/A	0.000	0.647
	Q184	1.764 (0.141)	-0.800 (0.094)	0.287 (0.079)	1.518 (0.124)	0.000	0.576
	Q186	2.158 (0.164)	-1.473 (0.112)	-0.445 (0.075)	0.623 (0.079)	0.021	0.149
Skepticism of Public Sectors	Q82	2.853 (1.388)	-1.878 (0.132)	-0.260 (0.065)	1.388 (0.102)	0.000	0.480
	Q83	2.888 (0.228)	-1.466 (0.104)	-0.070 (0.064)	1.126 (0.090)	0.022	0.149
	Q84	3.453 (0.294)	-1.966 (0.135)	-0.369 (0.063)	1.090 (0.085)	0.008	0.421
	Q87	2.924 (0.240)	-1.964 (0.140)	-0.309 (0.065)	1.163 (0.092)	0.000	0.611
	Q88	2.401 (0.191)	-1.030 (0.088)	0.508 (0.075)	1.692 (0.126)	0.000	0.603

	Q89	3.078 (0.255)	-1.903 (0.133)	-0.281 (0.064)	1.358 (0.099)	0.029	0.074
Civil Responsibilism	Q177	1.779 (0.244)	1.220 (0.123)	2.144 (0.208)	2.759 (0.291)	0.042	0.015
	Q179	3.669 (0.679)	1.520 (0.112)	2.186 (0.178)	2.553 (0.238)	0.025	0.252
	Q180	2.686 (0.389)	1.202 (0.100)	2.010 (0.167)	2.691 (0.264)	0.014	0.364
	Q181	2.749 (0.436)	1.575 (0.127)	2.565 (0.241)	3.663 (0.486)	0.067	0.005
	Q189	2.691 (0.499)	2.032 (2.032)	2.848 (0.313)	3.653 (0.505)	0.054	0.033
	Q192	2.105 (0.355)	1.935 (0.188)	3.069 (0.361)	3.390 (0.428)	0.029	0.210
Anti-intellectualism	Q158	8.376 (6.876)	-1.629 (0.119)	-0.963 (0.077)	0.615 (0.068)	0.054	0.018
	Q159	2.405 (0.247)	-1.989 (0.150)	-0.892 (0.083)	0.862 (0.088)	0.029	0.200
	Q163	1.697 (0.178)	-2.828 (0.271)	-1.422 (0.128)	0.453 (0.089)	0.031	0.162

Table S3 Correlation Matrix of State-Level Economic Variables

Economic Vulnerability - Correlation Matrix

Poverty Rate (2019)	1.000														
Median Income (2015)	-0.635	1.000													
Gini Coefficient (2019)	0.541	0.140	1.000												
Unemp. Insurance Tax Rate	-0.080	0.370	0.358	1.000											
Unemp. Insurance Amount	-0.522	0.557	-0.090	0.301	1.000										
Local Social Expenditure $/year	-0.270	0.588	0.013	0.317	0.429	1.000									
Uninsured Population	0.435	-0.440	0.050	-0.415	-0.472	-0.461	1.000								
Nest Egg Index	-0.830	0.639	-0.307	0.240	0.469	0.204	-0.542	1.000							
Dependency Ratio	0.250	-0.308	0.188	-0.179	-0.178	-0.372	0.268	-0.338	1.000						
Work-from-home ratio (raw)	-0.594	0.649	0.080	0.260	0.403	0.228	-0.301	0.628	-0.175	1.000					
WFH ratio (wage-adjusted)	-0.483	0.580	0.226	0.261	0.277	0.099	-0.205	0.576	-0.147	0.953	1.000				
Technology Sector Index	-0.609	0.501	-0.020	0.294	0.386	0.217	-0.350	0.671	-0.187	0.829	0.826	1.000			
Human Capital	-0.683	0.667	-0.148	0.324	0.447	0.450	-0.585	0.749	-0.282	0.789	0.728	0.839	1.000		
Tech. and Science Workforce	-0.622	0.490	-0.257	0.198	0.418	0.266	-0.305	0.630	-0.365	0.761	0.706	0.904	0.783	1.000	
Agriculture (%GDP)	-0.107	-0.033	-0.359	-0.331	0.024	0.090	-0.013	-0.128	0.137	-0.228	-0.327	-0.261	-0.007	-0.159	1.000

Table S4 Correlation Matrix of State-level Ideological Variables

Ideology-Correlation Matrix																			
Religiosity (General)	1.00																		
Biblical Inerrancy	0.41	1.00																	
Protestant Proportion	0.41	0.85	1.00																
Evangelical Proportion	0.37	0.82	0.89	1.00															
Belief in Heaven and Hell	0.41	0.90	0.86	0.78	1.00														
Religious Activity Attendance	0.39	0.79	0.61	0.58	0.83	1.00													
Preference for Small Gov.	0.14	0.05	0.18	0.19	0.22	0.10	1.00												
Belief that Gov. Aid is Harmful	0.33	-0.07	-0.11	-0.05	-0.14	-0.12	0.00	1.00											
Trust in State Government	0.44	0.43	0.32	0.37	0.34	0.45	-0.13	0.03	1.00										
Skepticism of Public Sector	-0.06	-0.13	-0.16	-0.08	-0.23	-0.22	-0.18	-0.22	0.08	1.00									
Civil Responsibilism	0.27	-0.12	-0.13	-0.11	-0.16	-0.14	-0.11	-0.09	-0.03	0.55	1.00								
Anti-intellectualism	0.29	0.19	0.20	0.17	0.13	0.17	-0.30	-0.30	0.62	-0.12	-0.13	1.00							
Science Education	-0.37	-0.57	-0.49	-0.52	-0.54	-0.49	-0.20	-0.38	-0.08	0.05	0.09	-0.10	1.00						
Anti-environmentalism	0.49	0.57	0.52	0.59	0.62	0.49	0.62	0.04	0.12	-0.33	-0.09	-0.16	-0.48	1.00					
Belief in Climate Change	-0.39	-0.53	-0.57	-0.59	-0.64	-0.48	-0.70	0.01	-0.01	0.34	0.17	0.06	0.49	-0.84	1.00				
Trump share in 2016 Election	0.55	0.75	0.66	0.66	0.79	0.74	0.50	0.12	0.29	-0.30	-0.12	0.06	-0.66	0.84	-0.82	1.00			
Conservativism advantage	0.43	0.63	0.65	0.67	0.73	0.56	0.60	0.04	0.15	-0.35	-0.22	-0.04	-0.43	0.86	-0.89	0.84	1.00		
Tightness	0.50	0.84	0.82	0.75	0.88	0.84	0.18	-0.13	0.38	-0.21	-0.16	0.21	-0.44	0.54	-0.61	0.76	0.71	1.00	
Collectivism (Except HI)	-0.15	0.42	0.11	0.10	0.29	0.42	-0.48	-0.15	0.20	0.23	-0.03	0.03	-0.11	-0.21	0.29	0.01	-0.21	0.23	1.00

Comment [TT13]: This is not a common term. Define it below.

Comment [TT14]: What is this? Are you sure this is the right word? Define below.

Table S5 Summary Statistics of Dependent Variables at the County Level

		Obs.	Mean	Std. Dev	Min	Max
Time Spent-Workplace	Total	2746	-25.05	6.47	-59.75	-0.74
	Mar-Jul	2746	-27.78	6.59	-60.92	-13.73
	Aug-Nov	2723	-20.51	6.95	-58.52	18.73
Time Spent-Home	Total	1750	7.16	3.34	-1.94	23.76
	Mar-Jul	1381	10.34	3.18	1.01	26.06
	Aug-Nov	1750	5.68	2.54	-2.60	20.62
Time Spent-Grocery/Pharmacy	Total	1607	2.26	11.27	-45.33	87.58
	Mar-Jul	1598	2.94	11.84	-45.33	78.05
	Aug-Nov	1607	-2.64	9.56	-56.90	54.76
Time Spent-Restaurants	Total	2433	281.00	272.93	0.00	4528.92
	Mar-Jul	2421	254.02	301.37	1.44	9257.35
staurants	Aug-Nov	2432	321.13	307.17	0.00	4321.85
Mask Coverage	July 2-July 17	3088	0.74	0.10	0.36	0.96
	Sep-Nov	629	88.13	5.66	68.11	97.95

Table S6 Summary Statistics of Independent Variables at the County Level

Variable	Obs.	Mean	Std. Dev.	Min	Max
Total Population	3,088	101256	323565	82	9818605
Poverty Rate (percentage)	3,088	15.46	6.32	0.00	50.60
Median Household Income 2017	3,088	50908	13275	22679	136191
Uninsured Population Percentage	3,088	0.18	0.05	0.03	0.39
Bachelor's Degree Percentage	3,088	18.87	8.50	3.70	70.10
Gini Coefficient	3,088	0.43	0.04	0.21	0.65
Indicator of Ruralness	3,088	5.25	3.47	1.00	12.00
Agricultural as %of GDP	3,088	2.13	2.59	0.00	29.25
Work-from-home percentage	3,086	0.27	0.04	0.00	0.50
Unemployment in 2010	3,088	9.36	3.15	2.10	28.80
Trump Vote in 2016	3,088	63.84	15.43	4.12	95.27
Evangelicals/1000 people	2,791	232.14	157.47	2.85	987.83
Catholics/1000 people	2,661	125.88	129.41	0.00	999.57
Religious Diversity	3,088	0.97	0.26	0.00	1.67
Belief in Climate Change	3,088	64.74	5.89	48.94	86.53
White population percentage	3,088	79.18	19.26	2.50	99.20
Latino population percentage	3,088	7.91	12.97	0.00	97.15
Male Population percentage	3,088	0.50	0.02	0.41	0.79

Note: the county-level average of work-from-home is much lower than the national average because more populous counties tend to have more people who can work from home yet count only once.

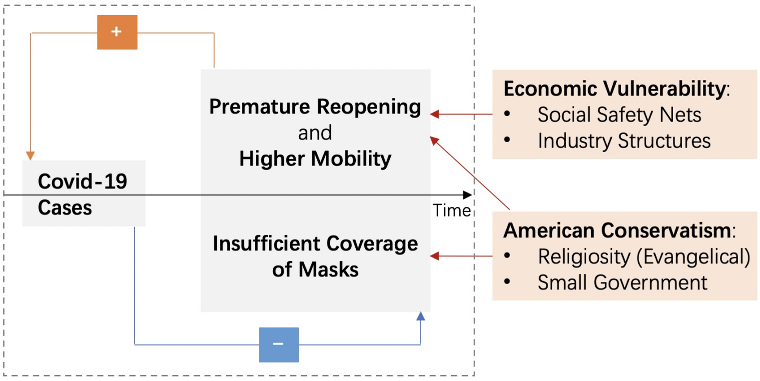
Table S7 Simple Pairwise Correlation – Cases/Response with Independent Variables

	Time Spent				Mask Wearing		Cases			
	Workplace	Home	Groceries	Restaurants	July 2-July 17	Oct - Nov	Mar 1-May 1	May 1-Sep 15	Sep 15-Nov 30	Mar 1-Nov 30
Total Population	-0.407	0.435	-0.274	-0.047	0.285	0.313	0.144	0.065	-0.119	-0.045
Poverty Rate (percentage)	0.143	-0.320	0.015	0.024	-0.041	-0.002	0.008	0.364	-0.121	0.082
Median Household Income	-0.500	0.660	-0.257	-0.061	0.284	0.309	0.115	-0.182	0.017	-0.058
Uninsured Population %	0.136	-0.242	-0.097	0.059	0.007	-0.210	-0.028	0.331	-0.225	-0.030
Bachelor's Degree %	-0.608	0.696	-0.318	-0.015	0.353	0.491	0.091	-0.133	-0.054	-0.099
Gini Coefficient	-0.121	0.093	-0.186	0.069	0.137	0.255	0.086	0.273	-0.146	0.027
Indicator of Ruralness	0.400	-0.519	0.277	-0.102	-0.456	-0.211	-0.157	-0.116	0.278	0.153
Agricultural as %of GDP	0.210	-0.271	0.031	-0.147	-0.211	-0.060	-0.082	0.041	0.111	0.102
Work-from-home %	-0.421	0.549	-0.361	-0.062	0.071	0.461	0.084	-0.032	0.099	0.083
Unemployment in 2010	0.116	-0.254	0.103	-0.009	0.226	-0.072	0.020	0.158	-0.388	-0.249
Trump Vote in 2016	0.537	-0.611	0.345	0.166	-0.502	-0.774	-0.198	-0.133	0.194	0.066
Evangelicals/1000 people	0.262	-0.337	0.061	0.309	-0.239	-0.446	-0.083	0.262	-0.037	0.094
Catholics/1000 people	-0.224	0.324	-0.149	-0.197	0.191	0.380	0.169	-0.044	0.162	0.137
Religious Diversity	-0.222	0.315	-0.149	-0.092	0.216	0.206	0.048	-0.060	0.012	-0.012
Belief in Climate Change	-0.531	0.622	-0.370	-0.173	0.501	0.716	0.190	0.084	-0.186	-0.085
White population %	0.282	-0.341	0.402	0.028	-0.364	-0.344	-0.188	-0.512	0.241	-0.084
Latino population %	-0.203	0.263	-0.318	-0.095	0.303	0.221	0.055	0.238	-0.097	0.046
Male Population %	0.087	-0.135	0.034	-0.117	-0.073	-0.210	0.019	0.084	0.136	0.162

Discussion S2 Further Discussion on COVID Response and Spread

In our main text, we carefully documented how economic vulnerability and American Conservatism predicts the failure of social distancing and mask coverage. Based upon our good knowledge of the causality between these two measures and COVID-19 spread, we would believe that EV and Conservatism are very likely to be contributors to COVID-19 spread and the red-drift of epicenters in the US. However, the main text does not include direct quantification of how COVID-19 cases are determined by economic vulnerability and American conservatism except for an aggregated demonstration at the state level. In the supplementary materials, we are providing a dynamic mediating model on this effect.

As discussed in the main text, EV may mainly impact COVID-19 cases through mobility, and ideology through both mobility and mask-wearing. Then when the cases increase rapidly as a result, the local governments might launch stronger measures to control the outburst, causing a decrease of mobility and increase of mask-wearing. When time goes by and cases begin to drop again, the urge to reopen and enjoy leisure may increase mobility and decrease mask wearing again, and this effect may be moderated by local economic and ideological backgrounds. This is a full feedback loop, and we use regression models in all these channels to demonstrate the effectiveness of each step. Furthermore, we use an instrumental variable approach to show that mobility and mask-wearing are crucial mediators of the effect of socioeconomic and ideological backgrounds on COVID-19 spread. The feedback loop in our model suggests that there is a reverse causality problem in a simple regression approach. For instance, if we simply put the COVID-19 cases at the left-hand side and mask wearing at the right-hand side, the expected results will be ambiguous because the fact that insufficient mask wearing leads to an increase in cases, while an increase in cases push people to put masks on.



To address this problem, we need to treat the system dynamically. We use a Granger-causality style modeling, always putting the current variables as the dependent variable and lagged variables as independent variables in each single regression. We use two stage least squares to establish the chain from variables of interest, anti-COVID measures and confirmed cases.

The feedback loop setup is formally modeled with a two stage least squares model. To estimate the model, we need a few assumptions of the transmission patterns in the United States. First, as in the main text, we assume that the social distancing and mask coverage at time T patterns are influenced by local socioeconomic features, policies (usually statewide, captured in state-culture fixed effects), and the local severity. Severity has two components: cumulative cases per capita, and recent new cases per capita (captured by increments at T-1 and T-2, i.e., 2 weeks ago and 4 weeks ago). Then, COVID-19 response usually has some time lags in affecting infection, and infection also have time lags in showing symptoms and confirmation (we know that the incubation period is between 1-14 days and the mean is 5 days (1-2), and it typically takes a few extra days for getting a confirmation). For simplicity, we assume that measures at T impact new infections at T+1, and these people are usually confirmed at T+2.

Another important setup is about infection dynamics. Recent research finds that COVID-19 patients are most infectious at the end of the incubation period and the beginning of the symptomatic period (around 9-10 days, 3-4), which in sum cover about half a month. Based on these findings, we look at increments rather than total cases, as the time span during which a patient can infect others is close to a time. Thus, we can roughly assume that every two weeks, the pool of infectious people refresh. Thus, we rely on the logarithm of *new* cases but not the total cases in our dynamic setup. We assume that dependent

Another point to note is that at different time periods, the effects in both stages of our causal chain are potentially heterogeneous. Thus, we ran 14 regressions from April to November and plot the coefficients in a dynamic coefficient plot. In every time period, we show an OLS and a 2SLS regression. The regression setup in the two stages is shown here, and we estimate it use the *ivregress* package with an 2SLS mode in Stata. Note that we are using a dynamic setup, so the time span of one regression covers two months (four time-units). The case increment (in log form) in at time T+2 is explained by the increment at T+1 and measures at T; while measures at T are further explained by EV, conservatism, other controls, state-culture fixed effects, and increment at T-1 and T-2.

A variable table is shown here:

Dependent Variables	Cases increment T+2
Lagged Dependent Variables	Cases increment T+1
Endogenous Variables	COVID Response
Exogenous Variables	EV, conservatism, cases increment T-1/T-2, controls, fixed effects

We use the results in the main body as the first stage of the IV regressions. For the second stages, we demonstrate the first-glance results in a graph and show the computed results in Table S12A and S12B.

Figure S9 Regression Coefficients of Working Time and Mask Coverage on Case Increments

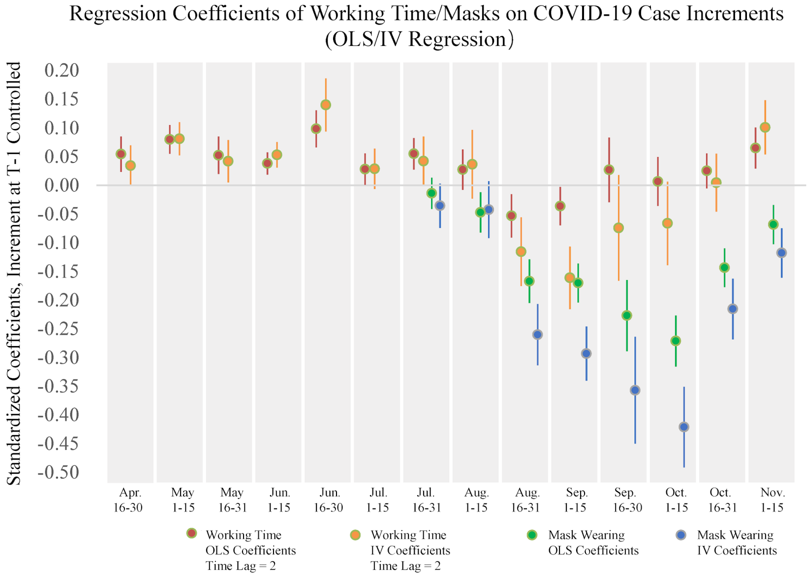


Figure 5: Coefficient plot of the second stage regression.

Left hand side: case increment (new cases) within the time span t, which is mentioned on the X axis. Right hand side: case increment (new cases) within the time span t-1, one term earlier than the left hand side and COVID-19 response measures (time spent in workplaces, and mask wearing within time span t-2. In OLS, regressions were conducted as mentioned above. In IV, workplace time and mask wearing were instrumented by political, ideological variables and other controls.

Above is the second-stage result of COVID-19 case increments as a function of the increment in the previous term, workplace time (more affected by economic vulnerability) and mask wearing (more affected by ideology). Note that before July, no mask-wearing is included due to data unavailability. In the second half of October and the first half of November, we are using the COVIDCast mask wearing data, and in all time before, we rely on the NYT-Dynata data as a proxy. We find robust evidence that predictive power of working time existed mainly before August, while afterwards the effect fades away. This might be explained by the reopening of all states in July. The predict power of mask wearing, however, has been always relatively large after August. This shows pretty solid evidence that in terms of Granger causality, mask coverage has a large effect on COVID control.

Discussion S3 and Figure S11 County-level Culture Fixed Effects, and Potential Cultural Impact on COVID-19 Response and Cases

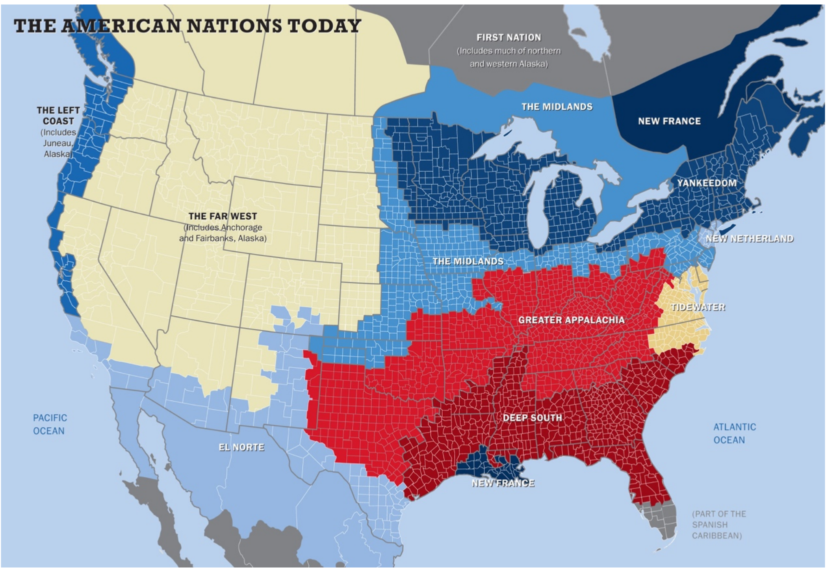
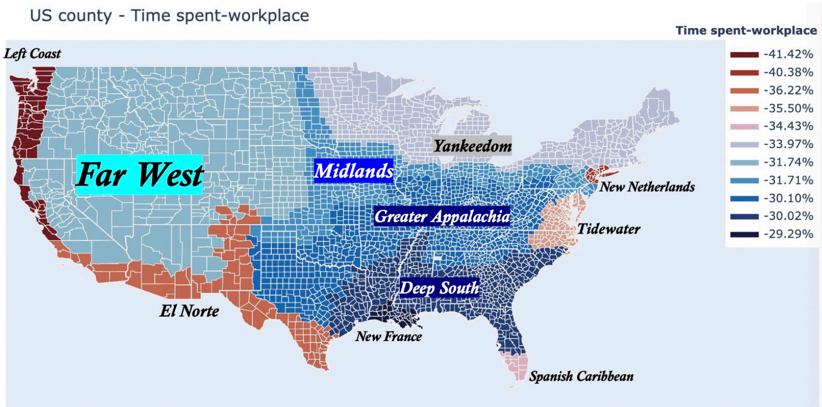
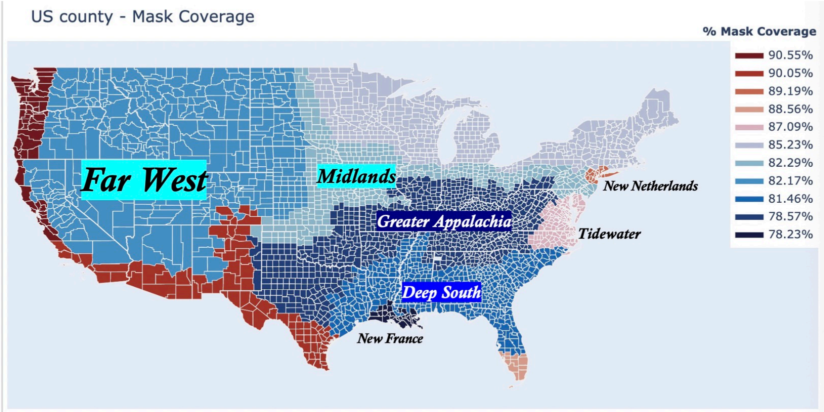
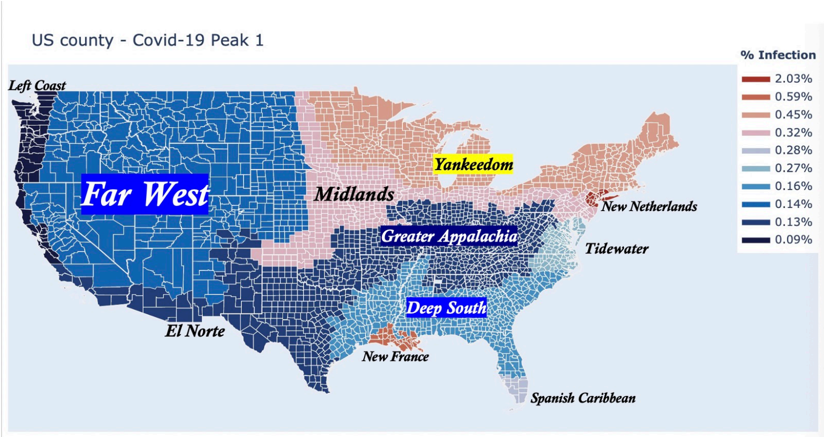


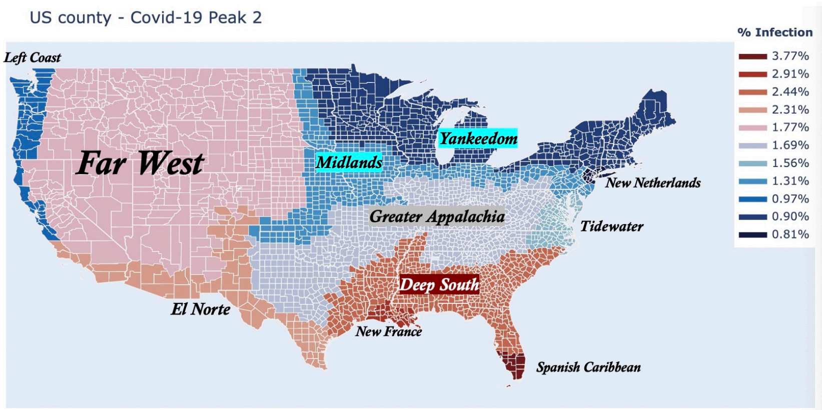
Figure S10A: American Nations Cultural Regions and Margin of Victory in 2016 Election
Source: https://www.maproomblog.com/2017/01/american-nations-applied-to-the-2016-election/





Figures S11B-S11C Culture and COVID Response (Workplace Time Spent-Aggregated, Mask Wearing-July)





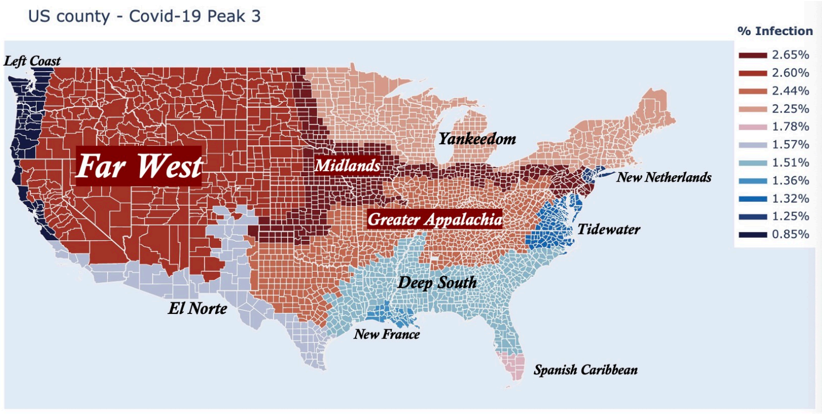


Figure S10D-S10F Confirmed Cases as a Percentage of Population at Three Peaks of Infection: Mar 1-Apr 30, May 1-Sep 15, Sep 16-Nov 30

This part shows the dynamics of confirmed cases on different cultural zones. First, their response intensities are different. For mobility reduction and mask wearing, Left Coast, New Netherlands and El Norte are among the highest; While Great Appalachia, Deep South and New France are among the lowest.

Such patterns are definitely impacted by various factors. Urbanization, ethnicity, economic vulnerability, and many other factors may have resulted in the patterns above. Yet, since it is a good continuous measure, and within many states, different cultural zones have significant differences in terms of response and cases, we still choose them as part of the fixed effects as they may have some joint effects with the state.

We call for future research to carefully study the potentially causal effects of American cultures on COVID response and cases.

Table S11 Detailed Results for Our Main County-level Regressions

Table S11A Working Outside/Stay at Home (Period 1 and 2)

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)
VARIABLES	Workplace	Workplace	Stay-at-home	Stay-at-home
Time period	Apr-Jul	Aug-Nov	Apr-Jul	Aug-Nov
Vote for Trump in 2016	0.202***	0.284***	-0.235***	-0.264***
	(0.0365)	(0.0451)	(0.0420)	(0.0385)
Evangelical Ratio (%)	0.0579***	-0.00165	-0.0809**	-0.0833***
	(0.0221)	(0.0272)	(0.0319)	(0.0271)
Catholic Ratio (%)	-0.00232	-0.0146	-0.0838***	-0.0110
	(0.0191)	(0.0238)	(0.0235)	(0.0216)
Religion Diversity	0.102***	0.0625**	-0.0757***	-0.0631***
	(0.0197)	(0.0243)	(0.0245)	(0.0221)
Belief that Climate Change	-0.0806***	0.0294	-0.0142	-0.00917
	(0.0271)	(0.0333)	(0.0300)	(0.0279)
General Poverty Rate	-0.0587*	-0.160***	0.160***	0.135***
	(0.0306)	(0.0379)	(0.0416)	(0.0373)
Median Household Income	-0.231***	-0.261***	0.422***	0.351***
	(0.0287)	(0.0351)	(0.0318)	(0.0293)
Uninsured Population	-0.123***	0.0724*	-0.141***	-0.0762**
	(0.0343)	(0.0417)	(0.0405)	(0.0371)
Bachelor’s Degree Coverage %	-0.338***	-0.126***	0.124***	0.191***
	(0.0290)	(0.0355)	(0.0338)	(0.0309)
Gini Coefficient	0.0867***	0.0241	-0.0317	-0.0368
	(0.0196)	(0.0242)	(0.0269)	(0.0241)
Ruralness Score	0.0674***	0.0956***	-0.0599**	-0.00886
	(0.0187)	(0.0230)	(0.0261)	(0.0219)
Agriculture Ratio (%GDP)	0.0559**	-0.0678**	-0.134***	-0.106***
	(0.0225)	(0.0275)	(0.0295)	(0.0260)
Working-from-home Ratio	-0.134***	-0.180***	0.101***	0.119***
	(0.0154)	(0.0190)	(0.0208)	(0.0182)
White Population %	0.0999**	0.0629	-0.0893*	-0.148***
	(0.0398)	(0.0486)	(0.0498)	(0.0440)
Latino Population %	0.0438	-0.0112	0.162***	0.0944***
	(0.0334)	(0.0407)	(0.0375)	(0.0360)
Constant	-0.746**	0.760*	0.527	1.556***
	(0.377)	(0.461)	(0.380)	(0.362)
Socioeconomic Controls	Yes	Yes	Yes	Yes
Cases Controls	May/Jul	Sep/Nov	May/Jul	Sep/Nov
Fixed Effects	State-culture	State-culture	State-culture	State-culture
Observations	2,368	2,350	1,346	1,670
R-squared	0.738	0.644	0.838	0.824

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table S11B Time at Restaurants and Groceries – Period 1 and 2
t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

	(1)	(2)	(3)	(4)
VARIABLES	Restaurant	Restaurant	Groceries	Groceries
Time period	Apr-Jul	Aug-Nov	Apr-Jul	Aug-Nov
Vote for Trump in 2016	0.162**	0.154*	0.368***	0.349***
	(0.0811)	(0.0813)	(0.0729)	(0.0731)
Evangelical Ratio (%)	0.132***	0.127**	-0.103**	-0.119**
	(0.0507)	(0.0509)	(0.0505)	(0.0508)
Catholic Ratio (%)	-0.0221	-0.0294	-0.00918	-0.0264
	(0.0435)	(0.0441)	(0.0423)	(0.0426)
Religion Diversity	0.0108	0.0134	-0.0733*	-0.0785*
	(0.0440)	(0.0441)	(0.0413)	(0.0415)
Belief that Climate Change	0.0322	0.0302	-0.00486	-0.0103
	(0.0596)	(0.0595)	(0.0519)	(0.0519)
General Poverty Rate	-0.173**	-0.176**	-0.0709	-0.0836
	(0.0702)	(0.0704)	(0.0681)	(0.0685)
Median Household Income	-0.0998	-0.107*	-0.219***	-0.269***
	(0.0628)	(0.0628)	(0.0546)	(0.0544)
Uninsured Population	-0.0550	-0.0608	0.0883	0.0489
	(0.0765)	(0.0759)	(0.0700)	(0.0693)
Bachelor’s Degree Coverage %	0.0721	0.0800	0.0776	0.0997*
	(0.0640)	(0.0639)	(0.0587)	(0.0585)
Gini Coefficient	0.0634	0.0551	-0.0521	-0.0705
	(0.0453)	(0.0453)	(0.0442)	(0.0441)
Ruralness Score	0.0217	0.0233	0.0588	0.0570
	(0.0423)	(0.0423)	(0.0421)	(0.0421)
Agriculture Ratio (%GDP)	-0.0549	-0.0487	-0.0784	-0.0689
	(0.0512)	(0.0510)	(0.0481)	(0.0479)
Working-from-home Ratio	-0.0849**	-0.0832**	-0.149***	-0.138***
	(0.0348)	(0.0349)	(0.0339)	(0.0340)
White Population %	-0.0323	-0.0159	-0.292***	-0.198**
	(0.0885)	(0.0876)	(0.0848)	(0.0835)
Latino Population %	0.0244	0.0178	-0.173***	-0.221***
	(0.0744)	(0.0741)	(0.0661)	(0.0667)
Constant	-2.225***	-2.152***	-2.084***	-1.706**
	(0.797)	(0.799)	(0.660)	(0.663)
Socioeconomic Controls	Yes	Yes	Yes	Yes
Cases Controls	May/Jul	Sep/Nov	May/Jul	Sep/Nov
Fixed Effects	State-culture	State-culture	State-culture	State-culture
Observations	2,068	2,068	1,527	1,527
R-squared	0.231	0.231	0.489	0.490

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table S11C Mask Coverage – Period 1 and 2
t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VARIABLES	(1) Mask (Jul)	(2) Mask (Sep-Nov)
Vote for Trump in 2016	-0.232***	-0.624***
	(0.0333)	(0.0685)
Evangelical Ratio (%)	-0.0317	-0.112*
	(0.0201)	(0.0660)
Catholic Ratio (%)	0.0270	0.0154
	(0.0169)	(0.0474)
Religion Diversity	0.0240	0.0481
	(0.0178)	(0.0478)
Belief that Climate Change	0.0822***	0.0941**
	(0.0251)	(0.0457)
General Poverty Rate	-0.0136	-0.0599
	(0.0263)	(0.0769)
Median Household Income	0.0919***	-0.130**
	(0.0260)	(0.0525)
Uninsured Population	0.0458	-0.169**
	(0.0303)	(0.0711)
Bachelor's Degree Coverage %	0.0916***	0.0888
	(0.0262)	(0.0578)
Gini Coefficient	-0.0207	-0.0340
	(0.0172)	(0.0465)
Ruralness Score	-0.173***	-0.120*
	(0.0170)	(0.0715)
Agriculture Ratio (%GDP)	0.00666	0.0739
	(0.0190)	(0.0585)
Working-from-home Ratio	-0.0272**	0.0106
	(0.0139)	(0.0352)
White Population %	0.0972***	0.316***
	(0.0362)	(0.0802)
Latino Population %	0.0362	0.276***
	(0.0276)	(0.0681)
Constant	0.797**	-2.943***
	(0.353)	(0.601)
Socioeconomic Controls	Yes	Yes
	Jul	Sep/Nov
Fixed effects	State-culture	State-culture
Observations	2,657	626
R-squared	0.737	0.837

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table S12 Results for Our Supplementary County-level Regressions – Second Stage (OLS/IV)

Table S12A OLS Results: COVID Case Increments and Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Cases Increment at	April	May	May	June	June	July	July	August	August	Sept.	Sept.	Octo.	Octo.
Time T-1	16-30	1-15	16-31	1-15	16-30	1-15	16-31	1-15	16-31	1-15	16-30	1-15	16-31
Time Spent-Work	0.034*	0.081***	0.042**	0.053***	0.140***	0.029	0.042*	0.036	-0.116***	-0.161***	-0.073	-0.066*	0.004
at Time T-2	(1.88)	(5.52)	(2.23)	(4.66)	(5.97)	(1.60)	(1.91)	(1.19)	(-3.80)	(-5.80)	(-1.57)	(-1.79)	(0.17)
Cases Increment at	0.307***	0.855***	0.626***	0.554***	0.591***	0.730***	0.684***	0.635***	0.410***	0.482***	0.444***	0.495***	0.598***
at Time T-1	(19.94)	(49.51)	(35.93)	(54.94)	(33.29)	(50.10)	(53.91)	(33.51)	(23.35)	(29.02)	(12.81)	(24.11)	(33.17)
Mask Coverage							-0.034*	-0.043*	-0.257***	-0.292***	-0.357***	-0.421***	-0.216***
July 2-July 17							(-1.76)	(-1.72)	(-9.55)	(-12.25)	(-7.56)	(-11.76)	(-8.01)
Constant	-0.012	-0.004	-0.000	-0.019*	0.010	-0.013	-0.027**	0.011	-0.009	-0.006	0.052*	0.032*	0.009
	(-0.76)	(-0.34)	(-0.02)	(-1.94)	(0.61)	(-0.91)	(-2.11)	(0.62)	(-0.53)	(-0.37)	(1.86)	(1.65)	(0.60)
Observations	1,978	2,023	2,367	2,354	2,360	2,349	2,355	2,363	2,355	2,357	1,034	1,623	2,338
R-squared	0.176	0.549	0.355	0.562	0.321	0.517	0.553	0.326	0.218	0.331	0.273	0.453	0.510

Table S12B IV Results: COVID Case Increments and Measures (2nd stage)

Cases Increment at Time T-1	(1) April 16-30	(2) May 1-15	(3) May 16-31	(4) June 1-15	(5) June 16-30	(6) July 1-15	(7) July 16-31	(8) August 1-15	(9) August 16-31	(10) Sept. 1-15	(11) Sept. 16-30	(12) Octo. 1-15	(13) Octo. 16-31
Cases Increment at	0.310***	0.853***	0.540***	0.553***	0.602***	0.728***	0.696***	0.617***	0.441***	0.561***	0.495***	0.531***	0.624***
Time T-1	(20.88)	(50.22)	(32.97)	(55.21)	(34.81)	(51.16)	(55.29)	(34.34)	(25.36)	(35.05)	(15.11)	(28.12)	(39.05)
Time Spent-Work	0.054***	0.080***	0.052***	0.037***	0.097***	0.028**	0.056***	0.028	-0.052**	-0.037**	0.027	0.007	0.025
at Time T-2	(3.49)	(6.31)	(3.15)	(3.76)	(5.86)	(1.98)	(4.03)	(1.56)	(-2.72)	(-2.17)	(0.95)	(0.30)	(1.63)
Mask Coverage							-0.013	-0.048***	-0.166***	-0.171***	-0.227***	-0.271***	-0.144***
in July							(-0.96)	(-2.68)	(-8.62)	(-10.00)	(-7.20)	(-11.96)	(-8.32)
Constant	-0.015	-0.007	-0.002	-0.021**	0.011	-0.006	-0.012	0.013	0.001	0.001	0.021	0.017	-0.003
	(-1.03)	(-0.56)	(-0.12)	(-2.13)	(0.68)	(-0.44)	(-0.98)	(0.80)	(0.08)	(0.08)	(0.79)	(0.90)	(-0.22)
Observations	2,061	2,111	2,488	2,477	2,483	2,471	2,478	2,487	2,477	2,481	1,067	1,735	2,460
R-squared	0.176	0.546	0.306	0.553	0.332	0.515	0.553	0.324	0.235	0.380	0.288	0.460	0.510

Table S13A Monthly Regression Results -- (Workplaces Apr-Nov)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Workplace	Workplace	Workplace	Workplace	Workplace	Workplace	Workplace	Workplace
Time	April	May	June	July	August	September	October	November
Vote for Trump in 2016	0.148***	0.168***	0.198***	0.199***	0.282***	0.248***	0.299***	0.299***
	(0.032)	(0.036)	(0.041)	(0.043)	(0.046)	(0.042)	(0.045)	(0.047)
Evangelical Ratio (%)	0.053***	0.047**	0.057**	0.019	-0.021	0.003	-0.003	0.001
	(0.019)	(0.022)	(0.025)	(0.026)	(0.032)	(0.026)	(0.027)	(0.029)
Catholic Ratio (%)	-0.019	-0.010	0.008	-0.021	0.056**	0.008	-0.021	-0.043*
	(0.017)	(0.019)	(0.021)	(0.022)	(0.026)	(0.022)	(0.023)	(0.025)
Religion Diversity	0.059***	0.095***	0.117***	0.089***	0.016	0.026	0.063***	0.084***
	(0.017)	(0.019)	(0.022)	(0.023)	(0.026)	(0.023)	(0.024)	(0.026)
Belief that Climate Change	-0.099***	-0.077***	-0.045	-0.034	0.028	0.037	0.024	0.062*
	(0.023)	(0.026)	(0.030)	(0.032)	(0.034)	(0.031)	(0.033)	(0.035)
General Poverty Rate	-0.008	-0.002	-0.112***	-0.200***	-0.150***	-0.167***	-0.149***	-0.093**
	(0.026)	(0.030)	(0.034)	(0.036)	(0.043)	(0.036)	(0.038)	(0.040)
Median Household Income	-0.207***	-0.191***	-0.241***	-0.236***	-0.230***	-0.228***	-0.278***	-0.307***
	(0.025)	(0.028)	(0.032)	(0.034)	(0.036)	(0.033)	(0.035)	(0.037)
Uninsured Population	-0.172***	-0.151***	-0.026	0.105***	0.178***	0.101**	0.043	-0.045
	(0.029)	(0.033)	(0.038)	(0.040)	(0.045)	(0.039)	(0.042)	(0.044)
Bachelor's Degree %	-0.377***	-0.392***	-0.273***	-0.142***	-0.024	-0.083**	-0.095***	-0.192***
	(0.025)	(0.028)	(0.032)	(0.034)	(0.038)	(0.033)	(0.035)	(0.037)
Gini Coefficient	0.085***	0.087***	0.068***	0.060***	-0.029	0.029	0.019	0.010
	(0.017)	(0.019)	(0.022)	(0.023)	(0.028)	(0.023)	(0.024)	(0.025)
Ruralness Score	0.053***	0.094***	0.105***	0.116***	0.131***	0.106***	0.091***	0.071***
	(0.016)	(0.018)	(0.021)	(0.022)	(0.026)	(0.021)	(0.023)	(0.024)
Agriculture Ratio (%GDP)	0.155***	0.078***	-0.016	-0.071***	-0.040	-0.062**	-0.075***	-0.040
	(0.019)	(0.022)	(0.025)	(0.026)	(0.030)	(0.026)	(0.027)	(0.029)

Working-from-home Ratio	-0.040***	-0.119***	-0.181***	-0.225***	-0.074***	-0.135***	-0.170***	-0.178***
	(0.013)	(0.015)	(0.017)	(0.018)	(0.022)	(0.018)	(0.019)	(0.020)
White Population %	-0.021	0.131***	0.198***	0.149***	-0.115**	-0.018	0.094*	0.211***
	(0.034)	(0.039)	(0.044)	(0.047)	(0.054)	(0.046)	(0.049)	(0.052)
Latino Population %	0.019	0.072**	0.056	0.046	-0.046	-0.014	-0.033	-0.013
	(0.029)	(0.032)	(0.037)	(0.039)	(0.044)	(0.039)	(0.041)	(0.043)
Socioeconomic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Case Controls	Total/Incre.	Total/Incre.	Total/Incre.	Total/Incre.	Total/Incre.	Total/Incre.	Total/Incre.	Total/Incre.
Fixed Effects	State-culture	State-culture	State-culture	State-culture	State-culture	State-culture	State-culture	State-culture
Observations	2,367	2,356	2,349	2,351	1,832	2,332	2,339	2,350
R-squared	0.814	0.768	0.698	0.664	0.711	0.684	0.641	0.579

Standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.10

Table 13A and 13B cover the detailed regression results of Figure 4.

Table S13B Monthly Regression Results (Stay-at-home, Apr-Nov)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Stay-at-home	Stay-at-home	Stay-at-home	Stay-at-home	Stay-at-home	Stay-at-home	Stay-at-home	Stay-at-home
Time	April	May	June	July	August	September	October	November
Vote for Trump in 2016	-0.212***	-0.265***	-0.255***	-0.227***	-0.217***	-0.271***	-0.269***	-0.270***
	(0.036)	(0.038)	(0.039)	(0.040)	(0.045)	(0.036)	(0.035)	(0.036)
Evangelical Ratio (%)	-0.099***	-0.077***	-0.125***	-0.099***	-0.154***	-0.110***	-0.041*	-0.054**
	(0.028)	(0.028)	(0.029)	(0.030)	(0.033)	(0.027)	(0.024)	(0.025)
Catholic Ratio (%)	-0.048**	-0.038*	-0.083***	-0.072***	-0.087***	-0.031	0.005	0.005
	(0.022)	(0.021)	(0.022)	(0.022)	(0.025)	(0.020)	(0.019)	(0.020)
Religion Diversity	-0.075***	-0.086***	-0.119***	-0.085***	-0.101***	-0.054***	-0.066***	-0.092***
	(0.021)	(0.021)	(0.022)	(0.023)	(0.026)	(0.021)	(0.020)	(0.020)
Belief that Climate Change	-0.002	-0.030	-0.012	-0.021	-0.015	0.003	-0.003	-0.029
	(0.026)	(0.027)	(0.028)	(0.028)	(0.032)	(0.026)	(0.025)	(0.026)

General Poverty Rate	-0.046	0.045	0.138***	0.186***	0.147***	0.158***	0.150***	0.119***
	(0.035)	(0.037)	(0.038)	(0.039)	(0.044)	(0.035)	(0.033)	(0.034)
Median Household Income	0.362***	0.380***	0.429***	0.444***	0.425***	0.322***	0.326***	0.318***
	(0.027)	(0.028)	(0.029)	(0.030)	(0.034)	(0.027)	(0.026)	(0.027)
Uninsured Population	0.063*	-0.014	-0.116***	-0.155***	-0.145***	-0.145***	-0.055*	-0.062*
	(0.035)	(0.035)	(0.037)	(0.038)	(0.042)	(0.034)	(0.033)	(0.033)
Bachelor’s Degree %	0.222***	0.231***	0.156***	0.103***	0.104***	0.154***	0.217***	0.217***
	(0.029)	(0.030)	(0.031)	(0.032)	(0.035)	(0.029)	(0.028)	(0.028)
Gini Coefficient	-0.030	-0.042*	-0.023	-0.036	-0.008	-0.047**	-0.050**	-0.043*
	(0.023)	(0.024)	(0.025)	(0.026)	(0.028)	(0.023)	(0.022)	(0.022)
Ruralness Score	-0.012	0.009	0.015	-0.012	0.005	-0.069***	-0.020	-0.033*
	(0.023)	(0.024)	(0.024)	(0.025)	(0.028)	(0.022)	(0.020)	(0.020)
Agriculture Ratio (%GDP)	-0.203***	-0.151***	-0.078***	-0.083***	-0.085***	-0.086***	-0.105***	-0.084***
	(0.025)	(0.026)	(0.028)	(0.028)	(0.031)	(0.025)	(0.024)	(0.024)
Working-from-home Ratio	0.045**	0.071***	0.129***	0.149***	0.139***	0.088***	0.103***	0.101***
	(0.018)	(0.019)	(0.019)	(0.020)	(0.022)	(0.018)	(0.016)	(0.017)
White Population %	0.012	-0.099**	-0.190***	-0.187***	-0.239***	-0.101**	-0.116***	-0.113***
	(0.041)	(0.043)	(0.045)	(0.046)	(0.052)	(0.042)	(0.040)	(0.041)
Latino Population %	0.175***	0.125***	0.115***	0.140***	0.156***	0.118***	0.104***	0.063*
	(0.032	(0.032)	(0.034)	(0.036)	(0.040)	(0.033)	(0.032)	(0.033)
Socioeconomic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Case Controls	Total/Incre.	Total/Incre.	Total/Incre.	Total/Incre.	Total/Incre.	Total/Incre.	Total/Incre.	Total/Incre.
Fixed Effects	State-culture	State-culture	State-culture	State-culture	State-culture	State-culture	State-culture	State-culture
Observations	1,267	1,329	1,369	1,362	1,371	1,402	1,723	1,711
R-squared	0.888	0.873	0.855	0.851	0.812	0.872	0.847	0.843

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table S14 Direct Effect Models
Regression between Cases and Economic/Ideological Variables (Different Timings)

	(1)	(2)	(3)	(4)	(5)
Confirmed Cases/100k	Mar-May	May-Jul	Jul-Sep	Sep-Nov	Mar-Nov
Vote for Trump in 2016	0.018	0.085**	0.080***	0.133***	0.247***
	(0.41)	(2.44)	(2.87)	(5.41)	(6.04)
Evangelical Ratio (%)	-0.012	-0.013	0.044**	0.040**	0.064**
	(-0.44)	(-0.58)	(2.46)	(2.56)	(2.47)
Catholic Ratio (%)	-0.024	-0.045**	0.055***	0.068***	0.081***
	(-1.01)	(-2.38)	(3.63)	(5.16)	(3.68)
Religion Diversity	-0.021	-0.015	0.019	-0.033**	-0.032
	(-0.85)	(-0.81)	(1.26)	(-2.44)	(-1.44)
Belief in Climate Change	0.058*	0.009	-0.038*	-0.016	-0.021
	(1.69)	(0.35)	(-1.74)	(-0.83)	(-0.65)
Cases/100k in the last period		0.705***	0.628***	0.805***	
		(43.95)	(51.26)	(64.80)	
General Poverty Rate	-0.042	0.011	0.088***	0.058***	0.120***
	(-1.28)	(0.45)	(4.36)	(3.28)	(4.06)
Median Household Income	0.107***	0.014	0.049**	-0.024	0.061*
	(3.01)	(0.50)	(2.22)	(-1.21)	(1.89)
Uninsured Population	0.160***	0.156***	0.028	-0.050**	0.109***
	(3.92)	(4.90)	(1.10)	(-2.22)	(2.92)
Bachelor's Degree Coverage %	-0.116***	0.028	0.006	0.033*	0.011
	(-3.34)	(1.03)	(0.27)	(1.75)	(0.34)
Gini Coefficient	0.063***	-0.037**	0.000	0.012	0.016
	(2.70)	(-2.02)	(0.01)	(0.92)	(0.74)
Ruralness Score	-0.058***	-0.005	0.003	0.015	-0.006
	(-2.89)	(-0.32)	(0.28)	(1.34)	(-0.30)
Agriculture Ratio (%GDP)	-0.050**	0.035**	-0.000	-0.008	-0.009
	(-2.52)	(2.24)	(-0.00)	(-0.78)	(-0.49)
Working-from-home Ratio	0.042**	0.039***	0.019	0.020*	0.070***
	(2.19)	(2.60)	(1.59)	(1.94)	(4.02)
White Population %	-0.244***	-0.307***	-0.206***	-0.163***	-0.571***
	(-5.05)	(-8.12)	(-6.71)	(-6.00)	(-12.95)
Latino Population %	0.066*	0.112***	0.047*	-0.009	0.109***
	(1.73)	(3.75)	(1.94)	(-0.41)	(3.12)
Constant	-0.299	-1.107**	-0.715	-0.797**	-2.038***
	(-0.41)	(-1.97)	(-1.59)	(-2.02)	(-3.10)
Fixed Effects	State-Culture	State-Culture	State-Culture	State-Culture	State-Culture
Observations	2,465	2,465	2,465	2,465	2,465
R-squared	0.382	0.667	0.797	0.847	0.576

t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: in these models, we put the confirmed cases at the left-hand side and the economic/ideological variables on the right-hand side. Our model suggests that Conservatism and EV do not predict more cases in the first peak but significantly do so in the second and third peaks.

Discussion S4: A Short Review on Denial of Science and Its Relationship with COVID-19

The failure of COVID-19 response in the United States is heavily linked to anti-intellectualism, or the denial of science. In the discussion part, we proposed some potential mechanisms about the anti-intellectual behaviors related to COVID-19. In this part of the supplementary material, we provide a more conceptualized framework to show a future direction on studying the burgeoning anti-intellectualism in the United States and offers policy implications on the practical interventions of COVID-19 response, such as mass vaccination.

Rejection of science (and in turn, belief in conspiracy theory) has been seen in many topics in the United States. Attitudes to climate change, vaccination and COVID-19 are three typical examples. People (especially Republicans) tend to cast doubt on well-accepted scientific consensus, and refuse to adapt their behaviors accordingly.

The psychological and economic foundations of rejection of science have been explained by recent scholars from many perspectives. One popular model is motivated reasoning (1-4). As Mooney (1) puts in 2011, "Scientific evidence is highly susceptible to selective reading and misinterpretation", people might selectively gather evidence that fits into their preexistent beliefs and deny the (possibly) apparent evidence that leads to conclusions against their prior thoughts. This cognitive bias is strengthened and deepened by identity politics, making conservatives and liberals diverge in many dimensions of understanding of science (5-8). People might find a political stance to build their identity, and then follow everything that is in accordance with their identity party's proposals through identity-driven motivated reasoning. This cognitive effect fits in both conservatives and liberals; for instance, conservatives tend to believe in fake science that is against climate change (9-11), while liberals believe more in fake news about the adverse effects of guns (6). Another important feature is that consecutive persuasion or communication of the science might backfire (1, 12-13). The persistence of these anti-intellectual belief makes it hard to correct the misinformation.

All these topics match, at least in terms of correlations, with anti-intellectual and politicization behaviors during COVID-19 (14-16), and this effect is stronger in men than women (17). However, these studies are not conducted with formal experiments, and partisanship, as discussed in the body of our paper, is correlated with many other potential confounders. For instance, we find that economic constraints seem to have a larger effect than partisanship on social distancing. Future experimental research awaits. As Pfizer and Moderna launches their vaccination in the market, we will have a good source of natural experiment to see the potential motivated reasoning processes as the vaccine is being accepted by the public. Anecdotally, conservatives and liberals both have their reasons to reject vaccination: conservatives are a general anti-vaccination group, while liberals are afraid of the potential danger of these vaccines as Donald Trump has consecutively claimed that the invention of the vaccines are due to his effort.

Comment [TT15]: Don't put the little r's there. It looks silly. People don't normally do that.

Another branch of literature talks about insufficient thinking, or reliance on non-analytical heuristics. Pennycook et al (18) demonstrated that belief in partisan fake news is mainly due to lack of reasoning rather than motivated reasoning. Also, other constructs such as delusionality, dogmatism, religious fundamentalism, and reduced analytic thinking are all linked with belief in conspiracy and fake news (19-20). This branch of literature tends to find constructs (especially personality and ideological ones) that are connected with insufficient reasoning. However, such research is still restrained with confounders such as IQ or other abilities. In terms of COVID-19, Pennycook et al (21) also found that belief in fake news is associated with lack of thinking: a simple nudging about thinking of the accuracy can significantly reduce the level of submission to misinformation. Indeed, if lack of reasoning is a source, it is natural to link with the literature of scarcity (22-23), since having to little will restrain people to think of daily dime-and-nickel issues which impairs people's reasoning abilities among more complicated issues. For instance, people suffering from scarcity is more inclined to use stereotypes on identifying Black faces (24). It is a natural extension that we link these two branches of literature, but it is still yet to be fully explored.

Economic factors that promote science denial is implied in many studies, but explicit discussions are scarce. A common story, usually denoted as organized science denial (25), is about how related firms communicate fake science or use spurious evidence when lobby about environmental issues, such as Freon (26), Smoking (27), and climate change (25, 28-29). Organized denial, or sometimes denoted as "rational motivated rejection of science" (3) is a typical interaction between economic entities (for instance, fossil fuel plants), political lobbying and social cognition. Yet, the literature on its psychological mechanisms is still short. COVID-19 offers an interesting natural experiment, and this paper also shows suggestive (but not causal) evidence that such mechanisms may exist in COVID response. There exist motivated economic entities (the traditional sector firms in which people who are not able to work from home), political lobbying (especially with the GOP politicizing COVID-19) and distorted social cognition. Further individual surveys are needed to test the existence of such a mechanism. Other mechanisms related to the interaction of economic and ideological problems may be related to the tightening Sino-US relations. A motivated reasoning against China may also lead to similar results, since China has used the most stringent measures against COVID-19. Thus, people who have anti-China affects may be more reluctant to cope with COVID-19 seriously. This effect, too, is potentially moderated by individual differences and many cognitive biases.

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Discussion S5: A Parametric Example of The Theoretical Model

We use a parametric example to document the theoretical model for a better understanding among non-economists.

Since we cannot spend negative time working, the optimization problem of a Democratic decision maker is:

$$MaxP(h) = Wh - C(h)\ s.t.\ h \geq 0$$

The optimization problem of a Republican decision maker is:

$$\max\ P(h) = (W + V_r)h - C(h) + G_r(W, h)$$

and for a Republican, $\partial G_r(0, h)/\partial h$ is bounded[5], and for any h, as $W \to \infty$, $G_d \to 0$.

Without losing generality, we can set: $V_r = 0.1, C(h) = 2h^2 + 0.05h$, and

$$G_r(W, h) = \begin{cases} 0.2h & if\ w < 0.05 \\ \dfrac{h}{100w} & if\ w \geq 0.05 \end{cases}$$

Then, we have for a Democrat, $W = h/4$, and $\frac{\partial h}{\partial W} = 1/4$. While for a Republican,

$$\frac{\partial h}{\partial W} = \begin{cases} 0 & if\ w < 0.05 \\ \dfrac{1 - \frac{1}{100w^2}}{4} & if\ w > 0.05 \end{cases}$$

A quick deduction shows that when w is very small (< 0.05), $\frac{\partial h}{\partial W} = 0$ as for democrats, the working hours is always 0, and for Republicans, $\frac{\partial h}{\partial W} = 1/4$. When w gets larger, Democrats start to work outside, with $h = \frac{W - 0.05}{4}$. However, at this time, w has a crowding out effect on Republicans since the reputation effect drops very fast for Republicans until w gets large enough. $\frac{\partial h}{\partial W}$ for Republicans may be negative when $0.05 < w < 0.1$. When w gets larger, say reaching over 0.5, then $\frac{\partial h}{\partial W}$ for both parties reach $1/4$, meaning that when economic vulnerability (EV) is really large, the marginal effect of EV on working hours will reach its upper bound for both parties.

[5] This boundary condition rules out the possibility that when there is no EV, a Republican will work infinitive time to increase her reputation.