Social Science & Medicine 305 (2022) 115091

Contents lists available at ScienceDirect

Social Science & Medicine

journal homepage: www.elsevier.com/locate/socscimed

Perceived risk, political polarization, and the willingness to follow COVID-19 mitigation guidelines

Ray Block Jr. [a], Michael Burnham [b,*], Kayla Kahn [b], Rachel Peng [c], Jeremy Seeman [d], Christopher Seto [e]

[a] Penn State Departments of Political Science and African American Studies, 308 Pond Laboratory, University Park, PA, 16802, USA
[b] Penn State Department of Political Science and the Center for Social Data Analytics, Pond Laboratory, University Park, PA, 16802, USA
[c] Penn State Donald P. Bellisario College of Communications and the Center for Social Data Analytics, 8 Carnegie Building University Park, PA, 16802, USA
[d] Penn State Department of Statistics and the Center for Social Data Analytics, 122 Chemistry Building University Park, PA, 16802, USA
[e] Penn State Department of Sociology and Criminology and the Center for Social Data Analytics, 1001 Oswald Tower University Park, PA, 16802, USA

ARTICLE INFO

Keywords:
COVID-19
Ideology
Political polarization
Adherence
Disease mitigation behavior
Risk perception
Social media
Public opinion

ABSTRACT

Objective: Risk assessment and response is important for understanding human behavior. The divisive context surrounding the coronavirus pandemic inspires our exploration of risk perceptions and the polarization of mitigation practices (i.e., the degree to which the behaviors of people on the political "Left" diverge from those on the "Right"). Specifically, we investigate the extent to which the political polarization of willingness to comply with mitigation behaviors changes with risk perceptions.
Method: Analyses use data from two sources: an original dataset of Twitter posts and a nationally-representative survey. In the Twitter data, negative binomial regression models are used to predict mitigation intent measured using tweet counts. In the survey data, logit models predict self-reported mitigation behavior (vaccination, masking, and social distancing).
Results: Findings converged across both datasets, supporting the idea that the links between political orientation and willingness to follow mitigation guidelines depend on perceived risk. People on the Left are more inclined than their Right-oriented colleagues to follow guidelines, but this polarization tends to decrease as the perceived risk of COVID-19 intensifies. Additionally, we find evidence that exposure to COVID-19 infections sends ambiguous signals about the risk of the virus while COVID-19 related deaths have a more consistent impact on mitigation behaviors.
Conclusions: Pandemic-related risks can create opportunities for perceived "common ground," between the political "Right" and "Left." Risk perceptions and politics interact in their links to intended COVID-19 mitigation behavior (as measured both on Twitter and in a national survey). Our results invite a more complex interpretation of political polarization than those stemming from simplistic analyses of partisanship and ideology.

1. Introduction

How individuals gauge (and respond to) risk is a fundamental topic in the social, behavioral, and actuarial sciences, and scholars have recently homed in on the way individuals respond to the COVID-19 pandemic (e.g. (Barrios and Hochberg, 2020; Calvillo et al., 2020; Clark et al., 2020; Harper et al., 2020)). Of particular relevance to policymakers is how citizens think about and react to risk with regard to disasters, and how political beliefs further shape risk perceptions and responses. Examining whether individuals view disasters as threatening—and what factors affect people's perceptions—can help policymakers understand and plan for how individuals will respond.

In this article, we join existing scholarship on perceived risk and disasters by leveraging data from the coronavirus pandemic—arguably the most challenging health crisis in living memory (e.g. (Barrios and Hochberg, 2020; Betsch et al., 2020; World Health Organization et al., 2020)). Specifically, we explore the relationship between risk perceptions, political orientation, and people's willingness to "adhere to" or "comply with" disease-spread mitigating behaviors like vaccinating, masking, and social distancing. Here, we focus on differences between

* Corresponding author. Penn State Department of Political Science, Pond Laboratory, University Park, PA, 16802, USA.
E-mail address: mlb6496@psu.edu (M. Burnham).

https://doi.org/10.1016/j.socscimed.2022.115091
Received 4 January 2022; Received in revised form 24 May 2022; Accepted 27 May 2022
Available online 2 June 2022
0277-9536/

those who lean Left in their political orientation (i.e., Democrats and liberals) versus those on the Right (i.e., Republicans and conservatives), and we explore how COVID-related decision making can reflect a uniquely political form of "motivated reasoning" (Bolsen and Palm, 2019; Druckman and McGrath, 2019; Epley and Gilovich, 2016; Kahan, 2015, 2016). We define such polarization more precisely later in the paper.

We extend the literature by presenting a more nuanced theory of the relationship between "political orientation" (a term that encompasses partisanship and ideology), risk, and mitigation. We hypothesize that not only do political orientation and risk both influence the willingness to engage in mitigating behaviors, but also that these two variables interact: as risk exposure or perception increases, the association between political orientation and mitigation willingness diminishes. Additionally, we hypothesize that within the context of the COVID-19 pandemic, infections can have ambiguous health outcomes and thus do not communicate the risk of the virus consistently. Deaths, by contrast, send a clearer risk signal and thus have a more profound impact on mitigation behavior. Researchers interested in the behavioral effects of exposure to the virus may be better served by using deaths as the unit of exposure rather than infections. We find support for our hypotheses across two different data sources. The first is an original data set of COVID-19-related tweets from politically-oriented users in the United States. The second is a nationally-representative public opinion survey of US adults. Replication materials and data can be found in the supplementary materials as well as an online archive located at https://github.com/MLBurnham/covid_threat_replication.

We begin by outlining a theory of risk perceptions, political orientation, and adherence/compliance. Next, we describe the research design and data. We then offer empirical tests for our theory and interpret the results. We conclude by contextualizing our findings within broader conversations about politics, public health, and the COVID-19 pandemic.

2. Background and theory

We are interested in the mitigation strategies recommended by the Centers for Disease Control and Prevention (CDC) and other public-health organizations to slow the spread of the coronavirus. Some of these recommended behaviors include wearing face masks in public, maintaining social distance, and getting the COVID-19 vaccine and booster shots (Center for Disease Control, 2021; Flaxman et al., 2020). We refer to these recommended practices as "mitigation behaviors," and we investigate the degree to which people are willing to follow them. This intent is henceforth called "compliance" or "adherence" (Block et al., 2020; Lennon et al., 2020). Despite subtle differences in connotation—"adherence" is arguably a non-pejorative and more patient-centered alternative to "compliance" (Chakrabarti, 2014; Gould and Mitty, 2010; Lutfey and Wishner, 1999; McKay and Verhagen, 2016; Myers Kenny, 1998)—both terms are commonly employed in COVID-19 research. We therefore use them interchangeably.

2.1. Risk perceptions in mitigating behavior adherence/compliance

Many researchers have demonstrated that perceived threats to one's health are associated with compliance behaviors (Ferrer and Klein, 2015). The Health Belief Model, one of the most popular frameworks on the subject, suggests that people are more motivated to avoid illness when they believe it is severe and their own susceptibility is high (Champion Skinner et al., 2008; Janz and Becker, 1984; Strecher and Rosenstock, 1997; Strecher et al., 1997). Protection Motivation Theory similarly describes how individuals are motivated to react in self-protective ways toward perceived health threats (Floyd et al., 2000; Norman Henk Boer et al., 2015; Prentice-Dunn and Rogers, 1986). Concerns for one's health have been found to increase compliance with health precautions with regard to COVID-19 specifically (Bechard et al., 2021; Clark et al., 2020), and perhaps most relevant to our theory is that fear of COVID-19 is a consistent predictor of increased compliance (Harper et al., 2020); for similar arguments, see (Carpenter, 2005; Trkman and Popovič Peter, 2021). These claims point to a common expectation regarding the association between risk perceptions and adherence/compliance. Our first hypothesis re-expresses this idea:

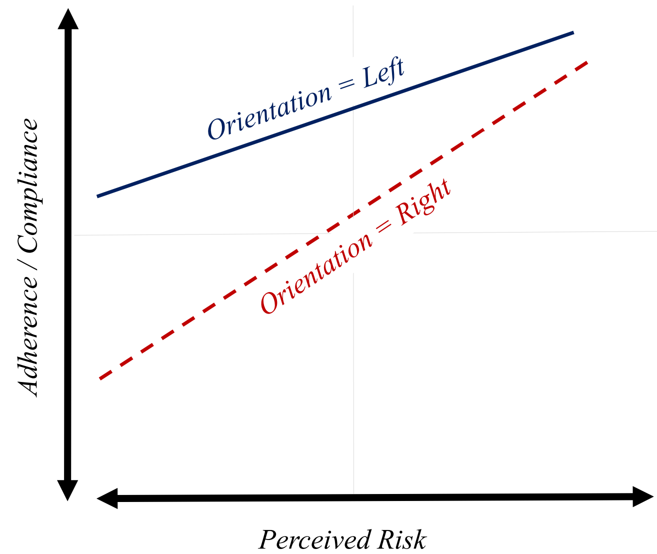

Fig. 1. How the political polarization of adherence/compliance changes with risk perceptions (Hypotheses 1, 2, 3, and 4).

Hypothesis 1. The greater the perceived risk of COVID-19 is, the more adherent/compliant people are to mitigating guidelines.

In addition to emphasizing risk perception as a response to illness severity, our theory maintains that perceived risk is also a function of personal experience, and some experiences matter more than others. Specifically, we hypothesize that COVID-19 related deaths are especially salient to risk perceptions and, consequently, adherence/compliance. There is some support for this in the literature. Human awareness of mortality can yield high motivation to engage in health protective behaviors (Emily et al., 2020; Goldenberg and Arndt, 2008). Furthermore, when mortality is made salient, messaging becomes more effective in bolstering adaptive health behavior intentions (Emily et al., 2022); see also (Horner et al., 2021). With regard to COVID-19 specifically, worry about one's fatality risk is highly predictive of broad fears of the virus (Kwasi Ahorsu et al., 2020). In contrast, COVID-19 infections often lead to more ambiguous outcomes. Infections are not necessarily fatal and may even be asymptomatic. Infections thus do not always send a clear risk signal and allow for greater discretion in interpreting that signal. Formally, we hypothesize:

Hypothesis 2. Exposure to COVID-19 deaths is more strongly associated with mitigation behavior adherence/compliance than exposure to COVID-19 infections.

2.2. Political polarization in mitigating behavior adherence/compliance

Right-oriented citizens are at odds with their Left-leaning colleagues with regards to the steps the nation should take to contain the pandemic. Research chronicles not only the Left's tendency to put coronavirus containment recommendations into practice, but also the Right's proclivity to eschew such guidelines (e.g. (Bélanger and Leander, 2020; Thomson-DeVeaux, 2020)). Even after taking other factors into account, political orientation remains a key motivator of people's behaviors, attitudes, and policy preferences in response to COVID-19 (Hunt et al., 2020; Calvillo et al., 2020; Clinton et al., 2021; Collins et al., 2021;

Kushner Gadarian et al., 2021; Grossman et al., 2020; Pennycook et al., 2020; Shao Feng, 2020). We base our third hypothesis on this set of recurring findings.

Hypothesis 3. Compared to their Right-oriented colleagues, people on the Left are more inclined to follow COVID-19 mitigating behaviors. Likewise, people on the Left (compared to the Right) are less prone to non-compliance.

2.3. *Risk and political orientation as intertwining concepts*

The above arguments pertain only to the separate effects of threat and political orientation on adherence/compliance. Because orientation- and risk-related sentiments coexist (Horner et al., 2021; Zeng, 2021), it is conceivable these concepts interact in their links to mitigation behaviors. As Fig. 1 displays, we argue that perceived risk conditions the association between political orientation and adherence/compliance.

The y-axis conveys variations in individuals' adherence/compliance. Readers can conceive of the values along the y-axis as representing the level or likelihood of adherence behaviors. Likewise, the x-axis indicates a person's perceptions of how threatening they believe the pandemic is to public and personal health. It makes no difference to our theory whether perceived risks are *real* or *imagined*; objective and subjective risk assessments often overlap and perceived risk is what will drive behavior (Freudenburg, 1988; Ling Yang and Nair, 2014). As we demonstrate later, the testable implications of our theory yield similar results regardless of whether the measured risk is real or perceived. Nevertheless, it is worth considering the extent to which perceived and actual risk correlate. Understanding discrepancies between such risk assessments can direct amelioration efforts (e.g. (Ezrina et al., 2022)).

The plotted lines in Fig. 1 represent our expectations regarding the conditional impact of perceived risk. Generally, we expect a positive correlation between risk perceptions and adherence (Hypothesis 1). While the slopes represent the expected direction of the *risk perceptions* and *adherence/compliance* relationship, the vertical distance between the lines communicates our expectation about Right-oriented people typically being less committed than their Left-leaning colleagues to COVID-mitigating behaviors (Hypothesis 2). The vertical distance at different levels of risk illustrates our prediction that risk alters the strength of this relationship. Regardless of political orientation, adherence should be strongest among those who perceive the highest risk. Conversely, we expect a larger adherence gap among those who perceive low COVID-19 risk. Admittedly, this "Left" versus "Right" characterization artificially dichotomizes the inherently continuous concept of political orientation. We present this simplified version of our argument for ease of communication.

It is hardly settled whether people on the Right trust science less than their Left-oriented colleagues (e.g. (Baumgaertner et al., 2018; Blank and Shaw, 2015; McCright et al., 2013; Pechar et al., 2018)); however, this pattern is unambiguous in the COVID-19 literature. Research on information seeking and anxiety confirms that the Right is more likely to both consume and share anti-science media messages and also less likely to trust science and health professionals (Calvillo et al., 2020; Rao et al., 2021; Reinhardt et al., 2021; Ruisch et al., 2021). Referring to the vertical axis in Fig. 1, people on the Right tend to have a lower "starting point" compared to their Left-leaning counterparts, indicating that, absent a meaningful concern about coronavirus, Right leaning individuals generally experience less anxiety than their Leftward colleagues (Mitchell et al., 2016). Thus, when exposure concerns do arise, there is more potential to increase the anxiety of those on the Right, whereas people on the Left tend not only to feel this stress already but are also already practicing mitigating behaviors (Druckman et al., 2021). Therefore, increasing concerns will produce more dramatic effects on the Right than the Left, on average.

We situate our expectation of these group differences in the impact of risk on adherence/compliance alongside research by Hetherington, MacKuen, and their team of collaborators (Hetherington and Mehlhaff, 2020; Mehlhaff et al., 2020). Specifically, the authors correlate their measure of risk perceptions and mitigation policies and, by sorting these correlations by party identification, confirm that polarization "shrinks as anxiety increases" [75, p. 17], presumably by weakening people's receptivity to anti-mitigation rhetoric. This demonstrates the limits of politically motivated reasoning: risk perceptions can alter the manner in which individuals process information, motivating skeptics to instead (re)evaluate public health information (Mehlhaff et al., 2020). Similarly, seminal work on the role of anxiety in information seeking (George et al., 2000) has been applied to research on COVID-19 (Erhardt et al., 2021; Newhagen and Bucy, 2020; Roccato et al., 2021). Particularly relevant is that, under conditions of heightened anxiety, individuals seek new information rather than relying on heuristics. We build upon the intuition of Hetherington and MacKuen et al., but rather than studying public *preferences* for mitigation policies, we believe it is equally vital to examine the degree to which the public intends to *participate* in collective mitigation efforts. Therefore, we focus on the links between risk perceptions and willingness to follow mitigation guidelines.

Inspired by the idea that the *risk* and *compliance* relationship can vary with political orientation, we make our final hypothesis:

Hypothesis 4. As perceived risk increases, polarization in mitigation behavior compliance decreases.More generally, our hypotheses stem from our desire to complicate conventional understandings of the role risk perceptions play in the Left vs. Right divide in mitigation practices. This allows us to place the study of polarization, risk, and mitigation into richer context.

3. Data and methods

To investigate the hypotheses above, we need data about diverse aspects of individuals' beliefs and experiences surrounding COVID-19. However, this is a challenging task for several reasons. First, different socioeconomic and demographic communities have different social and cultural beliefs surrounding public health (Bhui and Dinos, 2008; Street Paul, 2011); furthermore, COVID-19 has disproportionately affected some of these communities (Gausman and Langer, 2020; Kantamneni, 2020; Yaya et al., 2020). Therefore, a sound analysis relies on representative sampling. Second, COVID-19 mitigating behaviors and risk perceptions have normative social effects. How individuals disclose these may be contextually specific due to social desirability bias (Charles Patrick, 2018) or other heuristics that may contribute to positions varying in salience over time (Zaller, 1992, 2012; Zaller and Feldman, 1992). For example, exogenous events such as a newspaper headline read on the day a survey was taken may cause the threat of COVID-19 to be more or less salient to an individual, motivating them to express different opinions (Palm et al., 2021). Therefore, we also rely on being able to observe "revealed preferences" in addition to self-disclosed ones.

To combat these challenges, we perform our analyses on two separate data sources. The first is constructed from public posts on Twitter.

Table 1
The dependent variables and theoretically-central predictors, measured across the two data sets.

	Twitter data	Survey data
Willingness to adhere to COVID-19 mitigating guidelines	Text classification to identify tweets that advocate non-compliance with mitigating behaviors	Self-reported from survey questions about vaccination, masking, and social distancing
COVID-19 risk metric	Severity of COVID-19 infections and deaths by county	Self-reported perceived risk of COVID-19
Political orientation	Inferred from the political elites users follow with a bayesian network model	Self-reported from political party affiliation and 2020 voting record

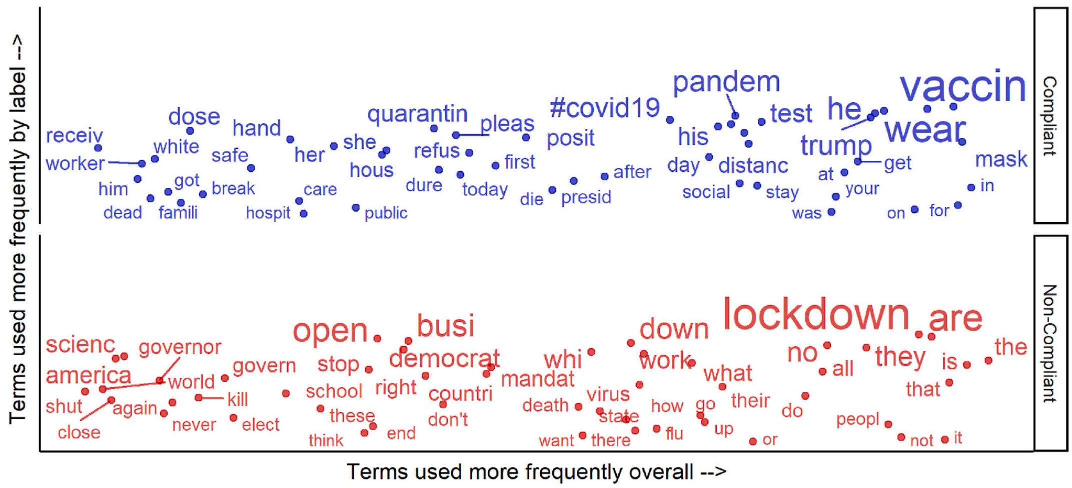

Fig. 2. The most significant words associated with the non-compliant and compliant labels as measured by Monroe et al.'s Fightin' Words statistic (Monroe et al., 2008).

We use natural language processing to identify posts advocating non-compliance with COVID-19 mitigation behaviors. The political orientation of Twitter users is inferred using social network analysis, and risk is measured using county level infection and death rates. The second data set is a nationally representative survey, administered by the African American Research Collaborative (AARC), in which respondents self-report their beliefs about and experiences with COVID-19 (Sanchez, Block; Shah et al., 2021). Details about the survey design are available at https://CovidVaccinePoll.com and in the supplemental materials. We refer to these sources of data as "Twitter" and "survey" data respectively.

The differences between these data sets are summarized in Table 1. Surveys can be representative of the US population while having responses that reflect both response instability and "true attitudes" (Bishop, 2004; Weisberg, 2009). A sample of Twitter posts across time is less susceptible to such instability, but is also less representative (Al Baghal et al., 2020). Both survey data and Twitter data have their limitations and biases, but observation from different perspectives provides a better grasp of the investigated phenomenon, as the triangulation method in social science research demonstrates (Hussein, 2009). Data triangulation employs the idea of using different sources of data, including different times, places, people, and collection methods, to increase the validity of evaluation and research findings (Denzin, 2017). It can also be viewed as "less a strategy for validating results and procedures than an alternative to validation which increases scope, depth and consistency in methodological proceedings" [45, p.227]. Therefore, in this study, we combine survey and social media data to increase the robustness of our analysis. Both analyses will follow the same general procedure, in which we model adherence intention to COVID mitigation based on demographic covariates, perceived risk, and political orientation, and interpret these models in the context of our hypotheses.

4. Study 1: non-compliant language on Twitter

4.1. Twitter data

The Twitter data set consists of all COVID-19 related tweets made between September 1, 2020 and February 28, 2021 from 23,467 politically-oriented and social-media active Twitter users in the United States. To compile this data, we collected a list of 561 US political elites and pundits on Twitter. This list consists of all members of the 116th Congress, as well as a list of pundits originally compiled by Barberá (2015) and updated by us to include notable individuals popularized since the 2015 publication, such as conservative pundit Ben Shapiro and environmental activist Greta Thunberg. For each elite, we collected a list of all of their followers for a total of 18,392,416 unique users. We then subset this list to those that follow at least three political elites. This served as a minimum threshold for a user's political engagement. We further subset the data to include only accounts that listed their state and city in their Twitter bio, follow over 100 users but fewer than the 99th percentile of total followers, post more frequently than 75% of users, posted within a week prior to initial data collection, and tweet in English. This maximizes the probability we sample politically-oriented users who are active on Twitter, located in the United States, but are not public figures or elites. We then selected a random sample of 40,000 users stratified by the population of US states plus the District of Columbia. This represented the maximum number of accounts we could reliably pull data from on a daily basis. Moderate attrition occurred over the course of data collection due to users deleting their accounts, changing privacy settings, or being banned. Additionally, users that either did not make COVID-19 related tweets or for which we were not able to compile the necessary dependent and independent variables were dropped from the data set. While we feel this process produces a justifiable sample for our purposes, it is important to note that the filters, attrition, and the non-representative nature of the Twitter population means this sample is not nationally generalizable.

4.2. Dependent variable

Our dependent variable is the number of *non-compliant* tweets a user made within the collection period. Non-compliant tweets are those that discourage, or imply an absence of, compliance by expressing disapproval of or rejecting COVID-19 safety precautions or downplaying the threat of the virus. We elaborate on this measurement rationale and coding rules in the Supplemental Materials.

To identify non-compliant tweets, we first used the list of keywords in the Supplemental Materials to subset the data to only COVID-19 related tweets. We randomly sampled 2000 COVID-19 tweets and hired two research assistants to label each for non-compliant language. Tweets were labeled with 92% agreement and a Cohen's Kappa of 0.81 ($z = 36.2$). Discrepancies between coders were adjudicated by the authors. We then trained a transformer neural network on the labeled tweets and used it to classify the rest of the data set. On an evaluation data set, tweets were classified with 86% accuracy with a Matthew's correlation coefficient of 0.66. Fig. 2 provides a qualitative description of results by showing commonly used words by label. Tweets labeled compliant are more likely to discuss vaccines, masks, social distancing, and testing. Non-compliant tweets more frequently discuss lockdowns, businesses, mandates, schools, and the flu.

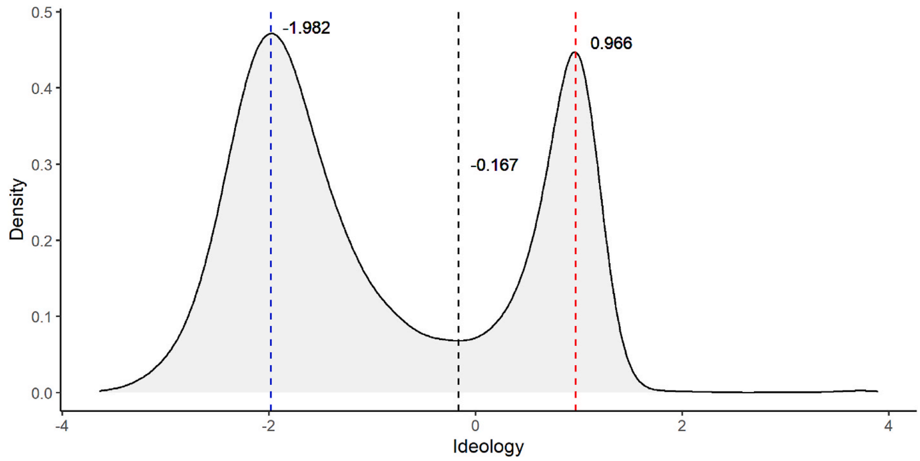

Fig. 3. The distribution of ideology among users in our sample with local minimum and maxima indicated. Ideology is measured using tweetscores (Barberá, 2015), which places users on an uni-dimensional left-right scale based on the elites they follow.

4.3. Independent variables

Our independent variables are COVID-19 risk and political orientation. For this first study, we measure risk by exposure rather than perception for a few reasons. First, measuring risk perception through text is a difficult task with no reliable way to validate our measurement. For example, dictionary methods that count the use of words associated with risk (e.g. "risk", "danger", "vulnerable") may provide some insight, but have not been validated against more objective measurements such as a survey. Perhaps more importantly, a text-based measure of risk perception invites simultaneity with the text-based measurement of noncompliance.

To measure risk exposure, we use the COVID-19 infection and death rates defined as the cumulative number of infections/deaths a user's county experienced on the final day of data collection, divided by the population of the county. For death and infection counts, we used the data set compiled by USAFacts. This data set aggregates data from the CDC, as well as public health agencies at state and county levels (USAFacts, 2021). To estimate political orientation, we used the Tweetscores method introduced by Barberá (2015). This approach uses Markov chain Monte Carlo methods to estimate beliefs on a Left-Right dimension based on the partisan political elites a user follows. Since it can be conceptualized as a measure of political ideology (Francis Havey, 2020; Liang, 2018; Mueller and Saeltzer, 2020), we will henceforth use that terminology to describe it. Tweetscores has been validated against campaign contributions and voting records and provides reliable and consistent estimates when sufficient network data is available (Barberá, 2015). We included only individuals with robust ideology estimates ($\widehat{R} \leq 1.1$) in our analysis. The ideological distribution of the sample is shown in Fig. 3 with the local minimum and maxima of the modes indicated.

4.4. Control variables

Because our dependent variable is text, we introduce additional control variables that may affect what individuals tweet about and how. The first is a series of county level demographic and socioeconomic controls. These include racial composition, median income, the population percent over 65, the population percent with a bachelor's degree, the urban population percent, and the Republican vote share in the 2020 general presidential election. Demographic data comes from the Census Bureau's American Community Survey (Census Bureau, 2019), and election data is from the MIT Election Lab (MIT Election Data and Science Lab, 2018).

Additionally, we fit each model with state level fixed effects. How a state responds to COVID-19 through lockdowns, mandates, testing availability, etc., as well as rhetoric from political leaders, may impact the way people discuss the pandemic. This also helps control for regionalisms and other geographic differences in speech that may affect tweet classification.

4.5. Empirical strategy

To test our hypotheses, we apply a combination of descriptive and regression analysis. Descriptive analysis and difference of means provide basic evidence that orientation is correlated with compliance and mitigation language. To control for additional variables and estimate the interaction effect between threat and ideology, we model the use of noncompliant language with negative binomial regression. This is because the dependent variable is highly dispersed count data. The base model is specified in Equation (1). T_i is the rate at which non-compliant tweets are made per unit of exposure. Ln(t_i) is the log of the total number of tweets a user made and is the exposure offset to account for the fact that users did not generate the same number of tweets during the collection period. R_i is the risk metric—either the infection rate or the death rate within a user's county. P_i represents a user's ideology and C_i is a vector of fixed effects and other controls described above.

$$T_i = exp(ln(t_i) + \beta_0 + \beta_1 R_i + \beta_2 P_i + \beta_3 C_i + \varepsilon) \tag{1}$$

If our first and third hypotheses are correct, we expect the coefficient on the risk metrics to be negative and significant, indicating the use of non-compliant language decreases as the level of threat increases, and that the coefficient on the ideology metric is positive and statistically significant, indicating the use of non-compliant language increases the more conservative a user is. To test if increased risk has a dampening effect on ideology (Hypothesis 4), we add an interaction term between our risk metric and ideology: $R_i \times P_i$ to the base model. This model is specified in Equation (2). We expect the interaction term will have a significant and negative coefficient, indicating the effect size of ideology on non-compliant language shrinks as the risk within an area increases.

$$T_i = exp(ln(t_i) + \beta_0 + \beta_1 D_i + \beta_2 P_i + \beta_3 R_i \times P_i + \beta_4 C_i + \varepsilon) \tag{2}$$

Power analysis was performed using the `InteractionPoweR` package to ensure tests were appropriately powered to detect substantive effect sizes (Baranger, 2022). Details and additional figures are in the Supplemental Materials.

4.6. Twitter results

The Twitter data shows strong evidence that conservatives are more

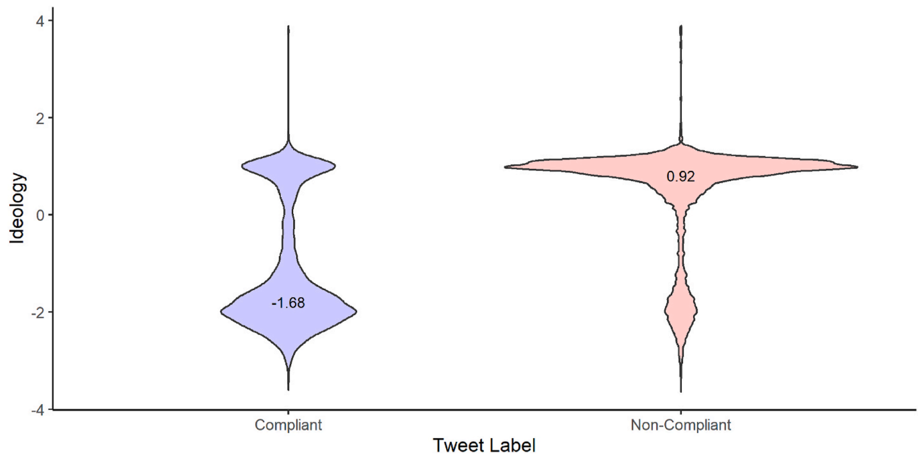

Fig. 4. The ideological distribution of tweet authors by label. Ideology is measured using tweetscores (Barberá, 2015), which places users on an uni-dimensional left-right scale based on the elites they follow. The large spike in the non-compliant violin indicates the overwhelming majority of non-compliant tweets are authored by conservatives.

Table 2
Non-compliant tweets by infection rate.

	Dependent variable:			
	Rate of Non-compliant Tweet Generation			
	(1)	(2)	(3)	(4)
Ideology	0.539***	0.558***	0.538***	0.555***
	(0.004)	(0.015)	(0.004)	(0.015)
Infection Rate	0.411	0.327	0.681	0.631
	(0.313)	(0.320)	(0.449)	(0.452)
Ideology x Infection		−0.219		−0.202
		(0.166)		(0.167)
Constant	−1.188***	−1.182***	−1.786***	−1.774***
	(0.147)	(0.147)	(0.589)	(0.590)
Control variables	No	No	Yes	Yes
State fixed Effects	Yes	Yes	Yes	Yes
Observations	23,476	23,476	23,476	23,476
Log Likelihood	−48,380.840	−48,379.980	−48,372.400	−48,371.670
Θ	3.627***	3.628***	3.633***	3.634***
	(0.074)	(0.074)	(0.074)	(0.074)
AIC	96,867.680	96,867.950	96,866.800	96,867.340

Note: *p<0.1; **p<0.05; ***p<0.01.

Table 3
Non-compliant tweets by death rate.

	Dependent variable:			
	Rate of Non-compliant Tweet Generation			
	(1)	(2)	(3)	(4)
Ideology	0.539***	0.557***	0.538***	0.555***
	(0.004)	(0.009)	(0.004)	(0.009)
Death Rate	14.667	9.824	22.231	18.262
	(11.292)	(11.605)	(14.956)	(15.119)
Ideology x Death		−11.840**		−11.847**
		(5.913)		(5.937)
Constant	−1.159***	−1.149***	−1.805***	−1.767***
	(0.144)	(0.144)	(0.591)	(0.592)
Control variables	No	No	Yes	Yes
State fixed Effects	Yes	Yes	Yes	Yes
Observations	23,476	23,476	23,476	23,476
Log Likelihood	−48,380.860	−48,378.820	−48,372.470	−48,370.440
Θ	3.627***	3.628***	3.633***	3.634***
	(0.074)	(0.074)	(0.074)	(0.074)
AIC	96,867.730	96,865.630	96,866.950	96,864.880

Note: *p<0.1; **p<0.05; ***p<0.01.

likely to use non-compliant language, providing preliminary support for our third hypothesis. As shown in Fig. 4, non-compliant tweets are concentrated among individuals at the conservative pole. The median ideology among non-compliant tweets is 0.92, indicating a strong conservative skew, and the median among other tweets is −1.68, indicating a strong liberal skew. A two-sided *t*-test shows a highly significant difference between the two groups ($t = 572.8$). Tweet author ideology and non-compliance classification are correlated at $\rho = 0.49$.

Results of the regression analysis are shown in Tables 2 and 3. Due to the number of variables and models, we present truncated tables here with binary indicators at the bottom of the table for models that include the vector of control variables. Complete tables with all coefficients are in the Supplemental Materials. Table 2 contains models that use infection as the risk metric and Table 3 contains models that use death as the risk metric. We find no evidence that infection or death rates alone are associated with the use of non-compliant language. Ideology, however, shows consistently large and significant effects. The positive coefficients indicate that increased conservatism is associated with more frequent non-compliant language, providing further evidence that polarization is linked to mitigation behavior.

The interaction coefficients in models two and four of both tables produce interesting results. The coefficient on the interaction between ideology and infection is both small and insignificant. The interaction with death rates, however, has a large and statistically significant relationship to non-compliant language. This indicates that the effect of ideology shrinks as county death rates increase. Fig. 5 plots the change in the ideology coefficient in model four of Table 3 — the fully specified model— as the death rate increases. The negative slope indicates the dampening effect that death rates have on the role ideology plays in non-compliant language. Between Twitter users in counties with the lowest death rates and the highest death rates, our model estimates a 10–15% reduction in the coefficient size on ideology. The wide bands on the plot indicate there is a fair degree of uncertainty as to how significantly death moderates ideology, but the effect is present, significant, and directionally consistent with our theory. The fact that death rates produce this effect while no such effect is found with infection rates supports our second hypothesis that deaths have a larger association with risk assessment than infections.

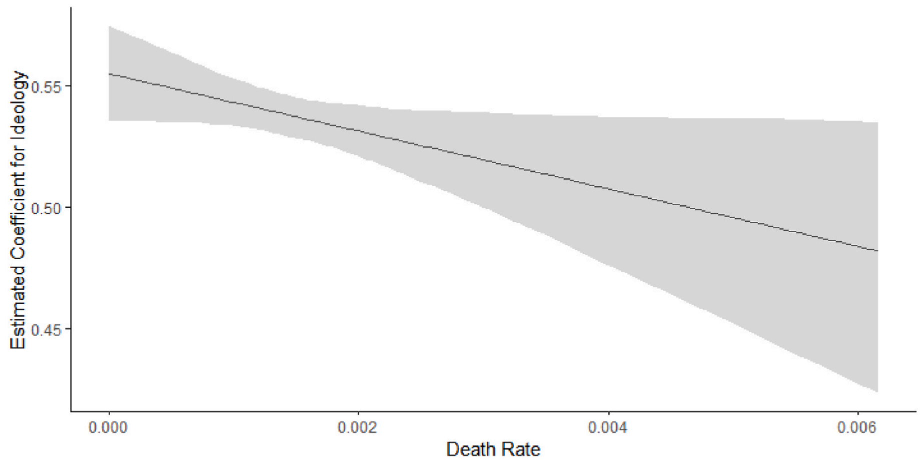

Fig. 5. The change in the estimated effect of ideology on non-compliant language as county level deaths increase. The negative slope indicates that the impact of ideology on non-compliant tweets is smaller in counties with higher death rates.

Table 4
Table of survey data key variable descriptions.

Variable Type	Variable	Question:	Levels
Predictor	Political orientation	"In the 2020 election, who did you vote for President" OR "Generally speaking, do you consider yourself to be [political party]"	1: Left-leaning 2: Right-leaning
	Self-disclosed COVID-19 concern	"How concerned are you that you might get COVID-19?"	1: Not at all concerned 2: A little concerned 3: Moderately concerned 4: Very concerned
	Proximity to COVID-19 infection	"Have you, a family member, or friend contracted COVID-19?"	1: No known infections 2: At least one known infection, not respondent 3: Respondent infected
	Proximity to COVID-19 death	"Do you know someone who has died because of COVID-19?"	1: No known deaths 2: At least one known death
Response	Vaccination status	"Which is closest to your plan regarding the COVID-19 vaccine?"	1: Vaccinated or unvaccinated and not hesitant 2: Unvaccinated and somewhat or very hesitant
	Adherence to indoor masking	"Over the next month, do you plan to follow, or not follow these practices: [wear a mask when indoors in a public place around other	1: All or some of the time 2: None of the time
	Adherence to social distancing	"Over the next month, do you plan to follow, or not follow these practices: [stay at least six feet away from other people when you are	1: All or some of the time 2: None of the time

5. Study 2: survey self-reported mitigating behaviors

5.1. Data and key variables

Survey data was collected by AARC from May to June 2021. A total of 20,280 US adults were contacted, of whom 12,288 completed the survey for a completion rate of 61%. The participant pool was secured via BSP Research, a polling firm that specializes in recruiting from minority communities and other hard-to-reach populations (Barreto et al., 2018), and respondents had to option to complete the survey via telephone or online. Responses are weighted based on an initial probability sample with oversampling for select racial and ethnic sub-populations, with final weights post-stratified to American Community Survey results for gender, age, education, nativity, and geography (African American Research Collaborative, 2021). Aside from the filters in the original survey methodology, we excluded 1871 individuals who do not identify as Left- or Right-leaning based on their 2020 presidential vote or self-disclosed party affiliation. The discrete nature of the survey's ideological identifiers means the excluded population has no identifiable orientation on the left-right scale, perhaps because participants are politically unengaged, adhere to ideologies that do not collapse into a left-right spectrum, or were unable to vote. Our analysis focuses on political orientation, so this excluded population falls outside the scope of our analysis.

Key variables are listed in Table 4. Aside from political orientation, there are three additional predictors of interest: self-disclosed concern over COVID-19, proximity to a COVID-19 infection, and proximity to a COVID-19 death. As dependent variables, we use dichotomized measures of respondents' self-reported adherence to mitigation tactics. We focus on adherence to vaccination in the main text of this paper. However, similar models were constructed for adherence to masking and social distancing. Results were generally consistent across models, and full regression tables are available in the Supplemental Materials. For all our analyses, the predictors in Table 4 are nominal categorical variables.

5.2. Modeling procedure

For each of the dependent variables (vaccination, masking, and social distancing), and predictors (COVID-19 concern, proximity to infection, and proximity to death), we fit four survey-weighted generalized linear models for the response log-odds as described below:

$$\mathrm{logit}(\texttt{Response}) \sim \texttt{Politics} + \texttt{Risk} \tag{3}$$

$$\mathrm{logit}(\texttt{Response}) \sim \texttt{Politics} + \texttt{Risk} + \texttt{Politics} \times \texttt{Risk} \tag{4}$$

$$\mathrm{logit}(\texttt{Response}) \sim \texttt{Controls} + \texttt{Politics} + \texttt{Risk} \tag{5}$$

$$\mathrm{logit}(\texttt{Response}) \sim \texttt{Controls} + \texttt{Politics} + \texttt{Risk} + \texttt{Politics} \times \texttt{Risk} \tag{6}$$

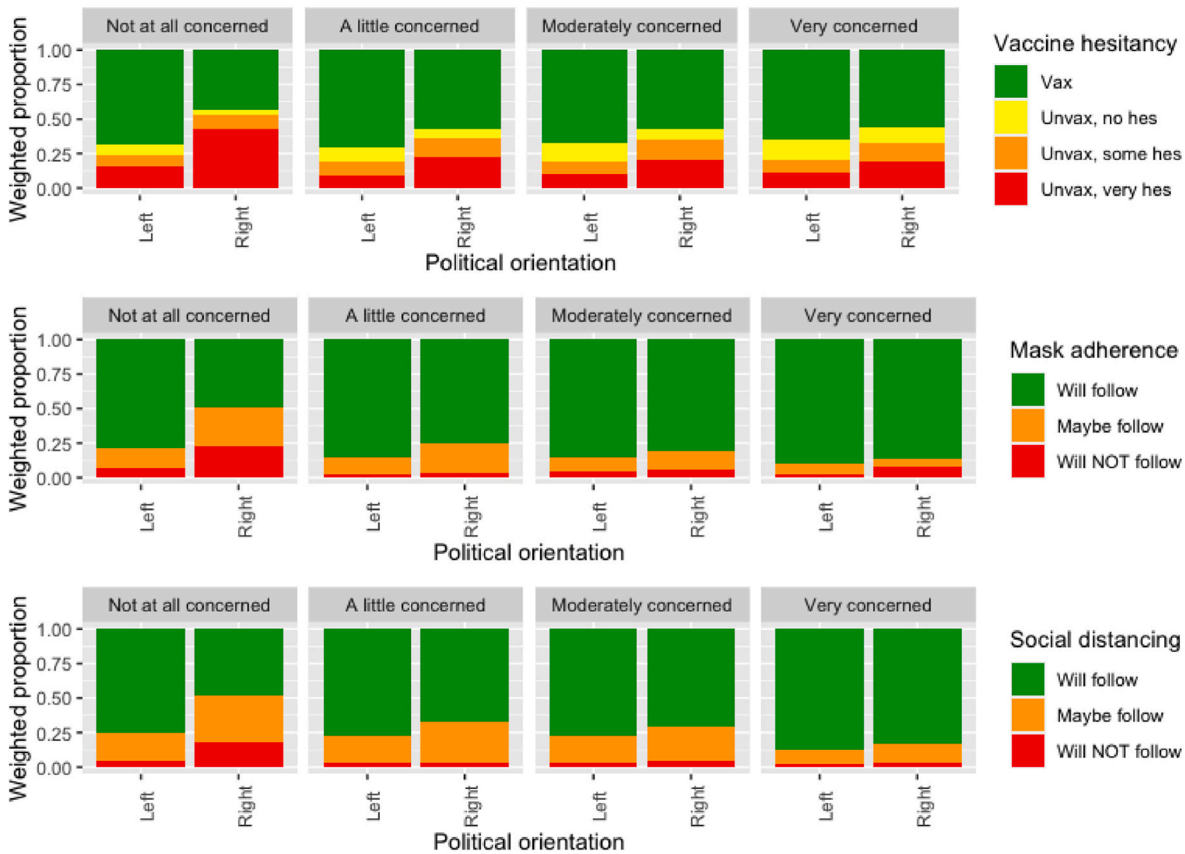

Fig. 6. Survey-weighted proportion of respondents adhering to mitigating behaviors by self-disclosed COVID-19 concern. Weights are constructed first using probability weighting with oversampling for select sub-populations, then by post-stratification to match American Community Survey demographics.

We refer to these four models as the base model without controls, interaction model without controls, base model with controls, and interaction model with controls, respectively. All models have fixed effects for political orientation and the risk measure of interest. Interaction models additionally contain a product term for political orientation and the risk metric. Models with controls include ordinal categorical variables (age, education, urban/rural, and income) and nominal categorical variables (gender and race). Ordinal categorical variables were reduced to binary variables according to the reduction with the greatest AIC improvement for the baseline vaccination by self-reported COVID concern model. All models are implemented using the `survey` package in `R` (Lumley, 2004). AIC values correspond to standard Rao-Scott approximations (Lumley and Scott, 2015). Power analysis was performed using the `InteractionPoweR` package in `R` to ensure tests were appropriately powered to detect substantive effect sizes (Baranger, 2022). Details and additional figures are in the Supplemental Materials.

The exploratory plots in Figs. 6–8 show potential alignment between our hypotheses and the survey data. In Fig. 6, we see that as concern over COVID-19 increases, differences in the distributions of adherence behaviors between Left-oriented and Right-oriented respondents decreases. Similar effects can be seen with proximity to COVID-19 death in Fig. 8. However, replacing self-reported concern with proximity to infection does not demonstrate the same phenomenon; in fact, from Fig. 7, it could be that Right-oriented respondents who have been infected with COVID-19 are *less* willing to practice mitigation strategies (Bostock, 2021; Diamond, 2020). We refer to the modeling results to test if this holds.

5.3. Survey results

Modeling results for vaccination status are available in Tables 5–7. We present truncated tables here with indicators for which models contain the control variables described above. Across all models, Right-oriented individuals are less likely than their Left-oriented colleagues to practice COVID-19 mitigating behaviors. Additionally, increased risk consistently corresponds to greater adherence to COVID-19 mitigating behaviors, regardless of which risk measure we investigate. Consistent with our hypothesis, a known death has a larger and more significant association with compliance than a known infection. When the respondents themselves are infected, however, we see in Table 6 that the size, significance, and direction of the coefficient is contingent upon the interaction effect. This provides further evidence that infections do not communicate threat unambiguously. The interaction between death and political orientation in Table 7 yields a parameter estimate that aligns with our hypothesis: Right-oriented respondents who knew someone that died of COVID-19 had about 20% higher odds of being vaccinated than Right-oriented respondents who did not. However, this point estimate is highly uncertain, as COVID-19 deaths are a relatively rare event among respondents, and interaction terms require significantly larger sample sizes to estimate than main effects (Leon and Heo, 2009).

Because infections show evidence of ambiguity as a risk indicator, and since deaths are statistically uncommon, we examine the models in Table 5 that use self reported concern to test our hypothesis on whether threat moderates the association between ideology and mitigation behavior. Model 4 in Table 5 contains results for the fully specified model with control variables and interaction effects between political orientation and concern about COVID-19. This model shows that Right-oriented individuals are less likely to get vaccinated. However, the positive and increasingly large coefficients on the interaction terms with the various levels of concern indicate that as concern increases, the effect of political orientation is dampened. In fact, Right-oriented respondents most concerned about COVID-19 were over 60% more likely

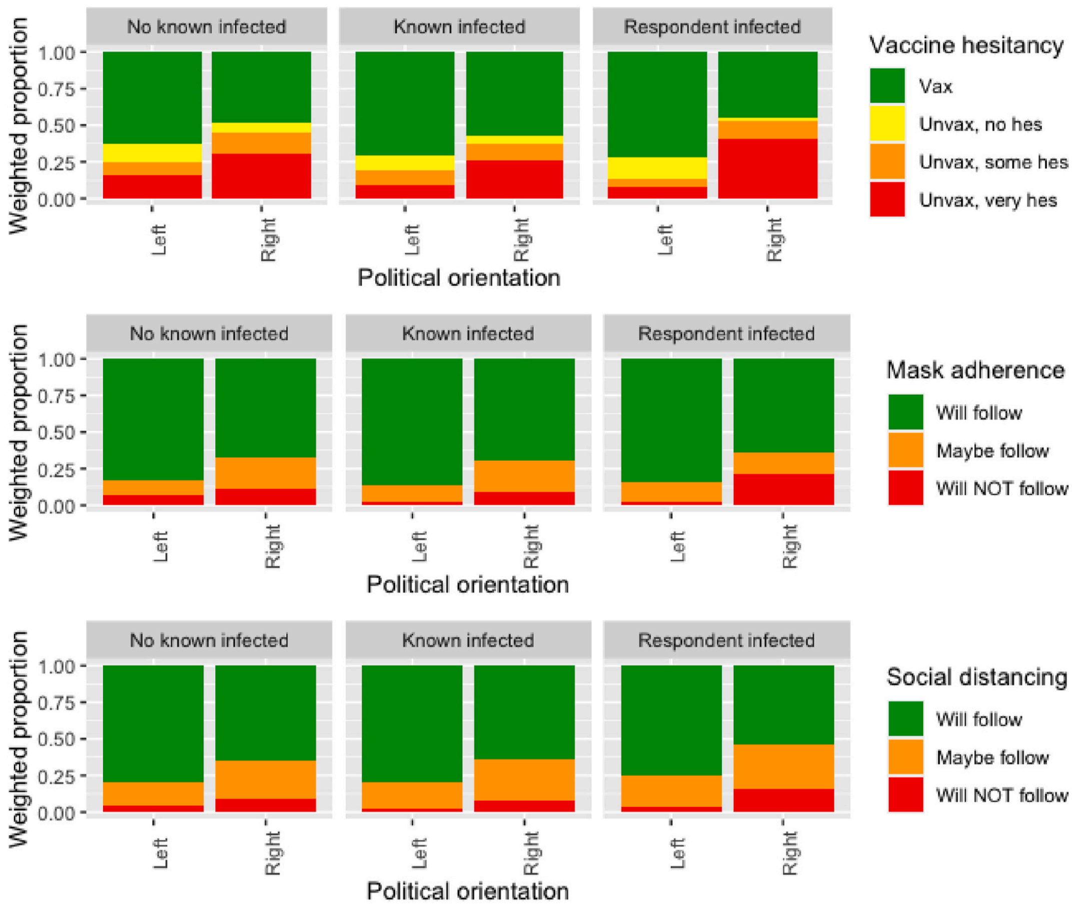

Fig. 7. Survey-weighted proportion of respondents adhering to mitigating behaviors by proximity to COVID-19 infection. Weights are constructed first using probability weighting with oversampling for select sub-populations, then by post-stratification to match American Community Survey demographics.

to be vaccinated than Right-oriented respondents least concerned about COVID-19. This lends further credence to the argument that risk perceptions alter the association between ideology and intended mitigating behaviors.

Finally, power analysis was performed to compare our observed effect size to different theoretical effect sizes for the interactions in Hypothesis 4 using the InteractionPoweR package (Baranger, 2022). Please see the Supplemental Materials for details.

6. Discussion

Our analyses highlight the important interplay between perceived risk and political orientation in their links to compliance/adherence to COVID-19 mitigation guidelines. Building upon prior literature, which demonstrates behavioral main effects of both risk perception (Hypotheses 1 and 2) and political orientation (Hypothesis 3), our results demonstrate that extant research only tells part of the story when modeling risk perceptions and political orientation in non-interactive ways. Specifically, the positive association between risk perception and adherence/compliance is strongest for politically Right-leaning individuals, compared to their Left-leaning counterparts (Hypothesis 4).

Prior research on political messaging and polarization provides context for these findings. Elites are divided when it comes to the seriousness of the pandemic (Ajzenman et al., 2020; M Golos et al., 2022; Green et al., 2020; Hansen et al., 2021), and the divisive elite-level rhetoric is crystallizing among citizens: conversations about the severity of COVID-19 are often bundled with preexisting partisan debates regarding the role of government (Bhanot and Hopkins, 2020; Collignon et al., 2021; DellaPosta, 2020; Gollwitzer et al., 2020; Grossman et al., 2020). While an in-depth discussion of political messaging is beyond the scope of this paper, our primary finding, that risk perceptions are more salient to the adherence/compliance of Right-leaning individuals, is consistent with the idea that—given such polarized rhetoric—Left-oriented individuals are already more likely to comply with mitigation behaviors, whereas Right-oriented individuals need a catalyst.

The results of our Twitter study are somewhat nuanced. When risk is operationalized as exposure to infections and deaths, there is little evidence that risk alone predicts compliance intention. Infection rates within a county show no significant evidence of correlation with compliance. Deaths however, show evidence of conditioning the association between ideology and compliance. In high-death contexts, threat is less ambiguous. Accordingly, when it comes to expressions of noncompliance, the gap between Right-vs. Left-oriented Twitter users narrows. While our analysis does not suggest that risk eliminates the role of ideology in the context of COVID-19 mitigation compliance, it does suggest that unambiguous risk signals are correlated with a non-trivial reduction in the role of ideology.

The argument that perceived risk alters the links between political orientation and adherence is further supported by results from the survey analyses. The conditional association between "concern" and vaccination status is especially robust. This finding complements the Twitter-data results in several key ways. First, the survey data are nationally representative, avoiding potential sampling bias in the Twitter data. Second, the survey data more directly measure individuals' subjective perceptions of COVID-19 risk by asking specifically about concern. The convergence of findings across both the Twitter and survey data increases our confidence in the study's main conclusion: Political

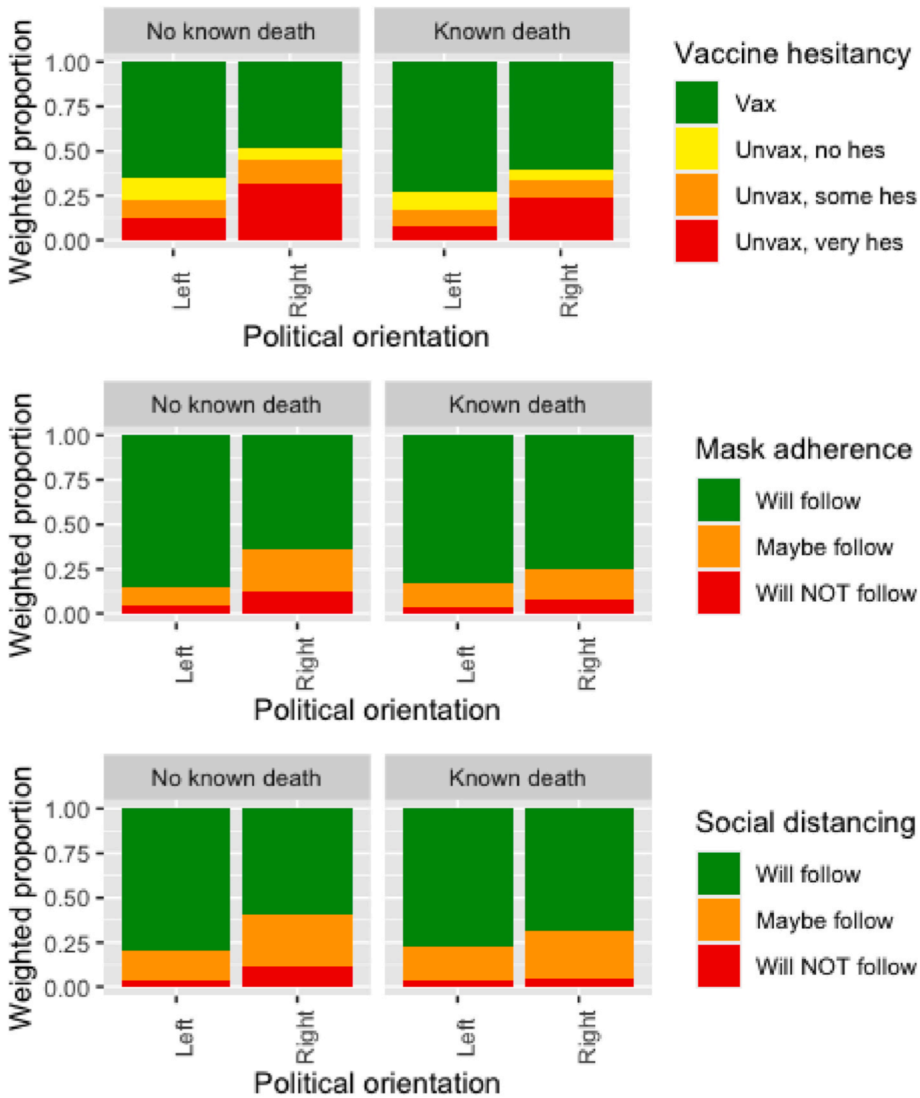

Fig. 8. Survey-weighted proportion of respondents adhering to mitigating behaviors by proximity to COVID-19 death. Weights are constructed first using probability weighting with oversampling for select sub-populations, then by post-stratification to match American Community Survey demographics.

orientation and risk perceptions interact in important ways in their links to COVID-19 mitigation.

6.1. Limitations

There are important limitations to both analyses, and we believe that transparency can motivate future research. Despite demographic controls, both datasets are inherently observational. The measurement mechanism changes how much our results correspond to lived beliefs or experiences. Analyses focused on messaging or other causal mechanisms, be they experimental or observational, are a logical next step to validate our conclusions. For the Twitter data, future studies might investigate the perceptual mechanisms through which areal death rates condition the links between ideology and adherence/compliance. Higher risk perceptions in these counties may be linked to greater objective risk, or higher probability of experiencing a death within one's social network and consequent subjective risk. It is also plausible that both mechanisms are salient, given the strong correlation between geographic proximity and social influence (Spiro et al., 2016). For the survey data in particular, the infrequency of respondents knowing someone who died of COVID-19 pushed disentangling these effects outside the scope of our study. Moreover, we excluded individuals who did not vote for a main-party candidate nor identify with a major political party. Although political orientation is a prerequisite for inclusion in our sample, we believe that future research may benefit from focusing on this sub-population.

6.2. Concluding remarks

Overall, our study's findings underscore the need for more a nuanced understanding of the role of politics in the pandemic. Dominant narratives often characterize ideological divisions as working against COVID-19 mitigation. Our research suggests that political polarization might not be as intractable a problem as conventionally believed. Acknowledgment among citizens of the risk that COVID-19 poses can counteract the divisive role of political orientation. The idea that risk can potentially "break through" suggests practical interventions wherein risk perceptions are modified (through elite counter-messaging, news and social media, etc.), thus reducing the consequences of politically motivated reasoning. By exploring how pandemic-related risks can create opportunities for perceived common ground, our results invite a more complex interpretation of political polarization than those stemming from simplistic analyses of partisanship and ideology.

Table 5
Vaccination by self-reported COVID concern.

	Dependent variable: Weighted log-odds of Vaccination			
	(1)	(2)	(3)	(4)
Risk: little concerned	0.532***	0.278*	0.541***	0.195
	(0.120)	(0.147)	(0.127)	(0.153)
Risk: moderately concerned	0.536***	0.259*	0.541***	0.165
	(0.132)	(0.151)	(0.136)	(0.159)
Risk: very concerned	0.557***	0.240	0.627***	0.211
	(0.148)	(0.164)	(0.151)	(0.170)
Politics: right-oriented	−0.937***	−1.261***	−1.205***	−1.660***
	(0.092)	(0.169)	(0.105)	(0.187)
Interaction: right-oriented x little concerned		0.389*		0.540**
		(0.228)		(0.241)
Interaction: right-oriented x moderately concerned		0.467*		0.652**
		(0.270)		(0.277)
Interaction: right-oriented x very concerned		0.585*		0.779**
		(0.316)		(0.319)
Constant	0.925***	1.143***	0.251	0.542**
	(0.096)	(0.116)	(0.192)	(0.212)
Control Variables	No	No	Y es	Y es
Observations	10,416	10,416	10,416	10,416
Log Likelihood	−5867.696	−5856.351	−5423.979	−5406.148
AIC	11,745.390	11,728.700	10,877.960	10,848.300

Note: *p<0.1; **p<0.05; ***p<0.01.

Table 6
Vaccination by proximity to COVID infection.

	Dependent variable: Weighted log-odds of Vaccination			
	(1)	(2)	(3)	(4)
Risk: Known infected	0.319***	0.316***	0.317***	0.292**
	(0.101)	(0.108)	(0.106)	(0.115)
Risk: Respondent infected	0.072	0.682***	0.132	0.770***
	(0.154)	(0.219)	(0.161)	(0.222)
Politics: right-oriented	−1.023***	−0.918***	−1.279***	−1.179***
	(0.091)	(0.149)	(0.104)	(0.168)
Interaction: right-oriented x Known infected		0.004		0.044
		(0.196)		(0.207)
Interaction: right-oriented x Respondent infected		−1.022***		−1.087***
		(0.318)		(0.327)
Constant	1.180***	1.124***	0.494**	0.426**
	(0.079)	(0.081)	(0.193)	(0.193)
Control Variables	No	No	Y es	Y es
Observations	10,416	10,416	10,416	10,416
Log Likelihood	−5896.084	−5871.087	−5456.736	−5429.562
AIC	11,800.170	11,754.170	10,941.470	10,891.120

Note: *p<0.1; **p<0.05; ***p<0.01.

Table 7
Vaccination by proximity to COVID death.

	Dependent variable: Weighted log-odds of Vaccination			
	(1)	(2)	(3)	(4)
Risk: Known death	0.427***	0.358***	0.466***	0.361***
	(0.097)	(0.104)	(0.101)	(0.109)
Politics: right-oriented	−1.001***	−1.044***	−1.272***	−1.339***
	(0.091)	(0.112)	(0.104)	(0.128)
Interaction: right-oriented x Known death		0.132		0.203
		(0.190)		(0.199)
Constant	1.196***	1.220***	0.500***	0.530***
	(0.063)	(0.066)	(0.184)	(0.186)
Control Variables	No	No	Y es	Y es
Observations	10,416	10,416	10,416	10,416
Log Likelihood	−5878.453	−5877.612	−5435.311	−5433.270
AIC	11,762.910	11,763.220	10,896.620	10,894.540

Note: *p<0.1; **p<0.05; ***p<0.01.

Credit author statement

Ray Block: Conceptualization, Data Curation, Funding acquisition, Visualization, Writing-Original Draft, Writing-Review and Editing. **Michael Burnham:** Conceptualization, Methodology, Software, Validation, Data Curation, Visualization, Writing-Original Draft, Writing-Review and Editing, Project Administration. **Kayla Kahn:** Conceptualization, Investigation, Writing-Original Draft, Writing-Review and Editing. **Rachel X. Peng:** Conceptualization, Investigation, Writing-Original Draft, Writing-Review and Editing. **Jeremy Seeman:** Methodology, Software, Validation, Data Curation, Visualization, Writing-Original Draft, Writing- Review and Editing. **Christopher Seto**: Conceptualization, Investigation, Data Curation, Writing-Original Draft, Writing-Review and Editing.

Acknowledgements

We thank participants at the Penn State Sociology Colloquium Series for their helpful comments. The authors are also grateful to the members of the African American Research Collaborative, 2021 COVID group. Listed in alphabetical order by last name, the group includes Matt Barreto, Erica Bernal-Martinez, Ray Block Jr., Gayle Chacon, Annabelle De St. Maurice, Henry Fernandez, Ray Foxworth, Matt Hildreth, Robert Lennon, Marcella Nunez-Smith, Gabriel Sanchez, Arnav Shah, Peter Szilagyi, and Janelle Wong. This work was supported by the Commonwealth Fund, the Robert Wood Johnson Foundation, and the WK Kellogg Foundation.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2022.115091.

References

African American Research Collaborative, July 2021. Methodology Statement. American COVID-19 Vaccine Poll.
Ajzenman, Nicolas, Cavalcanti, Tiago, Da Mata, Daniel, 2020. Leaders' speech and risky behaviour during a pandemic. VoxEU. org 2.
Al Baghal, Tarek, Sloan, Luke, Curtis, Jessop, Williams, Matthew L., Burnap, Pete, 2020. Linking twitter and survey data: the impact of survey mode and demographics on consent rates across three UK studies. Soc. Sci. Comput. Rev. 38 (5), 517–532.
Baranger, David, 2022. InteractionPoweR: Power Analysis for Interactions via Simulation. R package version 0.1.0.5.
Barberá, Pablo, 2015. Birds of the same feather tweet together: bayesian ideal point estimation using twitter data. Polit. Anal. 23 (1), 76–91.
Barreto, Matt A., Frasure-Yokley, Lorrie, Vargas, Edward D., Wong, Janelle, 2018. Best practices in collecting online data with asian, black, latino, and white respondents: evidence from the 2016 collaborative multiracial post-election survey. Polit. Groups Ident. 6 (1), 171–180.
Barrios, John M., Hochberg, Yael, 2020. Risk Perception through the Lens of Politics in the Time of the Covid-19 Pandemic. National Bureau of Economic Research. Technical report.
Baumgaertner, Bert, E Carlisle, Juliet, Justwan, Florian, 2018. The influence of political ideology and trust on willingness to vaccinate. PLoS One 13 (1), e0191728.
Bechard, Lauren E., Bergelt, Maximilian, Neudorf, Bobby, Tamara, C DeSouza, Middleton, Laura E., 2021. Using the health belief model to understand age differences in perceptions and responses to the covid-19 pandemic. Front. Psychol. 12, 1216.
Bélanger, Jocelyn, Leander, Pontus, 2020. What motivates COVID rule breakers? The answer turns out to Be complicated. Sci. Am. 9 (December).

Betsch, Cornelia, Wieler, Lothar H., Habersaat, Katrine, 2020. Monitoring behavioural insights related to covid-19. Lancet 395 (10232), 1255–1256.

Bhanot, Syon, Hopkins, Daniel J., 2020. Partisan Polarization and Resistance to Elite Messages: Results from a Survey Experiment on Social Distancing. *Available at: SSRN 3593450*,.

Bhui, Kamaldeep, Dinos, Sokratis, 2008. Health beliefs and culture. Dis. Manag. Health Outcome 16 (6), 411–419.

Bishop, George F., 2004. The Illusion of Public Opinion: Fact and Artifact in American Public Opinion Polls. Rowman & Littlefield Publishers.

Blank, Joshua M., Shaw, Daron, 2015. Does partisanship shape attitudes toward science and public policy? the case for ideology and religion. Ann. Am. Acad. Polit. Soc. Sci. 658 (1), 18–35.

Block Jr., Ray, Berg, Arthur, Lennon, Robert P., Miller, Erin L., Nunez-Smith, Marcella, 2020. African american adherence to covid-19 public health recommendations. HLRP: Health Literacy Res. Pract. 4 (3), e166–e170.

Bolsen, Toby, Palm, Risa, 2019. Motivated reasoning and political decision making. In: Oxford Research Encyclopedia of Politics.

Bostock, Bill, December 6, 2021. Medics Slam Rep. Matt Gaetz for Saying COVID-19 Is the Best Way to Protect against Getting COVID-19. Business Insider.

Calvillo, Dustin P., Ross, Bryan J., Garcia, Ryan JB., Smelter, Thomas J., Rutchick, Abraham M., 2020. Political ideology predicts perceptions of the threat of covid-19 (and susceptibility to fake news about it). Soc. Psychol. Personal. Sci. 11 (8), 1119–1128.

Carpenter, Roger, 2005. Perceived threat in compliance and adherence research. Nurs. Inq. 12 (3), 192–199.

Census Bureau, U.S., 2019. American community survey. https://www.census.gov/programs-surveys/acs/data/data-tables.html.

Center for Disease Control, May 23, 2021. Implementation of Mitigation Strategies for Communities with Local COVID-19 Transmission. US Department of Health and Human Services.

Chakrabarti, Subho, 2014. What's in a name? compliance, adherence and concordance in chronic psychiatric disorders. World J. Psychiatr. 4 (2), 30.

Champion, Victoria L., Skinner, Celette Sugg, et al., 2008. The health belief model. Health Behav. Health Educ.: Theor. Res. Pract. 4, 45–65.

Charles, Jennifer LK., Patrick, V., 2018. Dattalo. Minimizing social desirability bias in measuring sensitive topics: the use of forgiving language in item development. J. Soc. Serv. Res. 44 (4), 587–599.

Clark, Cory, Davila, Andrés, Regis, Maxime, Kraus, Sascha, 2020. Predictors of covid-19 voluntary compliance behaviors: an international investigation. Global Trans. 2, 76–82.

Clinton, Joshua, Cohen, Jon, Lapinski, John, Trussler, Marc, 2021. Partisan pandemic: how partisanship and public health concerns affect individuals' social mobility during covid-19. Sci. Adv. 7 (2), eabd7204.

Collignon, Sofia, Makropoulos, Iakovos, Rüdig, Wolfgang, 2021. Consensus secured? elite and public attitudes to "lockdown" measures to combat covid-19 in england. J. Elections, Public Opin. Parties 31 (Suppl. 1), 109–121.

Collins, Robert N., Mandel, David R., Schywiola, Sarah S., 2021. Political identity over personal impact: early us reactions to the covid-19 pandemic. Front. Psychol. 12 (555).

DellaPosta, Daniel, 2020. Pluralistic collapse: the "oil spill" model of mass opinion polarization. Am. Socio. Rev. 85 (3), 507–536.

Denzin, Norman K., 2017. The Research Act: A Theoretical Introduction to Sociological Methods. Routledge.

Diamond, Dan, December 16, 2020. 'We want them infected': trump appointee demanded 'herd immunity' strategy, emails reveal (Then-HHS science adviser Paul Alexander called for millions of Americans to be infected as means of fighting Covid-19). Politico.com. https://www.politico.com/news/2020/12/16/trump-appointee-demanded-herd-immunity-strategy-446408, 2020.

Druckman, James N., McGrath, Mary C., 2019. The evidence for motivated reasoning in climate change preference formation. Nat. Clim. Change 9 (2), 111–119.

Druckman, James N., Klar, Samara, Krupnikov, Yanna, Levendusky, Matthew, Ryan, John Barry, 2021. Affective polarization, local contexts and public opinion in America. Nat. Human Behav. 5 (1), 28–38.

Emily, P Courtney, Goldenberg, Jamie L., Boyd, Patrick, 2020. The contagion of mortality: a terror management health model for pandemics. Br. J. Soc. Psychol. 59 (3), 607–617.

Emily, P Courtney, Felig, Roxanne N., Goldenberg, Jamie L., 2022. Together we can slow the spread of covid-19: the interactive effects of priming collectivism and mortality salience on virus-related health behaviour intentions. Br. J. Soc. Psychol. 61 (1), 410–431.

Epley, Nicholas, Gilovich, Thomas, 2016. The mechanics of motivated reasoning. J. Econ. Perspect. 30 (3), 133–140.

Erhardt, Julian, Freitag, Markus, Filsinger, Maximilian, Wamsler, Steffen, 2021. The emotional foundations of political support: how fear and anger affect trust in the government in times of the covid-19 pandemic. Swiss Polit. Sci. Rev. 27 (2), 339–352.

Ezrina, Emilia, Dong, Huamei, Block Jr., Ray, Lennon, Robert P., 2022. Preferred Information Source Correlates to COVID-19 Risk Misperception. Health Literacy Research and Practice. Revised and resubmitted to HLRP.

Ferrer, Rebecca A., Klein, William MP., 2015. Risk perceptions and health behavior. Curr. Opin. Psychol. 5, 85–89.

Flaxman, Seth, Mishra, Swapnil, Gandy, Axel, Unwin, H.Juliette T., Mellan, Thomas A., Coupland, Helen, Whittaker, Charles, Zhu, Harrison, Berah, Tresnia, Eaton, Jeffrey W., et al., 2020. Estimating the effects of non-pharmaceutical interventions on covid-19 in europe. Nature 584 (7820), 257–261.

Floyd, Donna L., Prentice-Dunn, Steven, Rogers, Ronald W., 2000. A meta-analysis of research on protection motivation theory. J. Appl. Soc. Psychol. 30 (2), 407–429.

Francis Havey, Nicholas, 2020. Partisan public health: how does political ideology influence support for covid-19 related misinformation? J. Computat. Soc. Sci. 3 (2), 319–342.

Freudenburg, William R., 1988. Perceived risk, real risk: social science and the art of probabilistic risk assessment. Science 242 (4875), 44–49.

Gausman, Jewel, Langer, Ana, 2020. Sex and gender disparities in the covid-19 pandemic. J. Wom. Health 29 (4), 465–466.

George, E Marcus, Neuman, W Russell, MacKuen, Michael, 2000. Affective Intelligence and Political Judgment. University of Chicago Press.

Goldenberg, Jamie L., Arndt, Jamie, 2008. The implications of death for health: a terror management health model for behavioral health promotion. Psychol. Rev. 115 (4), 1032.

Gollwitzer, Anton, Martel, Cameron, Brady, William J., Knowles, Eric D., Van Bavel, Jay, 2020. Partisan Differences in Physical Distancing Predict Infections and Mortality during the Coronavirus Pandemic. *Available at: SSRN 3609392*.

Gould, Elaine, Mitty, Ethel, 2010. Medication adherence is a partnership, medication compliance is not. Geriatr. Nurs. 31 (4), 290–298.

Green, Jon, Edgerton, Jared, Naftel, Daniel, Shoub, Kelsey, Cranmer, Skyler J., 2020. Elusive consensus: polarization in elite communication on the covid-19 pandemic. Sci. Adv. 6 (28), eabc2717.

Grossman, Guy, Kim, Soojong, Rexer, Jonah M., Thirumurthy, Harsha, 2020. Political partisanship influences behavioral responses to governors' recommendations for covid-19 prevention in the United States. Proc. Natl. Acad. Sci. Unit. States Am. 117 (39), 24144–24153.

Hansen, Michael A., Johansson, Isabelle, Sadowski, Kalie, Joseph, Blaszcynski, Meyer, Sarah, 2021. The partisan impact on local government dissemination of covid-19 information: assessing us county government websites. Canad. J. Polit. Sci./Rev. Canad. Sci. Polit. 54 (1), 150–162.

Harper, Craig A., Satchell, Liam P., Dean, Fido, Latzman, Robert D., 2020. Functional fear predicts public health compliance in the covid-19 pandemic. Int. J. Ment. Health Addiction 1–14.

Hetherington, Marc J., Mehlhaff, Isaac D., August 18, 2020. American attitudes toward COVID-19 are divided by party. The pandemic itself might undo that. The Washington Post, Monkey Cage. https://www.washingtonpost.com/politics/2020/08/18/american-attitudes-toward-covid-19-are-divided-by-party-pandemic-itself-might-undo-that/.

Horner, Dylan E., Sielaff, Alex, Tom, Pyszczynski, Greenberg, Jeff, 2021. The role of perceived level of threat, reactance proneness, political orientation, and coronavirus salience on health behavior intentions. Psychol. Health 1–20.

Hunt, Allcott, Boxell, Levi, Conway, Jacob, Gentzkow, Matthew, Thaler, Michael, Yang, David, 2020. Polarization and public health: partisan differences in social distancing during the coronavirus pandemic. J. Publ. Econ. 191, 104254.

Hussein, Ashatu, 2009. The use of triangulation in social sciences research. J. Comp. Soc. Work 4 (1), 106–117.

Janz, Nancy K., Becker, Marshall H., 1984. The health belief model: a decade later. Health Educ. Q. 11 (1), 1–47.

Kahan, Dan M., 2015. The Politically Motivated Reasoning Paradigm. Emerging Trends in Social & Behavioral Sciences, Forthcoming.

Kahan, Dan M., 2016. The politically motivated reasoning paradigm, part 2: unanswered questions. Emerg. Trends Soc. Behav. Sci. 1–15.

Kantamneni, Neeta, 2020. The Impact of the Covid-19 Pandemic on Marginalized Populations in the united states: A Research Agenda.

Kushner Gadarian, Shana, Goodman, Sara Wallace, Pepinsky, Thomas B., 2021. Partisanship, health behavior, and policy attitudes in the early stages of the covid-19 pandemic. PLoS One 16 (4), e0249596.

Kwasi Ahorsu, Daniel, Lin, Chung-Ying, Imani, Vida, Saffari, Mohsen, Griffiths, Mark D., Pakpour, Amir H., 2020. The fear of covid-19 scale: development and initial validation. Int. J. Ment. Health Addiction 1–9.

Lennon, Robert P., Sakya, Surav M., Miller, Erin L., Snyder, Bethany, Yaman, Tonguç, E Zgierska, Aleksandra, Mack T Ruffin, I.V., Jodi Van Scoy, Lauren, 2020. Public intent to comply with covid-19 public health recommendations. HLRP: Health Literacy Res. Pract. 4 (3), e161–e165.

Leon, Andrew C., Heo, Moonseong, 2009. Sample sizes required to detect interactions between two binary fixed-effects in a mixed-effects linear regression model. Comput. Stat. Data Anal. 53 (3), 603–608.

Liang, Hai, 2018. Broadcast versus viral spreading: the structure of diffusion cascades and selective sharing on social media. J. Commun. 68 (3), 525–546.

Ling Yang, Elaine Chiao, Nair, Vikneswaran, 2014. Tourism at risk: a review of risk and perceived risk in tourism. Asia-Pac. J. Innov. Hospit. Tourism (APJIHT) 3 (2), 1–21.

Lumley, Thomas, 2004. Analysis of complex survey samples. J. Stat. Software 9 (1), 1–19. R package verson 2.2.

Lumley, T., Scott, A., 2015. Aic and bic for modeling with complex survey data. J. Surv. Statis. Methodol. 3 (1), 1–18.

Lutfey, Karen E., Wishner, William J., 1999. Beyond" compliance" is" adherence". improving the prospect of diabetes care. Diabetes Care 22 (4), 635–639.

M Golos, Aleksandra, Hopkins, Daniel J., Bhanot, Syon P., Buttenheim, Alison M., 2022. Partisanship, Messaging, and the Covid-19 Vaccine: Evidence from Survey Experiments. American Journal of Health Promotion, 08901171211049241.

McCright, Aaron M., Dentzman, Katherine, Charters, Meghan, Dietz, Thomas, 2013. The influence of political ideology on trust in science. Environ. Res. Lett. 8 (4), 044029.

McKay, Carly D., Verhagen, Evert, 2016. 'compliance'versus 'adherence'in Sport Injury Prevention: Why Definition Matters.

Mehlhaff, Isaac D., Ryan, Timothy J., Hetherington, Marc, MacKuen, Michael, 2020. Where Motivated Reasoning Withers and Looms Large: Fear and Partisan Reactions to the Covid-19 Pandemic. Working paper.
MIT Election Data and Science Lab, 2018. County Presidential Election Returns 2000-2020.
Mitchell, Rabinowitz, Latella, Lauren, Stern, Chadly, Jost, John T., 2016. Beliefs about childhood vaccination in the United States: political ideology, false consensus, and the illusion of uniqueness. PLoS One 11 (7), e0158382.
Monroe, Burt L., Colaresi, Michael P., Quinn, Kevin M., 2008. Fightin'words: lexical feature selection and evaluation for identifying the content of political conflict. Polit. Anal. 16 (4), 372–403.
Mueller, Samuel David, Saeltzer, Marius, 2020. Twitter Made Me Do it! Twitter's Tonal Platform Incentive and its Effect on Online Campaigning. Information, Communication & Society, pp. 1–26.
Myers, Lynn B., Kenny, Midence, 1998. Concepts and Issues in Adherence.
Newhagen, John E., Bucy, Erik P., 2020. Overcoming Resistance to Covid-19 Vaccine Adoption: How Affective Dispositions Shape Views of Science and Medicine. Harvard Kennedy School Misinformation Review.
Norman, Paul, Henk Boer, Seydel, Erwin R., Mullan, Barbara, 2015. Protection motivation theory. Pred. Chang. Health Behav. 70–106.
Palm, Risa, Bolsen, Toby, Kingsland, Justin T., 2021. The effect of frames on covid-19 vaccine resistance. Front. Polit. Sci. 3, 41.
Pechar, Emily, Bernauer, Thomas, Mayer, Frederick, 2018. Beyond political ideology: the impact of attitudes towards government and corporations on trust in science. Sci. Commun. 40 (3), 291–313.
Gordon Pennycook, Jonathon McPhetres, Bence Bago, and David G Rand. Beliefs about covid-19 in Canada, the UK, and the USA: a novel test of political polarization and motivated reasoning. PsyArXiv, 10, 2020.
Prentice-Dunn, Steven, Rogers, Ronald W., 1986. Protection motivation theory and preventive health: beyond the health belief model. Health Educ. Res. 1 (3), 153–161.
Rao, Ashwin, Morstatter, Fred, Hu, Minda, Chen, Emily, Burghardt, Keith, Ferrara, Emilio, Lerman, Kristina, et al., 2021. Political partisanship and antiscience attitudes in online discussions about covid-19: twitter content analysis. J. Med. Internet Res. 23 (6), e26692.
Reinhardt, Madeleine, Findley, Matthew B., Countryman, Renee A., 2021. Policy liberalism and source of news predict pandemic-related health behaviors and trust in the scientific community. PLoS One 16 (6), e0252670.
Roccato, Michele, Russo, Silvia, Colloca, Pasquale, Cavazza, Nicoletta, 2021. The lasting effects of the covid-19 pandemic on support for anti-democratic political systems: a six-month longitudinal study. Soc. Sci. Q. 102 (5), 2285–2295.
Ruisch, Benjamin Coe, Moore, Courtney, Granados Samayoa, Javier, Boggs, Shelby, Ladanyi, Jesse, Russell, Fazio, 2021. Examining the left-right divide through the lens of a global crisis: ideological differences and their implications for responses to the covid-19 pandemic. Polit. Psychol. 42 (5), 795–816.
Gabriel R Sanchez and Ray Block Jr. Bunche scholars collaborate on COVID-19 vaccine research. Polit. Sci., August 12, 2021.
Shah, Arnav, Schneider, Eric C., Zephyrin, Laurie, Barreto, Matt A., Block Jr., Ray, Sanchez, Gabriel R., Henry, Fernandez, June 16, 2021. What do Americans think about getting vaccinated against COVID-19? Findings from a national poll. CommonwealthFund.org. https://www.commonwealthfund.org/publications/2021/jun/what-do-americans-think-about-getting-vaccinated-against-covid-19. (Accessed 16 June 2021).
Shao, Wanyun, Feng, Hao, 2020. Confidence in political leaders can slant risk perceptions of covid–19 in a highly polarized environment. Soc. Sci. Med. 261 (1982), 113235.
Spiro, Emma S., Almquist, Zack W., Butts, Carter T., 2016. The persistence of division: geography, institutions, and online friendship ties. Socius 2, 1–15.
Strecher, Victor J., Rosenstock, Irwin M., 1997. The health belief model. Camb. Handb. Psychol. Health Med. 113 (117).
Strecher, Victor J., Champion, Victoria L., Rosenstock, Irwin M., 1997. The Health Belief Model and Health Behavior.
Street, Richard L., Paul, Haidet, 2011. How well do doctors know their patients? factors affecting physician understanding of patients' health beliefs. J. Gen. Intern. Med. 26 (1), 21–27.
Thomson-DeVeaux, Amelia, July 23, 2020. Republicans and Democrats see COVID-19 very differently. Is that making people sick? FiveThirtyEight. https://fivethirtyeight.com/features/republicans-and-democrats-see-covid-19-very-differently-is-that-making-people-sick/, 2020.
Trkman, Marina, Popovič, Aleš, Peter, Trkman, 2021. The impact of perceived crisis severity on intention to use voluntary proximity tracing applications. Int. J. Inf. Manag. 61, 102395.
USAFacts, Feb 2021. Detailed Methodology and Sources: Covid-19 Data. https://usafacts.org/articles/detailed-methodology-covid-19-data/.
Weisberg, Herbert F., 2009. The total survey error approach. In: The Total Survey Error Approach. University of Chicago Press.
World Health Organization, et al., 2020. Risk Communication and Community Engagement Readiness and Response to Coronavirus Disease (Covid-19): Interim Guidance, 19 March 2020. World Health Organization. Technical report.
Yaya, Sanni, Yeboah, Helena, Charles, Carlo Handy, Otu, Akaninyene, Labonte, Ronald, 2020. Ethnic and racial disparities in covid-19-related deaths: counting the trees, hiding the forest. BMJ Global Health 5 (6), e002913.
Zaller, John, 1992. The Nature and Origins of Mass Opinion. Cambridge university press.
Zaller, John, 2012. What nature and origins leaves out. Crit. Rev. 24 (4), 569–642.
Zaller, John, Feldman, Stanley, 1992. A simple theory of the survey response: answering questions versus revealing preferences. Am. J. Polit. Sci. 579–616.
Zeng, Chen, 2021. A relational identity-based solution to group polarization: can priming parental identity reduce the partisan gap in attitudes toward the covid-19 pandemic. Sci. Commun. 43 (6), 687–718.