Economics Predicts Mobility, and Partisanship Predicts 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

Keywords: COVID-19, social distancing, economic vulnerability, masks, partisanship, incentive and motivation

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Abstract

The US experienced multiple sustained outbreaks of COVID-19 in 2020. From March to November, the spread of COVID-19 in the US showed puzzling patterns: the epicenter drifted from densely populated, Democratic urban centers to sparsely populated, Republican rural areas. We link this pattern to the failure of two measures: social distancing and mask wearing. With a behavioral model incorporating extrinsic incentives (money returns that mitigate urgent economic scarcity) and intrinsic motivations (partisanship expressivity), we hypothesize that economic vulnerability—the risk that individuals or collectivities could be damaged by repeated financial shocks and instabilities—is the key predictor of failure of social distancing. On the other hand, given the low cost of mask wearing, Republican Partisanship and Conservatism plays the leading role in predicting mask coverage. We empirically test these hypotheses at the county and state level. Using Standardized Seemingly Unrelated Regressions and coefficient tests, we show that economic vulnerability largely predicts mobility, and ideology largely predicts mask wearing and does less for mobility. We explore the time heterogeneity of COVID response and further document that Conservatism and Trump-support had a larger effect on COVID response after August.

Word count = 187

Significance Statement

Failures of social distancing and mask coverage are two major contributors to COVID-19 numbers in US. We find the former is mostly strongly predicted by economic vulnerability, and the latter by Republican partisanship. Using a theoretical model and econometric analysis by interdisciplinary datasets, we examine the heterogenous effects of economic and ideological factors on COVID-19 response across different measures and time periods. We offer a large-scale, real-world test of motivation theories and demonstrate that the partial effects of extrinsic and intrinsic incentives on behaviors can depend on their relative magnitudes. This paper may have important implications for future coping with COVID-19 and other epidemics: policy makers should carefully handle the economic incentives and psychological motivations about compliance to anti-pandemic measures.

Word count = 120

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 nationwide, with nearly all states experiencing high infection and death rates. Despite the alarming numbers, the compliance to COVID prevention measures, including mask wearing and shelter-in-place among others, has large regional variances. The current research examines the behavior of local populations to understand the lack of compliance with expert advice and orders.

Noticeably, there are several distinctive patterns in this public health catastrophe, which motivate a systematic investigation of the contributing social and behavioral factors. Firstly, the United States has left the power to individual states (See Fig. 1 and SM) to start and end COVID-related policies (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, 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, deviant from almost any other developed country in the world[1]. The drift has been heading to less urbanized areas, despite much lower population densities.

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. However, there is large state level variance in the pandemic control, and much of the variance may correspond with states being labeled as either "red" or "blue," defined by their Trump or Republican leaning (3). In April (5), the seven initially heavily attacked Northeastern States (NY, NJ, CT, MA, RI, DE and PA) formed a coalition promoting collaborative coping and smart reopening. These states launched longer stay-at-home orders in comparison to other states (see SM) and kept COVID-19 numbers in control from May to October.

In sum, there were sizeable within-US differences in COVID-19 control throughout 2020. This motivates us to investigate the social and behavioral factors behind the abovementioned distinctive patterns empirically with county level and state level administrative and behavioral data.

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[1] The state (province/region for other countries)-level Pearson bivariate correlation 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 0.80 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)

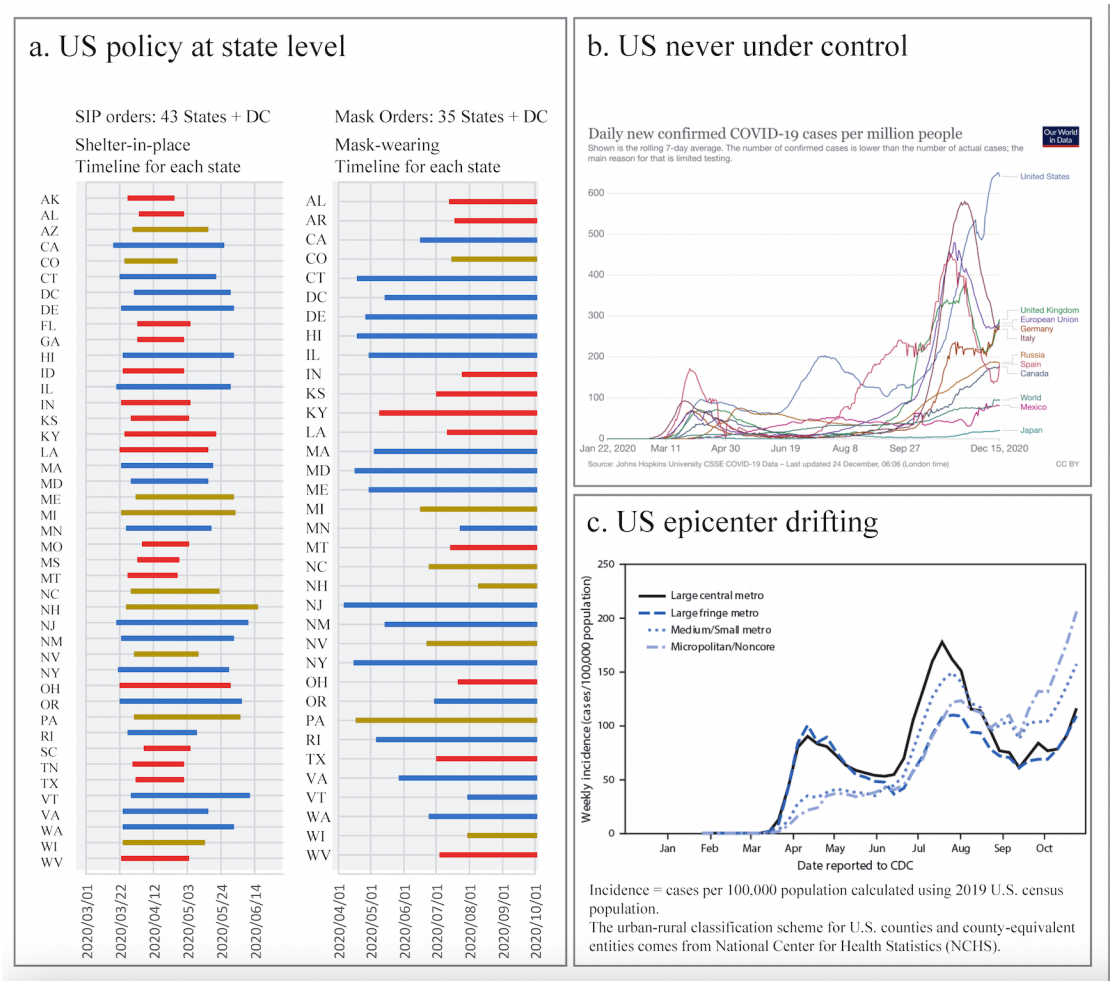


Figure 1A: COVID Response and Spread in the USA

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.

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 started in Nov., thus was 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.

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 to these two measures.

From a behavioral science perspective (3), individual compliance to social distancing (SD) and mask coverage depends on multiple factors. First, the major deterrent for shelter-in-place is that a sizable population cannot work remotely from home[2] (16). The economic incentives and intrinsic motivation are the forces that drive individuals to go out to work during the pandemic, while the perceived risk associated with contracting COVID-19 is the restraining force that keep individuals from working outside home. These three forces are likely to be impacted by unique factors.

Specifically, the economic incentive is to make money, which is impacted by individuals' financial status (17-18). During a pandemic, except for essential workers, who compose only a small proportion of the population, people usually work away from home only when their need for money is intense. Most workers are unable to telecommute (16, 19). Therefore, if the government were to keep shutting down non-essential sectors, these people, without sufficient social safety nets, would face severe financial difficulties. Thus, as shelter-in-place orders are introduced, urgent economic needs surge and make it difficult for the local governments to maintain social distancing policies.

We conceptualize the intrinsic incentive as any nonfinancial reward, including demonstrating ideological values and building reputation in communities, from noncompliance to COVID-related measures. Republicans and Democrats may have different reputation and value concerns on social distancing and mask wearing (20-23). Specifically, we suggest that Republicans might opt to go out to work or refuse a mask regardless of the pandemic severity to express their partisanship and ideology. Firm Republicans may believe that working—and not social distancing—enhance their reputation in a conservative community (24-26). This may be attributed to the "information cocoon" effect (27). These people get information mostly from conservative media, which had repetitive claims on the "flu" analogy and unnecessity of mask wearing by former President Trump and some GOP representatives (28-29). Such exposure to biased information sources reinforces the politicization of perception in COVID-19 related norms (29-30). Past studies have shown the highly negative impact of Republican partisanship and American Conservatism on the risk

[2] 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.

perception of COVID-19 (21-22, 31-33), and thereby social distancing (20-26) and virus spread (20, 33).

Economic theories (34) predict that the relative strength of partial effects of the different types of incentives on individual behavior 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 signal their identity by working away from home to win the support of their conservative communities. In this case, the partial effects of economic incentives are low while the reputational motivations are high. However, when economic need is high, individuals' non-compliance behavior may be attributed to either their urgency to work or Republican values. In this case, reputational motivations are crowded out by the strong partial effect of economic incentives. A detailed theory model is in the Methods section.

Consequently, people with a high vulnerability to economic shocks from COVID-19 are more susceptible to working outside. Magnifying this to the regional level, we predict that economic vulnerability (EV) will predict social distancing failure. 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 (35-36), less coverage of insurances (37), less protection for unemployment (38), and lower intellectual human capital (39). 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). Consistent with the observation, many Southern states had a high level of unemployment filings during the first two months of the COVID-19 outbreak (40). Southern conservatives also save less than residents of other states and other high-income countries (41-42). 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 predictions and empirical observations indicate that at least for certain regions, economic vulnerability is likely high enough to be the major determinant of mobility. 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 (43). Thus, the economic incentives to mask non-compliance are low. As the current literature and polls show (44-46), masks have been highly politicized during the pandemic. Almost all Democrats endorse masks, but the proportion is much lower among Republicans, since many firm Republicans refuse to do so for partisanship expressivity. Furthermore, they may do so to show their religious values or attitudes against large governments. Refusal of mask wearing is mainly promoted by political and ideological factors[3], as conservatives tend to have a lower risk perception of COVID-19 infection and death (31), and they simultaneously tend to refuse mask coverage to express their values and political stance (43, 47). Consequently, we establish our second hypothesis:

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

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

Results

County-level analysis.

The empirical analysis consists of the quantification of county-level economic vulnerability and partisanship effects on social distancing and mask coverage.

Our main indicator for social distancing includes four measures of Google Mobility Trend (48) about 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. We use two sets of masks wearing data: the New York Times-Dynata Survey (49) that covers >2,000 counties and 250,000 respondents from July 2-July 17, and Carnegie Mellon University's COVIDCast dataset (50) that covers fewer counties (~600) from September to November.

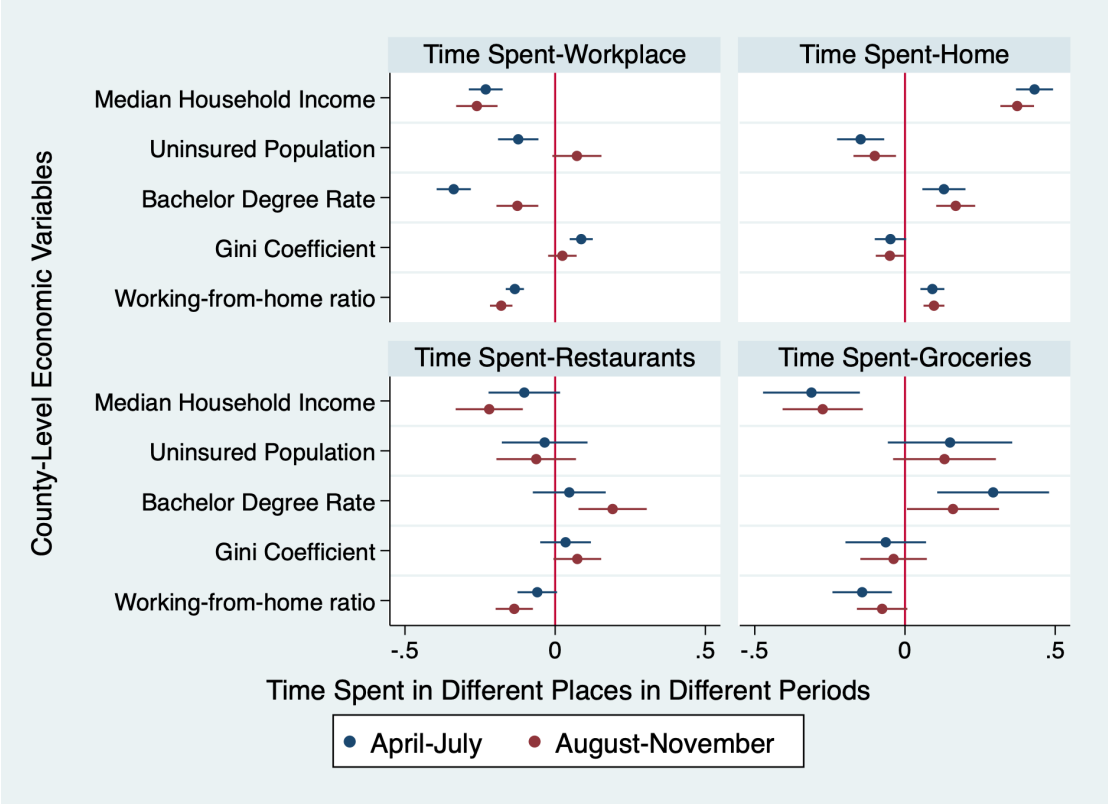
In the main results, we separate the timeline into two periods: First, from April to July, during which many parts of the country were under a shelter-in-place order, or at least some restrictive orders about enforcing social distancing. Secondly, from August to November, during which most places reopened (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 presidential election 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, controlling for variables that may impact mobility but are independent to either EV or ideology, such as temperature.

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, and other needs, such as dining in and shopping, are generally minimized and have a lower correlation with staying home[4]. 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, 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

[4] As mentioned before, 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 correlations between time spent at home and other constructs are much lower. And the work-from-home ratio is <40% for almost all states in the US.

stores is less impacted by economic vulnerability, and more by Republican partisanship (see SM for detailed discussions).



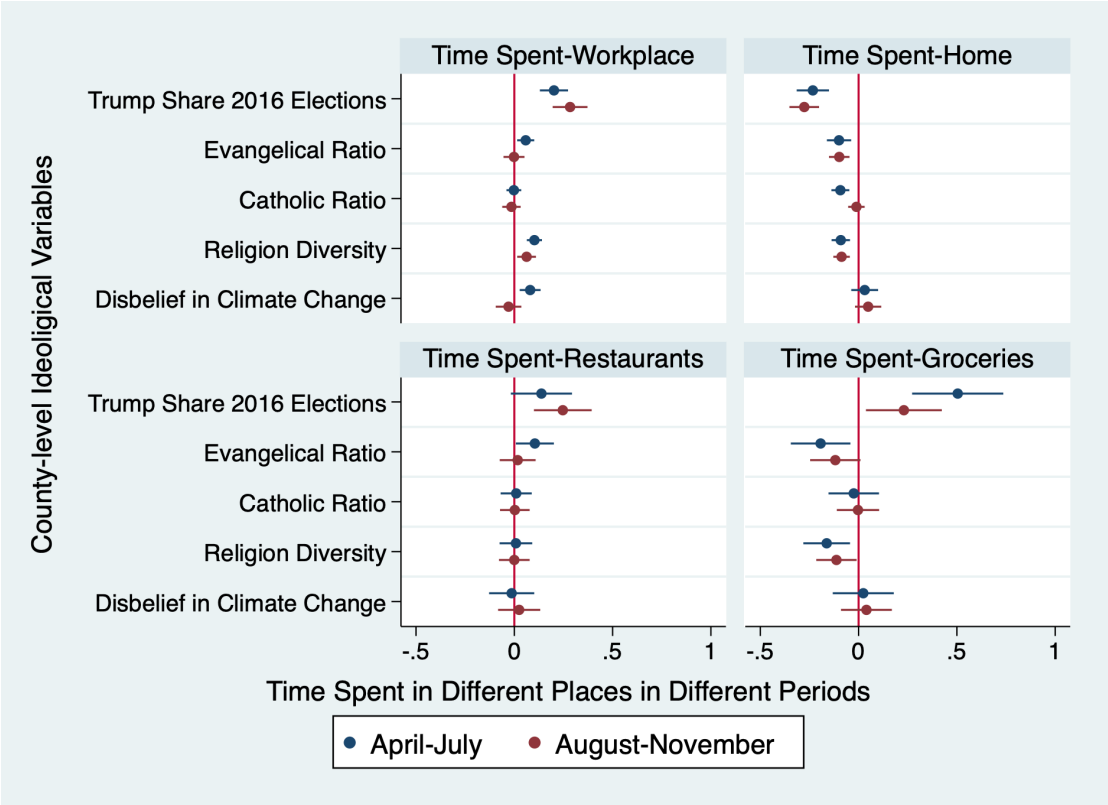


Figure 2A and 2B. Standardized Regression coefficient plot for economic and ideological variables on mobility. County-level economic vulnerability (indicated by median household income, uninsured population, bachelor degree rate, Gini coefficient, and working-from-home ratio) as well as Trump share 2016 had significant predictive power on mobility. Models are conducted with Ordinary Least Squares (OLS), controlling for lagged cases per capita, recent speed of infection, demographic and geographic variables, and regional fixed effects (interaction of state and cultural zone). The round point is the point estimate value, while the error bars 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.

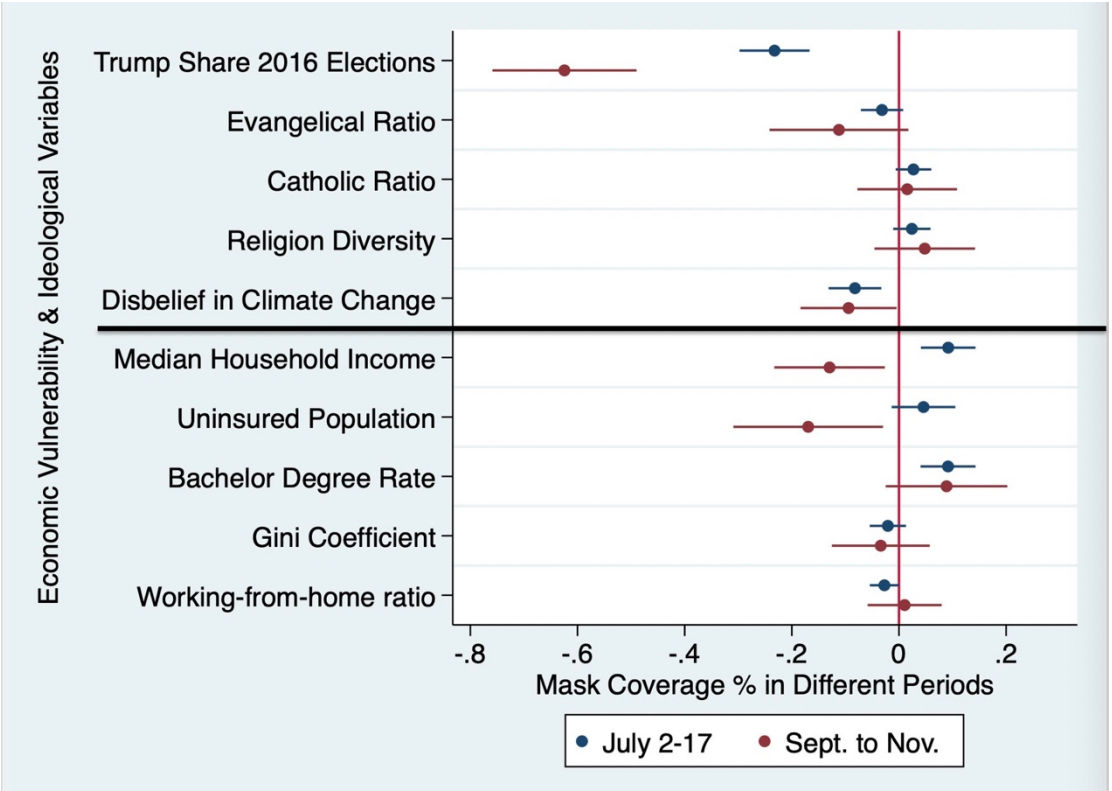


Figure 3. Regression coefficient plot for economic and ideological variables and mask coverage. Trump share 2016 had the largest predictive power on mask coverage on the county level.

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 theoretical model (see Methods) predict 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 workplace.
(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 partisanship.
(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 predictions, 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 (52-53) 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 (Apr-Jul)		**Period 2 (Aug-Nov)**	
	Bachelor's	Earnings	Bachelor's	Earnings
	Working time: Republican			
χ^2	**5.3**	0.36	3.99(Rev)	0.15
P	0.0214	0.548	0.0457**	0.697
	Stay-at-home time: Republican			
χ^2	2.62	**13.4**	3.13(Rev)	**4.12**
P	0.105	0.000***	0.077*	0.042**
	Mask: Republican			
χ^2	8.49	15.38	30.44	102.26
P	0.000***	0.000***	0.000***	0.000***
	Working-Mask			
χ^2	37	11.53	0.26	33.74
P	0.000***	0.000***	0.6076	0.000***
	Working-Mask: Republican			
χ^2	0.34		16.4	

P	0.56	0.000***

Table 1A: The first three rows of this table refer to the within-regression comparison of the standardized regression coefficients of partisanship (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 reversed to 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 (Apr-Jul) vs Period2 (Aug-Nov)		
	Republican	Bachelor's	Earnings
		Working	
χ^2	**3.41**	**35.33**	0.89
P	0.065*	0.000***	0.345
		Stay-at-home	
χ^2	1.04	0.95	**3.22**
P	0.307	0.33	0.073*
		Mask	
χ^2	**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 went down and that of political ideology went up. Interestingly, the Pearson correlations between mask wearing and the Trump Voting Share in 2020 and 2016 elections (county level) are respectively -0.52 and -0.48 for July, but as high as -0.80 and -0.77 for October, and -0.74 and -0.72 in November. The highest salience of partisanship seemed to be around the election. COVID response seemed to be more politicized close to the election days.

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.

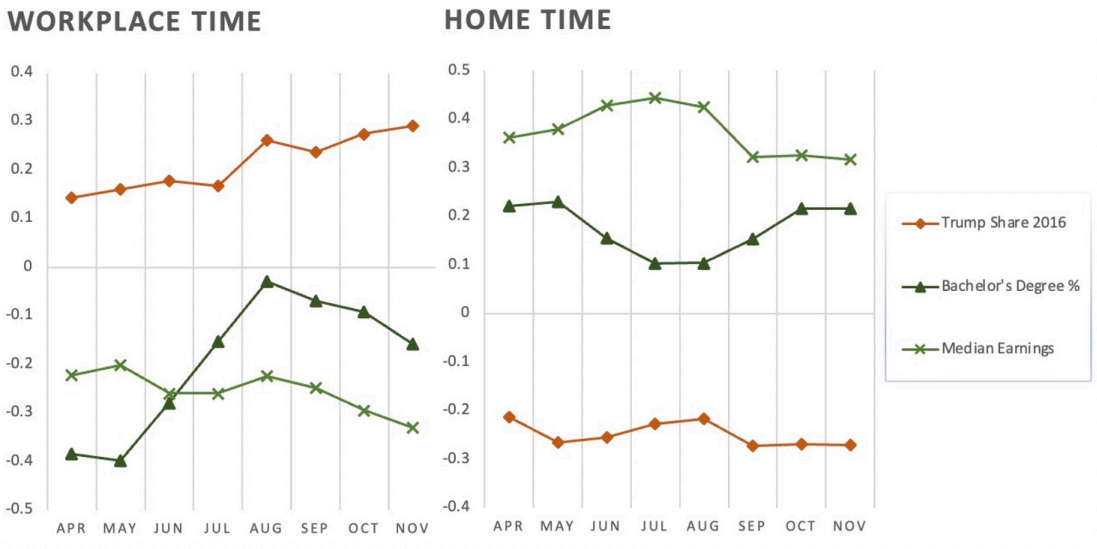


Figure 4: This is a time series plot for the standardized regression coefficients of two representative economic variables and partisanship on the time length spent at workplaces and at home. Each point is a regression coefficient of the result in certain time periods, in which the dependent variable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

General Discussion

A short review of the drifting of epicenters

In our county-level analysis, we show clear time-varying effects in the predictive power of our target variables on COVID-19 response: in earlier times, economic vulnerability prevailed and after August, partisanship ones. State-level analysis also support these patterns (for details, see SM). This drives us to look into the whole spread history. 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 ideological factors. 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 reopening designed for economic recovery (54). These premature reopening orders took place in Southern states with worse social safety nets (55-56), justifying the economic vulnerability story. Consequently, religious activities rebounded immediately with large gatherings and hardly any mask adherence. This turned churches to a crucial source of COVID-19 spread (57). Little change happened 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 non-compliance to mask wearing and for large numbers of cases in this period. The Midwest red states are different from 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 (58-59). 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 construct and analyze economic vulnerability and ideological factors independently. Nevertheless, these two variables may have significant interactions, especially with regards to political stances. It has been noted that economic inequality may lead to political polarization, which subsequently leads to politicization of crucial issues (60), from global warming (61), family relationships (62-63), to COVID-19 response (64).

Economic inequality may have significantly altered social cognitive processes (65-66). Current literature on motivated reasoning, and more specifically, the model of "motivated denial of science", suggests that the denial of science can be a rational operation that serves explicit political and economic goals (67-69). This might explain the COVID-19 response in red states: economically vulnerable collectivities might appeal for the denial of scientific consensus of COVID-19 because they are economically more inclined to early reopening.

Lastly, we have not formally discussed the role of race and ethnicity in the analysis. For example, some evidence (see SM) shows that when economic vulnerability and partisanship is controlled, counties with a larger African American population tend to have a lower mask coverage rate. This might be associated with a higher proportion of essential workers (who may feel difficult to wear masks throughout) or mask stigmatization (African Americans, especially men, may be afraid to be regarded as malicious due to stereotypes and racism, 73). Even within red states, counties with a large minority population tend to have higher COVID infection rates. These findings suggest that people of color are subject to asymmetrically high shocks from COVID-19 (74).

Future research will focus on 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 COVID prevention measures and cases across time. However, the potential 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 or ideological variables and COVID response, we need to conduct experiments. Future research can reduce the macro-level analysis to the individual level, and investigate with laboratory experiments on whether these factors causally impact individual attitudes and behaviors.

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 (34), 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 satisfies 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 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 $W \to \infty$, $G_r \to 0$.

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[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.

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

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 reboot), and no effect when EV is 0 (mask 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 is available in SM for further demonstration.

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 use standardized regressions to make the coefficients comparable. First, in one regression on mask wearing and social distancing, we compare the standardized coefficients of the key variables using simple t-tests;

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

In addition, we compare the coefficients *across* these two regressions. As all independent variables for the two regressions are the same, we are able to use the Seemingly Unrelated Regressions model on these two measures. As the beta's are the same across the regressions, we can test whether the variables of interest have different coefficients across two regressions 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. Given the aggregated nature of these data, the exact number and demographics of participants are unknown. No statistical methods were used to predetermine sample size (in terms of the number of included US counties), and we are covering available 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. Table 1 describes the dependent variables.

Table 1.

Variable	**Level**	**Data Description**	**Source**
Cases and Deaths	County and State (see SM)	Daily confirmed cases and deaths of COVID-19 at the county and state level from Feb.15, 2020 to Nov. 30, 2020.	CDC of the United States
Population	County and State (SM)	Population of the regions to be studied in 2019; used to compute per capita cases and deaths.	CDC of the United States
Social Distancing I	County and State (SM)	A dataset that shows how visits to places, such as workplaces and homes, are changing in each geographic region. Time Span: Mar-	Google Mobility Trends (48)

		Nov 2020.	
Social Distancing II	County and State (SM)	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. Time Span: Oct-Nov 2020.	Safegraph (75), Downloaded from COVIDCast (50)
Mask Wearing I	County and State (SM)	A dataset with 250,000 survey responses on mask use 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
Mask Wearing II	County and State (SM)	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)

For the NYT Mask Wearing data, the aggregation is computed (weighted average by population); for the remaining variables, the state-level data is directly available on the source websites.

Independent Variables

Economic vulnerability indicators capture the state in which local residents might face a cash shortage during the COVID outbreak. Individuals short in cash might oppose lockdown or stay-at-home orders to have their basic needs fulfilled. 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 income and the lack of sufficient social safety nets will both contribute to economic precariousness. We obtain 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 (see SM).

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 measure two types of variables: economic and ideological. Economic variables include 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), proportion of population able to work from home (non-adjusted and adjusted; derived from the employment population and wage from NAICS two-digit sectors). Ideological variables include 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 (76)), proportion of people believing in climate change (percentage point, 77).

Detailed state-level analysis as well as additional notes for the data sources and summary statistics can be found in our Supplementary Materials.

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