Northwestern | INSTITUTE FOR POLICY RESEARCH

Working Paper Series

WP-20-38

The Role of Race, Religion, and Partisanship in Misinformation About COVID-19

James Druckman
Payson S. Wild Professor of Political Science and IPR Fellow Northwestern University

Katherine Ognyanova
Assistant Professor of Communication, Rutgers University

Matthew Baum
Marvin Kalb Professor of Global Communications, Harvard Kennedy School

David Lazer
Distinguished Professor of Political Science and Computer and Information Science, Northeastern University

Roy Perlis
Professor of Psychiatry, Harvard Medical School

John Della Volpe
Director of Polling, Institute of Politics, Harvard Kennedy School

Mauricio Santillana
Assistant Professor in Pediatrics, Harvard Medical School

Hanyu Chwe
Network Science, Northeastern University

Alexi Quintana
Network Science, Northeastern University

Matthew Simonson
Network Science, Northeastern University

Version: August 10, 2020

DRAFT

Please do not quote or distribute without permission.

ABSTRACT

Concerns about misinformation among the public abound. While this is not new, the rise of social media has stimulated scholars, across the social sciences, to explore the spread of misinformation and tactics for correcting misperceptions. Surprisingly, little work explores the correlates of misinformation in varying contexts–that is, how do factors such as group affiliations, media exposure, and lived experiences influence levels of misinformation? The researchers address these questions by investigating misinformation about COVID-19, focusing on the role of racial/ethnic, religious, and partisan groups. They also compare the impact of group affiliations with other factors such as media exposure and disease vulnerability. Using a large survey, they find that minorities, those with high levels of religiosity, and those with strong partisan identities–across parties–exhibit significantly greater levels of misinformation than those with contrasting group affiliations. Moreover, the authors show these effects exceed those stemming from other variables (e.g., social media usage, number of COVID-19 cases in one's county), and do not reflect acquiescence to believing any information regardless of its truth value. Their results have implications for understanding the sources of misinformation and how to combat it. It further accentuates the importance of developing targeted interventions for these high-risk groups.

The authors thank Robin Bayes and Jennifer Lin for helpful research assistance.

"The most astonishing thing about the pandemic was the complete mystery which surrounded it. Nobody seemed to know what the disease was, where it came from or how to stop it. Anxious minds are inquiring today… In spite of the repeated statement that [some information] has been discredited, there are many well-informed persons who believe [it]."

--Major George A. Soper (1919: 501, 503)

This statement, from a 1919 *Science* article on the Spanish Flu, could most certainly apply to the COVID-19 pandemic. Like the Spanish Flu, COVID-19 has upended health, economic, and social systems. Yet, one notable difference is the information environment in which we live today. While misinformation was obviously a concern a century ago – as is mentioned in the quote – the speed with which misinformation can spread today is unprecedented. Misinformation about COVID-19 can have severe consequences, with people ignoring health advice that can delay economic recovery and becoming hostile to groups they misattribute as being responsible (van Bavel et al. 2020: 464; also see Swire-Thompson and Lazer 2020). Not surprisingly, these concerns have led to a large number of explorations into COVID-19 misinformation (e.g., Cinelli et al. 2020, Krause et al. 2020, Li et al. 2020, Pennycook et al. 2020, Ricard and Medeiros 2020, Singh et al. 2020); however, nearly all of this work focuses on social media and misinformation spread. While certainly a crucial topic, much less work explores who in fact is misinformed. Isolating those more likely to be misinformed allows communities and practitioners to identify such individuals and apply targeted interventions for enhancing accurate information (e.g. Pennycook et al. 2020, van Bavel et al. 2020: 464).

In this paper, we explore the correlates of misinformation about COVID-19. We begin in the next section with a brief review of work on science misinformation, leading to a set of expectations, focused on group level correlates of misinformation. Our focus on groups stems from a concern that inter-personal dynamics and shared belief systems often generate vulnerability to misinformation. By identifying groups that are most likely to be misinformed, this process provides guidance to entities who are interested in working on interventions to benefit these distinct communities. Beyond group level variables, we investigate a host of other relevant factors such as mental health (i.e., major depressive symptoms), media exposure (e.g., to Fox News, social media), and COVID-19 experiences (e.g., having had the virus).

We test our hypotheses with a large data set of more than 18,000 individuals from across the United States (and weighted to be representative of the country). We find clear evidence that populations more vulnerable to the disease and its consequences tend to be the most vulnerable to misinformation. Perhaps most notably African-Americans, who have been otherwise disproportionally affected by the disease, are also significantly more misinformed. To be clear, we do not see or believe there to be a connection between misinformation and the disproportionate contraction of the virus, as the latter stems from living conditions, work circumstances, and health situations (see https://www.cdc.gov/coronavirus/2019-ncov/need-extra-precautions/racial-ethnic-minorities.html). Our finding, nonetheless, highlights the importance of taking steps to ensure vulnerable populations are suitably informed when managing the disease.

We also find sizeable effects based on religiosity, as well as partisan gaps that reflect group attachments with the parties. With a disease that quickly became politicized in the United States, these individuals are vulnerable insofar as they tend to rely on identity affirmation rather than systematic assessment of information (Achen and Bartels 2017). All of these group level results, too, dwarf the impact of other variables such as social media usage and direct experiences with COVID-19. Our results offer a crucial portrait of those susceptible to the consequences of misinformation and also contribute to the general knowledge on misinformation about science.

Science Misinformation

Misinformation has become a global problem that affects all aspects of life and garners much attention in the political sphere (e.g., Jerit and Zhao 2020). This is in part due to the 2016 U.S. election, when the Russian government created fake social media avatars with names like “Blacktivist” and “army_of_jesus” to stoke partisan outrage, duping millions of Americans into sharing memes about the turpitude of opposing partisans (e.g., Grinberg et al. 2019). Misinformation about science, however, poses a distinct challenge. Science seeks to provide systematic knowledge to improve decision-making (Dietz 2013), but the present media environment undermines the privileged cultural authority of science by allowing anyone to claim to be “scientific.” When people are misinformed about science, it can lead to disastrous individual decision-making and collective consequences that could undercut the well-being and economies of societies. The COVID-19 pandemic has brought this reality into even starker relief. Misinformation filled the communication space quickly, as an early paper on the social consequences of COVID-19 explained: “Fake news and misinformation about COVID-19 have proliferated widely on social media, with potentially dangerous consequences” (van Bavel et al. 2020: 464). These concerns, more generally, have led to a cottage industry of social scientists exploring the nature of misinformation and its spread on social media (e.g., Bode and Vraga 2018, Allcott et al. 2019, Grinberg et al. 2019, Guess et al. 2019, Pennycook and Rand 2019) and/or investigating tactics to correct misinformed opinions (e.g., Flynn et al. 2017, Jerit and Zhao 2020).

Here we ask a distinct question: what group level characteristics lead one to be more likely to believe misinformation – meaning information that is "false, misleading, or unsubstantiated… [and] are not supported by clear evidence and expert opinion" (Nyhan and Reifler 2010: 304, 305; also see Levy et al. n.d.)? Our focus on groups reflects the reality that inter-personal relations, socio-economic realities, and shared belief systems all can contribute to misinformation among particular social groups. Indeed, our survey respondents ranked "family and social groups" as their second-most important source of COVID-related news, just behind local television. Moreover, identifying group correlates of misinformation is a crucial question if we are to target interventions to ameliorate misinformation and its consequences (Scheufele and Krause 2019). It also is an area that has received less general attention than work on social media transmission. This is particularly the case with COVID-19.

We focus on three highly salient dimensions of group identity – one ascriptive, one social, and one political. The first is racial and ethnic affiliation. Numerous studies find differences in science literacy, interest, and attitudes by race. For example, racial and ethnic minorities often report significantly less confidence in science and are less scientifically literate, as measured by factual knowledge (Plutzer 2013, National Academies of Sciences, Engineering, and Medicine 2016, Allum et al. 2018).[1] Further, in the case of health information, immigrants and minority groups tend to have less access to medical professionals, and can be more difficult to reach with health-related information and interventions (Katz et al. 2012). Communities of color also have distinct communication and media ecologies, a factor known to have important implications for the prevalence of health and science misperceptions in social groups (Walter et al. 2018). African-American and Latino communities often rely more heavily on interpersonal

[1] The exact group level rationale for these differences remains somewhat unclear, as they do not seem to stem from variations in education/knowledge, religion, or economic circumstance (e.g., Allum et al. 2018).

resources to stay informed (Kim et al. 2018), which could potentially increase their susceptibility to uncorrected misinformation. A further possibility is that misinformation campaigns deliberately target minority communities, as was the case with the 2016 election interference from Russia and has been the case with the anti-vaccine movement (exploiting distrust in the medical establishment among minorities, given past egregious exploitations of African-Americans in experiments).[2]

While we do not have evidence regarding COVID-19 along these lines, the literature to-date nonetheless leads us to the expectation that, all else constant, relative to whites, minorities will be more likely to be misinformed (*hypothesis 1*). Despite the lack of clarity on the precise mechanism, racial/ethnic group effects are particularly crucial to explore with COVID-19, given the widely documented disproportionate effects of the disease on communities of color, which presumably motivated the Center for Disease Control to explicitly highlight the need to prevent the spread of misinformation in minority communities.[3] More generally, data on racial differences among adults adds to what one recent study referred to as a "sparse" literature (Allum et al. 2018: 861).

A second central identity factor is one's religiosity, that is, the extent to which one defines him/herself as a religious person, rather than his/her religious denomination. Indeed, those who hold stronger religious beliefs tend to be less scientifically literate (Sherkat 2011) and less deferential to scientists (Blank and Shaw 2015). One possible underlying mechanism is that religiosity correlates with intuitivist thinking that privileges faith and symbols over the systematic empirical observation that defines science (Oliver and Wood 2018). This leads to the

[2] See, e.g., https://www.yonder-ai.com/resources/the-disinformation-report/; https://abcnews.go.com/health/rfk-jrs-york-city-vaccine-forum-highlights-concerns/story?id=66158336.
[3] See https://www.cdc.gov/coronavirus/2019-ncov/need-extra-precautions/racial-ethnic-minorities.html.

expectation that, all else constant, as religiosity increases, people will be more likely to be misinformed (*hypothesis 2*).

Finally, the politicization of science over past quarter-century (Lupia 2013) makes partisan group identity relevant. While some point to a partisan divide, with Republicans or conservatives being less trusting of science (e.g. Gauchat 2012), we focus on the nature of partisan identity itself: that is, the strength with which one identifies with their party (e.g., thinks in terms of "we" rather than "they") (Huddy et al. 2015). When one has such a strong group identity, a primary motivation becomes distinguishing one's self from the other group (Kahan 2015). Insofar as many scientific issues become politicized, as mentioned, with different parties endorsing distinct perspectives, those with strong partisan identities will be more likely to accept congenial information, regardless of its accuracy, if it coheres with their stances. They assess information for identity congruence rather than factual accuracy (Druckman 2012). The exact impact of partisan social identity, then, depends on the nature of the misinformation and which party's side it agrees with, but overall, holding the partisan slant of information constant, we expect those with stronger partisan identities to be more likely to be misinformed (*hypothesis 3*).

Of course, these three group level factors – race/ethnicity, religiosity, and partisan social identity – neither exhaust relevant group features nor other attributes that correlate with believing misinformation. Nonetheless, they capture crucial group dynamics that encompass targeted groups for misinformation campaigns, a style of thinking, and motivations for group identity. Studying these group dynamics also fill lacunae in the misinformation literature and provide guidance for targeting interventions with those groups.

Finally, as we discuss below, there are a set of other correlates widely studied when it comes to misinformation including media usage, direct experiences (e.g., with COVID-19), and mental health. We will study these variables as correlates as well, and compare their impact against those of the group level measures.

Data

We focus on misinformation about COVID-19; as mentioned, concern about the spread of COVID-19 misinformation emerged as soon as the pandemic began and a number of works explore the presence, spread, and possible correction of misinformation. Yet, little, if any, scholarship looks at group level correlates, as we do. Our data come from an online survey with a national sample, collected via the panel management company PureSpectrum. The data is weighted to represent the country on key demographics including gender, age, race and ethnicity, education, and U.S. region. Descriptive characteristics of the sample, along with means and standard deviations of predictors and control variables included in our models, are available in Table 2 below. We collected the data from May 16, 2020 to June 1, 2020, and a total of 18,132 respondents completed the survey.

We included two misinformation batteries (see Table 1). One asked respondents whether a series of statements about COVID-19 were inaccurate or accurate – this battery contained 7 inaccurate statements, including that the virus was created as a weapon in a Chinese lab, that President Trump shared plans to declare martial law, etc. (see Table 1). These items assess facts about COVID-19, such that misinformation could result in problematic beliefs (e.g., attributing blame to China or believing the risks are different than they actually are). The second battery asked respondents about the effectiveness or ineffectiveness of ways to prevent COVID-19, such as taking a flu vaccine or using a hot air hand dryer. This included six inaccurate statements that, if believed, could lead to damaging health behaviors. Importantly, each battery included a smaller set of three correct information items (e.g., a vaccine currently does not exist and wearing a face mask is a preventive measure).[4] We use these in our analyses to ensure any results about misinformation do not simply reflect an acquiescence bias, such that certain individuals are more likely to agree with statements generally. The correct and incorrect statements were presented to participants in a randomized order. We display the full set of statements in Table 1.[5]

[Insert Table 1 About Here]

The first two panels of the table show that the level of misinformation varied across items, ranging from only 3% believing that applying sesame oil to your skin is an effective treatment to 20% believing *only* people older than 60 are at risk for the virus (presumably reflecting confusion about high risk versus any risk). Overall, though, the level of misinformation is modest (e.g., the percentages for each item are all under a quarter of the respondents). Consider an index where we count the number of misinformed statements each respondent believed, *across* the two batteries; the average respondent believed 1.57 (std. de. = 1.89) pieces of misinformation. In Figure 1, we display the distribution of the number of misinformed beliefs: 34% had no misinformed beliefs and only 22% of the sample holds 3 or more misinformed beliefs. The median respondent had just 1 misinformed belief – thus, the level of misinformation is limited, which itself is interesting, given widespread concerns. That said,

[4] We recognize that technically a vaccine exists, but none were sufficiently developed to be marketed and distributed to the public (at the time of data collection).

[5] The particular items offered three response items – accurate/effective, inaccurate/not effective, and not sure. We count someone as being misinformed on an item if they choose accurate or effective when in fact the statement is inaccurate/ineffective. We do this because we are interested in who holds clearly false beliefs (or not), rather than degrees of uncertainty per se. This is particularly relevant for several of the items which are not "demonstrably false" but rather simply unsubstantiated to-date (Flynn et al. 2017), meaning "not sure" is not always wholly inaccurate. We take the same approach in accounting correct information – counting it as correct only if the respondent said accurate or effective when it was so. If we instead treated the responses as a scale from inaccurate/ineffective to not sure to accurate/effective, our main results are largely the same (see the appendix).

we emphasize that even some amounts misinformation – such as a belief in taking ineffective and possibly hazardous antidotes – can be extremely damaging.

[Insert Figure 1 About Here]

Interestingly, when it comes to correct beliefs, people are generally on target, as displayed in the last two panels of Table 1. The range is 66% when it comes to declaration of a national emergency to 95% knowing that washing one's hands constitutes an effective antidote. The average respondent held 4.99 (1.22) out of 6 correct beliefs (across the two batteries). Figure 2 displays the distribution, showing 41% correctly endorsed all the correct statements, and 76% of the sample correctly identified at least 5 pieces of information. The median respondent correctly identified 5 out of 6 statements. Overall, the median respondent held only 1 out of 13 misperceptions and held 5 out of 6 correct perceptions. The population as a whole is not horribly misinformed. Nonetheless, as mentioned, even one incorrect belief (e.g., needlessly taking an ineffective vaccine that can have side effects) can have negative consequences and thus understanding the correlates remains important.

[Insert Figure 2 About Here]

The survey contained measures of our main explanatory variables, as displayed in Table 2. First, for racial/ethnic group, we asked respondents to identify the group that best describes them, from which we created variables to identify Hispanic, African-American, and Asian-American respondents. (We recognize the bluntness of our racial/ethnic classifications, and encourage future work to explore intersectional dynamics more carefully.) Second, for religiosity, we asked respondents the frequency with which they attend religious services on a six-point scale ranging from never to more than once a week, a common measure to capture religious devotion (see, e.g., the General Social Survey).[6] Third, we asked people to report their partisan affiliation and then, to measure partisan identity, we asked partisans a four-item partisan as social identity scale that asked, for example, how often they talk about their party using "we" instead of "they," and the personal importance of being a member of the given party (Huddy et al. 2015).

As mentioned, we also explore/measure other sources of misinformation, including individual attributes, communication environment, and COVID-19 situation – all of which we have reason to suspect may impact misinformation levels and serve as interesting points of comparisons with the group level variables (i.e., we refer to these as comparison point control variables). Of particular interest with individual level variables is one's mood; Scheufele and Krause (2019: 7665) explain there "is some evidence that a person's emotional state can shape the accuracy of his or her [scientific] beliefs." Yet, exactly how this works remains understudied. We focus here on major depressive symptoms as a manifestation of emotionality – an extremely salient factor when it comes to COVID-19, given levels of major depressive disorder in the US are 3 times what they were relative to pre-COVID-19 times (Ognyanova et al. 2020).

For communication, we focus on two variables – exposure to Fox News, given that prior work demonstrates it as a key source of misinformation about COVID-19 (Motta et al. 2020, Simonov et al. 2020), and accessing social media for COVID-19 information, given aforementioned concerns about misinformation on social media (e.g., Cinelli et al. 2020).[7]

---

[6] While we did not specify in the question, we presume respondents answered this question in terms of their habitual attendance rather than any alterations caused due to COVID-19.

[7] As mentioned, many point to social media as a culprit in spreading misinformation, even though extant empirical evidence suggests this is fairly concentrated (e.g., Grinberg et al. 2019, Guess et al. 2019). With scientific topics that introduce risk, though, there are additional layers of concern since uncertainties become multiplied, leading to the potential of a "misinfodemic" (Krause et al. 2020). As one *New York Times* article put it: "Surge of Virus Misinformation Stumps Facebook and Twitter" (Frenkel et al. 2020).

Finally, we look at COVID-19 situational factors that may affect information consumption. The idea here is that individuals more affected by the relevant science – i.e., issue publics – are more motivated to seek out and obtain more accurate information (e.g., Hutchings 2003, Brenes Peralta et al. 2017). In some instances, individual attributes drive acute issue interest (e.g., age and Medicare), but in other cases, context acts as the determinative factor. For instance, those who experience extreme climate anomalies have relatively accurate perceptions of them – they are acutely affected and, thus, update their beliefs accordingly (Ripberger et al. 2017). We capture these dynamics with three variables, including the number of COVID-19 cases in one's county, if the respondent believes he/she had or has COVID-19, and if the respondent has a medical condition that makes him/her particularly vulnerable to COVID-19.

Aside from these "comparison point" control variables, we measured variables that have otherwise been shown to affect levels of science literacy and misinformation (e.g., Allum et al. 2018, Scheufele and Krause 2019: 7663-7666) including gender, age, education, living in rural settings, self-reported informedness on COVID-19, amount of inter-personal discussion about COVID-19, and exposure to various media networks and Trump's COVID-19 press conferences.[8] The full list of explanatory variables, along with descriptive statistics, appears in Table 2.

[Insert Table 2 About Here]

Results

We test our hypotheses by merging the two misinformation modules, as we did above in Figure 1. Specifically, we count the number of misinformation items a respondent endorsed as

[8] We excluded income due to significant item non-response, but our results are robust to including it; it does not have a significant relationship with misinformation, but we find that higher income correlates with more accurate information.

true/accurate. We do the same with the correct information modules. (We present the results for each module separately in the appendix; they largely replicate the merged results.) We then regress these counts (using Poisson regressions) on the explanatory variables. All models cluster the standard errors based on county. Also, all results are robust to including state fixed effects.[9]

We present the regression results in the Appendix, focusing here on the predicted number of misinformation / correction information items by the relevant groups, holding all other variables at their mean values, along with 95% confidence intervals.[10]

[Insert Figure 3 About Here]

Figure 3 shows strong support for our hypotheses. Specifically, per hypothesis 1, we see substantial disparities across racial/ethnic group in the, all else constant, predicted values of misinformation from our main misinformation model. The average White respondent believes 1.33 of the 13 pieces of misinformation; yet, that significantly increases for African-Americans, Hispanics, and Asian-Americans with respective scores of 1.89, 1.70, and 1.63 ($p < .01$ for all three groups, relative to Whites). Given that well over half of the sample believes 0 or 1 piece of misinformation, the disparity of tending towards 2 is meaningful and potentially consequential. To assess which particular pieces of misinformation underlie the effect, we analyze each independently in the appendix. We find fairly uniform effects across individual items, such that no particular item drives the racial/ethnic group findings and they are fairly consistent across both the facts and prevention items. Put another way, it is *not* the case that groups are susceptible to specific items of misinformation, but rather that there tends to be a general group tendency.

[9] The models that generate the partisan identity results differ from the others insofar as, for those, we exclude pure Independents, as is typical when exploring partisan social identity and related concepts (e.g., Druckman and Levendusky 2019).
[10] We derived the predicted values based on *Clarify* (Tomz et al. 2003).

Next, turning to religiosity, we compare those who never attend religious services (35% of the sample) against those who attend once a week (19% of the sample).[11] We again see a notable and significant jump from 1.28 pieces of misinformation to 1.70 ($p < .01$) – confirming hypothesis 2.[12] When we look at the individual items (see the appendix), we find religiosity is positively associated with every single item. Finally, we turn to partisan identity, which presents perhaps the most striking results. The graph here displays, for each party, those with the lowest level of partisan identity (just 1% of the sample), those strictly at the median level (12% of the sample), and those with the highest level (5% of the sample).[13] For both parties, we find stronger partisan identity is associated with significant increases in misinformation. Among Democrats, as partisan identity varies from weakest to strongest, the amount of misinformation increases from 1.08 to 1.63. Among Republicans, the corresponding increase is notably larger, from 1 to 2.12, representing the largest movement in the data. (The impact of partisan social identity is significant at the .01 level for both parties, with the added effect among Republicans being significant at the .05 level.) Here, in contrast to our other findings, we find particular items stand out (see the appendix). Specifically, Democrats with strong identities are particularly likely to accept as true that COVID can be transmitted via mosquito bites and 5G wireless usage, as well as several of the ineffective antidotes, including the flu and pneumonia vaccines and applying sesame oil. It is not clear to us why strongly identified Democrats tended to believe these particular pieces of misinformation. Strongly identified Republicans endorse the belief that the virus was created as a weapon in a Chinese lab and the belief about the usefulness of taking

[11] The more religious category includes those who attend more than once a week but that constitutes only 7% of the sample.
[12] The impact of religion seems monotonic with there being roughly a .10 increase in level of misinformation for each category of attendance.
[13] Recall partisan social identity is measured by taking the average across 4 distinct items each on a 5 point scale, and thus the percentages at particular values are more spread out (i.e., there are more than 5 categories).

antibiotics. This relationship is much clearer than the Democratic one insofar as these beliefs cohere, at some level, with statements by President Trump, such as when he stated in late April 2020 that he has a “high degree of confidence” that COVID-19 originated in a Chinese laboratory.

[Insert Figure 4 About Here]

In Figure 4, we present results for point of comparison control variables. As previously noted, we chose these as distinct types of attributes that represented interesting points of comparison with the group based results. Results for all other control variables appear in the appendix. Beginning with mental health, the figure shows that moving from no depressive symptoms to moderate and then to severe depression (as defined by standard PHQ-9 cut-points; see Kroenke et al. 2001) correlates with a significant increase in misinformation ($p < .01$). Of course, the causal status of this relationship is ambiguous, as it could be that misinformation stimulates anxiety and depression, but, regardless, it is an intriguing dynamic that suggests depressive symptoms may make one more vulnerable to act on incorrect information that could further exacerbate mental health challenges. (In particular, a broad literature supports the notion of a negative cognitive bias among individuals with major depressive disorders, such that they may be more likely to recall negative concepts; see, for example, Beevers et al. 2019.)

Turning to media consumption, the results show that exposure to Fox News increases belief in misinformation ($p < .01$). Perhaps most unexpected is that consuming news about COVID via social media is associated with a small but significant decrease in misinformation from 1.52 to 1.39 ($p < .01$). This is contrary to common narratives about the spread of misinformation in social media, although it coheres with other evidence that misinformation is often highly concentrated within such networks. It also may be that, in the case of COVID-19, social media allows for the sharing of direct experiences that counters information from other mass communication outlets such as Fox News or messages from President Trump.[14] Regardless, the finding certainly warrants further investigation, given it does counter what one may expect.

Finally, we see no direct effect of an increase in the number of cases in one's county or increased vulnerability to the virus on susceptibility to misinformation. Having had COVID-19 is linked to a marginal increase in believing some inaccurate information (of .08), possibly reflecting cognitive impairment that may impact the ability to fact-check (that said, this is an intriguing finding in need of further exploration as the virus spreads). Overall, though, direct experience with the disease has much smaller effects than the group level variables discussed above. Further, the effect sizes of all these variables, with the exception of Fox News, is dwarfed by the group level variables. This makes clear that group level variables are, in our data, more salient in driving misinformation effects.

We next turn to our analysis of correct information – again, to assess whether the misinformation results stem from acquiescence bias, with particular respondents merely endorsing beliefs more often, regardless of their veracity. Figure 5 presents the predicted number of correct beliefs by groups, with 95% confidence intervals. It clearly shows that the above results reflect actual misinformation dynamics and not acquiescence bias. For instance, African Americans and Hispanics hold significantly fewer correct beliefs than Whites, while Asian-Americans do not differ from Whites. We see that more religious individuals hold significantly fewer correct beliefs; as partisan identity becomes stronger, the trend, albeit not statistically significant, is also toward fewer correct beliefs. Overall, it is clear that the group bases of

[14] The survey included another item about consuming news from media websites; when added to the model, this has a significant negative impact on misinformation but the social media variable remains significant. Thus is not simply proxy for on-line news consumption.

misinformation established above are authentic results and, in several cases, individuals from the same groups that hold higher numbers of misinformed beliefs also hold fewer correct beliefs.

[Insert Figures 5 and 6 About Here]

In Figure 6, we present results on the other variables, which reveal the same dynamics insofar as their effects on correct information are largely the inverse of their effects on misinformation. For example, exhibiting more depressive symptoms correlates with significantly less correct information, while social media use leads to a marginally significant increase in correct information. We also see watching Fox News connects with less correct information, as does stronger partisan social identity, although it is not statistically significant here. Again, we see little effect of the COVID-19 variables concerning cases, vulnerability, or having the disease.[15]

Conclusion

Misinformation about science is a major concern as it can undermine efforts for a healthy and productive society. Even small bits of misinformation can have deleterious effects. While scholars have put substantial efforts into studying the spread of misinformation on social media and ways to correct misperceptions, few have studied the correlates of misinformation. We did so in the case of COVID-19. We focused on group level variables, as they strike us as particularly meaningful – the mechanisms reflect relations, contextual situations, and/or belief systems. Further, information on group dynamics provides guidance on where to intervene.

[15] The appendix tables show a significant impact of cases for both misinformation and correct information, but the substantive effects are minuscule. Otherwise, when it comes to the control variables not presented here: the most consistent results are predictably that women, older individuals, and more educated individuals possess significantly fewer misinformed beliefs and significantly more correct beliefs. Watching Trump news conferences leads to more false beliefs but has no effect on correct beliefs, as does CNN (which jumps from 1.50 to 1.58; although MSNBC has no significant effect, so our Fox results are not simply capturing the effect of any cable television watching). More inter-personal discussion about COVID-19 and following COVID-19 information closely increases correct beliefs but has no effect on misinformation.

While we recognize limitations in our data – such as the use of a cross-sectional non-probability (but weighted) sample, and the possibility of incomplete selection of the specific misinformation stories on which we focused – our findings nonetheless offer some important insights that we hope stimulate scholarship on the group level correlates of misinformation. Specifically, we find that minorities, particularly African-Americans, exhibit significantly higher levels of misinformation and lower levels of correct information, relative to Whites. While the precise mechanism at work remains unclear, the finding itself is of immediate relevance in light of the disproportionate impact of COVID-19 on minority communities. As mentioned, other factors besides misinformation, such as living situation, work circumstances, and health conditions, largely explain the disproportionate impact; however, ensuring correct information can help ensure optimal steps are taken to deal with the high incidence in these populations. We also find that religiosity and partisan social identity – two measures of group affiliations – increase the likelihood of being misinformed. In these cases, we suspect a style of thinking that relies on empirical observation/science (for religiosity) and a need to identify with the group (for party) drives the findings. Of course, further work is needed to pinpoint the processes.

These findings provide guidance about which communities would most benefit from better information messaging. There are a host of challenges to implementing public health measures during the COVID-19 pandemic, ranging from the politicization of the virus to physical and social challenges. Misinformation about the virus itself adds to the hurdles; misinformation can impede adherence to closures, mask-wearing, and should it become available, the application of a vaccine. Clearly, public health policymakers, moving forward, need to account for factors like race/ethnicity, religiosity, and partisan identity to develop strategies to minimize the damages of misinformation.

References

Achen, C. H., & Bartels, L. M. (2017). *Democracy for realists: Why elections do not produce responsive government* (Vol. 4). Princeton University Press.

Allcott, H., Gentzkow, M., & Yu, C. (2019). Trends in the diffusion of misinformation on social media. *Research & Politics*, *6*(2), 2053168019848554.

Allum, N., Besley, J., Gomez, L., & Brunton-Smith, I. (2018). Science education disparities in science literacy. *Science*, *360*(6391), 861–862.

Beevers, C. G., Mullarkey, M. C., Dainer-Best, J., Stewart, R. A., Labrada, J., Allen, J., McGeary, J. E., & Shumake, J. (2019). Association between negative cognitive bias and depression: A symptom-level approach. *Journal of Abnormal Psychology*, *128*(3), 212–227.

Blank, J. M., & Shaw, D. (2015). Does partisanship shape attitudes toward science and public policy? The case for ideology and religion. *The ANNALS of the American Academy of Political and Social Science*, *658*(1), 18–35.

Bode, L., & Vraga, E. K. (2018). See something, say something: Correction of global health misinformation on social media. *Health Communication*, *33*(9), 1131–1140.

Brenes Peralta, C., Wojcieszak, M., Lelkes, Y., & Vreese, C. de. (2017). Selective exposure to balanced content and evidence type: The case of issue and non-issue publics about climate change and health care. *Journalism & Mass Communication Quarterly*, *94*(3), 833–861.

Cinelli, M., Quattrociocchi, W., Galeazzi, A., Valensise, C. M., Brugnoli, E., Schmidt, A. L., … Scala, A. (2020). The covid-19 social media infodemic. *arXiv Preprint arXiv:2003.05004*.

Dietz, T. (2013). Bringing values and deliberation to science communication. *Proceedings of the National Academy of Sciences*, *110*(Supplement 3), 14081–14087.

Druckman, J. N. (2012). The politics of motivation. *Critical Review*, *24*(2), 199–216.

Druckman, J. N., & Levendusky, M. S. (2019). What do we measure when we measure affective polarization? *Public Opinion Quarterly*, *83*(1), 114–122.

Flynn, D., Nyhan, B., & Reifler, J. (2017). The nature and origins of misperceptions: Understanding false and unsupported beliefs about politics. *Political Psychology*, *38*, 127–150.

Frenkel, S., Alba, D., & Zhong, R. (2020). Surge of virus misinformation stumps facebook and twitter. *The New York Times*.

Gauchat, G. (2012). Politicization of science in the public sphere: A study of public trust in the united states, 1974 to 2010. *American Sociological Review*, *77*(2), 167–187.

Grinberg, N., Joseph, K., Friedland, L., Swire-Thompson, B., & Lazer, D. (2019). Fake news on twitter during the 2016 us presidential election. *Science*, *363*(6425), 374–378.

Guess, A., Nagler, J., & Tucker, J. (2019). Less than you think: Prevalence and predictors of fake news dissemination on facebook. *Science Advances*, *5*(1), eaau4586.

Huddy, L., Mason, L., & Aarøe, L. (2015). Expressive partisanship: Campaign involvement, political emotion, and partisan identity. *American Political Science Review*, *109*(1), 1–17.

Hutchings, V. L. (2003). *Public opinion and democratic accountability: How citizens learn about politics*. Princeton University Press.

Jerit, J., & Zhao, Y. (2020). Political misinformation. *Annual Review of Political Science*, *23*, 77–94.

Kahan, D. M. 2015. Climate-science communication and the measurement problem. *Advances in Political Psychology, (S1)36,* 1-43.

Katz, V.S., Ang, A., & Suro, R. (2012). An ecological perspective on U.S. Latinos' health communication behaviors, access, and outcomes." *Hispanic Journal of Behavioral Sciences, 34 (3),* 437-456.

Kim, Y.C., Matsaganis, M.D., Wilkin, H.A., & Jung, J.Y. eds. 2018. *The communication ecology of 21st century urban communities*. New York, NY: Peter Lang Inc.

Krause, N. M., Freiling, I., Beets, B., & Brossard, D. (2020). Fact-checking as risk communication: The multi-layered risk of misinformation in times of covid-19. *Journal of Risk Research*, 1–8.

Kroenke, K., Spitzer, R. L., & Williams, J. B. (2001). The PHQ-9: validity of a brief depression severity measure. *Journal of General Internal Medicine*, *16*(9), 606–613.

Levy, J., Bayes, R., Bolsen, T. & Druckman, J. N. (N.d.). "Science and the politics of misinformation." In Tumber, H., & Waisbord, S., eds., *Routledge Companion to Media Misinformation & Populism*. New York: Routledge.

Li, H. O. Y., Bailey, A., Huynh, D., & Chan, J. (2020). YouTube as a source of information on covid-19: A pandemic of misinformation? *BMJ Global Health*, *5*(5), e002604.

Lupia, A. (2013). Communicating science in politicized environments. *Proceedings of the National Academy of Sciences*, *110*(Supplement 3), 14048–14054.

Motta, M., Stecula, D., & Farhart, C. (2020). How right-leaning media coverage of covid-19 facilitated the spread of misinformation in the early stages of the pandemic in the U.S. *Canadian Journal of Political Science/Revue Canadienne de Science Politique*, 1–8.

National Academies of Sciences, Engineering, and Medicine. 2016. *Science Literacy: Concepts, Contexts, and Consequences*. Washington, DC: National Academies Press.

Nyhan, B., & Reifler, J. (2010). When corrections fail: The persistence of political misperceptions. *Political Behavior*, *32*(2), 303–330.

Ognyanova, K., Perlis, R.H., Baum, M.A., Lazer, D., Druckman, J.N., Santillana, M., & Volpe, J.D. (2020). The state of the nation: A 50-state COVID-19 survey report #4. https://covidstates.net/COVID19%20CONSORTIUM%20REPORT%20JUNE%202020.pdf

Oliver, J. E., & Wood, T. J. (2018). *Enchanted america: How intuition and reason divide our politics*. University of Chicago Press.

Pennycook, G., McPhetres, J., Zhang, Y., Lu, J. G., & Rand, D. G. (2020). Fighting covid-19 misinformation on social media: Experimental evidence for a scalable accuracy-nudge intervention. *Psychological Science*, 0956797620939054.

Pennycook, G., & Rand, D. G. (2019). Fighting misinformation on social media using crowdsourced judgments of news source quality. *Proceedings of the National Academy of Sciences*, *116*(7), 2521–2526.

Plutzer, E. (2013). The racial gap in confidence in science: Explanations and implications. *Bulletin of Science, Technology & Society*, *33*(5-6), 146–157.

Ricard, J., & Medeiros, J. (2020). Using misinformation as a political weapon: COVID-19 and bolsonaro in brazil. *The Harvard Kennedy School Misinformation Review*.

Ripberger, J. T., Jenkins-Smith, H. C., Silva, C. L., Carlson, D. E., Gupta, K., Carlson, N., & Dunlap, R. E. (2017). Bayesian versus politically motivated reasoning in human perception of climate anomalies. *Environmental Research Letters*, *12*(11), 114004.

Scheufele, D. A., & Krause, N. M. (2019). Science audiences, misinformation, and fake news. *Proceedings of the National Academy of Sciences*, *116*(16), 7662–7669.

Sherkat, D. E. (2011). Religion and scientific literacy in the united states. *Social Science Quarterly, 92*(5), 1134-1150.

Simonov, A., Sacher, S. K., Dubé, J.-P. H., & Biswas, S. (2020). "The persuasive effect of fox news: Non-compliance with social distancing during the covid-19 pandemic." National Bureau of Economic Research.

Singh, L., Bansal, S., Bode, L., Budak, C., Chi, G., Kawintiranon, K., … Wang, Y. (2020). A first look at covid-19 information and misinformation sharing on twitter. *arXiv Preprint arXiv:2003.13907*.

Swire-Thompson, B., & Lazer, D. (2020). Public health and online misinformation: Challenges and recommendations. *Annual Review of Public Health*, *41*, 433–451.

Tomz, M., Wittenberg, J., & King, G. (2003). Clarify : Software for interpreting and presenting statistical results. *Journal of Statistical Software* 8 (1). https://doi.org/10.18637/jss.v008.i01.

Van Bavel, J. J., Baicker, K., Boggio, P. S., Capraro, V., Cichocka, A., Cikara, M., … others. (2020). Using social and behavioural science to support covid-19 pandemic response. *Nature Human Behaviour*, 1–12.

Walter, N., Ball-Rokeach, S.J., Xu, Y. & Broad, G.M. (2018). Communication ecologies: Analyzing adoption of false beliefs in an information-rich environment. *Science Communication*, *August,* 1-19.

Table 1: Outcome Variables

	Percentage Believe
Misinformation on Facts About COVID-19	
Only people older than 60 are at risk for coronavirus	20%
Mosquito bites can transmit coronavirus	6%
Coronavirus was created as a weapon in a Chinese lab	19%
Holding your breath for 10 seconds without coughing shows you do not have coronavirus	8%
President Trump shared plans to declare martial law	11%
Humans originally got coronavirus by eating bats	17%
Coronavirus is linked to the use of 5G wireless	4%
Average Count	.85 (std. dev.: 1.12)
Misinformation on Preventing COVID-19	
Flu vaccines	16%
Pneumonia vaccines	12%
Hot air hand dryers	16%
Taking antibiotics	15%
Rinsing your nose with saline	12%
Applying sesame oil to your skin	3%
Average Count	.73 (1.22)
Correct Information on Facts About COVID-19	
President Trump has declared a national emergency	66%
The coronavirus outbreak and measures taken against it caused a spike in unemployment numbers	88%
There is currently no vaccine against the coronavirus	80%
Average Count	2.34 (.82)
Correct Information on Preventing COVID-19	
Wearing a face mask	79%
Staying away from other people	91%
Washing your hands with soap	95%
Average Count	2.64 (.73)

Table 2: Independent Variables

Variable	Measure	Average (Std. Dev.) / Percentage
Group Variables		
Minority Status: African American, Hispanic, Asian-American	Dichotomous variables for racial/ethnic group.	African-American: 12% Hispanic: 15% Asian-American: 6%
Religiosity	6-point scale measuring how often attend religious services.	2.79 (1.72)
Partisanship (Republican)	7-point scale of partisan affiliation.	3.78 (2.11)
Partisan Social Identity	Average of 4 5-point scale items (alpha = .86) with higher scores indicating stronger partisan identity (Huddy et al. 2015)	3.27 (.91)
Comparison Point Control Variables		
Major depressive symptoms	Average of 9 4-point scale PHQ-9 items (alpha = .92) with higher scores indicating greater depressive symptom frequency/severity.	1.73 (.74)
Exposure to Fox News	Dichotomous variable for obtaining COVID-19 information from the network in the last 24 hours.	33%
COVID-19 Cases in County	Number of county COVID-19 cases.	557.09 (2627.65)
Had COVID-19	Dichotomous variable if believed had COVID-19.	12%
Vulnerable to COVID-19	Dichotomous variable indicating if a health conditions crates vulnerability to COVID-19.	18%
Other Control Variables		
Female	Dichotomous variable indicating if female.	52%
Age	Self-reported age.	46.50 (18.08)
Education	7-point scale from low to high education.	2.97 (1.15)
Rural Setting	6-point scale indicating extent of rural-ness (using the Center for Disease Control's urban-rural county classification scheme).	2.82 (1.54)
COVID-19 Information	4-point scale indicating closeness of following COVID-19 news.	3.15 (.79)
Discussion on COVID-19	6-point scale indicating how often talk about COVID-19.	4.13 (1.33)
Networks: CNN, MSNBC	Dichotomous variables for obtaining COVID-19 information	CNN: 34% MSNBC: 17%

	from each network in the last 24 hours.	
Trump Press Briefing	Dichotomous variables for obtaining COVID-19 information from Trump's press briefing in the last 24 hours.	22%
Social Media	Dichotomous variables for obtaining COVID-19 information from social media website or mobile instant message app in the last 24 hours.	46%

Figure 1: Distribution of Misinformation

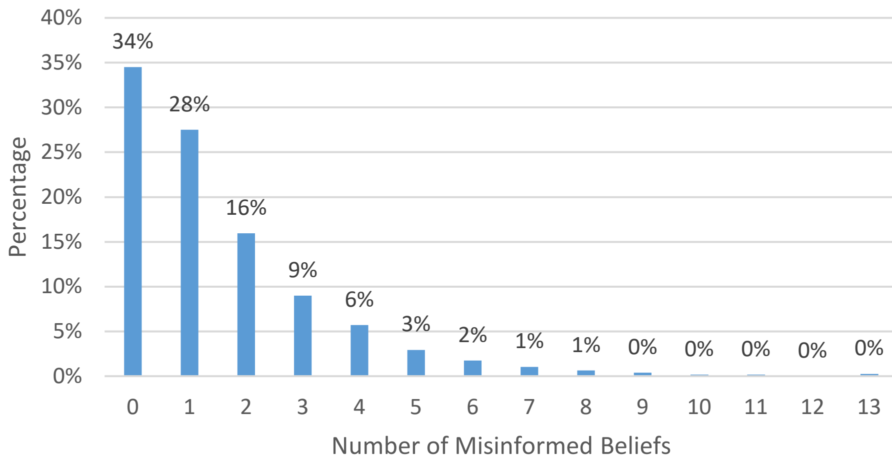
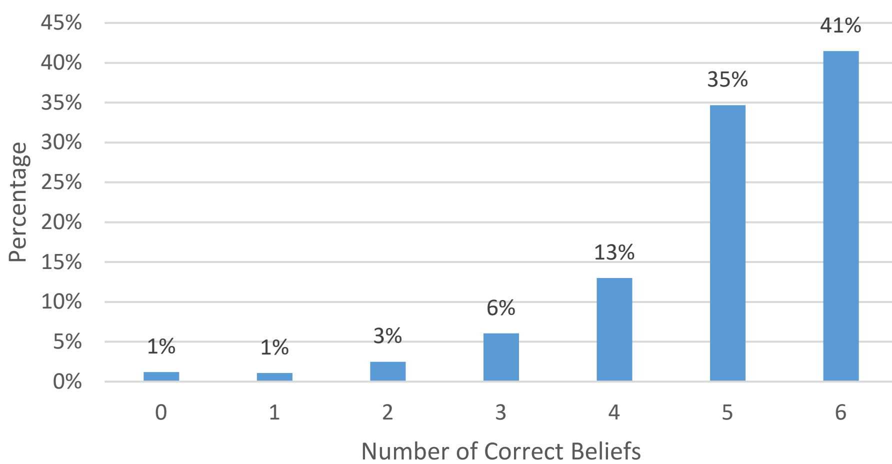


Figure 2: Distribution of Correct Information



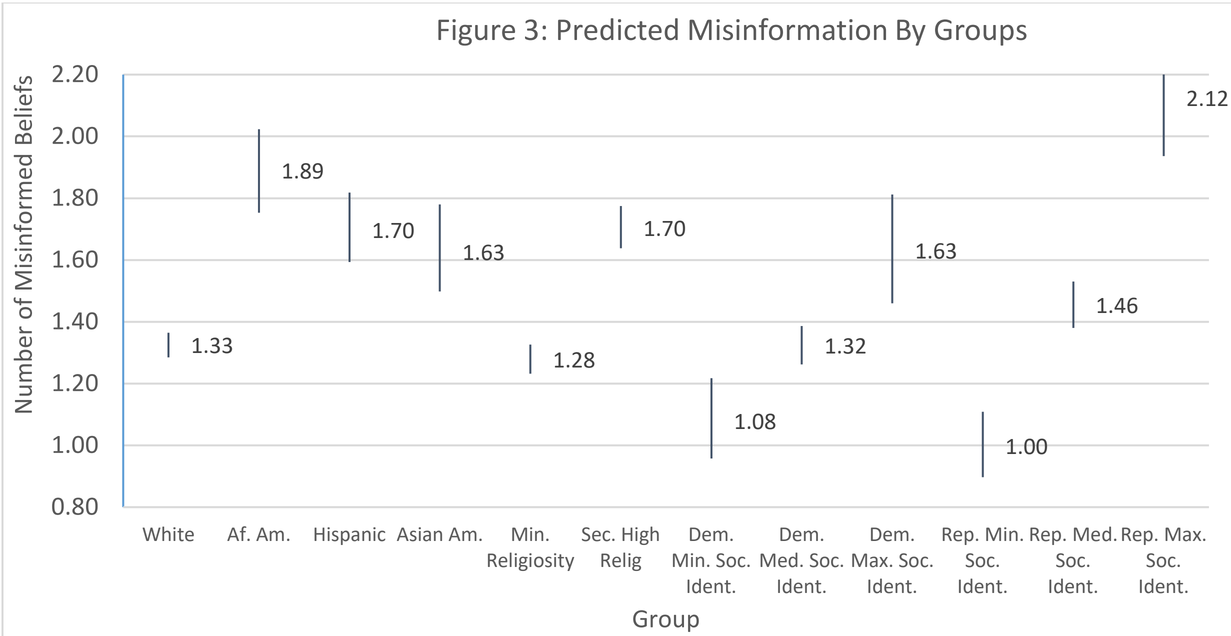


Figure 3: Predicted Misinformation By Groups
Number of Misinformed Beliefs
2.20
2.00
1.80
1.60
1.40
1.20
1.00
0.80
1.33
1.89
1.70
1.63
1.28
1.70
1.08
1.32
1.63
1.00
1.46
2.12
White
Af. Am.
Hispanic
Asian Am.
Min. Religiosity
Sec. High Relig
Dem. Min. Soc. Ident.
Dem. Med. Soc. Ident.
Dem. Max. Soc. Ident.
Rep. Min. Soc. Ident.
Rep. Med. Soc. Ident.
Rep. Max. Soc. Ident.
Group

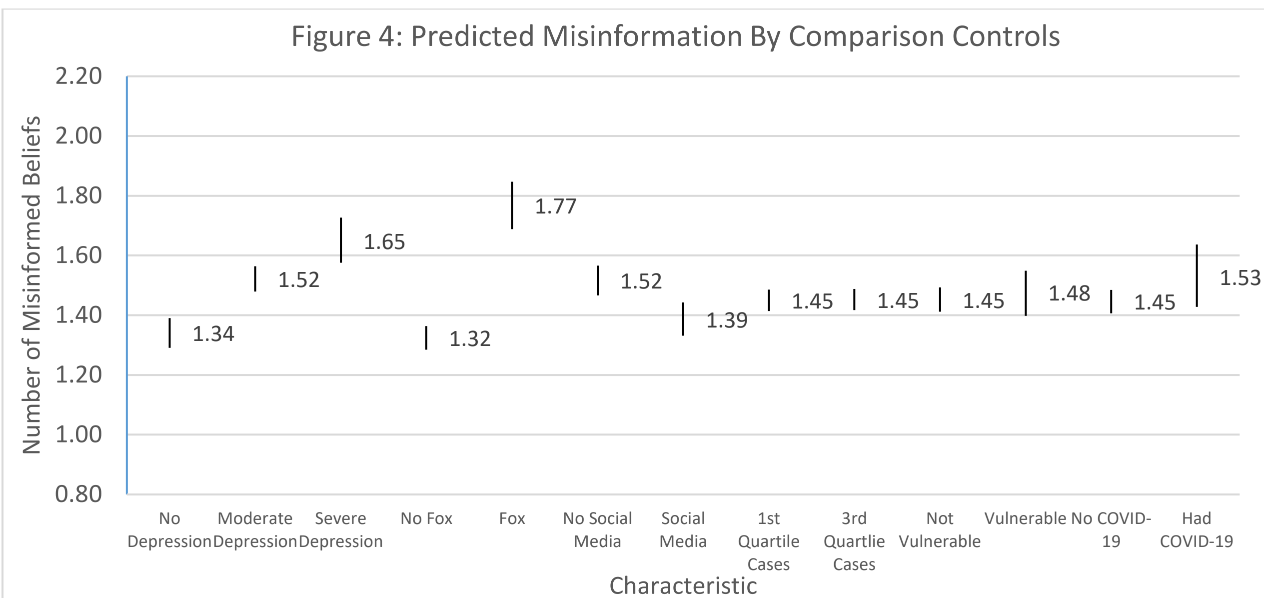


Figure 4: Predicted Misinformation By Comparison Controls
Number of Misinformed Beliefs
2.20
2.00
1.80
1.60
1.40
1.20
1.00
0.80
1.34
1.52
1.65
1.32
1.77
1.52
1.39
1.45
1.45
1.45
1.48
1.45
1.53
No Depression
Moderate Depression
Severe Depression
No Fox
Fox
No Social Media
Social Media
1st Quartile Cases
3rd Quartlie Cases
Not Vulnerable
Vulnerable
No COVID-19
Had COVID-19
Characteristic

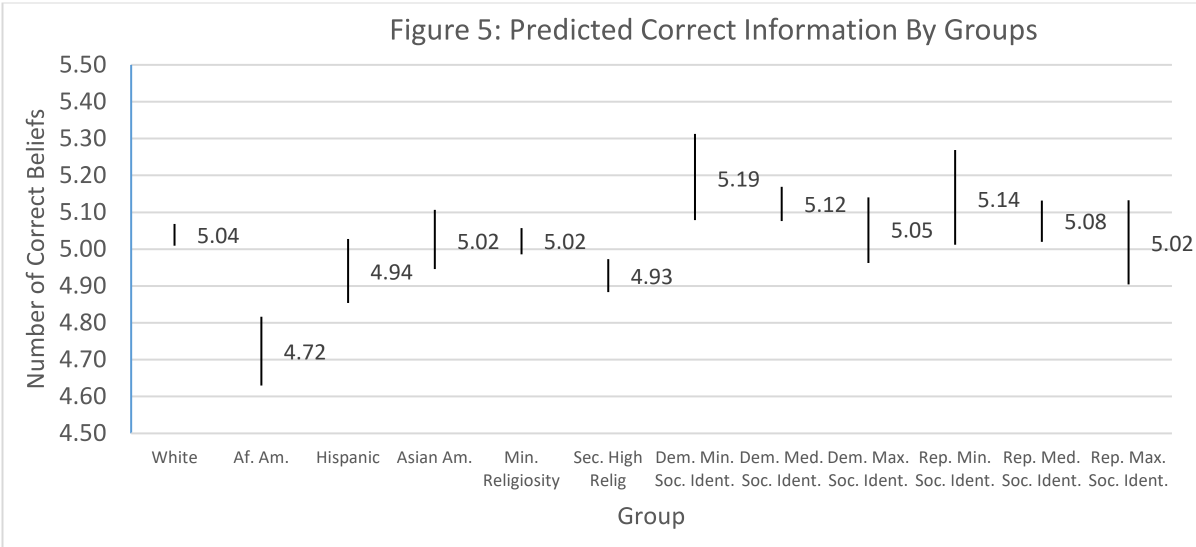


Figure 5: Predicted Correct Information By Groups
Number of Correct Beliefs
5.50
5.40
5.30
5.20
5.10
5.00
4.90
4.80
4.70
4.60
4.50
5.04
4.72
4.94
5.02
5.02
4.93
5.19
5.12
5.05
5.14
5.08
5.02
White
Af. Am.
Hispanic
Asian Am.
Min. Religiosity
Sec. High Relig
Dem. Min. Soc. Ident.
Dem. Med. Soc. Ident.
Dem. Max. Soc. Ident.
Rep. Min. Soc. Ident.
Rep. Med. Soc. Ident.
Rep. Max. Soc. Ident.
Group

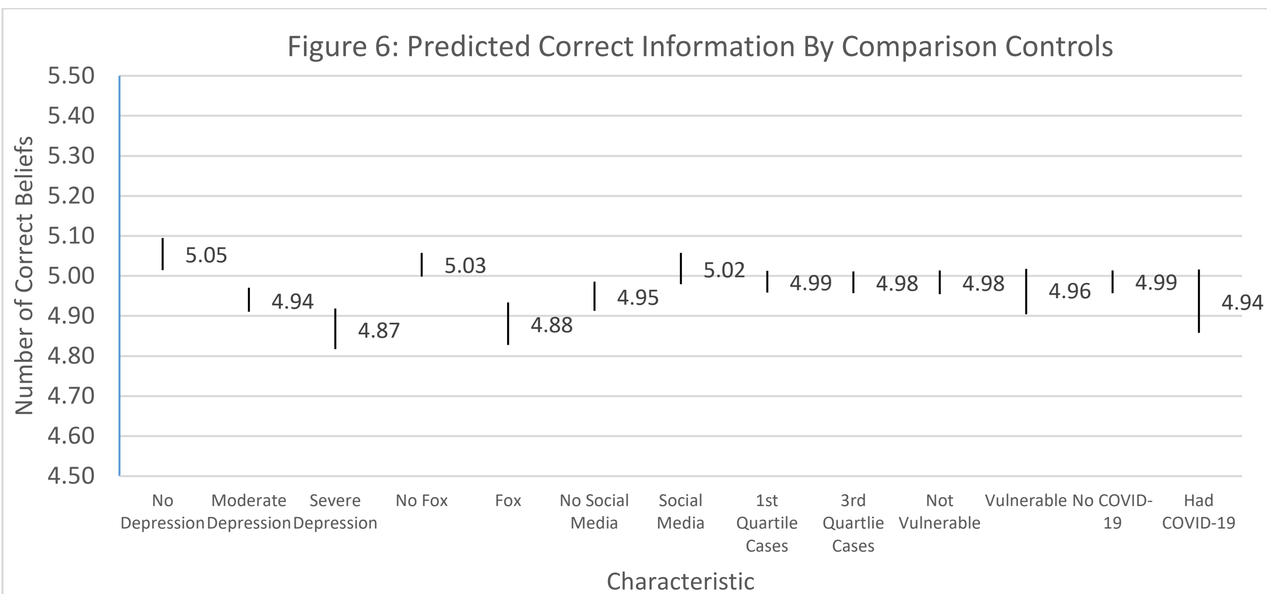


Figure 6: Predicted Correct Information By Comparison Controls
Number of Correct Beliefs
5.50
5.40
5.30
5.20
5.10
5.00
4.90
4.80
4.70
4.60
4.50
5.05
4.94
4.87
5.03
4.88
4.95
5.02
4.99
4.98
4.98
4.96
4.99
4.94
No Depression
Moderate Depression
Severe Depression
No Fox
Fox
No Social Media
Social Media
1st Quartile Cases
3rd Quartlie Cases
Not Vulnerable
Vulnerable
No COVID-19
Had COVID-19
Characteristic

Appendix

All models cluster the standard errors based on county. The results are robust to including state fixed effects, although we do not present those models here (partially because they did not always converge when using *Clarify* to arrive at the predicted values reported in the text). With the exception of the partisan variables, Figures 3-6 come from the models in Table A-1.Table A-2 (and A-7) look at the distinct modules while Tables A-3, A-4, and A-5 look at the particular items.

Tables A-6 to A-10 look at the impact of partisanship as a social identity (i.e., the partisan effects displayed in Figures 3 and 5 come from A-6). As noted in the text, these models exclude pure Independents, as is typical in the literature (Druckman and Levendusky 2019). Tables A-11 and A-12 replicate the main result tables (Tables A-1 and A-6) but using the 3 point scales that incorporate the "not sure" response options (see note in the paper). The main change for the results is that only Republicans exhibit significantly greater misinformation with increased social identity (and increased social identity across parties leads to less accurate information).

All significance tests in the tables are two-tailed.

Table A-1: Misinformation and Correct Information Regressions for Figures 3 - 6

	(1) Misinfo	(2) Correct Info
Partisanship (Republican)	0.030***	-0.002
	(0.008)	(0.001)
Rural	0.005	0.001
	(0.009)	(0.002)
Female	-0.057**	0.022***
	(0.026)	(0.006)
African-American	0.353***	-0.065***
	(0.042)	(0.011)
Hispanic	0.246***	-0.020**
	(0.040)	(0.009)
Asian-American	0.204***	-0.003
	(0.047)	(0.009)
Other Race/Ethnicity	0.003	-0.045**
	(0.136)	(0.019)
Age	-0.007***	0.001***
	(0.001)	(0.000)
Education	-0.074***	0.019***
	(0.014)	(0.003)
Religiosity	0.072***	-0.005***
	(0.008)	(0.002)
Mental Health	0.111***	-0.020***
(Depression)	(0.019)	(0.004)
Had COVID-19	0.053	-0.010
	(0.038)	(0.008)
Vulnerable to	0.015	-0.004
COVID-19	(0.032)	(0.006)
COVID-19 Cases	0.000**	-0.000*
In County	(0.000)	(0.000)
COVID-19 Information	0.033	0.057***
	(0.021)	(0.004)
Discussion on	-0.001	0.014***
COVID-19	(0.011)	(0.002)
Fox News	0.289***	-0.030***
	(0.028)	(0.006)
CNN	0.052*	0.002
	(0.031)	(0.006)
MSNBC	0.013	-0.002
	(0.038)	(0.007)
Trump Press Briefings	0.111***	0.010
	(0.029)	(0.006)
Social Media	-0.091***	0.014**
	(0.027)	(0.005)
Constant	0.137	1.320***
	(0.099)	(0.025)
Observations	15,910	16,140

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A-2: Separate Regressions for Accurately Identifying Ineffective Antidotes, Incorrect Facts, Effective Antidotes and Correct Facts

	(1) Not Effective	(2) Wrong Info	(3) Effective	(4) Correct Info
Partisanship (Republican)	0.024**	0.036***	-0.013***	0.010***
	(0.010)	(0.009)	(0.002)	(0.002)
Rural	0.008	0.006	-0.003	0.006**
	(0.012)	(0.010)	(0.002)	(0.003)
Female	-0.054	-0.068**	0.023***	0.022***
	(0.036)	(0.027)	(0.006)	(0.008)
African-American	0.471***	0.243***	-0.035***	-0.107***
	(0.057)	(0.044)	(0.013)	(0.015)
Hispanic	0.353***	0.156***	0.014	-0.061***
	(0.055)	(0.045)	(0.010)	(0.013)
Asian-American	0.303***	0.106**	0.020**	-0.032**
	(0.073)	(0.044)	(0.009)	(0.013)
Other Race/Ethnicity	0.020	-0.030	-0.033*	-0.060*
	(0.140)	(0.154)	(0.019)	(0.031)
Age	-0.004***	-0.010***	0.001***	0.001***
	(0.001)	(0.001)	(0.000)	(0.000)
Education	-0.068***	-0.078***	0.012***	0.027***
	(0.018)	(0.014)	(0.003)	(0.004)
Religiosity	0.080***	0.063***	-0.003*	-0.007***
	(0.010)	(0.008)	(0.002)	(0.002)
Mental Health	0.117***	0.129***	-0.012**	-0.033***
(Depression)	(0.028)	(0.020)	(0.005)	(0.005)
Had COVID-19	0.049	0.054	-0.044***	0.025**
	(0.052)	(0.038)	(0.009)	(0.011)
Vulnerable to	0.088*	-0.039	-0.006	0.000
COVID-19	(0.046)	(0.033)	(0.007)	(0.009)
COVID-19 Cases	0.000***	0.000	-0.000	-0.000*
In County	(0.000)	(0.000)	(0.000)	(0.000)
COVID-19 Information	0.039	0.011	0.055***	0.057***
	(0.031)	(0.021)	(0.005)	(0.006)
Discussion on	-0.018	0.013	0.010***	0.019***
COVID-19	(0.017)	(0.012)	(0.003)	(0.003)
Fox News	0.346***	0.241***	-0.036***	-0.022***
	(0.039)	(0.031)	(0.007)	(0.009)
CNN	0.094**	0.030	0.017***	-0.014
	(0.044)	(0.033)	(0.007)	(0.009)
MSNBC	0.053	-0.040	0.010	-0.014
	(0.050)	(0.045)	(0.007)	(0.010)
Trump Press Briefings	0.121***	0.116***	-0.005	0.026***
	(0.043)	(0.031)	(0.007)	(0.009)
Social Media	-0.089**	-0.099***	0.004	0.024***
	(0.039)	(0.029)	(0.006)	(0.007)
Constant	-0.863***	-0.291***	0.760***	0.487***
	(0.142)	(0.107)	(0.030)	(0.031)
Observations	16,152	16,232	16,306	16,321

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A-3: Item by Item Misinformation (Facts) Regressions

	(1) Older	(2) Mosquito	(3) China	(4) Tensec	(5) Martial	(6) Bats	(7) Wireless
Partisanship (Republican)	0.031**	0.006	0.200***	0.001	-0.030	-0.012	0.029
	(0.016)	(0.026)	(0.018)	(0.027)	(0.019)	(0.017)	(0.032)
Rural	-0.011	-0.007	0.077***	-0.014	0.030	-0.017	-0.087**
	(0.020)	(0.031)	(0.019)	(0.033)	(0.024)	(0.020)	(0.039)
Female	-0.102*	-0.393***	0.030	-0.056	-0.028	-0.178***	-0.093
	(0.052)	(0.091)	(0.058)	(0.078)	(0.071)	(0.052)	(0.106)
African-American	0.079	0.629***	0.492***	0.562***	0.282***	-0.116	0.805***
	(0.087)	(0.127)	(0.094)	(0.133)	(0.102)	(0.091)	(0.154)
Hispanic	0.126	0.380**	0.295***	0.290**	0.104	0.014	0.628***
	(0.088)	(0.148)	(0.095)	(0.117)	(0.111)	(0.088)	(0.163)
Asian-American	0.099	0.191	0.061	0.347**	0.264**	0.059	-0.056
	(0.102)	(0.173)	(0.111)	(0.140)	(0.132)	(0.096)	(0.194)
Other Race/Ethnicity	-0.134	-0.022	0.255	-0.182	0.019	-0.397*	0.491
	(0.188)	(0.338)	(0.181)	(0.390)	(0.241)	(0.203)	(0.354)
Age	-0.008***	-0.025***	0.002	-0.010***	-0.008***	-0.027***	-0.020***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.004)
Education	-0.068***	-0.207***	-0.209***	-0.118***	-0.070**	0.029	-0.076
	(0.026)	(0.048)	(0.031)	(0.042)	(0.033)	(0.025)	(0.050)
Religiosity	0.051***	0.087***	0.075***	0.164***	0.070***	0.045***	0.166***
	(0.016)	(0.028)	(0.017)	(0.024)	(0.021)	(0.016)	(0.033)
Mental Health	0.047	0.415***	0.157***	0.112**	0.236***	0.117***	0.386***
(Depression)	(0.034)	(0.064)	(0.042)	(0.052)	(0.048)	(0.036)	(0.068)
Had COVID-19	0.048	-0.118	0.082	0.066	0.153*	0.056	0.229*
	(0.082)	(0.123)	(0.086)	(0.115)	(0.092)	(0.074)	(0.130)
Vulnerable to	-0.066	0.250**	0.024	-0.135	-0.169*	-0.060	0.015
COVID-19	(0.066)	(0.109)	(0.077)	(0.109)	(0.091)	(0.070)	(0.134)
COVID-19 Cases	-0.000	0.000	-0.000	0.000	-0.000	0.000	0.000
In County	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
COVID-19 Information	0.079*	0.087	-0.049	-0.049	-0.015	0.031	-0.173**
	(0.040)	(0.066)	(0.041)	(0.061)	(0.051)	(0.038)	(0.076)
Discussion on	-0.009	-0.006	-0.016	-0.007	0.051*	0.064***	0.033
COVID-19	(0.022)	(0.042)	(0.026)	(0.037)	(0.030)	(0.024)	(0.051)
Fox News	0.171***	0.374***	0.455***	0.465***	0.168**	0.083	0.732***
	(0.060)	(0.101)	(0.062)	(0.091)	(0.072)	(0.060)	(0.113)
CNN	0.112*	0.108	-0.209***	0.282***	-0.014	0.113*	-0.105
	(0.061)	(0.110)	(0.074)	(0.099)	(0.078)	(0.060)	(0.129)
MSNBC	-0.095	0.095	-0.310***	-0.128	0.049	0.083	0.099
	(0.082)	(0.127)	(0.098)	(0.118)	(0.098)	(0.076)	(0.159)
Trump Press Briefings	0.065	-0.058	0.398***	0.030	0.296***	-0.113*	0.225*
	(0.069)	(0.110)	(0.063)	(0.097)	(0.083)	(0.067)	(0.121)
Social Media	-0.135**	-0.344***	-0.006	-0.066	-0.225***	-0.005	-0.404***
	(0.054)	(0.100)	(0.062)	(0.090)	(0.073)	(0.053)	(0.114)
Constant	-1.370***	-2.410***	-2.582***	-2.566***	-2.379***	-1.095***	-3.211***
	(0.198)	(0.354)	(0.219)	(0.301)	(0.247)	(0.208)	(0.377)
Observations	16,459	16,423	16,440	16,459	16,427	16,444	16,460

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A-4: Item by Item Misinformation (Antidotes) Regressions

	(1) Fluvacc	(2) Peneum	(3) Hotair	(4) Antibio	(5) Saline	(6) Sesame
Partisanship (Republican)	-0.001	0.032	0.052***	0.036*	0.015	0.018
	(0.018)	(0.021)	(0.016)	(0.020)	(0.019)	(0.032)
Rural	0.008	-0.018	0.037*	0.025	0.008	-0.116**
	(0.020)	(0.024)	(0.020)	(0.023)	(0.022)	(0.047)
Female	-0.020	0.123*	-0.084	-0.155**	-0.081	-0.392***
	(0.060)	(0.068)	(0.061)	(0.068)	(0.066)	(0.132)
African-American	0.542***	0.651***	0.499***	0.722***	0.214**	0.783***
	(0.095)	(0.104)	(0.098)	(0.092)	(0.109)	(0.182)
Hispanic	0.519***	0.386***	0.343***	0.505***	0.246**	0.263
	(0.093)	(0.104)	(0.094)	(0.098)	(0.111)	(0.209)
Asian-American	0.667***	0.249*	-0.012	0.454***	0.319**	0.192
	(0.121)	(0.142)	(0.094)	(0.135)	(0.129)	(0.193)
Other Race/Ethnicity	0.006	0.101	-0.008	-0.225	0.024	0.424
	(0.219)	(0.262)	(0.197)	(0.211)	(0.268)	(0.493)
Age	-0.002	-0.002	-0.001	-0.020***	0.005*	-0.021***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.005)
Education	-0.095***	-0.079**	-0.063**	-0.127***	-0.014	-0.150**
	(0.032)	(0.034)	(0.028)	(0.032)	(0.034)	(0.071)
Religiosity	0.072***	0.075***	0.078***	0.111***	0.112***	0.192***
	(0.019)	(0.020)	(0.015)	(0.019)	(0.019)	(0.038)
Mental Health	0.128***	0.145***	0.150***	0.107**	0.144***	0.298***
(Depression)	(0.046)	(0.049)	(0.039)	(0.046)	(0.052)	(0.109)
Had COVID-19	-0.013	-0.022	0.111	0.017	0.159	0.068
	(0.083)	(0.100)	(0.075)	(0.101)	(0.107)	(0.178)
Vulnerable to	0.038	0.243***	0.041	0.147*	0.165*	0.046
COVID-19	(0.077)	(0.083)	(0.074)	(0.077)	(0.089)	(0.177)
COVID-19 Cases	0.000	-0.000	0.000	0.000**	0.000***	0.000
In County	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
COVID-19 Information	0.073	0.115**	-0.003	0.059	-0.005	0.107
	(0.045)	(0.056)	(0.044)	(0.048)	(0.060)	(0.125)
Discussion on	-0.074***	-0.046	0.023	-0.059**	0.038	0.038
COVID-19	(0.027)	(0.032)	(0.025)	(0.029)	(0.033)	(0.068)
Fox News	0.411***	0.445***	0.283***	0.498***	0.396***	0.750***
	(0.071)	(0.077)	(0.065)	(0.068)	(0.076)	(0.141)
CNN	0.163**	0.170**	0.030	0.053	0.177**	0.202
	(0.065)	(0.078)	(0.071)	(0.076)	(0.084)	(0.156)
MSNBC	0.115	0.014	0.039	0.007	0.090	0.118
	(0.083)	(0.099)	(0.083)	(0.091)	(0.090)	(0.176)
Trump Press Briefings	0.140*	0.135	0.070	0.250***	0.159*	-0.064
	(0.073)	(0.082)	(0.068)	(0.070)	(0.082)	(0.173)
Social Media	-0.106	-0.223***	-0.049	-0.086	-0.024	-0.567***
	(0.065)	(0.074)	(0.060)	(0.064)	(0.076)	(0.142)
Constant	-2.118***	-2.909***	-2.512***	-1.547***	-3.410***	-3.748***
	(0.240)	(0.240)	(0.252)	(0.240)	(0.297)	(0.623)
Observations	16,379	16,385	16,383	16,373	16,370	16,381

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A-5: Item by Item Correct Information (Facts and Antidotes) Regressions

	(1) Nat Emerg	(2) Unemploy	(3) No Vac	(4) Face Mask	(5) Stay Away	(6) Wash Hands
Partisanship (Republican)	0.147***	-0.010	-0.044***	-0.187***	-0.101***	-0.020
	(0.013)	(0.020)	(0.016)	(0.015)	(0.021)	(0.031)
Rural	0.038**	0.057**	-0.013	-0.050***	-0.019	0.018
	(0.017)	(0.024)	(0.019)	(0.019)	(0.027)	(0.039)
Female	0.082*	0.150**	0.119**	0.102**	0.328***	0.461***
	(0.047)	(0.071)	(0.057)	(0.052)	(0.077)	(0.105)
African-American	-0.197***	-0.623***	-0.792***	-0.127	-0.520***	-0.676***
	(0.073)	(0.100)	(0.088)	(0.102)	(0.131)	(0.164)
Hispanic	-0.249***	-0.400***	-0.263***	0.200**	0.049	-0.011
	(0.076)	(0.097)	(0.090)	(0.095)	(0.139)	(0.170)
Asian-American	-0.138	-0.315***	-0.119	0.328***	0.147	-0.172
	(0.086)	(0.109)	(0.097)	(0.122)	(0.154)	(0.161)
Other Race/Ethnicity	-0.422***	-0.170	-0.170	-0.183	-0.545**	-0.136
	(0.154)	(0.206)	(0.196)	(0.172)	(0.218)	(0.290)
Age	-0.004**	0.016***	0.015***	0.012***	0.009***	0.008**
	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)	(0.004)
Education	0.022	0.150***	0.309***	0.061**	0.166***	0.234***
	(0.023)	(0.034)	(0.031)	(0.029)	(0.041)	(0.056)
Religiosity	-0.008	-0.040*	-0.064***	-0.009	-0.080***	-0.038
	(0.012)	(0.021)	(0.016)	(0.016)	(0.022)	(0.034)
Mental Health	-0.141***	-0.103**	-0.210***	-0.075*	-0.107*	-0.266***
(Depression)	(0.032)	(0.045)	(0.038)	(0.039)	(0.055)	(0.074)
Had COVID-19	0.190***	0.039	0.056	-0.399***	-0.377***	-0.361***
	(0.067)	(0.101)	(0.086)	(0.072)	(0.107)	(0.132)
Vulnerable to	0.035	-0.010	-0.045	-0.013	-0.057	-0.232*
COVID-19	(0.056)	(0.095)	(0.067)	(0.065)	(0.099)	(0.126)
COVID-19 Cases	-0.000	-0.000**	-0.000	0.000	-0.000***	-0.000
In County	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
COVID-19 Information	0.226***	0.252***	0.353***	0.420***	0.504***	0.414***
	(0.031)	(0.049)	(0.040)	(0.039)	(0.054)	(0.069)
Discussion on	0.069***	0.123***	0.088***	0.066***	0.112***	0.097**
COVID-19	(0.019)	(0.028)	(0.023)	(0.021)	(0.032)	(0.042)
Fox News	0.209***	-0.258***	-0.444***	-0.214***	-0.548***	-0.484***
	(0.054)	(0.075)	(0.062)	(0.061)	(0.080)	(0.115)
CNN	-0.104*	-0.201**	0.079	0.299***	0.259**	-0.060
	(0.053)	(0.081)	(0.067)	(0.065)	(0.103)	(0.126)
MSNBC	-0.212***	-0.096	0.217**	0.242***	0.097	0.355**
	(0.063)	(0.100)	(0.088)	(0.086)	(0.135)	(0.173)
Trump Press Briefings	0.321***	0.167*	-0.142*	-0.106*	-0.071	0.228
	(0.059)	(0.087)	(0.072)	(0.058)	(0.088)	(0.147)
Social Media	0.088**	0.403***	0.000	-0.120**	0.026	0.528***
	(0.044)	(0.072)	(0.059)	(0.053)	(0.082)	(0.117)
Constant	-0.675***	-0.161	-0.547***	0.118	0.446	0.769*
	(0.161)	(0.236)	(0.201)	(0.193)	(0.300)	(0.429)
Observations	16,425	16,427	16,436	16,410	16,409	16,410

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A-6: Misinformation and Correct Information Regressions for Figures 3 and 5 (Partisans)

	(1) Misinfo	(2) Correct Info
Republican (Dummy)	-0.164	-0.011
	(0.113)	(0.023)
Partisan Social Identity	0.103***	-0.007
	(0.027)	(0.005)
Rep. * Partisan Soc.	0.086**	0.001
Identity	(0.034)	(0.007)
Rural	0.005	0.002
	(0.011)	(0.002)
Female	-0.084***	0.027***
	(0.032)	(0.007)
African-American	0.337***	-0.059***
	(0.052)	(0.012)
Hispanic	0.267***	-0.020*
	(0.053)	(0.012)
Asian-American	0.245***	0.006
	(0.060)	(0.011)
Other Race/Ethnicity	0.228	-0.041*
	(0.223)	(0.023)
Age	-0.008***	0.001***
	(0.001)	(0.000)
Education	-0.052***	0.010***
	(0.015)	(0.003)
Religiosity	0.069***	-0.008***
	(0.009)	(0.002)
Mental Health	0.131***	-0.032***
(Depression)	(0.022)	(0.005)
Had COVID-19	0.038	-0.016
	(0.041)	(0.011)
Vulnerable to	0.000	-0.002
COVID-19	(0.040)	(0.007)
COVID-19 Cases	0.000**	-0.000
In County	(0.000)	(0.000)
COVID-19 Information	-0.010	0.055***
	(0.026)	(0.005)
Discussion on	-0.008	0.010***
COVID-19	(0.015)	(0.002)
Fox News	0.323***	-0.028***
	(0.036)	(0.007)
CNN	0.068*	-0.001
	(0.036)	(0.007)
MSNBC	-0.007	-0.007
	(0.050)	(0.008)
Trump Press Briefings	0.096***	0.006
	(0.035)	(0.007)
Social Media	-0.095***	0.015**
	(0.032)	(0.006)
Constant	0.009	1.437***
	(0.136)	(0.033)
Observations	10,038	10,157

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A-7:
Separate Regressions for Accurately Identifying Ineffective Antidotes, Incorrect Facts, Effective Antidotes and Correct Facts (Partisans)

	(1) Misinfo	(2) Not Effective	(3) Correct Info	(4) Effective Info
Republican (Dummy)	-0.203	-0.142	-0.029	0.006
	(0.128)	(0.155)	(0.033)	(0.027)
Partisan Social Identity	0.088***	0.118***	-0.020***	0.006
	(0.030)	(0.035)	(0.007)	(0.004)
Rep. * Partisan Soc.	0.111***	0.069	0.026***	-0.023***
Identity	(0.039)	(0.047)	(0.010)	(0.008)
Rural	0.012	-0.001	0.005	-0.001
	(0.011)	(0.015)	(0.003)	(0.003)
Female	-0.081**	-0.091**	0.035***	0.020***
	(0.033)	(0.045)	(0.009)	(0.007)
African-American	0.262***	0.415***	-0.095***	-0.036***
	(0.057)	(0.067)	(0.018)	(0.012)
Hispanic	0.192***	0.336***	-0.049***	0.003
	(0.056)	(0.068)	(0.017)	(0.012)
Asian-American	0.149**	0.343***	-0.012	0.022**
	(0.059)	(0.090)	(0.017)	(0.011)
Other Race/Ethnicity	0.259	0.166	-0.042	-0.038
	(0.239)	(0.218)	(0.041)	(0.025)
Age	-0.010***	-0.006***	0.001**	0.001**
	(0.001)	(0.002)	(0.000)	(0.000)
Education	-0.065***	-0.036*	0.017***	0.005
	(0.017)	(0.021)	(0.005)	(0.004)
Religiosity	0.050***	0.085***	-0.011***	-0.006**
	(0.011)	(0.012)	(0.003)	(0.002)
Mental Health	0.152***	0.129***	-0.042***	-0.026***
(Depression)	(0.023)	(0.033)	(0.006)	(0.006)
Had COVID-19	0.047	0.033	0.014	-0.046***
	(0.045)	(0.053)	(0.013)	(0.013)
Vulnerable to	-0.082**	0.119**	-0.003	-0.001
COVID-19	(0.042)	(0.057)	(0.011)	(0.008)
COVID-19 Cases	0.000	0.000***	-0.000	-0.000
In County	(0.000)	(0.000)	(0.000)	(0.000)
COVID-19 Information	-0.051*	0.016	0.056***	0.053***
	(0.027)	(0.038)	(0.007)	(0.006)
Discussion on	0.020	-0.043**	0.014***	0.006**
COVID-19	(0.017)	(0.020)	(0.004)	(0.003)
Fox News	0.287***	0.357***	-0.022**	-0.033***
	(0.036)	(0.050)	(0.010)	(0.008)
CNN	0.053	0.116**	-0.010	0.009
	(0.040)	(0.050)	(0.010)	(0.008)
MSNBC	-0.060	0.033	-0.018	0.006
	(0.054)	(0.065)	(0.013)	(0.009)
Trump Press Briefings	0.093**	0.121**	0.021*	-0.008
	(0.037)	(0.051)	(0.011)	(0.008)
Social Media	-0.104***	-0.096**	0.025***	0.007
	(0.035)	(0.045)	(0.008)	(0.007)
Constant	-0.364***	-1.010***	0.670***	0.815***
	(0.141)	(0.186)	(0.042)	(0.034)

Observations	10,218	10,180	10,264	10,255

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A-8: Item by Item Misinformation (Facts) Regressions (Partisans)

	(1) Older	(2) Mosquito	(3) China	(4) Tensec	(5) Martial	(6) Bats	(7) Wireless
Republican (Dummy)	-0.128	0.577	-0.468	-0.640	-0.654**	0.224	0.100
	(0.232)	(0.425)	(0.287)	(0.417)	(0.306)	(0.255)	(0.556)
Partisan Social Identity	0.111**	0.270***	0.085	0.053	0.104	0.058	0.222**
	(0.049)	(0.085)	(0.072)	(0.095)	(0.067)	(0.053)	(0.103)
Rep. * Partisan Soc.	0.104	-0.180	0.421***	0.178	0.135	-0.079	0.004
Identity	(0.072)	(0.128)	(0.088)	(0.124)	(0.091)	(0.080)	(0.164)
Rural	0.006	0.040	0.081***	-0.027	0.009	0.003	-0.127**
	(0.024)	(0.038)	(0.024)	(0.038)	(0.031)	(0.025)	(0.053)
Female	-0.092	-0.363***	-0.048	-0.129	-0.030	-0.173***	-0.048
	(0.065)	(0.121)	(0.074)	(0.101)	(0.088)	(0.067)	(0.142)
African-American	0.111	0.585***	0.573***	0.599***	0.214	-0.027	0.722***
	(0.113)	(0.169)	(0.122)	(0.161)	(0.131)	(0.117)	(0.189)
Hispanic	0.156	0.444**	0.403***	0.135	0.210	0.019	0.630***
	(0.106)	(0.197)	(0.123)	(0.154)	(0.147)	(0.116)	(0.202)
Asian-American	0.211*	0.325	0.259*	0.324*	0.058	0.085	-0.172
	(0.127)	(0.202)	(0.140)	(0.172)	(0.178)	(0.118)	(0.243)
Other Race/Ethnicity	0.044	0.328	0.678**	0.313	0.256	0.036	0.966**
	(0.364)	(0.479)	(0.274)	(0.504)	(0.374)	(0.308)	(0.460)
Age	-0.009***	-0.023***	-0.002	-0.011***	-0.008***	-0.026***	-0.021***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.006)
Education	-0.046	-0.190***	-0.216***	-0.107**	-0.033	0.038	-0.057
	(0.033)	(0.060)	(0.039)	(0.049)	(0.041)	(0.033)	(0.062)
Religiosity	0.024	0.067*	0.068***	0.133***	0.095***	0.025	0.161***
	(0.020)	(0.037)	(0.023)	(0.030)	(0.026)	(0.022)	(0.042)
Mental Health	0.068	0.534***	0.216***	0.170**	0.244***	0.108**	0.393***
(Depression)	(0.045)	(0.078)	(0.051)	(0.069)	(0.058)	(0.045)	(0.082)
Had COVID-19	0.061	-0.153	0.005	0.146	0.189*	0.027	0.238
	(0.103)	(0.146)	(0.100)	(0.141)	(0.112)	(0.097)	(0.159)
Vulnerable to	-0.123	0.150	-0.061	-0.224*	-0.169	-0.044	0.015
COVID-19	(0.089)	(0.148)	(0.100)	(0.128)	(0.112)	(0.088)	(0.165)
COVID-19 Cases	0.000	0.000*	-0.000	0.000	0.000	0.000	0.000
In County	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
COVID-19 Information	0.015	-0.012	-0.163***	-0.148*	-0.138**	0.034	-0.189*
	(0.053)	(0.090)	(0.056)	(0.087)	(0.068)	(0.056)	(0.100)
Discussion on	-0.005	0.057	-0.014	-0.019	0.061	0.070**	0.039
COVID-19	(0.029)	(0.058)	(0.034)	(0.047)	(0.041)	(0.031)	(0.070)
Fox News	0.162**	0.524***	0.530***	0.652***	0.116	0.138*	0.914***
	(0.075)	(0.123)	(0.078)	(0.106)	(0.094)	(0.077)	(0.144)
CNN	0.156**	0.109	-0.209**	0.335***	0.122	0.087	0.037
	(0.076)	(0.133)	(0.091)	(0.121)	(0.099)	(0.074)	(0.161)
MSNBC	-0.059	0.052	-0.299**	-0.136	-0.128	0.107	-0.132
	(0.100)	(0.157)	(0.127)	(0.129)	(0.115)	(0.092)	(0.203)
Trump Press Briefings	0.014	0.033	0.283***	0.006	0.358***	-0.116	0.180
	(0.088)	(0.146)	(0.081)	(0.113)	(0.101)	(0.087)	(0.158)
Social Media	-0.140**	-0.386***	-0.016	-0.027	-0.359***	0.035	-0.570***
	(0.065)	(0.138)	(0.078)	(0.105)	(0.087)	(0.067)	(0.148)
Constant	-1.559***	-3.752***	-1.983***	-2.310***	-2.484***	-1.351***	-3.794***
	(0.265)	(0.468)	(0.322)	(0.419)	(0.330)	(0.287)	(0.586)
Observations	10,349	10,323	10,340	10,352	10,330	10,342	10,355

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A-9: Item by Item Misinformation (Antidotes) Regressions (Partisans)

	(1) Fluvacc	(2) Peneum	(3) Hotair	(4) Antibio	(5) Saline	(6) Sesame
Republican (Dummy)	0.018	0.153	-0.156	-0.613**	-0.220	-0.272
	(0.287)	(0.314)	(0.264)	(0.289)	(0.309)	(0.596)
Partisan Social Identity	0.122**	0.172***	0.117*	0.111*	0.150**	0.323***
	(0.055)	(0.064)	(0.061)	(0.061)	(0.065)	(0.112)
Rep. * Partisan Soc.	-0.008	-0.007	0.128	0.222**	0.060	0.083
Identity	(0.086)	(0.092)	(0.080)	(0.091)	(0.090)	(0.163)
Rural	-0.004	-0.015	0.013	0.012	0.005	-0.113**
	(0.026)	(0.029)	(0.024)	(0.028)	(0.028)	(0.050)
Female	-0.094	0.083	-0.105	-0.262***	-0.056	-0.430***
	(0.077)	(0.087)	(0.073)	(0.082)	(0.084)	(0.154)
African-American	0.555***	0.516***	0.527***	0.656***	0.093	0.594**
	(0.111)	(0.123)	(0.125)	(0.116)	(0.138)	(0.234)
Hispanic	0.538***	0.262**	0.365***	0.465***	0.346**	0.106
	(0.116)	(0.124)	(0.119)	(0.122)	(0.137)	(0.263)
Asian-American	0.744***	0.283	0.043	0.491***	0.341**	0.268
	(0.148)	(0.180)	(0.119)	(0.178)	(0.166)	(0.230)
Other Race/Ethnicity	0.154	0.142	0.233	-0.591	0.331	1.254**
	(0.368)	(0.479)	(0.294)	(0.380)	(0.418)	(0.513)
Age	-0.002	-0.004	-0.004*	-0.022***	0.003	-0.028***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)
Education	-0.090**	-0.055	-0.011	-0.079**	0.017	0.039
	(0.038)	(0.043)	(0.033)	(0.038)	(0.040)	(0.070)
Religiosity	0.078***	0.085***	0.074***	0.125***	0.130***	0.182***
	(0.023)	(0.024)	(0.020)	(0.023)	(0.024)	(0.047)
Mental Health	0.160***	0.153***	0.141***	0.117**	0.175***	0.328***
(Depression)	(0.056)	(0.057)	(0.048)	(0.058)	(0.064)	(0.119)
Had COVID-19	-0.022	0.004	0.128	-0.091	0.149	0.014
	(0.095)	(0.113)	(0.094)	(0.122)	(0.113)	(0.172)
Vulnerable to	-0.017	0.279***	0.106	0.209**	0.231**	0.303
COVID-19	(0.093)	(0.103)	(0.089)	(0.095)	(0.110)	(0.203)
COVID-19 Cases	0.000	-0.000	0.000	0.000**	0.000***	0.000
In County	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
COVID-19 Information	0.021	0.095	-0.041	0.088	-0.046	-0.018
	(0.058)	(0.074)	(0.060)	(0.062)	(0.070)	(0.153)
Discussion on	-0.107***	-0.099***	0.015	-0.089**	0.019	0.006
COVID-19	(0.032)	(0.037)	(0.032)	(0.037)	(0.040)	(0.075)
Fox News	0.419***	0.382***	0.349***	0.540***	0.420***	0.754***
	(0.089)	(0.094)	(0.086)	(0.085)	(0.099)	(0.170)
CNN	0.194**	0.245***	0.030	0.031	0.143	0.345*
	(0.087)	(0.094)	(0.080)	(0.091)	(0.099)	(0.193)
MSNBC	0.096	0.076	-0.029	-0.026	0.045	0.131
	(0.110)	(0.123)	(0.102)	(0.112)	(0.112)	(0.202)
Trump Press Briefings	0.133	0.236**	0.000	0.161*	0.178*	0.184
	(0.086)	(0.099)	(0.088)	(0.092)	(0.103)	(0.184)
Social Media	-0.091	-0.244***	-0.039	-0.072	-0.045	-0.723***
	(0.075)	(0.091)	(0.071)	(0.080)	(0.092)	(0.160)
Constant	-2.169***	-3.095***	-2.603***	-1.740***	-3.749***	-4.574***
	(0.338)	(0.340)	(0.316)	(0.328)	(0.383)	(0.757)
Observations	10,316	10,315	10,314	10,309	10,306	10,314

Robust standard errors in parentheses

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

Table A-10: Item by Item Correct Information (Facts and Antidotes) Regressions (Partisans)

	(1) Nat Emerg	(2) Unemploy	(3) No Vac	(4) Face Mask	(5) Stay Away	(6) Wash Hands
Republican (Dummy)	-0.121	-0.328	-0.121	0.037	0.631	0.113
	(0.212)	(0.346)	(0.256)	(0.261)	(0.383)	(0.472)
Partisan Social Identity	-0.129***	-0.136*	-0.000	0.210***	0.109	0.126
	(0.042)	(0.070)	(0.059)	(0.062)	(0.088)	(0.102)
Rep. * Partisan Soc.	0.277***	0.113	-0.024	-0.319***	-0.362***	-0.097
Identity	(0.064)	(0.103)	(0.078)	(0.080)	(0.113)	(0.147)
Rural	0.039*	0.069**	-0.021	-0.025	0.016	0.039
	(0.022)	(0.034)	(0.025)	(0.025)	(0.037)	(0.049)
Female	0.111*	0.291***	0.238***	0.079	0.382***	0.421***
	(0.059)	(0.098)	(0.075)	(0.071)	(0.108)	(0.138)
African-American	-0.122	-0.563***	-0.874***	-0.224*	-0.645***	-0.592***
	(0.095)	(0.130)	(0.114)	(0.126)	(0.158)	(0.184)
Hispanic	-0.155	-0.301**	-0.350***	0.035	-0.056	-0.078
	(0.099)	(0.131)	(0.123)	(0.127)	(0.187)	(0.233)
Asian-American	-0.029	-0.155	-0.038	0.412***	0.281	-0.131
	(0.123)	(0.135)	(0.152)	(0.152)	(0.230)	(0.215)
Other Race/Ethnicity	-0.347	0.206	-0.294	-0.257	-0.736*	0.161
	(0.217)	(0.394)	(0.347)	(0.260)	(0.391)	(0.562)
Age	-0.006***	0.014***	0.014***	0.010***	0.006	0.001
	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.006)
Education	-0.006	0.110**	0.253***	0.025	0.055	0.186***
	(0.028)	(0.045)	(0.043)	(0.037)	(0.055)	(0.070)
Religiosity	-0.013	-0.082***	-0.118***	-0.024	-0.123***	-0.100**
	(0.017)	(0.027)	(0.021)	(0.022)	(0.032)	(0.048)
Mental Health	-0.177***	-0.200***	-0.263***	-0.151***	-0.295***	-0.510***
(Depression)	(0.043)	(0.055)	(0.046)	(0.053)	(0.072)	(0.094)
Had COVID-19	0.181**	-0.016	-0.079	-0.419***	-0.346**	-0.464***
	(0.085)	(0.115)	(0.117)	(0.096)	(0.148)	(0.180)
Vulnerable to	-0.009	-0.060	0.006	0.060	-0.009	-0.300*
COVID-19	(0.074)	(0.127)	(0.092)	(0.086)	(0.133)	(0.164)
COVID-19 Cases	-0.000	-0.000*	-0.000	0.000	-0.000***	-0.000
In County	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
COVID-19 Information	0.259***	0.297***	0.318***	0.406***	0.571***	0.472***
	(0.042)	(0.066)	(0.056)	(0.049)	(0.066)	(0.086)
Discussion on	0.052**	0.081**	0.108***	0.055*	0.070*	0.013
COVID-19	(0.025)	(0.037)	(0.029)	(0.030)	(0.042)	(0.055)
Fox News	0.191***	-0.303***	-0.409***	-0.176**	-0.592***	-0.474***
	(0.074)	(0.095)	(0.083)	(0.077)	(0.112)	(0.141)
CNN	-0.090	-0.191*	0.065	0.283***	0.110	-0.261
	(0.065)	(0.106)	(0.085)	(0.089)	(0.136)	(0.164)
MSNBC	-0.250***	-0.113	0.222**	0.232**	0.040	0.199
	(0.082)	(0.129)	(0.112)	(0.114)	(0.167)	(0.204)
Trump Press Briefings	0.346***	0.131	-0.223**	-0.153**	-0.101	0.353*
	(0.076)	(0.111)	(0.097)	(0.073)	(0.110)	(0.199)
Social Media	0.044	0.451***	0.080	-0.131*	0.158	0.524***
	(0.059)	(0.091)	(0.072)	(0.071)	(0.108)	(0.159)
Constant	0.245	0.669*	-0.092	-0.303	0.841*	1.663***
	(0.236)	(0.352)	(0.308)	(0.314)	(0.474)	(0.596)
Observations	10,327	10,329	10,335	10,320	10,313	10,323

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A-11: Misinformation and Correct Information Regressions Using Full Scales

	(1) Misinfo	(2) Correct Info
Partisanship (Republican)	0.010***	-0.003
	(0.002)	(0.002)
Rural	0.001	0.001
	(0.002)	(0.002)
Female	-0.002	0.040***
	(0.007)	(0.007)
African-American	0.160***	-0.081***
	(0.013)	(0.013)
Hispanic	0.086***	-0.033***
	(0.013)	(0.013)
Asian-American	0.080***	-0.011
	(0.012)	(0.011)
Other Race/Ethnicity	0.042	-0.046**
	(0.035)	(0.021)
Age	-0.003***	0.001***
	(0.000)	(0.000)
Education	-0.060***	0.016***
	(0.004)	(0.003)
Religiosity	0.019***	-0.008***
	(0.002)	(0.002)
Mental Health (Depression)	0.037***	-0.030***
	(0.006)	(0.005)
Had COVID-19	-0.011	-0.031***
	(0.011)	(0.011)
Vulnerable to COVID-19	0.032***	0.001
	(0.009)	(0.007)
COVID-19 Cases In County	0.000***	-0.000
	(0.000)	(0.000)
COVID-19 Information	-0.023***	0.065***
	(0.006)	(0.005)
Discussion on COVID-19	-0.010***	0.015***
	(0.003)	(0.003)
Fox News	0.082***	-0.045***
	(0.008)	(0.008)
CNN	0.015*	0.003
	(0.008)	(0.008)
MSNBC	-0.022**	-0.007
	(0.010)	(0.009)
Trump Press Briefings	0.045***	0.008
	(0.009)	(0.008)
Social Media	-0.021***	0.019***
	(0.007)	(0.007)

Constant	1.752***	2.468***
	(0.027)	(0.030)
Observations	16,504	16,504
R-squared	0.158	0.078

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A-12: Misinformation and Correct Information Regressions (Partisans)

	(1) Misinfo	(2) Correct Info
Republican (Dummy)	-0.030	-0.011
	(0.033)	(0.031)
Partisan Social Identity	0.009	-0.013**
	(0.007)	(0.006)
Rep. * Partisan Soc.	0.022**	-0.001
Identity	(0.010)	(0.009)
Rural	0.001	0.004
	(0.003)	(0.003)
Female	-0.009	0.046***
	(0.009)	(0.009)
African-American	0.156***	-0.079***
	(0.016)	(0.015)
Hispanic	0.086***	-0.035**
	(0.018)	(0.017)
Asian-American	0.074***	-0.000
	(0.016)	(0.015)
Other Race/Ethnicity	0.062	-0.042
	(0.060)	(0.026)
Age	-0.003***	0.001***
	(0.000)	(0.000)
Education	-0.049***	0.009**
	(0.005)	(0.004)
Religiosity	0.024***	-0.010***
	(0.003)	(0.003)
Mental Health	0.044***	-0.044***
(Depression)	(0.007)	(0.006)
Had COVID-19	-0.013	-0.043***
	(0.013)	(0.015)
Vulnerable to	0.029**	0.001
COVID-19	(0.011)	(0.010)
COVID-19 Cases	0.000***	-0.000
In County	(0.000)	(0.000)
COVID-19 Information	-0.031***	0.069***
	(0.008)	(0.007)
Discussion on	-0.010**	0.013***
COVID-19	(0.004)	(0.003)
Fox News	0.092***	-0.041***
	(0.010)	(0.010)
CNN	0.016	-0.001
	(0.010)	(0.010)
MSNBC	-0.023*	-0.015

	(0.012)	(0.012)
Trump Press Briefings	0.046***	0.006
	(0.011)	(0.010)
Social Media	-0.025***	0.021***
	(0.009)	(0.008)
Constant	1.703***	2.566***
	(0.039)	(0.043)
Observations	10,376	10,374
R-squared	0.154	0.078

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1