Partisanship, Health Behavior, and Policy Attitudes

in the Early Stages of the COVID-19 Pandemic

Shana Kushner Gadarian
Department of Political Science
Syracuse University
sgadaria@maxwell.syr.edu

Sara Wallace Goodman
Department of Political Science
University of California, Irvine
swgood@uci.edu

Thomas B. Pepinsky
Department of Government
Cornell University
pepinsky@cornell.edu

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Individual choices made during the 2020 coronavirus (COVID-19) pandemic shape the course of the virus's spread and the risks facing human populations. Yet the response to COVID-19 in the United States has been deeply political, and elite messaging from the administration of President Donald J. Trump may have produced a differential mass public health response among his supporters. To estimate the extent of these differences, we conducted an original survey of 3,000 American citizens between March 20-23 to collect data on health behavior, attitudes, and opinions about how to respond to the crisis. Measuring partisanship as party affiliation, intended 2020 Presidential vote, and self-placed ideological positioning, we find that political differences are the single most consistent factor that differentiates' Americans health behaviors and policy preferences. These results suggest that in the United States, public health messaging must deliberately transcend political cleavages in order to produce widely shared pro-social health behavior.

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The coronavirus (COVID-19) pandemic has affected nearly every aspect of economic, social and political life in the United States. Crucially, this public health emergency is taking place in a media environment saturated with misinformation, rancorous partisan infighting, and messaging from the President that undermines health experts and undercuts national unity, from referring to COVID-19 as a "Chinese" or "Wuhan" virus, downplaying its severity by comparing it to the seasonal flu, and saying it was "under control" and that "the government is doing a great job"(Qiu and Bouchard 2020). The early days of the pandemic in the US only exacerbated this environment with further uncertainty, revealing severe mismanagement from the federal government and the Centers from the Disease Control (CDC) (Wang et al. 2020), most prominently in the lack of nationwide test availability (Khazan 2020). And, divergence in containment and mitigation strategies between state governors exposed the deeply political nature of public health responses in 2020 (Elliott March 26, 2020).

This politicization of the public health response to COVID-19 raises the possibility that mass behavior in response to the crisis will differ according to partisanship. To investigate the extent of these differences, this paper reports the results from a novel survey in the first phase of widespread school closures and shelter-in-place policymaking (March 20-23, 2020). In contrast to existent survey results, ours is a *pre-registered*, *IRB-approved* analysis of the partisan politics of COVID-19 that adjusts flexibly for a wide range of demographic and geographic differences. We find consistent partisan differences among Americans not only in terms of their desired public health and public policy responses, but also on health behavior, like hand-washing and social distancing practices. We find, in fact, that partisanship is the single most consistent factor explaining differences across survey responses. Our findings suggest that addressing the dominant and divisive role of partisanship needs to be central in public health messaging.

Partisan and Mass Public Opinion in during Public Health Crises

Partisanship is among the most powerful forces in American political life. Americans pay little attention to politics most of the time (Achen and Bartels 2017), but use their partisan identification as a guide to help choose political candidates during elections (Campbell et al. 1960), form attitudes (Zaller 1992) and process information (Lodge and Taber 2013). Partisanship is also social identity (Huddy et al. 2015) that is increasingly tied to other important identities (Mason 2018; White et al. 2014) and even personality type (Hetherington and Weiler 2018). Increasing partisan polarization on the elite level (Lee 2015) and the rise of ideologically aligned media (Grossman and Hopkins 2016) combine to make partisans not only prefer their own party members over those in the opposite party (Iyengar and Westwood 2015) but also actively dislike members of the other party (Webster and Abramowitz 2017).

Partisan polarization also extends to the public's evaluations of the president's performance in health crises as well as their own health behaviors. During the Obama administration, Republicans reported more concern over Ebola than Democrats (Nyhan 2014) and Republicans in the public were less likely to get the H1N1 vaccine, particularly if they paid close attention to right wing media sources (Baum 2011). The public generally takes cues on what issues to be concerned about and what policy positions to take from the leaders of their own party (Zaller 1992) but also can use the president's position as a benchmark for policy preferences (Berinsky 2007). That is, approval of the President transfers to approve of policy positions, and vice versa. And President Trump is one of the most divisive executives in history, with approval rating more polarized by party than over any president in the modern polling era (Jones 2019).

Generally, when people are concerned about health crises, they put their trust in medical experts more than political leaders (Albertson and Gadarian 2015). However, in this highly polarized era, the president and conservative media in turn, have publicly disagreed with public health experts about how serious the coronavirus pandemic is and what types of policies can effectively manage it (Tankersly et al. 2020). Having multiple messages increases noise and will likely increase the role of partisanship for cuing—on evaluating the threat of coronavirus as well as support for behaviors and policies to mitigate it. In other words, Trump is so popular among Republicans and so unpopular among Democrats that his position on any coronavirus-related issue may be enough information for individuals to take positions, even if they operate with low information and even if it is not the traditional position of their political party.

Data and Methods

We fielded a large, nationally-representative survey of American adults ($N = 3000$) between March 20 and March 23—one week exactly after Trump declared a national emergency—in order to evaluate the relationship between partisan and political affiliations and health behaviors and policy preferences. We collected information on four kinds of outcome variables: *health behaviors* (e.g., hand washing, self-quarantining), *health attitudes* (e.g., understanding of the scale of the threat, level of worry about COVID-19), *health policy views* (e.g., should public events be cancelled, should costs be waived for COVID-19 related treatment), and *public policy views* (e.g., should elections be delayed, should interest rates be lowered, should air travel be suspended). These are examples; we present a full list of dependent variables in the Supplemental Materials (Table S1). We also collected information on demographic covariates as well as three measures of political orientations and affiliations: partisan affiliation (Democrat, Republican, or Other, calculated from the Pew Research standard "PID3" variable), intended 2020 Presidential vote choice (for Trump, for the Democrat, or for a third party or other), and ideological positioning (conservative, liberal, and moderate or non-ideological). All analyses were preregistered in an analysis plan made available at the Evidence in Governance and Politics website.[1]

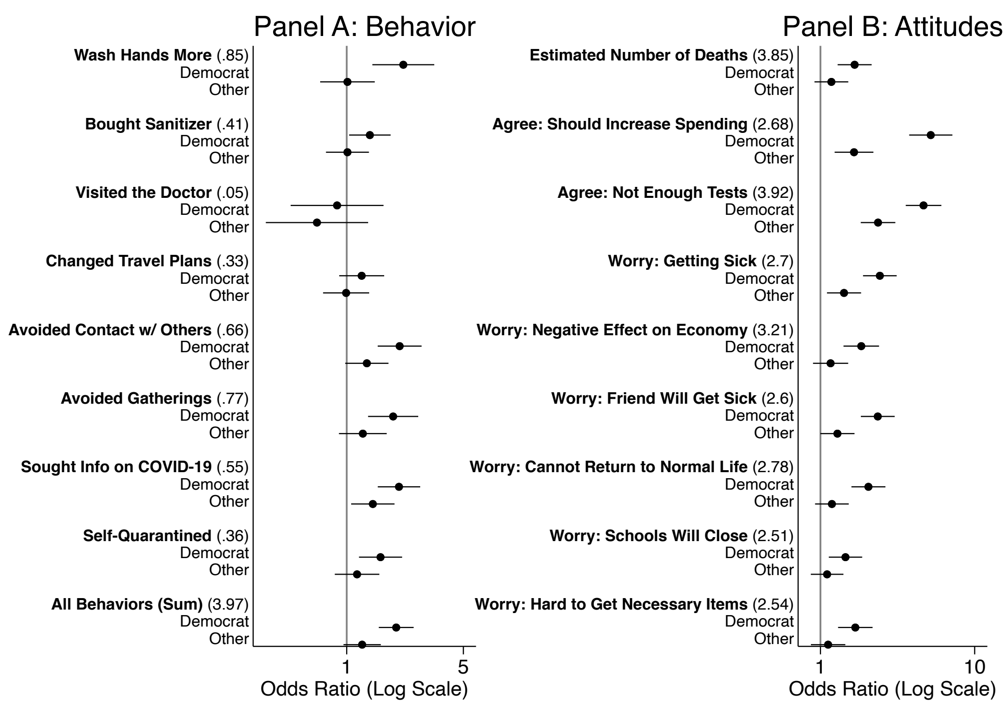
We model the relationship between political variables and outcome variables using a flexible covariate adjusted logistic regression approach (with ordinal logistic regressions for ordinal dependent variables). We include as covariates a full range of dummy variables for gender, four age categories, race (white versus nonwhite), marital status (married versus other), sixteen income levels, six education levels, five categories of news consumption, five categories of attention to the news, and state of residence. This broad array of indicator variables allows for factors such as age and education to have nonlinear relationships with outcome variables. Results using ordinary least squares regression—or representing age, education, income, and news attention as continuous variables—are substantively identical. Given the large number of dependent variables, we implement a strict Bonferroni correction when estimating standard errors and confidence intervals, correcting for nine comparisons each for health views and health behaviors (nominal $\alpha = 0.05 \rightarrow 0.0056$) and for twenty comparisons for the policy outcomes (nominal $\alpha = 0.05 \rightarrow 0.0025$).

[1] http://egap.org/design-registrations. See Supplemental Materials for pre-analysis plan and description of variances from that plan.

Results

We present results for the partisan affiliation variable only because analyses are substantively identical using intended vote choice or ideological positioning (Supplemental Materials, Figures S1-S4). Because our research design does not model the assignment of political affiliation or partisan identity, our statistical correlations cannot be interpreted as causal relationships. Nevertheless, under an assumption of unconfoundedness conditional on observed covariates (Rubin 1990) combined with a parametric functional form assumption, these correlations would have a causal interpretation. Our results for the first two collections of outcome variables are found in Figure 1.

Figure 1: Partisanship and Health Attitudes

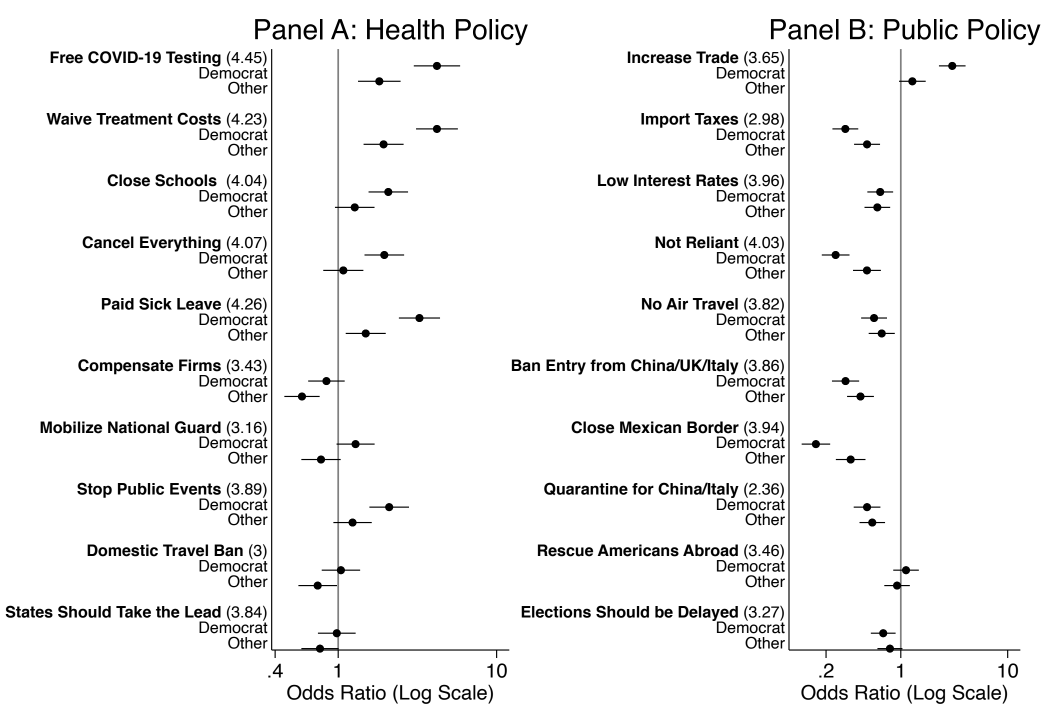


Note: estimates are odds-ratios comparing Democrats and Others (unaffiliated or identifying with a third party) to self-identified Republicans. Odds ratios greater than 1 imply the respondent is more likely report a behavior or to express a view. 95% confidence intervals are adjusted for nine comparisons using a Bonferroni correction. For each dependent variable, the number in parentheses is the proportion saying yes (Panel A) or the mean response on a five-point scale (Panel B).

We find strong evidence in Panel A that relative to Republicans, Democrats are more significantly likely to report having adopted a number of health behaviors in response to COVID-19. These behaviors collectively reflect a practice of "social distancing" and align with CDC recommendations for preventing spread. In Panel B, we also find strong evidence that relative to Republicans, Democrats exhibit more worrying attitudes about the pandemic. Democrats believe that the death toll is higher, that spending on public health responses should be increased, and are more likely to report an array of worries about the consequences of COVID-19 for their lives, including getting sick and resource scarcity.

The results from Figure 1 on health behaviors and attitudes reveal a stark partisan divide in public views of and individual responses to COVID-19. In Figure 2, we find that these also spill over to policy preferences.

Figure 2: Partisanship and Policy Preferences



Note: Odds ratios greater than 1 imply the respondent is more likely to support a policy. 95% confidence intervals are adjusted for twenty comparisons using a Bonferroni correction. For each dependent variable, the number in parentheses is the mean response on a five-point scale.

In Panel A, we observe strong partisan differences in public health responses that are consistent with left-leaning ideological preferences, such as socializing the costs of diagnosis and treatment. We also observe that Democrats are much more likely to support some measures that support social distancing (such as cancelling public events and covering workers with paid sick leave). There are no partisan differences in support for firms, restrictions on travel, or support for state governments taking the lead in the public health response.

These partisan effects are also observed in an array of trade and immigration policy responses that have been framed as possible pandemic mitigation and compensation measures. Contrary to traditional models of partisan trade and economic policy preferences, Democrats are more likely to support free trade and to oppose import taxes in response to COVID-19; they are also less likely to support expansionary macroeconomic policy to support economic growth. Democrats are also far less supportive than Republicans of policies designed to halt the spread of COVID-19 through restrictions on travel or movement, both across national borders and within them. Finally, Democrats are less likely to support delaying elections until the COVID-19 threat has passed.

One possible explanation for these results is that if Democrats tend to live in urban or cosmopolitan locations that are themselves more affected by COVID-19 in this first phase of spread, then these correlations are simply reflecting objective conditions of the pandemic. Our state dummy variables, however, account for any differences by state, which minimizes this particular inferential threat. Furthermore, we estimate multilevel regression models (Figures S5-S8) with state-level random intercepts (Gelman and Hill 2006) that control for state-level

COVID-19 diagnoses and state-level COVID-19 deaths as of March 23.[2] Our findings about partisanship remain unchanged, and objective state-level indicators of COVID-19 severity are never correlated with any outcome variable.

To confirm the importance of partisanship, we adopt a regularized regression approach to select what variables among the political and demographic predictors above best predict the outcomes above. Specifically, for each of the 38 outcomes, we use (linear) lasso regression (Tibshirani 1996) to select from among the 100 predictors we included in the analysis above, and check to see whether partisanship is among them (we allow the penalization to be data-driven, following methods in Belloni et al. 2012). This approach selects our variable capturing Democrats in 30 out of 38 regressions (see Tables S2-S5). The next most commonly selected variable is a dummy for respondents who have completed a High School education only, selected in only 16 regressions. These findings comprise powerful evidence that in addition to being a consistent predictor of health behaviors and attitudes, partisanship is the most consistently related to health behaviors and attitudes among the predictors we have included.

Discussion

Our results collectively describe a broad political divide in reaction to COVID-19: Republicans are less likely than Democrats to report responding with CDC-recommended behavior, and are less concerned about the pandemic, yet are more likely to support policies that restrict trade and movement across borders as a response to it. Democrats, by contrast, have responded by changing their personal health behaviors, and supporting policies that socialize the costs of testing and treatment. Partisanship is a more consistent predictor of behaviors, attitudes, and preferences than anything else that we measure.

[2] Available at https://covidtracking.com/data/.

Because an effective public health response to a rapidly-moving influenza pandemic such as COVID-19 requires consistent participation and collective action across communities (Germann et al. 2006; Fisher and Wilder-Smith) in addition to broader public health interventions (Hatchett et al. 2007), our findings have disturbing implications for crisis management. An effective strategy for mitigating the damage of COVID-19 requires citizens to practice social distancing measures and state and local governments to participate in them regardless of political leanings or partisan affiliations. The current COVID-19 public health campaign must exhibit bipartisan solidarity through a common message, endorsed across parties and by political elites of all persuasions, to slow the pandemic and ease the strain on health services ("flatten the curve").

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Supplementary Materials:

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Table S1: List of Dependent Variables

Variable Name	**Description**	**Distribution**
washhands	Washing hands more often	2564 1 selected 436 0 not selected
boughtsanitizer	Bought hand sanitizer	1221 1 selected 1779 0 not selected
visitdoctor	Gone to the doctor	141 1 selected 2859 0 not selected
changedtravel	Altered travel plans	988 1 selected 2012 0 not selected
avoidcontact	Avoid physical contact	1980 1 selected 1020 0 not selected
avoidgatherings	Avoid large gatherings	2317 1 selected 683 0 not selected
soughtinfo	Looked for information about coronavirus in the media	1638 1 selected 1362 0 not selected
selfquarantine	Self-quarantined	1070 1 selected 1930 0 not selected
changehealth	Washhands + boughtsanitizer + visitdoctor + changedtravel + avoidcontact + avoidgatherings + soughtinfo + selfquarantine	
numberdeaths	Estimate of Coronavirus deaths in the US	29 0 None 269 1 1-25 832 2 25-100 1198 3 100-200 348 4 200-500 324 5 More than 500
spendingincrease	*Reverse coding of* Should federal spending on preventing infectious diseases increase or decrease	2110 1 Increasing spending 810 2 No change 78 3 Decreasing spending 2 . skipped
notenoughtests	*Reverse coding of* We have enough coronavirus tests in my state	1369 1 Strongly disagree 414 2 Somewhat disagree 914 3 Neither agree nor disagree 171 4 Somewhat agree 117 5 Strongly agree

		15 . skipped
getsick	Worried: You will get sick from coronavirus	391 1 Not at all worried 1017 2 Somewhat worried 689 3 Worried 901 4 Very worried 2 . skipped
negativeeconomy	Negative impact on economy	147 1 Not at all worried 583 2 Somewhat worried 767 3 Worried 1501 4 Very worried 2 . skipped
friendsick	Friend gets sick	418 1 Not at all worried 1098 2 Somewhat worried 763 3 Worried 720 4 Very worried 1 . skipped
cannotreturn	Cannot return to way things were	360 1 Not at all worried 910 2 Somewhat worried 764 3 Worried 965 4 Very worried 1 . skipped
schoolsclosed	Schools will be closed	654 1 Not at all worried 951 2 Somewhat worried 614 3 Worried 780 4 Very worried 1 . skipped
hardgetitems	Hard to get items you need	482 1 Not at all worried 1126 2 Somewhat worried 669 3 Worried 720 4 Very worried 3 . skipped
increasetrade	Increase trade	136 1 Strongly disagree 229 2 Somewhat disagree 929 3 Neither agree nor disagree 925 4 Somewhat agree 765 5 Strongly agree 16 . skipped
importtaxes	Increase taxes on foreign imports	418 1 Strongly disagree 481 2 Somewhat disagree 1166 3 Neither agree nor disagree 580 4 Somewhat agree 345 5 Strongly agree 10 . skipped
lowinterest	Keep interest rates low	84 1 Strongly disagree 176 2 Somewhat disagree 669 3 Neither agree nor disagree 912 4 Somewhat agree

		1145 5 Strongly agree 14 . skipped
notreliant	Not be reliant on other countries	112 1 Strongly disagree 213 2 Somewhat disagree 514 3 Neither agree nor disagree 786 4 Somewhat agree 1363 5 Strongly agree 12 . skipped
noairtravel	Halt all international air travel	170 1 Strongly disagree 335 2 Somewhat disagree 541 3 Neither agree nor disagree 774 4 Somewhat agree 1174 5 Strongly agree 6 . skipped
banentry	Ban the entry of citizens of China/Italy/Great Britain	171 1 Strongly disagree 246 2 Somewhat disagree 626 3 Neither agree nor disagree 733 4 Somewhat agree 1215 5 Strongly agree 9 . skipped
entrymexico	Impose entry restrictions at the US-Mexico border	182 1 Strongly disagree 235 2 Somewhat disagree 532 3 Neither agree nor disagree 661 4 Somewhat agree 1380 5 Strongly agree 10 . skipped
quarantine	Quarantine Chinese/Italians in the United States	1198 1 Strongly disagree 481 2 Somewhat disagree 689 3 Neither agree nor disagree 274 4 Somewhat agree 342 5 Strongly agree 16 . skipped
rescueUS	Rescue US citizens from abroad	206 1 Strongly disagree 373 2 Somewhat disagree 929 3 Neither agree nor disagree 794 4 Somewhat agree 686 5 Strongly agree 12 . skipped
freetesting	Make all testing for COVID-19 free for all Americans	66 1 Strongly disagree 86 2 Somewhat disagree 315 3 Neither agree nor disagree 480 4 Somewhat agree 2041 5 Strongly agree

		12 . skipped
waivecosts	The government should waive insurance costs and hospital fees for treating COVID-19	74 1 Strongly disagree 175 2 Somewhat disagree 439 3 Neither agree nor disagree 607 4 Somewhat agree 1697 5 Strongly agree 8 . skipped
closeschools	Close all schools in order to contain the spread of coronavirus	111 1 Strongly disagree 201 2 Somewhat disagree 485 3 Neither agree nor disagree 855 4 Somewhat agree 1332 5 Strongly agree 16 . skipped
canceleverything	Ban public events	106 1 Strongly disagree 200 2 Somewhat disagree 460 3 Neither agree nor disagree 846 4 Somewhat agree 1379 5 Strongly agree 9 . skipped
paidleave	Grant paid leave to anyone diagnosed with coronavirus	89 1 Strongly disagree 129 2 Somewhat disagree 420 3 Neither agree nor disagree 640 4 Somewhat agree 1713 5 Strongly agree 9 . skipped
compensatefirms	Provide compensation to American companies	263 1 Strongly disagree 410 2 Somewhat disagree 707 3 Neither agree nor disagree 984 4 Somewhat agree 626 5 Strongly agree 10 . skipped
nationalguard	Mobilize the National Guard to enforce quarantines	428 1 Strongly disagree 468 2 Somewhat disagree 866 3 Neither agree nor disagree 670 4 Somewhat agree 560 5 Strongly agree 8 . skipped
stopevents	Sporting and other public events should continue to take place	1413 1 Strongly disagree 578 2 Somewhat disagree 476 3 Neither agree nor disagree 298 4 Somewhat agree 228 5 Strongly agree 7 . skipped

travelban	Domestic travel ban	583 1 Strongly disagree 542 2 Somewhat disagree 713 3 Neither agree nor disagree 599 4 Somewhat agree 551 5 Strongly agree 12 . skipped
stateslead	State governments should lead	105 1 Strongly disagree 261 2 Somewhat disagree 605 3 Neither agree nor disagree 1065 4 Somewhat agree 955 5 Strongly agree 9 . skipped
delayelections	Elections should be delayed	594 1 Strongly disagree 329 2 Somewhat disagree 564 3 Neither agree nor disagree 700 4 Somewhat agree 805 5 Strongly agree 8 . skipped

Different Measures of Partisanship

Figure S1: Behaviors and Attitudes, by Trump Support

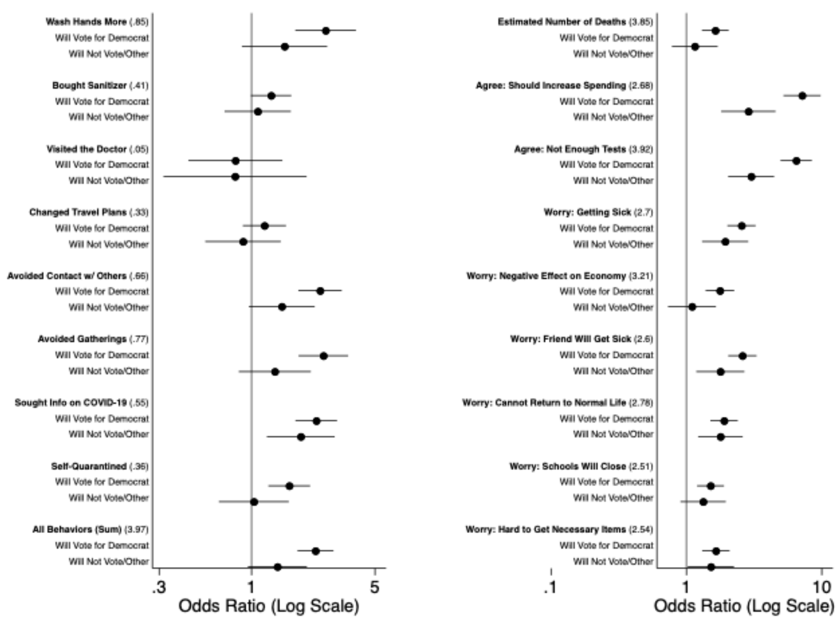


Figure S2: Behaviors and Attitudes, by Ideology

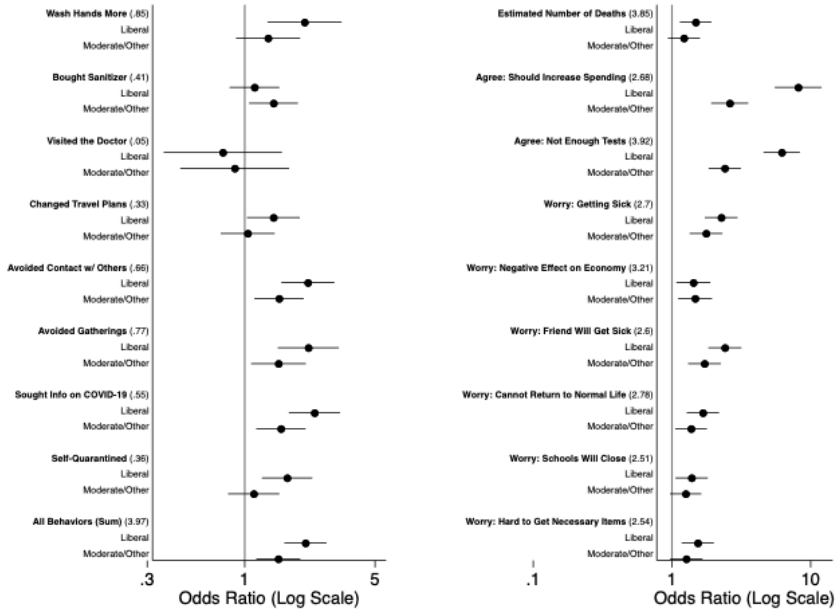


Figure S3: Policies, by Trump Support

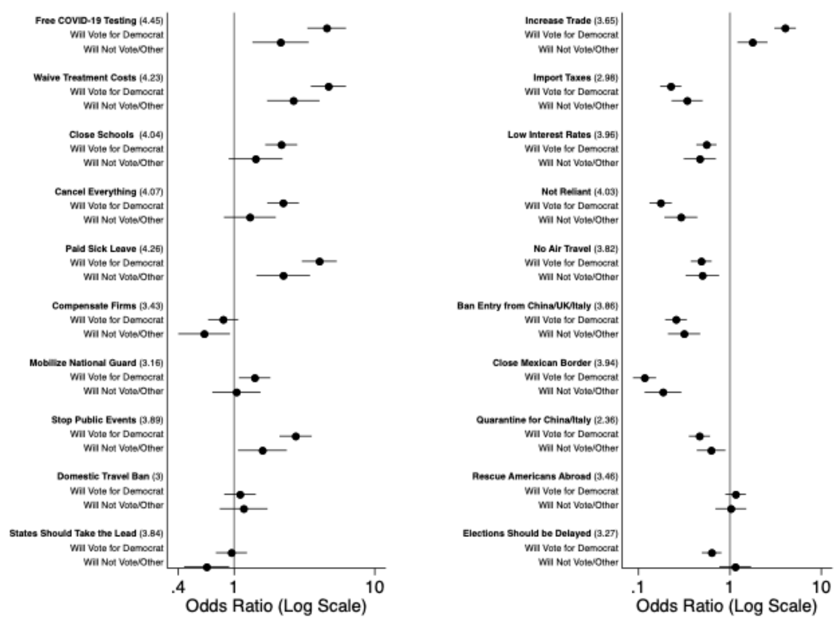
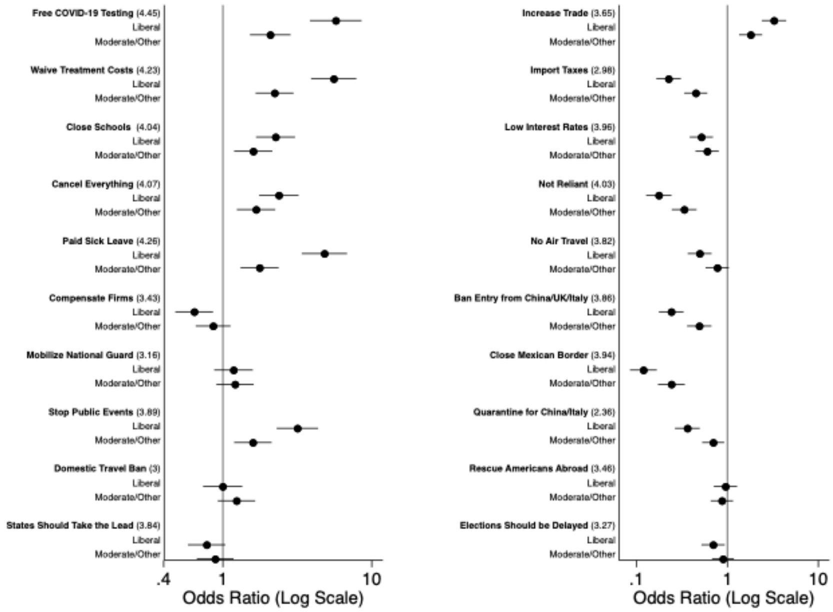


Figure S4: Policies, by Ideology



Multilevel Models

In this section we present results from multilevel models that differ from the main specifications in the text as follows: instead of state fixed effects, we include random effects by state and include state-level deaths from COVID-19 as of March 23 (*Deaths*) and state-level positive diagnoses of COVID-19 as of March 23 (*Positive*) as predictors. We estimate linear multilevel models throughout.

Our main conclusions are two: *first*, state-level predictors *Death* and *Positive* are never significantly correlated with any dependent variable, and *second*, their inclusion never changes our inferences about the partisanship variables.

Figure S5: Health Behaviors, Multilevel Models

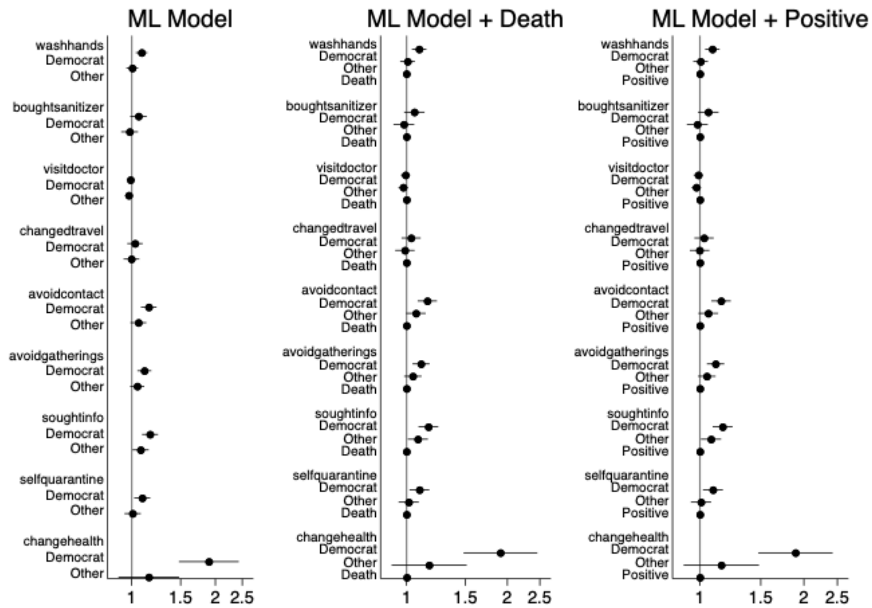


Figure S6: Health Attitudes, Multilevel Models

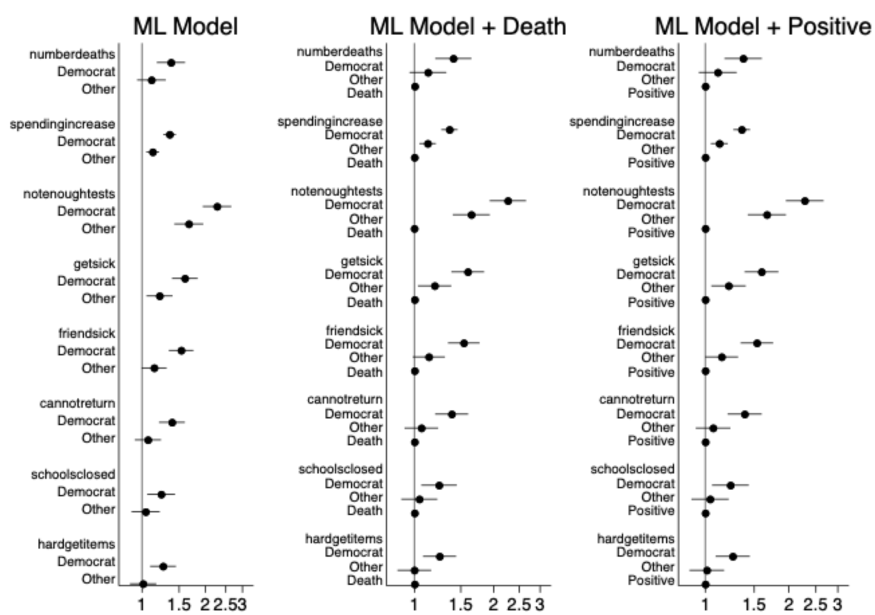


Figure S7: Health Policy, Multilevel Models

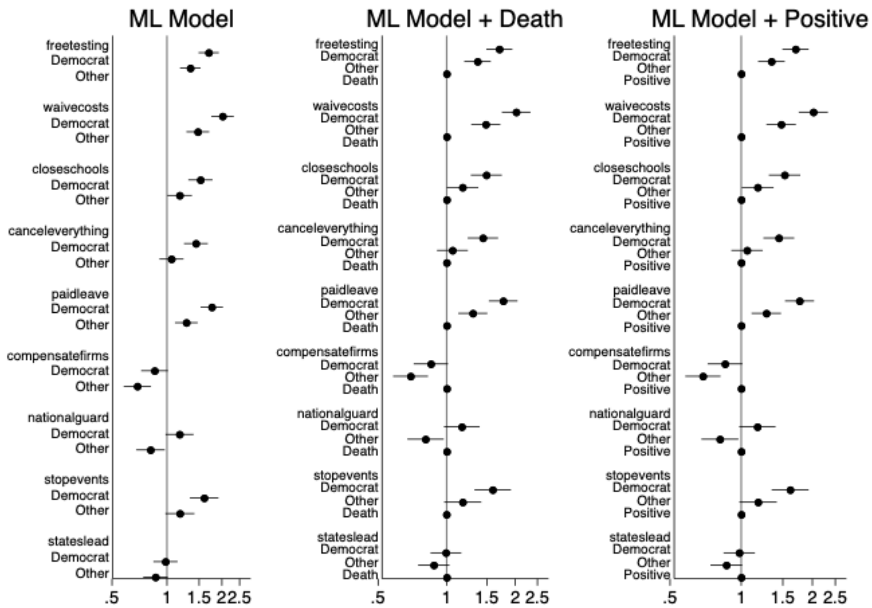
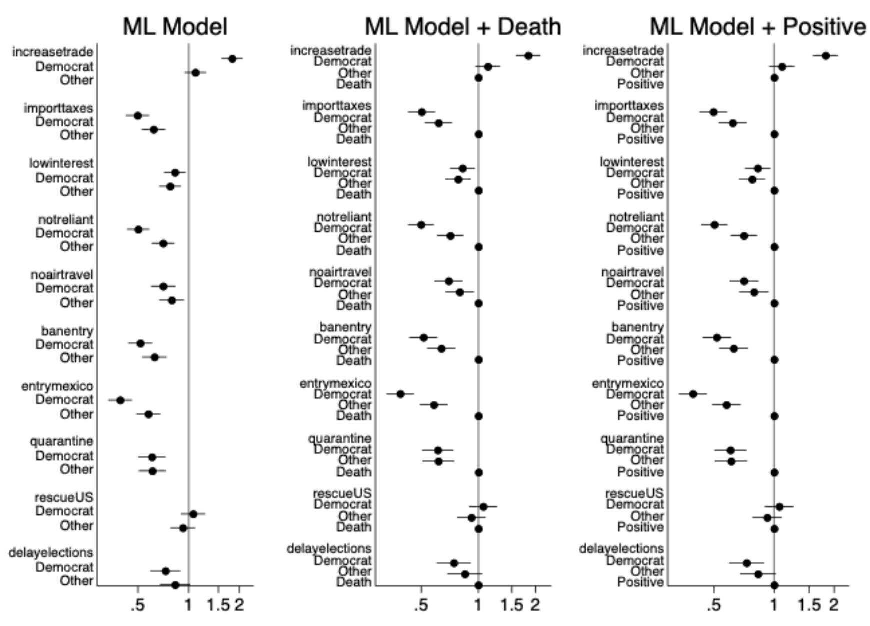


Figure S8: Public Policy, Multilevel Models



Regularized Regression Models

Below, we show the results of our regularized regression analysis using a linear lasso. Each table provides the OLS regression coefficients from post-lasso selected predictors only. Empty cells imply that the lasso did not select that predictor.

Table S2: Lasso Selected Predictors, Health Behaviors

	washhands	bought sanitizer	visit doctor	changed travel	avoid contact	avoid gatherings	soughtinfo	self quarantine	change health
Democrat	0.05	0.02			0.06	0.03	0.07	0.04	0.46
4-year	0.00								
newsfreq=5	-0.01					-0.02			-0.51
newsattention=5	-0.03			-0.04	-0.11	-0.13	-0.18		-0.67
white		-0.02							
newsfreq=4		-0.01					-0.06		-0.28
income=13			-0.03						
Connecticut			-0.03						
Idaho			-0.03						
Massachusetts			-0.03						
Montana			-0.03						
Utah			-0.03						
High school graduate				-0.06		-0.00	-0.08		-0.14
Post-grad				0.08	0.03	0.01	0.03		0.28
income=14				0.06					
newsattention=4				-0.08	-0.05	-0.01	-0.09		-0.42
newsfreq=3					-0.08		-0.07		-0.54
70-						0.04			
newsattention=3							-0.04		-0.02
50-								-0.01	
newsfreq=2									-0.18
Observations	3000	3000	3000	3000	3000	3000	3000	3000	3000

Table S3: Lasso Selected Predictors, Health Attitudes

	number deaths	spending increase	notenough tests	getsick	negative economy	friendsick	cannot return	schools closed	hardget items

Democrat	0.12	0.20	0.41	0.29	0.13	0.30	0.23	0.09	0.13
70-	0.05							-0.31	-0.11
newsfreq=3	-0.04	-0.03							
newsattention=5		-0.14			-0.10				
Other			0.02						
white			0.05						
High school graduate			-0.07		-0.00				
newsattention=4			-0.02	-0.02	-0.09	-0.02			
gender				0.01					0.01
newsfreq=2				-0.01		-0.07			
income=11					0.05				
newsfreq=4							-0.00		
Observations	3000	2998	2985	2998	2998	2999	2999	2999	2997

Table S4: Lasso Selected Predictors, Health Policy Preferences

	free testing	waive costs	close schools	cancel everything	paid leave	compensate firms	national guard	stop events	travel ban	stateslead
Democrat	0.27	0.37	0.24	0.24	0.33		0.13	0.23		
gender			0.02	0.07		0.14	0.02	0.01	0.35	
70-				0.02						
newsfreq=2				-0.12						
newsfreq=4				-0.02						
Other						-0.07	-0.06		-0.00	-0.01
white							-0.00	0.08	-0.17	
High school graduate							0.07	-0.02	0.18	
newsattention=4								-0.06		
newsattention=5								-0.15		
Post-grad									-0.06	
Observations	2988	2992	2984	2991	2991	2990	2992	2993	2988	2991

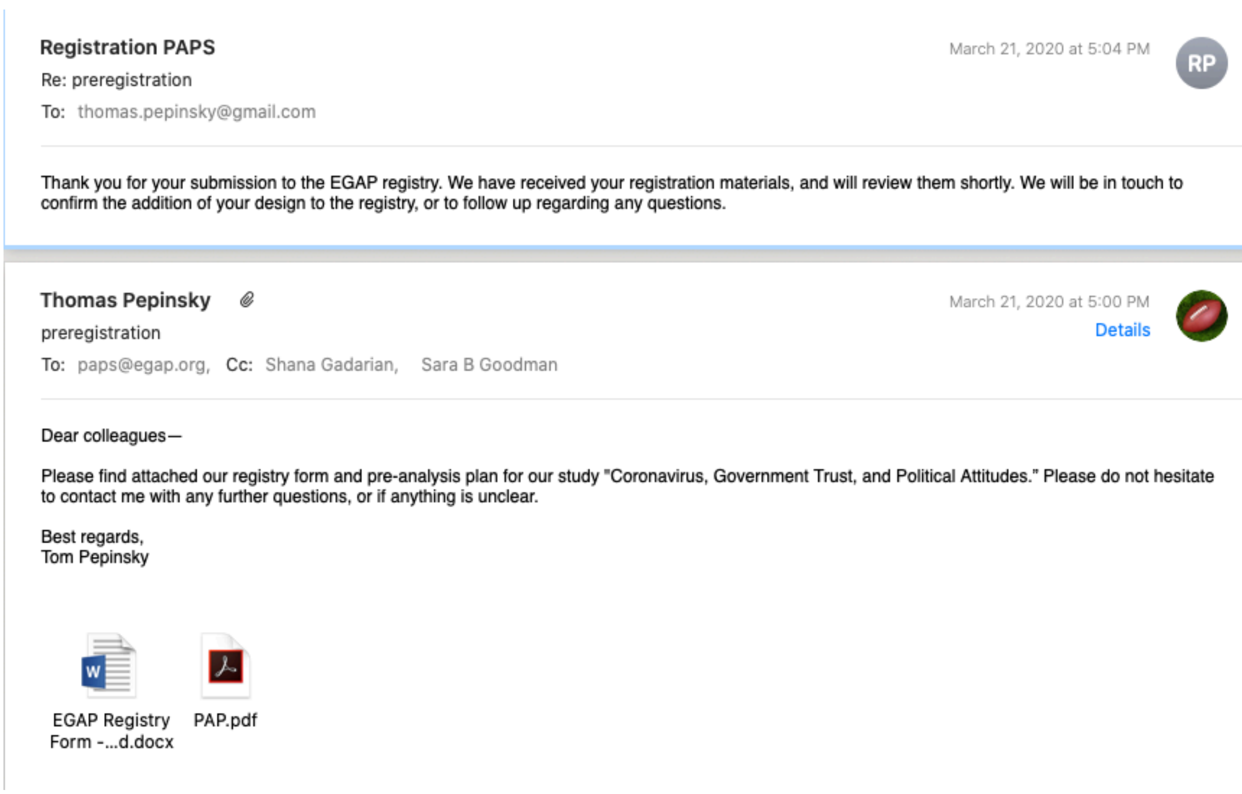
Table S5: Lasso Selected Predictors, Public Policy Preferences

	increase trade	import taxes	lowinterest	notreliant	noair travel	banentry	entry mexico	quarantine	rescueUS	delay elections
Democrat	0.43	-0.30		-0.35	-0.00	-0.23	-0.58	-0.01		
newsattention=4	-0.03							0.06		0.02
Other		-0.01	-0.00			-0.05	-0.13			

gender		0.01			0.08					0.25
High school graduate		0.12		0.03	0.21	0.12	0.14	0.31		0.03
Post-grad		-0.05			-0.12			-0.17		-0.06
newsattention=3		0.07								
50-				0.08		0.03	0.08			-0.03
4-year						-0.02				
70-							0.04			
white								-0.13		
income=2								0.03		
newsfreq=2									-0.08	
newsattention=5									-0.03	
Observations	2984	2990	2986	2988	2994	2991	2990	2984	2988	2992

Preanalysis Plan

We submitted a preanalysis plan to the Evidence in Governance and Politics network on March 21, 2020, before we had access to the survey results, which we received on March 24. A screenshot of the confirmation email appears below.



Registration PAPS
March 21, 2020 at 5:04 PM
Re: preregistration
To: thomas.pepinsky@gmail.com

Thank you for your submission to the EGAP registry. We have received your registration materials, and will review them shortly. We will be in touch to confirm the addition of your design to the registry, or to follow up regarding any questions.

Thomas Pepinsky
March 21, 2020 at 5:00 PM
preregistration
Details
To: paps@egap.org, Cc: Shana Gadarian, Sara B Goodman

Dear colleagues—

Please find attached our registry form and pre-analysis plan for our study "Coronavirus, Government Trust, and Political Attitudes." Please do not hesitate to contact me with any further questions, or if anything is unclear.

Best regards,
Tom Pepinsky

EGAP Registry Form -...d.docx
PAP.pdf

We reproduce the full preanalysis plan below. The preanalysis plan contains plans to study a number of different outcomes that we do not include in this manuscript; these will be explored in separate research projects.

Here, we describe two variances between the analytical procedures that we outlined in the preanalysis plan and the analysis in this manuscript.

1. In the PAP we describe Bonferroni corrections correcting for 27 comparisons (target p-value of 0.05 would be 0.05 / 27 = 0.0019). In this manuscript, we separate Bonferroni corrections by attitudes and views (9 comparisons each), and policies (20 comparisons). Importantly, this choice affects none of our estimates of statistical significance.
2. In the PAP we describe the covariate adjustments as
   - Age (binned at 18-34, 35-49, 50-69, 70+)
   - Marital status (Married versus other)
   - Race (White versus other)
   - Income (scale)
   - Education (scale)
   - Region of resident (dummies)

   In our manuscript, we adopt add gender to these covariate adjustments, replace region of resident with state of resident, and add variables for interest in the news and frequency of news consumption. Again, these choices affect none of our estimates of statistical significance, and are indeed more conservative than the preanalyzed version.

Our analysis is otherwise identical to that which we specified in our preanalysis plan.

FULL PREANALYSIS PLAN BEGINS BELOW

Preanalysis Plan

Coronavirus, Government Trust, and Political Attitudes

Shana Kushner Gadarian
Department of Political Science
Syracuse University
sgadaria@maxwell.syr.edu

Sara Wallace Goodman
Department of Political Science
University of California, Irvine
swgood@uci.edu

Thomas B. Pepinsky
Department of Government
Cornell University
pepinsky@cornell.edu

March 21, 2020

This document outlines the analysis procedures for a study on public responses to the coronavirus pandemic in the United States. Our discussion in this document focus on our analysis of the *first round* of this survey. A subsequent document will discuss our prospective analysis of the *second round* of this survey.

Our overarching metahypothesis is that demographic and partisan factors will shape individual responses about the coronavirus pandemic.

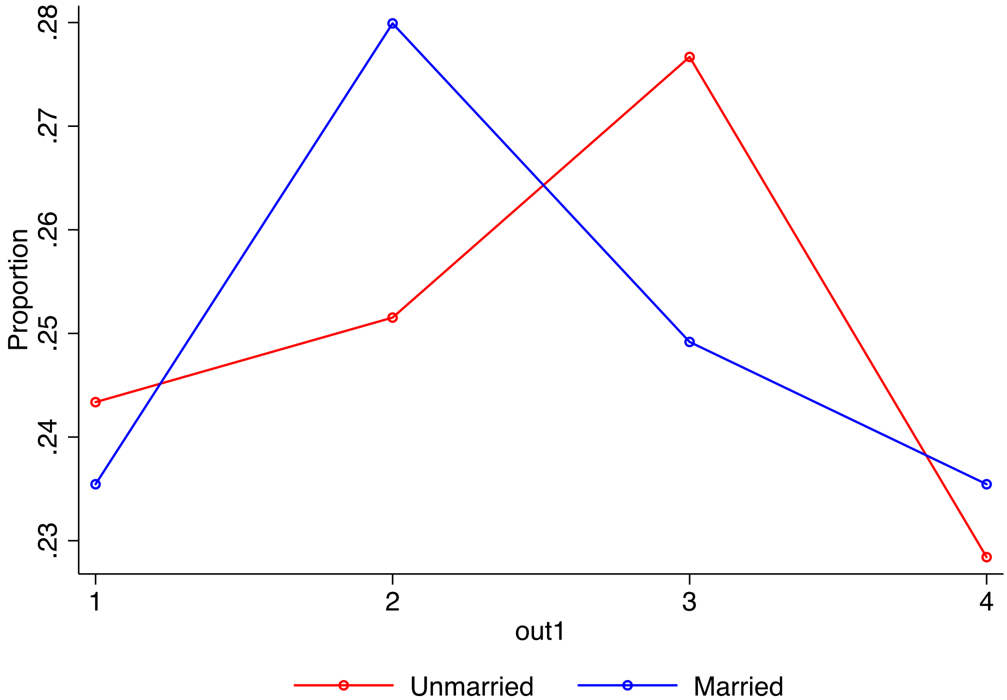
Observational Analysis

The bulk of our analysis will be descriptive and we will interpret results using a graphical approach. We describe first an observational analysis where we describe differences in respondents based on their demographic attributes and political and attitudinal characteristics.

Our key demographic variables of interest are
- Age (binned at 18-34, 35-49, 50-69, 70+)
- Marital status (Married versus other)
- Race (White versus other)
- Income (scale)
- Education (scale)
- Region of resident (dummies)

Our key political attributes of interests are
- Democratic versus other, based on the 7 point PID scale (values 0, 1, and 2 coded as Democrat, the rest as other)
- Intended vote choice in 2020 (Trump definitely or likely, versus all alternatives)
- Participation index (count of self-reported activities)
- Trade orientation
- Immigration orientation
- Racial resentment
- News consumption
- Social media sources (count of number of media sources)
- Authoritarian personality index (4 items)

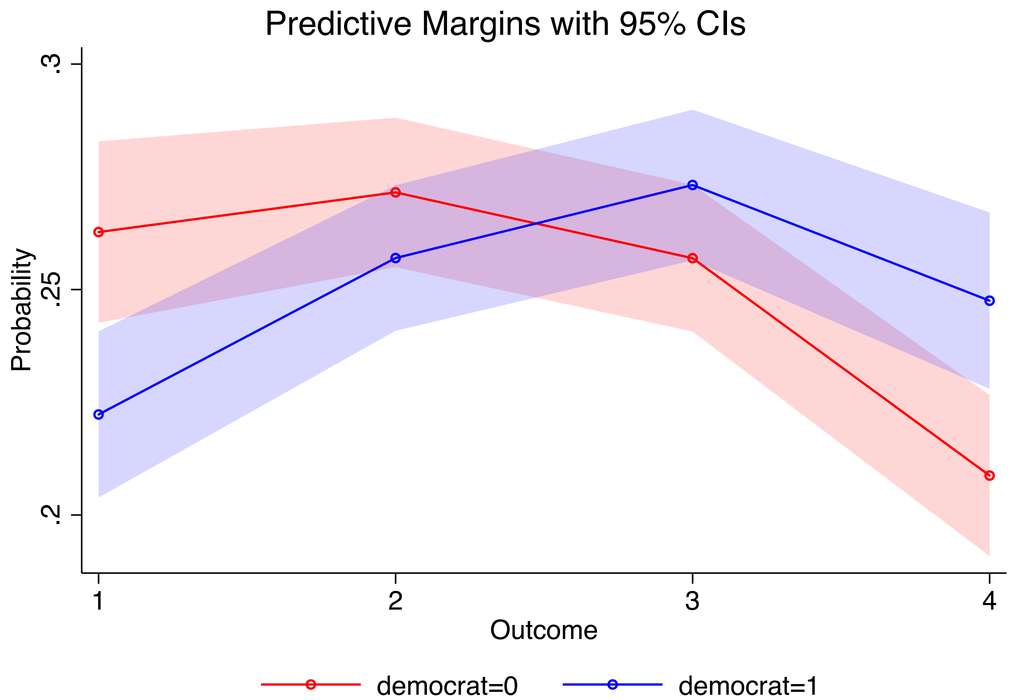
We will describe support for policies according to each of these demographic variables. We will do this by creating graphs that compare the level of support for policies according to various groups within the data. An example using simulated data appears below.



When we describe political attributes of interest, we will plot both unadjusted comparisons and adjusted comparisons, derived from ordinal logistic regression models that predict the probability of each response category adjusted for the demographic covariates of interest, with cluster robust standard errors. So, to describe differences support for *Out1* between Democrats and Non-Democrats we will estimate, in Stata,

```
ologit out1 i.democrat age race marital i.income i.education
     i.region, robust
margins, at(democrat=(0 1)) plot(__swapxp recastci(rarea))
```

A sample result again using simulated data appears below.



We will make inferences about the statistical significance of differences based on regression coefficients and standard errors, but we will use the graphical approach to describe the substantive importance of these results.

We will always include the demographic variables in any covariate-adjusted model: age (continuous), marital status (binary), race (binary), income (factor), education (factor), region (factor).

Given the sheer number of dependent variables that we have collected, we run into severe multiple comparison problems: almost certainly we will find statistically significant partial correlations between political variables and policy preferences when measured at conventional levels. A standard Bonferroni correction is extremely conservative. We have 5 prospective behavior questions and 22 policy preference questions, meaning that a Bonferroni-corrected target p-value of 0.05 would be 0.05 / 27 = 0.0019. We will use this as our benchmark for describing results as "statistically significant at $p < .05$ under the Bonferroni correction." We will also adjust p-values based on the Holm method, and use them to describe results that are "statistically significant at $p < .05$ under the Holm correction." When we report results that are based on unadjusted comparisons, we will always note that they are "unadjusted and therefore too optimistic" or some such language.

We will pair this analysis with an exploratory factor analysis of the policy outcomes, to uncover latent dimensions of policy response. We are agnostic at the present as to what these dimensions are, but we will use standard methods to extract factor scores and then will use those as dependent variables in analyses such as those described above. Neither Bonferroni nor Holm corrections will be applied to analyses that use factor scores as dependent variables.

We hypothesize further that the coronavirus threat will lead to greater levels of anxiety, fear, and anger among our respondents. We collect information about respondents' emotional reactions to the crisis (anger, anxiety, sadness, hope, and disgust) and will explore how these vary by demographic group as with the policy responses above. These analyses of emotional responses will be descriptive only in nature. However, we hypothesize that these emotional responses will break down along partisan lines, with anxiety and fear increasing among Democrats and Trump opponents and anger increasing among Republicans and Trump supporters. We will test these predictions using the ordered logistic regression approach described above, with a Bonferroni correction of 0.05 / 5 = 0.01.

We hypothesize that the coronavirus threat broadly leads to higher levels of trust in government institutions. We collect information on trust in the CDC, the FDA, DHS, President Trump, Vice President Pence, State Health Agencies, and the Surgeon General. We predict that the trust in all governmental institutions will be higher among Republicans and Trump supporters as well as but higher among Democrats and Trump opponents, but that among Democrats, those anxious about coronavirus will be less trusting of President Trump and Vice President Pence. We will test these predictions using the ordered logistic regression approach described above, with a Bonferroni correction of 0.05 / 7 = 0.007.

Finally, we expect that responds who display higher levels of anxiety and anger about coronavirus will be more likely to support immigration restrictions and efforts to expand the domestic economy among both Democrats and Republicans, since messages from both parties are emphasizing such active policy responses.

Additional Non-Survey Data

We plan to complement our survey data with demographic, economic, and health data at the zip code and state levels, which we will then join to the survey dataset. We will explore variation in survey responses based on local median household income, insurance coverage, and racial characteristics (specifically, White/Non-Hispanic and Asian). Our main hypotheses are that support for active responses will be higher in those localities that are wealthier and more diverse. We are agnostic as to whether we will find greater support for active policy responses in localities that have more insurance coverage.

Experimental Analysis

We have implemented a three-arm factorial experiment. The first factor (partisan valence of the CDC) has three treatments and a control, the second (nature of crisis threat) has two treatments and a control, and the third (Trump commentary) has one treatment and a control. Treatment effects are defined as differences in potential outcomes between combinations of treatment states. There are twenty potential outcomes in total:

Table 6: Potential Outcomes

Y_{000}	Y_{010}	Y_{020}	Y_{011}	Y_{021}
Y_{100}	Y_{110}	Y_{120}	Y_{111}	Y_{121}
Y_{200}	Y_{210}	Y_{220}	Y_{211}	Y_{221}
Y_{300}	Y_{310}	Y_{320}	Y_{311}	Y_{321}

We do not calculate power explicitly, but we can infer from a simple 2 x 2 x 2 factorial design that we are insufficiently powered to estimate the broad range of interactive treatment effects available. We therefore focus on estimating overall treatment effects of each factor.

Main Hypotheses

Our main hypotheses are that partisan valence reduces overall support for policy responses and reduce willingness to change personal health behaviors; that mentioning the threat to the economy increases support for active economic responses, but mentioning the threat to border security increases support for anti-immigrant and anti-minority policy responses; and that commentary by President Trump reduces overall support for all policy responses.

Our method will be to estimate what Muralidharan et al. (2020) term “long” and “short” regressions for the treatments and interactions, both with and without covariate adjustments. The “long” model includes each factor and their interactions (here represented as binary treatments for purposes of exposition):

$$Y = \beta_0 + \beta_1 T_1 + \beta_2 T_2 + \beta_3 T_1 T_2 + \cdots + \beta_{20} T_1 T_2 T_3 + \varepsilon$$

The “short” model eliminates the interactions:

$$Y = \beta_0 + \beta_1 T_1 + \beta_2 T_2 + \beta_3 T_3 + \varepsilon$$

We will use OLS with robust standard errors to estimate treatment effects. We will estimate these in Stata using the commands

```
reg out1 i.t1##i.t2##i.t3, robust
```

for the long model and

```
reg out1 i.t1 i.t2 i.t3, robust
```

for the short model. Using simulated data again, the coefficients of each main effect test the effects of each level versus the untreated state, as below for the long model:

out1	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf. Interval]	
t1						
1	.027942	.1414353	0.20	0.843	-.249379	.305263
2	-.0036922	.1471359	-0.03	0.980	-.2921906	.2848062
3	-.0071234	.1456452	-0.05	0.961	-.292699	.2784522
t2						
1	-.0988013	.1459819	-0.68	0.499	-.3850369	.1874344
2	.1685045	.1398075	1.21	0.228	-.1056247	.4426337
t1#t2						
1 1	.1170304	.1974391	0.59	0.553	-.2701006	.5041615

The interpretation of the short model is delicate. We will interpret these as the "a composite treatment effect that includes a weighted-average of the interactions with other treatments" as described by Muralidharan et al. (2020). This is a quantity of academic interest. We will highlight cases where both long and short models provide the same result and also when they do not, and highlight that where the short model results are statistically significant but the long models are not, resolving the interpretation differences requires us to focus on differences in estimands.

For covariate adjusted models, we will follow Lin (2013) by interacting each treatment variable with mean-centered covariates, yielding

```
reg out1 i.t1##i.t2##i.t3##c.mc_*, robust
```

for the long model and

```
reg out1 i.t1##c.mc_* i.t2##c.mc_* i.t3##c.mc_*, robust
```

for the short model, where `c.mc_*` picks out any variable that has been mean-centered based on the command

```
local mods "age race marital income education west south east
midwest"
foreach var of local mods {
     summarize `var'
     generate mc_`var' = `var' - r(mean)
}
```

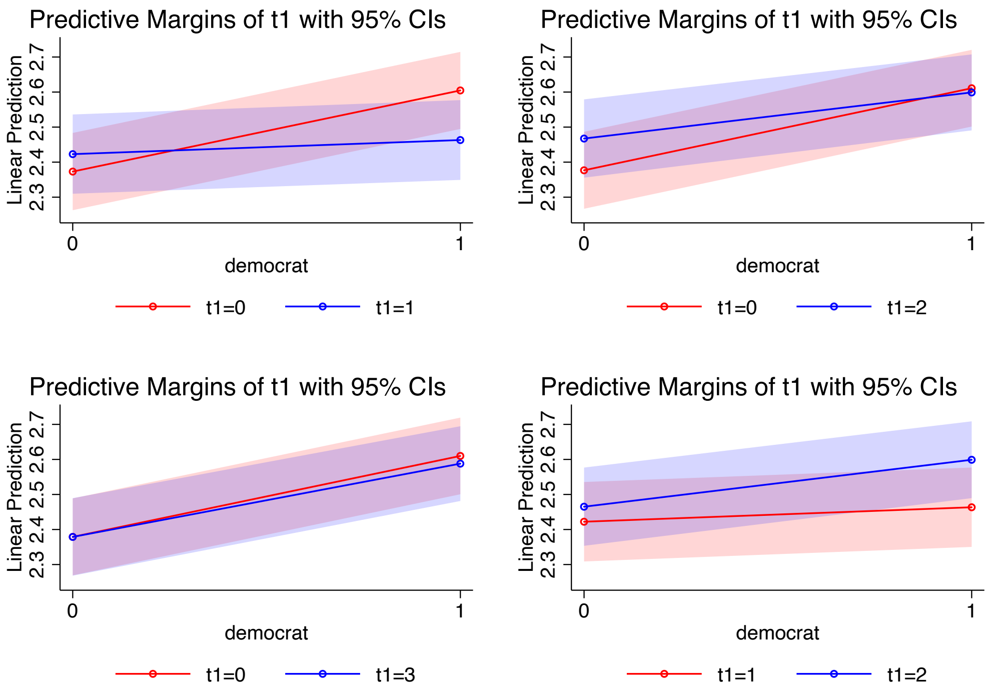
When mean-centering the factor variables age, income, and education, we will treat them as continuous.

We will apply the Bonferroni and Holm corrections to the experimental results as well, but we anticipate that these will be too conservative to yield any statistically significant results given the already low effective sample sizes. We will clarify, when reporting results without such multiple comparison corrections, that these results were not adjusted for multiple comparisons, and are therefore insufficiently conservative and should be treated as provisional. We will use an inductive approach—focusing on the factor scores extracted as part of the analysis described above—to group policy responses.

Conditional Hypotheses

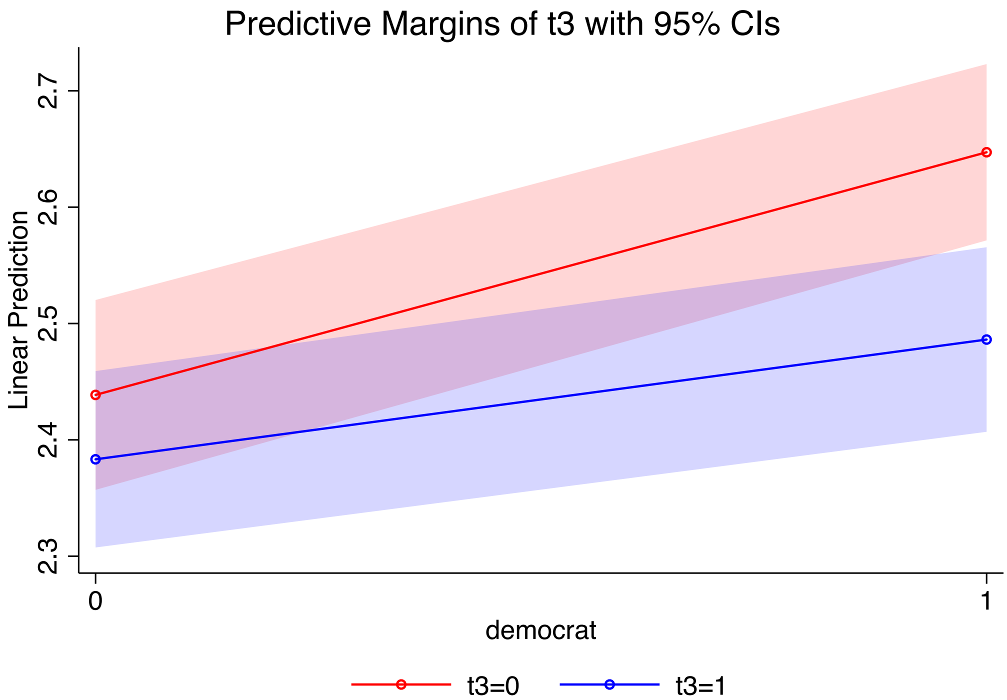
One key hypothesis is that the effects of partisan valence and President Trump's commentary on policy responses vary systematically according to the partisan identity and intended vote choice of the respondent. We will study this by interacting the partisan and vote choice dummies with each of the treatment states and then adopting a graphical approach to study predicted values. We will calculate treatment effects of partisan valence versus the control state (Democrat versus control, Republican versus control, bipartisan versus control, and Democrat versus Republican), as follows:

```
reg out1 i.t1##i.t2##i.t3##i.democrat, robust
margins t1 if t1==0 | t1==1, at(democrat=(0 1)) plot(
     recastci(rarea) name(demcont, replace))
margins t1 if t1==0 | t1==2, at(democrat=(0 1)) plot(
     recastci(rarea) name(repcont, replace))
margins t1 if t1==0 | t1==3, at(democrat=(0 1)) plot(
     recastci(rarea) name(bipcont, replace))
margins t1 if t1==1 | t1==2, at(democrat=(0 1)) plot(
     recastci(rarea) name(demrep, replace))
graph combine demcont repcont bipcont demrep, ycommon
```



Likewise, we will calculate treatment effects of Trump commentary as follows:

```
reg out1 i.t1##i.t2##i.t3##i.democrat, robust
margins t3 , at(democrat=(0 1)) plot( recastci(rarea))
```



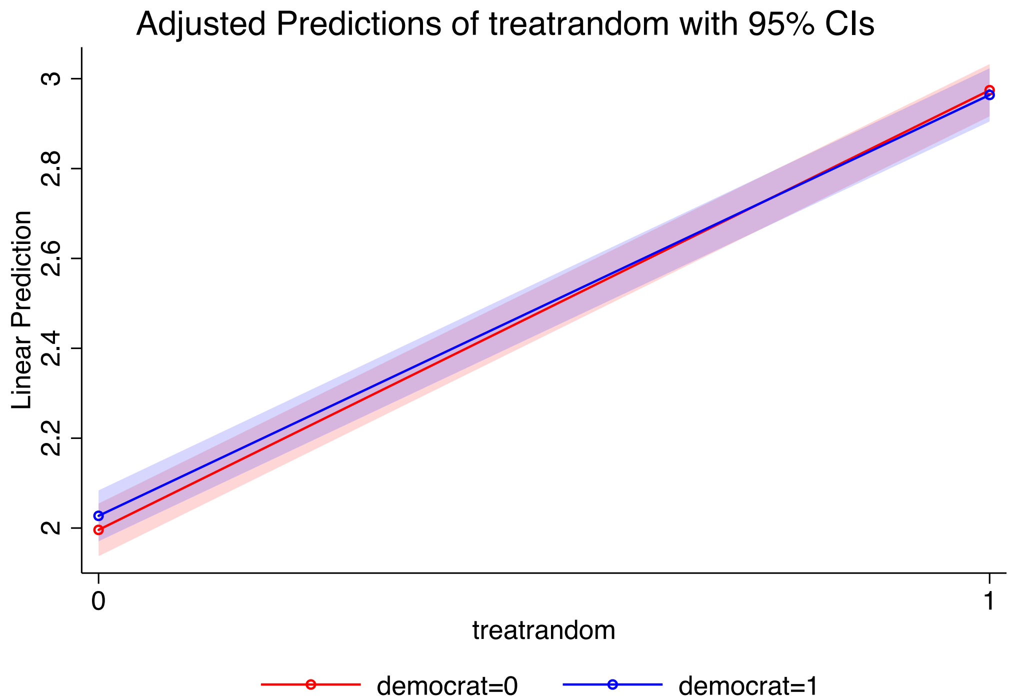
We will adopt a similar approach to analyze our emotional and trust in government dependent variables, where again we predict that the effects of partisan valence and President Trump's commentary on emotional responses vary systematically according to the partisan identity and intended vote choice of the respondent.

Several of our policy outcomes contain randomized responses. For these we will estimate both the effect of the randomized policy outcome on support for the policy and its interaction with political and demographic variables of interest. Our main hypotheses are that support for anti-Chinese policies will be larger among Republicans, among Trump supporters, among those who score highly on racial resentment items, and among whites. To estimate treatment effects, the baseline and covariate adjusted models are

```
reg out3 i.treatran, robust
reg out3 i.treatran##c.mc_*, robust
```

For these analyses, our main hypotheses are that support for anti-Chinese policies will be higher among Republicans, among Trump supporters, among those who score highly on racial resentment items, and among whites. To estimate conditional effects and test these hypotheses, we again follow a graphical approach.

```
reg out3 i.treatran##i.democrat, robust
reg out3 i.treatran##c.mc_*##i.democrat, robust
margins treatran, at(democrat=(0 1)) plot(__swapxp
     recastci(rarea))
```



We anticipate a range of additional exploratory analyses that test how other demographic factors (such as age, religious attendance, and others) shape policy responses. We will be clear to describe any such analyses as exploratory.