The Influence of Social Network Partisan Composition on Covid-19 Pandemic-Related Beliefs

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Abstract

Mixed findings have been produced from the literature on the influence of social networks in altering public opinion. The sudden emergence of the Covid-19 pandemic resulted in a response among U.S. politicians and citizens split across party lines. This novel and partisan issue presents an opportunity to conduct a critical retest of the influence of the partisan composition of one's social network on behavior. I use data from the ANES 2020 Social Media Study and ordered probit regression models to study the effect of the partisan composition of one's social network on support for mask mandates and confidence in the CDC. I find no support that heterogeneous partisan networks affect pandemic-related beliefs and nearly no support that homogenous partisan networks affect pandemic-related beliefs.

It would be difficult to imagine that our minds operate in a vacuum when forming opinions on political issues. The opinions of those around us such as family, friends, and co-workers, as well as our personal experiences and predispositions certainly interact in the development of our stances on political issues. Political scientists have long studied the effects of these exogenous interpersonal influences on the opinions and attitudes of citizens. Scholars have found a strong influence of the partisan composition or the level of disagreement in one's social network on political behavior (Huckfeldt, Johnson, and Sprague 2004; Mutz 2006; Mutz and Mondak 2006; Klar 2014; Huckfeldt, Mendez, and Osborn 2004; Lupton, Singh, and Thornton 2015; Visser and Mirabile 2004).

However, research on this topic has resulted in mixed findings. Researchers have variously found that both heterogenous and homogenous partisan social networks increase the importance of partisanship, that priming the concept of morality results in the disappearance of any effect of heterogenous networks, that there is no difference between the attitudes of those in heterogenous and homogenous partisan social networks, and that disagreement in one's social network does not affect partisan motivated reasoning (Levendusky, Druckman, and McLain 2016; Bloom and Levitan 2011; Robison, Leeper, and Druckman 2018; Robison 2020).

I test the effect of the partisan composition of one's social network on a generally yet-to-be-explored political issue, the Covid-19 pandemic. With a pandemic response characterized by polarization and partisanship, citizens were naturally divided along partisan lines in their support for and behavior concerning the various restrictions put in place to slow or stop the spread of the virus. Even politicians were divided in their support for and implementation of these restrictions. The Covid-19 pandemic presents a novel and partisan issue that offers a perfect opportunity to conduct a critical retest in the literature on the influence of social networks on political beliefs. I use data primarily from the ANES 2020 Social Media Study and two ordered probit regression models to evaluate the effect of the partisan composition of one's social network on support for mask requirements and confidence in the CDC. I find nearly no support that the partisan composition of one's social network affects pandemic attitudes.

Disagreement in Social Networks

Huckfeldt, Johnson, and Sprague (2004) and Mutz (2006) argue that a heterogeneous partisan composition in one's social network contributes to opinion ambivalence, thus the weakening of partisan attachments by subjecting people to disagreement or cross-pressures. However, there is disagreement about disagreement, with debate regarding the level of disagreement that occurs between citizens. Huckfeldt, Johnson, and Sprague (2004) argue that disagreement is the average condition for citizens in the American electorate. They argue that findings related to disagreement in social networks are overstated because they are conditional on other variables related to social networks. Mutz (2006) argues that disagreement is low, with citizens not generally exposing themselves to such. When citizens are exposed to disagreement, however, they see an increase in opinion ambivalence.

Scholars have found no shortage of support for the effect of exposure to disagreement on citizens' political behavior. Research has suggested that heterogeneous networks result in individuals having a greater awareness of the rationale of the viewpoints of others, leading to greater political tolerance (Mutz and Mondak 2006). Citizens exposed to heterogeneous networks are more likely to have less polarized opinions toward a political candidate (Huckfeldt, Mendez, and Osborn 2004). One study concludes that partisans of all groups that engaged in homogenous networks saw an increase in partisan-motivated reasoning, while those in heterogeneous networks pursued more accuracy-based evaluations (Klar 2014). Exposure to heterogeneous networks moderates the relationship between partisanship and core values and partisanship and candidate evaluations, suggesting that individuals in heterogeneous networks are less reliant on partisanship (Lupton, Singh, and Thornton 2015). Individuals in homogenous networks are more resistant to attitude change than individuals in heterogeneous networks, thus, homogenous networks increase attitude strength (Visser and Mirabile 2004). One study even finds that the effects of partisan media spread through discussion networks. Homogenous discussion networks polarize while heterogeneous networks polarize less because of the mix of information (Druckman, Levendusky, and McLain 2018).

However, mixed findings have been produced from this literature. One study finds that compared to a no-discussion baseline, both heterogeneous and homogenous discussion groups increase the importance of partisan identification (Levendusky, Druckman, and McLain 2016). For non-moral issues, increased network heterogeneity predicts increased persuasion, but when identical messages are presented in a way that primes a concept of morality, any effect of network heterogeneity disappears (Bloom and Levitan 2011). Others find that individuals in heterogeneous networks do not report stronger or weaker attitudes compared to those in homogenous discussion networks (Robison, Leeper, and Druckman 2018). There is also limited evidence to conclude that disagreement affects partisan differences in political knowledge or evaluations of the economy, suggesting that disagreement does not attenuate partisan-motivated reasoning (Robison 2020).

The Covid-19 Pandemic as a Case Study

After the emergence of a novel coronavirus in late 2019, the World Health Organization declared a global pandemic on March 11th, 2020 (Cucinotta 2020). Once the Covid-19 pandemic hit the United States and was subsequently declared a national emergency on March 13th, 2020, one might logically assume that partisans would unite across party boundaries (The White House 2023). One would hope that politicians would abstain from giving an opinion on the emerging health emergency, thereby giving way to apolitical science agencies and medical experts. However, with the election of 2020 coinciding with the emergence of the pandemic, both Democrats and Republicans were quick to politicize the issue of the health and safety of Americans. President Donald Trump contradicted the CDC and other experts on the expected date of the vaccine and baselessly accused the FDA and Pfizer of politicizing vaccine development (Lovelace Jr. and Higgins-Dunn 2020; Sanford 2020; McDonald 2021; McGinley, Johnson, and Dawsey 2020). Then Democratic presidential candidate, Joe Biden, called Trump xenophobic for labeling Covid-19 a virus of foreign origin and claimed that all of the Covid-19 deaths were on President Trump's hands. Once he became president, he contradicted himself on vaccine mandates and made two senior FDA officials resign by pressuring them to approve an unnecessary and untested blanket recommendation for a booster shot (Bloomberg Quicktake: Now 2020; The Independent 2020; CBS News 2020; CBS News 2021; Brufke 2021).

A slew of research shows that partisanship was the greatest indicator in explaining variation in attitudes about the pandemic and how individuals would behave concerning pandemic response measures. Democrats and Republicans differed in nearly all aspects of the Covid-19 pandemic response, from prevention measures to their perception of the danger of the disease. As early as March 2020, Democrats, as opposed to Republicans, were significantly more likely to report having adopted several health behaviors to combat Covid-19. Partisan affiliation was the most common behavioral predictor across 38 dependent variables affecting health behavior, health attitudes, views of government health and public policy for Covid-19 response, and pandemic fears of 3,000 Americans (Gadarian et al. 2021).

A study asking respondents to answer 173 positive and negative statements about face masks found significant differences in attitudes. Republicans have significantly fewer positive attitudes toward face masks than Democrats and Independents (Hopkins and Whatley 2022). Actual mask usage was lower in counties where the majority of voters support Donald Trump and have a greater interest in Fox News (Gonzalez et al. 2021). When it comes to trust in scientific agencies during the pandemic, there is a significant gap between Republicans and other partisans. Liberals' trust in the World Health Organization and science experts is significantly higher than both conservatives and moderates (Kerr et al. 2021). During the beginning months of the pandemic, trust in the CDC fell significantly among Republicans, with views among Democrats and Independents changing little. Individuals who expressed lower trust in scientists also reported less compliance with behavior related to recommendations on pandemic prevention measures. Furthermore, partisans differed in their perceived danger of Covid-19. Republicans were significantly less likely to worry about themselves or their family members getting sick with Covid-19 (Hamilton and Safford 2021). Liberals' risk perceptions of Covid-19 were significantly higher than both conservatives and moderates (Kerr, et al 2021).

Therefore, this issue presents an effective case to study the effect of social networks on political behavior. Since pandemic response measures became so clearly a partisan issue, it allows for the possibility that the partisan makeup of one's social network may affect one's beliefs concerning pandemic prevention measures. One's social network has the potential to weaken or strengthen partisan attachments and strengthen partisan-motivated reasoning or accuracy-based evaluations depending on the partisan composition of one's social network (Huckfeldt, Johnson, and Sprague 2004; Mutz 2006; Lupton, Singh, and Thornton 2015; Klar 2014).

Argument

I theorize that those with more homogenous partisan social networks will fall deeper into their partisan attitudes as surrounding oneself with in-partisans will confirm their partisan attitudes and beliefs by increasing partisan-motivated reasoning and developing a higher resistance to attitude change (Klar 2014; Visser and Mirabile 2004). Those with heterogeneous social networks will separate from characteristic partisan attitudes because surrounding oneself with out-partisans reduces the effect of partisan attachments, opens one to justifications for beliefs other than one's own, increases political tolerance for the views of others, and results in more accuracy-based evaluations (Huckfeldt, Johnson, and Sprague; Mutz 2006; Lupton, Singh, and Thornton 2015; Mutz and Mondak 2006; Klar 2014).

With mixed results in the literature regarding social networks, I offer a critical retest of the effect of homogenous and heterogeneous partisan social networks on political behavior. I explore the effect of one's social network partisan composition on partisans' confidence in the Center for Disease Control (CDC) and support for masking requirements in public. Republicans with an increasing number of Democrats in their social network will deviate from their party's characteristic pandemic attitudes and have greater confidence in the CDC and greater support for masking requirements. Republicans with increasing Republicans in their social networks will be more entrenched in characteristic partisan pandemic beliefs, having little confidence in the CDC and low support for masking requirements. Democrats with an increasing number of Republicans in their social network will have less confidence in the CDC and support for masking requirements. Democrats, who mostly have Democrats in their social networks, will have greater confidence in the CDC and support for masking requirements. Thus, my hypotheses are as follows:

Hypothesis 1: Increasing levels of in-partisans in one's social network (a more homogenous network) will result in an increased probability of one expressing partisan congruent beliefs related to the Covid-19 pandemic.

Hypothesis 2: Increasing levels of out-partisans in one's social network (a more heterogeneous network) will result in an increased probability of one expressing partisan incongruent beliefs related to the Covid-19 pandemic.

Data and Operationalization

I use data from the American National Election Study's (ANES) 2020 Social Media Study published on electionstudies.org on November 8th, 2021. This survey is a pre/post-survey that occurred before and following the 2020 presidential election respectively. The ANES uses an online panel survey with probability sampling to gather respondents. A total of 5,277 respondents around the United States completed both portions of the survey. The sample was provided by NORC at the University of Chicago and targeted any U.S. citizen over the age of 18. The pre-election portion was conducted from August 20th through September 17th, 2020, and the post-election portion was conducted from November 1st, 2020, through January 1st, 2021. I also gather replication data from the article "Political Partisanship Influences Behavioral Responses to Governors' Recommendations for COVID-19 Prevention in the United States" by Guy Grossman, Soojong Kim, Jonah M. Rexer, and Harsha Thirumurthy. Their data was gathered during March 2020 and was published by Jonah M. Rexer on February 12th, 2021, on the Harvard Dataverse. The variables of interest in the replication data are the partisanship of the governors and the daily Covid-19 deaths at the state level. Datasets are merged through each U.S. state's respective Federal Information Processing Standards (FIPS) code.

My unit of analysis is the respondents surveyed in the ANES Social Media Study. The primary independent variables of interest include a binary measure of the partisanship of the ANES respondents (0 = Democrats, 1 = Republicans). This partisanship measure includes all individuals in the ANES survey who chose to identify themselves with a major party, regardless of whether they identified themselves as weak or strong partisans. I use a binary measure of partisanship because there is a data scarcity issue for Independents concerning the network measures. In addition, I have no theoretical expectations about individuals who do not identify as partisan. ANES respondents were asked to "Think about your friends and family. How many are Democrats, and how many are Republicans? Your best guess is fine." This response was separated into two variables, which I recode so that zero represents the lowest category. The number of Republicans in one's social network is operationalized as a five-scale measure (none or almost none (0), a few (1), about half (2), a lot (3), and all or nearly all (4)). A separate variable measures the number of Democrats in one's social network. This variable is operationalized in the same way as the Republican social network variable. My dependent variables of interest are ANES respondents' support for masking requirements in public and confidence in the CDC. ANES respondents were asked how much confidence they have in the Center for Disease Control on a five-scale measure, which I again recode so that zero represents the lowest category (none (0), a little (1), a moderate amount (2), a lot (3), a great deal (4)). ANES respondents were asked whether they "favor, oppose, or neither favor nor oppose requiring everyone to wear a mask in public." This variable is a five-scale measure which I recode so that higher values denote more support for mask requirements (oppose strongly (0), oppose somewhat (1), neither (2), favor somewhat (3), favor strongly (4)).

I use a variety of standard control variables commonly used in studies of political behavior such as a respondent's level of attention to politics, gender, age, race, education level, yearly household income, frequency of keeping up with the news, employment status, marital status, and political ideology. I also use several controls that may affect the behavior of respondents concerning the Covid-19 pandemic such as self-identified general health, whether a respondent is covered by health insurance, the number of people in a respondent's household, partisanship of the state's governor, the average daily Covid-19 state deaths, whether they know a person who contracted Covid, and the presence of mask mandates in one's state.

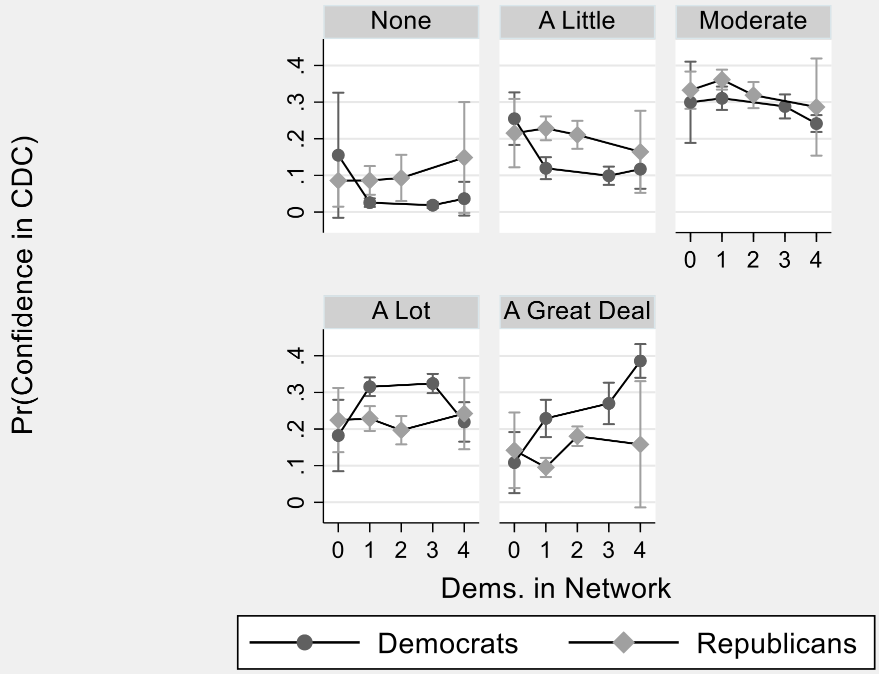
The inclusion of the partisanship of a state's governor as a control is important because governors varied widely in their support for and implementation of various pandemic response measures, which strongly affected citizen response to such measures (Gusmano, et al. 2020: Grossman, et al. 2020). Although the replication data was gathered in March of 2020, before the ANES survey was conducted, no new Governors were elected during the time of the ANES survey. Although the daily number of state deaths was gathered in March of 2020 as well, I believe this measure of state deaths serves as a satisfactory control for the general magnitude of the intensity of state-level deaths per day. The general magnitude of these deaths remained relatively unaltered even as the ANES survey started later in the year. I divide the state deaths variable by 1,000 to remove the zero effect in the regression output. Additionally, I control for statewide mask mandates using information from Ballotpedia. A dummy variable denotes whether a statewide mask mandate was in place during the entirety of the ANES survey. An additional dummy variable accounts for the five states that implemented a mask mandate while the survey was already taking place. A table of summary statistics can be found in Figure 1 in the Appendix.

I utilize two ordered probit regression models to evaluate my hypotheses. I utilize ordered probit models as my dependent variables are measured on five-point scales, with the increase between each value on this scale being logically ordered to represent increasing values of confidence in the CDC and support for mask requirements. In both regression models, a triple interaction is performed between the measure of partisanship and the two measures of the partisan makeup of one's social network. While this is not ideal, I must utilize a triple interaction due to the nature of how responses to these questions were gathered. The number of Republicans in one's social network and the number of Democrats in one's social network were gathered in two separate measures. Therefore, a triple interaction is needed to account for 1) how many Republicans are in one's social network, 2) how many Democrats are in one's social network, and 3) the partisanship of the respondent. Including the partisanship of the respondent is important because this denotes whether one's social network is mostly homogenous or heterogenous based on the respective levels of Republicans and Democrats in their social network. For both regression models, there is a relatively equal proportional reduction in error. For the confidence in the CDC model, the percent correctly predicted is 36.70% with a proportional reduction in error of 8.330. For the support for mask requirements model, there is a percent correctly predicted of 63.05% with a proportional reduction in error of 8.205. For all predicted probability and first differences calculations, I use an observed values approach, holding all covariates that are not of direct relevance to the figures at their observed values. I was unable to test for the parallel regression assumption being met due to the intense model specification, with a large number of parameters due to the triple interaction. The extensive regression output for both ordered probit models can be found in Figures 2 and 3 in the Appendix.

Results

The predicted probabilities for the first regression model with confidence in the CDC as the dependent variable can be seen in Figures 1 and 2. Figure 1 shows the predicted probability of varying levels of confidence in the CDC based on one's composition of Democrats in their social network. As the value of the network variable increases, Democrats will observe a more homogenous network and Republicans a more heterogeneous network. As the composition of Democrats in one's network increases, the predicted probability of a Democrat having no confidence in the CDC decreases. Similarly, as the composition of Democrats in one's network increases, the predicted probability of Democrats having a great deal of confidence in the CDC increases substantially. These results support my expectation in the first hypothesis. For Republicans, as the composition of Democrats in their social networks increases, we observe a slight increase in the predicted probability of Republicans expressing no confidence in the CDC. While we again observe a slight increase in the predicted probability of Republicans having a great deal of confidence in the CDC going from having a few Democrats in their social network to about half, the predicted probability remains relatively constant in its entirety. This result runs counter to my expectation in the second hypothesis.

Figure 1: Pred. Prob. of Confidence in the CDC based on Dems. in Network

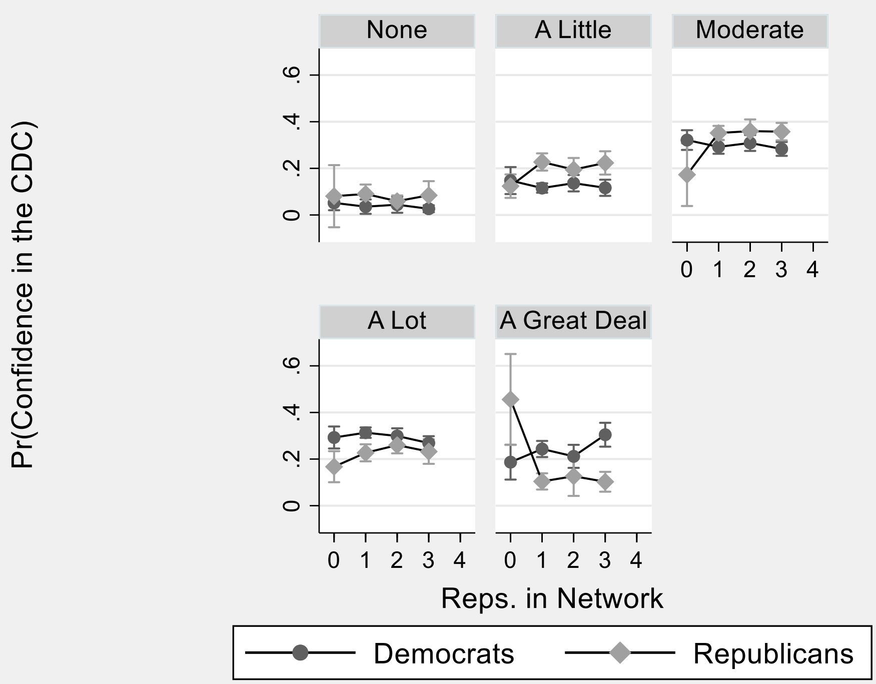


All other covariates set to observed values
95% CIs Reported, N = 3390 Individuals
Composition of Dems. in network increases as variable increases

Figure 2 shows the predicted probability of having varying levels of confidence in the CDC based on the composition of Republicans in one's social network. As the value of the network variable increases, Republicans will observe a more homogenous network and Democrats a more heterogeneous network. Returning to examining the first hypothesis, as the composition of Republicans in one's social network increases, the predicted probability of having no confidence in the CDC remains relatively constant for Republicans. The predicted probability of Republicans having a great deal of confidence in the CDC again remains relatively constant as the composition of Republicans in one's social network increases. Except for a sharp drop in the predicted probability of having a great deal of confidence in the CDC as Republicans go from having no Republicans to a few Republicans in their network. This result runs counter to my expectation. In examining support for the second hypothesis, as the composition of

Republicans in one's social network increases, the predicted probability of Democrats having no confidence in the CDC remains relatively constant. The predicted probability of Democrats having a great deal of confidence in the CDC slightly increases as the composition of Republicans in one's network increases. This result again runs counter to my expectation. Based on the predicted probability results of my confidence in the CDC model, I find no support for my second hypothesis and limited support for the first hypothesis, that is, Democrats have an increasing level of confidence in the CDC as the composition of Democrats in their social network increases.

Figure 2: Pred. Prob. of Confidence in the CDC based on Reps. in Network



All other covariates set to observed values
95% CIs Reported, N = 3390 Individuals
Composition of Reps. in network increases as variable increases

The predicted probabilities for the second regression model with support for mask requirements as the dependent variable can be seen in Figures 3 and 4. Figure 3 shows the predicted probability of varying levels of support for mask requirements based on the composition of Democrats in one's social network. As the value of the network variable increases, Democrats will observe a more homogenous network and Republicans a more heterogeneous network. The figure shows that as the composition of Democrats in one's social network increases, the predicted probability of Democrats strongly opposing mask requirements remains relatively constant. The predicted probability of Democrats strongly favoring mask requirements substantially increased as the composition of Democrats in one's social network increased. This seems to generally support my expectation in the first hypothesis. For Republicans, as the composition of Democrats in their network increases, the predicted probability for every level of support for mask requirements remains relatively constant. This runs counter to my expectation in the second hypothesis.

Figure 3: Pred. Prob. of Support for Mask Requirements based on Dems. in Network

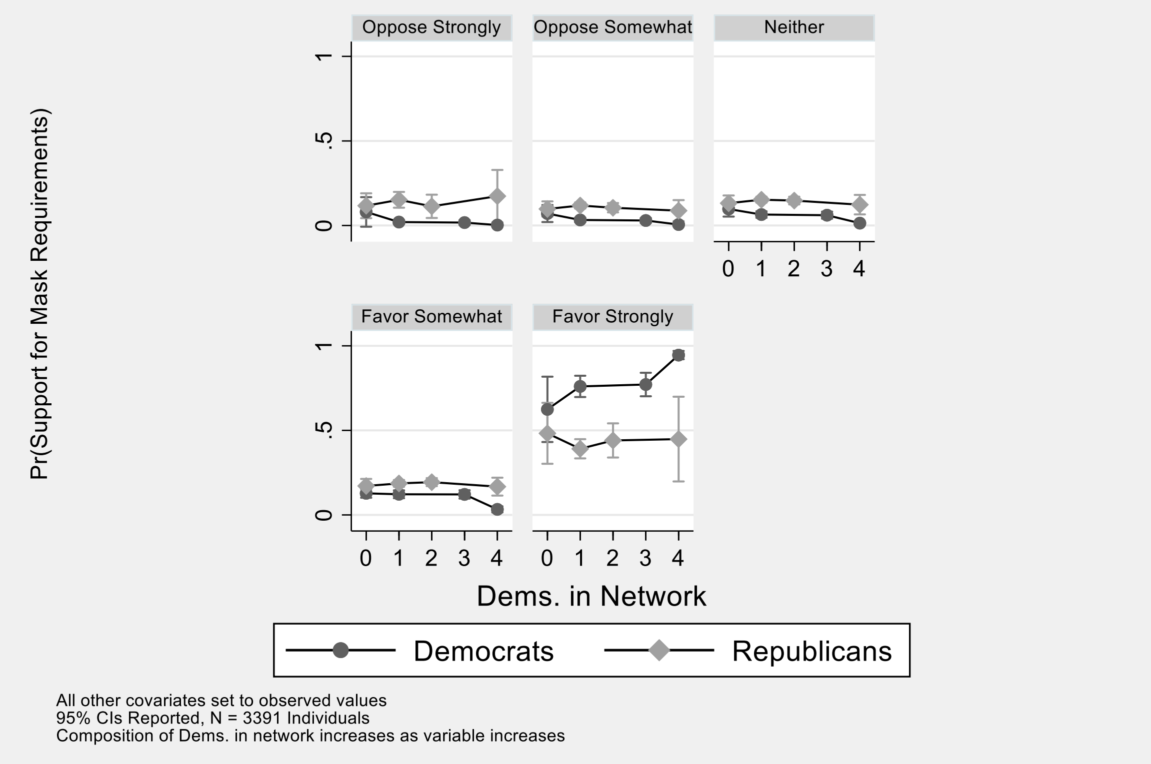
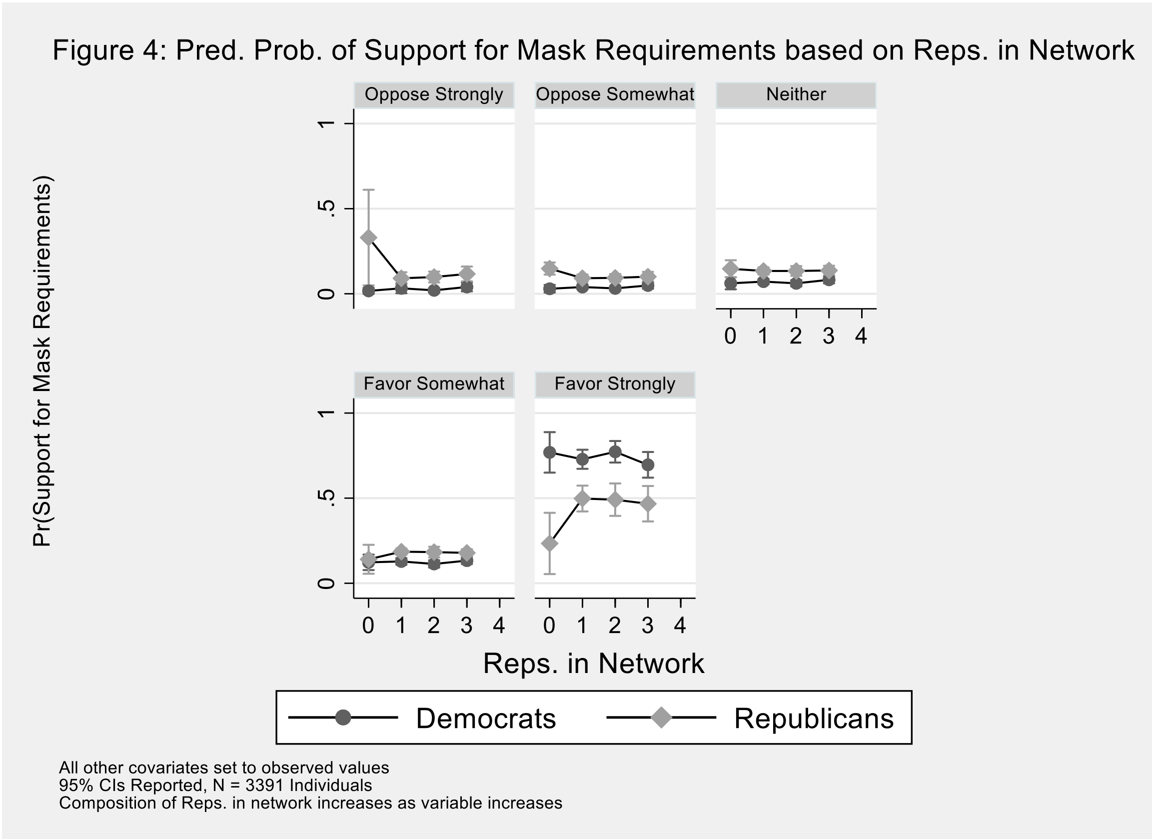


Figure 4 shows the predicted probability of varying levels of support for mask requirements based on the composition of Republicans in one's social network. As the value of the network variable increases, Republicans will observe a more homogenous network and Democrats a more heterogeneous network. As the composition of Republicans in one's network increases, the predicted probability of support for mask requirements at each level of support remains relatively constant for Republicans. With the exception that the predicted probability for Republicans strongly opposing mask requirements decreases going from none or almost none to a few Republicans in network. Similarly, the predicted probability for Republicans strongly favoring mask requirements increases going from none or almost none to a few Republicans in network. In general, this runs counter to my expectation in the first hypothesis. For Democrats, the predicted probability for each level of support for mask requirement remains relatively constant as the composition of Republicans in one's network increases. This is with the exception of a slight decrease in the predicted probability of strongly favoring mask requirements as the composition of Republicans in one's network increases. Generally, these results do not conform to my expectation in the second hypothesis. Like the results in the CDC confidence model, the results for the support for mask requirements model provide no support for my second hypothesis and mixed support for my first hypothesis. That is, as the composition of Democrats in one's network increases, the predicted probability of Democrats strongly favoring mask requirements increases.

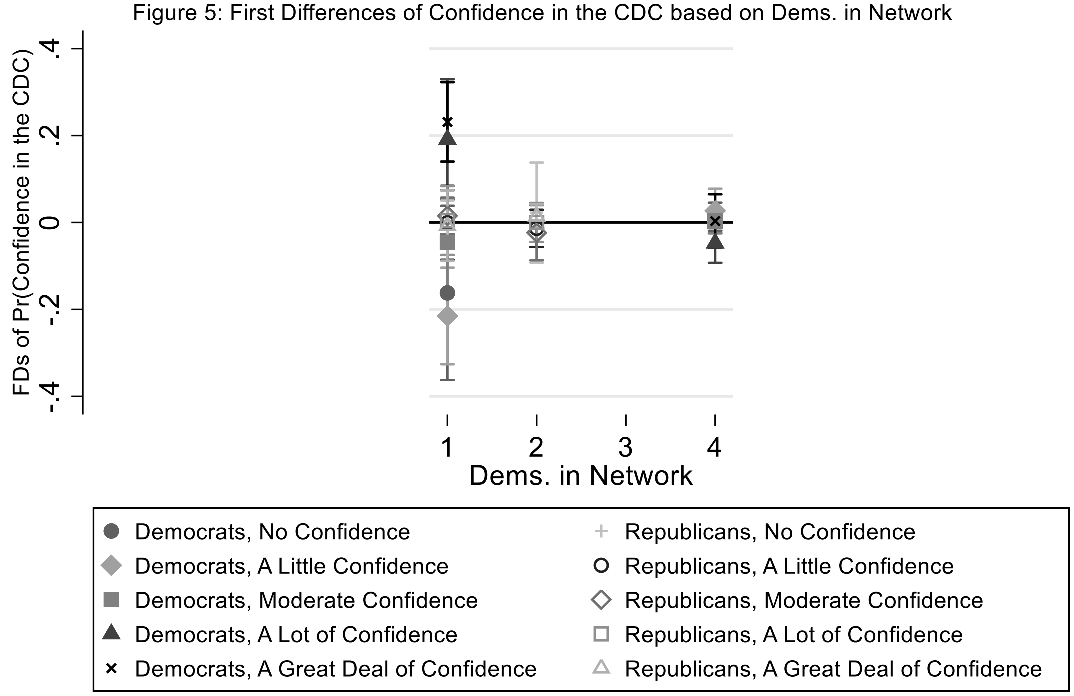


In Figures 5 through 8, we can observe the first differences for the changes in predicted probabilities to interpret the statistical significance of the relationships we observe in Figures 1 through 4. Interpreting statistical significance visually from these graphs proves difficult due to the overlapping of several confidence intervals. In general, we see very little support for statistical significance at the traditional 95% confidence level. Figure 5 shows that when Democrats go from none or almost none to a few Democrats in their social network, there is a statistically significant increase in the predicted probability of Democrats having a great deal of confidence in the CDC, in line with my expectation in the first hypothesis. In Figure 6, we can see that as Democrats see an increase of Republicans in their social network from about half to a lot, there is a statistically significant increase in the predicted probability of having a great deal of confidence in the CDC, counter to my expectation in the second hypothesis. Also, as

Republicans go from none or almost none to a few Republicans in their social network, there is a statistically significant decrease in the predicted probability of having a great deal of confidence in the CDC, in line with the first hypothesis.

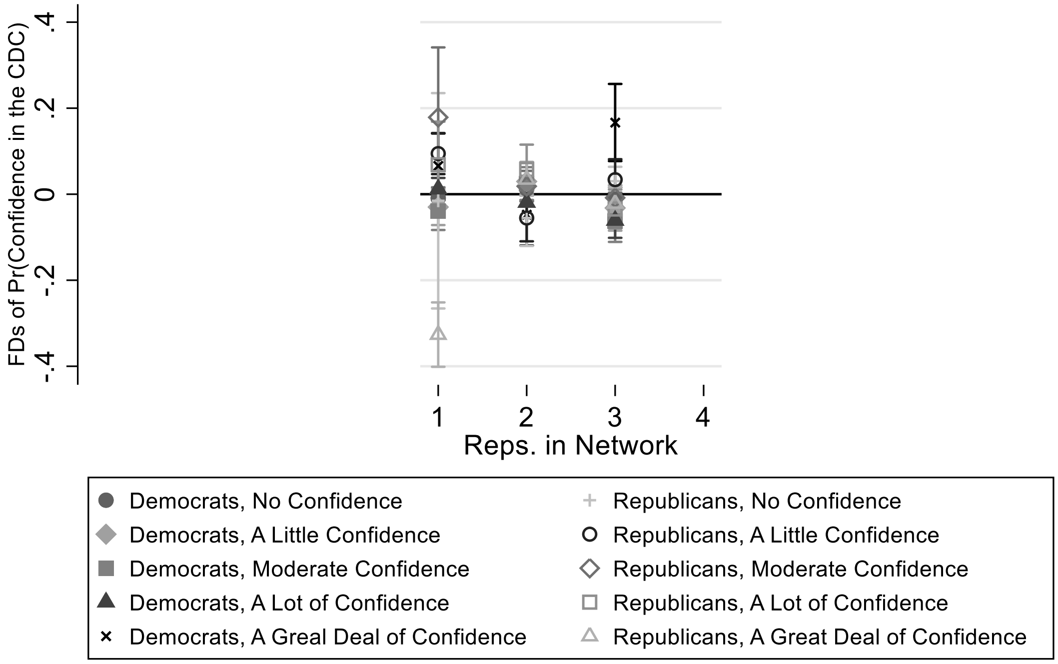
Figure 7 demonstrates that Democrats who go from having a lot to all or nearly all Democrats in their social network have a statistically significant increase in the predicted probability of strongly favoring masking requirements, in line with the first hypothesis. Figure 8 demonstrates that Republicans who go from having none or almost none to a few Republicans in their social network see an increase in the predicted probability of strongly favoring masking requirements, counter to the first hypothesis.

Figure 5: First Differences of Confidence in the CDC based on Dems. in Network



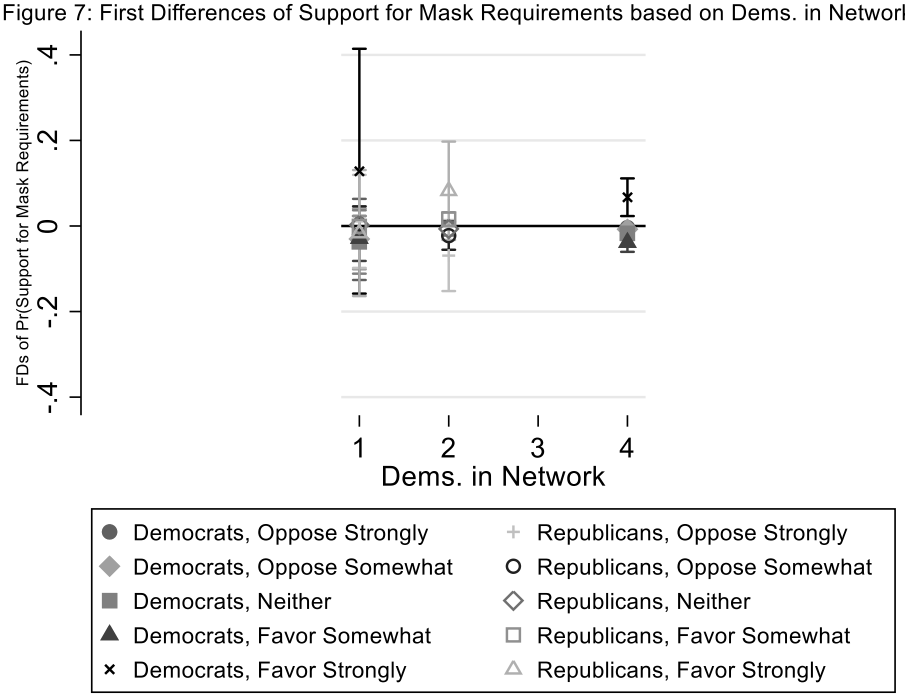
All other covariates set to observed values
95% CIs Reported, N = 3390 Individuals
FDs comparing change in composition of Dems.in network on confidence in the CDC

Figure 6: First Differences of Confidence in the CDC based on Reps. in Network



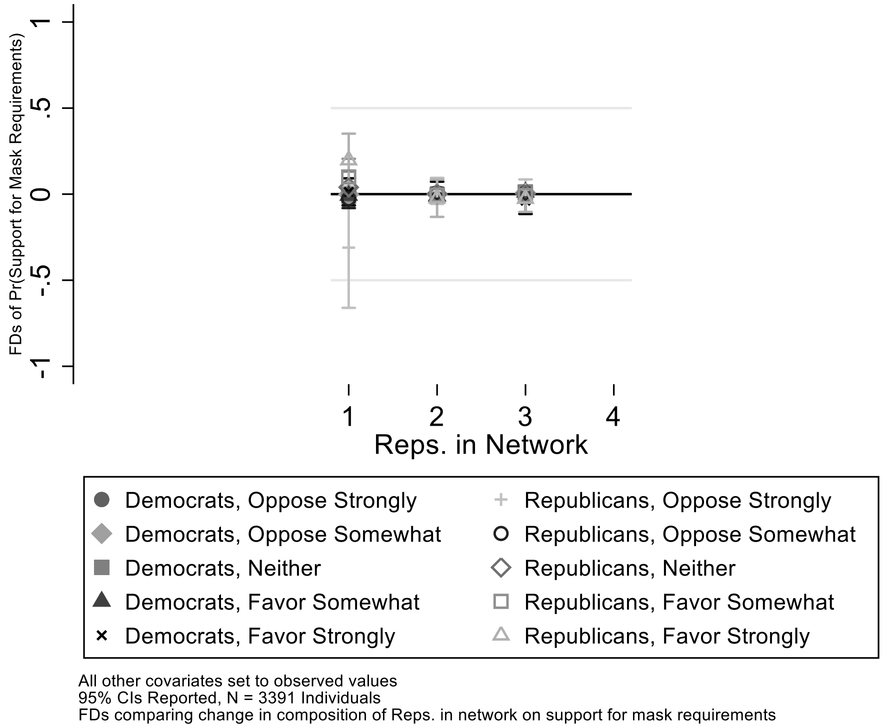
All other covariates set to observed values
95% CIs Reported, N = 3390 Individuals
FDs comparing change in composition of Reps. in network on confidence in the CDC

Figure 7: First Differences of Support for Mask Requirements based on Dems. in Network



All other covariates set to observed values
95% CIs Reported, N = 3391 Individuals
FDs comparing change in composition of Dems. in network on support for mask requirements

Figure 8: First Differences of Support for Mask Requirements based on Reps. in Network



Discussion

Klofstad, Sokhey, and McClurg (2013) revisit central theoretical arguments in the social network literature, that is, the central works of Huckfeldt, Johnson, and Sprague (2004) and Mutz (2006). Klofstad, Sokhey, and McClurg argue that an inconsistent conceptualization of disagreement results in the differing theoretical arguments present in the literature. A measure of disagreement in one's network is a challenging measure for a myriad of reasons. At what point do networks become disagreeable? Huckfeldt, Johnson, and Sprague (2004) measure disagreement as discord in the vote choice of a respondent and their discussant. This measure could be seen as measuring the absence of agreement rather than the presence of disagreement. Mutz (2006) measures respondents' perceptions of how much they disagree with discussants in their network. She creates an index of disagreement which includes shared vote preferences, partisan preferences, perceptions of disagreement, perceptions of shared opinion, etc. A strength of this measure is that it does not rely solely on vote choice for determining the level of disagreement in one's network. However, I concur with Klofstad and company that Mutz's approach may overlook more common and less intense disagreement discussions. We can classify any discussion as falling on a spectrum of agreement, one extreme being complete agreement and the other being complete disagreement.

Klofstad and company argue that how one defines disagreement has important implications for one's understanding of the concept, and thus what one may find when studying it. They find that individuals in heterogeneous networks, defined in terms of general disagreement, have more ambivalent partisan preferences than those in homogenous networks. However, when one measures disagreement as partisan disagreement, rather than general disagreement, they find that individuals in heterogeneous networks have stronger partisan preferences. This means that especially when studying political behavior, the conceptualization of disagreement matters for the results. The issues with the measure of disagreement I utilize are no exception to these issues. I focus exclusively on partisan disagreement, which is not necessarily an issue, but my measure of disagreement is sub-optimal. The ANES measure of social network partisan composition is separated into two variables. The number of Republicans in one's network is measured with one variable and the number of Democrats in one's network is measured with another. This leaves more room for self-reported inaccuracy. Respondents have more room to report nonsensical answers such as having both large portions of Republicans and Democrats in their network rather than considering the actual proportion of partisan composition of their network. A better measure would consider the even split of partisans in a single measure, accounting for the simultaneous makeup of in-partisans and out-partisans in one's network. I believe my study, and the social network literature at large, would greatly benefit from a more optimal and concrete measure of network disagreement.

Selection bias is also a potential problem in the social network literature. Could those who choose to embed themselves in out-partisan networks operate systematically differently than those who do not subject themselves to disagreement in their network? Are people who have diverse partisan networks already people more likely to consider the viewpoint of the other side, harboring less polarized opinions and attitudes? This is an important question and by no means a debate solved in the literature. It is also possible that social networks did not have much of an influence at this particular time, with this particular issue, because of pandemic lockdowns. People were less likely to interact with their usual social networks, regardless of the partisan heterogeneity or homogeneity of them. In the heat of the pandemic, when the ANES survey was conducted, people were certainly less likely to leave home. Many were also likely working from home at least part of the time. If any exogenous force was strong enough to move opinion on Covid-19-related attitudes and beliefs it very well could have been the media or online social networks.

Conclusion

I ask whether heterogeneous or homogenous partisan social networks will affect political behavior concerning Covid-19 pandemic-related attitudes. In my first hypothesis, I expect that homogenous social networks will result in partisans being more entrenched in characteristic partisan attitudes related to the Covid-19 pandemic. In my second hypothesis, I expect that heterogeneous networks will result in partisans separating from characteristic partisan attitudes related to the Covid-19 pandemic. In sum, I find no support for my second hypothesis. That is, based on my analysis, there is no support that Democrats or Republicans in heterogeneous networks experience attitudes incongruent with their party's characteristic attitudes on Covid-19 pandemic-related beliefs. Specifically, confidence in the CDC and support for mask requirements. I find minimal support for my first hypothesis. When Democrats go from having none or almost none to a few Democrats in their social network, there is a substantive and statistically significant increase in the predicted probability of having a great deal of confidence in the CDC. Also, when Democrats go from having a lot to nearly all Democrats in their social network, there is a substantive and statistically significant increase in the predicted probability of strongly favoring mask requirements. This relationship generally occurs with Democrats only, with the exception that as Republicans go from having none or almost none to a few Republicans in their social network, there is a substantive and statistically significant decrease in the predicted probability of having a great deal of confidence in the CDC.

However, these are the only relationships in support of the first hypothesis that reach both substantive and statistical significance. In general, there is both mixed and minimal support for my first hypothesis. Thus, my analysis suggests that, in general, homogenous social networks do not result in Republicans or Democrats becoming more entrenched in their characteristic partisan attitudes related to the Covid-19 pandemic. My results conform to those findings in the literature that conclude that the partisan composition of discussion networks does not result in a change in political beliefs. As mentioned, those in the field should continue to study the effect of social networks on different types of political behavior. It would greatly benefit those studying the effects of social networks on political behavior to reach some sort of consensus on how to think about and measure disagreement so that greater consensus in the literature becomes possible.

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Appendix

Appendix Figure 1: Summary Statistics

VARIABLES	N	mean	sd	min	max
Age	5,750	50.50	16.88	18	80
# of People in Household	5,750	2.977	1.601	1	6
Know Someone with Covid	5,746	1.447	0.497	1	2
Rep. Governor	5,717	0.434	0.496	0	1
Confidence in the CDC (DV)	5,273	2.340	1.158	0	4
Male	5,750	0.505	0.500	0	1
Covered by Health Insurance	5,648	0.924	0.265	0	1
Statewide Mask Mandate During Survey	5,717	0.758	0.429	0	1
Statewide Mask Mandate Implemented During Survey	5,717	0.0360	0.186	0	1
State Deaths (divided by 1000)	5,717	0.0226	0.0920	0	1.282
White	5,750	0.693	0.461	0	1
Employed	5,750	0.605	0.489	0	1
Married	5,750	0.538	0.499	0	1
Education Level	5,750	2.397	1.058	0	4
Attention to Politics	5,274	2.812	0.988	0	4
Self-Identified General Health	5,738	1.560	0.979	0	4
Attention to News	5,626	2.172	0.846	0	3
Income Level	5,750	9.363	4.208	0	17
Dems. In Network (IV)	5,261	2.039	1.077	0	4
Reps. In Network (IV)	5,264	1.836	1.048	0	4
Support for Mask Requirements (DV)	5,277	3.056	1.335	0	4
Ideology	5,264	3.036	1.814	0	6
Partisanship (0 = Dem., 1 = Rep.) (IV)	3,550	0.454	0.498	0	1

Appendix Figure 2: Ordered Probit Regression of Confidence in the CDC on Covariates

	Covariates
Dems. in Network (0)	0
	(.)
Dems. in Network (1)	1.519^{**}
	(0.581)
Dems. in Network (2)	1.335^{*}

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	(0.602)
Dems. in Network (3)	1.367**
	(0.471)
Dems. in Network (4)	1.623***
	(0.459)
Reps. in Network (0)	0
	(.)
Reps. in Network (1)	0.231
	(0.867)
Reps. in Network (2)	0.255
	(0.866)
Reps. in Network (3)	2.014**
	(0.645)
Reps. in Network (4)	1.961**
	(0.725)
Dems. in Network (0) X Reps. in Network (0)	0
	(.)
Dems. in Network (0) X Reps. in Network (1)	0
	(.)
Dems. in Network (0) X Reps. in Network (2)	0
	(.)
Dems. in Network (0) X Reps. in Network (3)	0
	(.)
Dems. in Network (0) X Reps. in Network (4)	0
	(.)
Dems. in Network (1) X Reps. in Network (0)	0
	(.)
Dems. in Network (1) X Reps. in Network (1)	-0.0707
	(0.949)
Dems. in Network (1) X Reps. in Network (2)	-0.221
	(0.963)

Dems. in Network (1) X Reps. in Network (3)	-2.056** (0.752)
Dems. in Network (1) X Reps. in Network (4)	-2.147* (0.883)
Dems. in Network (2) X Reps. in Network (0)	0 (.)
Dems. in Network (2) X Reps. in Network (1)	0.0685 (0.963)
Dems. in Network (2) X Reps. in Network (2)	0.102 (0.955)
Dems. in Network (2) X Reps. in Network (3)	-2.062* (0.801)
Dems. in Network (2) X Reps. in Network (4)	-5.267 (218.7)
Dems. in Network (3) X Reps. in Network (0)	0 (.)
Dems. in Network (3) X Reps. in Network (1)	0.0583 (0.877)
Dems. in Network (3) X Reps. in Network (2)	0.0130 (0.897)
Dems. in Network (3) X Reps. in Network (3)	-1.736* (0.685)
Dems. in Network (3) X Reps. in Network (4)	-0.605 (1.011)
Dems. in Network (4) X Reps. in Network (0)	0 (.)
Dems. in Network (4) X Reps. in Network (1)	-0.235 (0.874)
Dems. in Network (4) X Reps. in Network (2)	-1.050 (0.990)

Dems. in Network (4) X Reps. in Network (3)	3.196 (218.7)
Dems. in Network (4) X Reps. in Network (4)	-1.796 (0.917)
Partisanship (0)	0 (.)
Partisanship (1)	2.407** (0.734)
Dems. in Network (0) X Partisanship (0)	0 (.)
Dems. in Network (0) X Partisanship (1)	0 (.)
Dems. in Network (1) X Partisanship (0)	0 (.)
Dems. in Network (1) X Partisanship (1)	-3.657*** (1.104)
Dems. in Network (2) X Partisanship (0)	0 (.)
Dems. in Network (2) X Partisanship (1)	3.188 (218.7)
Dems. in Network (3) X Partisanship (0)	0 (.)
Dems. in Network (3) X Partisanship (1)	-1.806 (1.277)
Dems. in Network (4) X Partisanship (0)	0 (.)
Dems. in Network (4) X Partisanship (1)	-2.334* (0.923)
Reps. in Network (0) X Partisanship (0)	0 (.)
Reps. in Network (0) X Partisanship (1)	0

	(.)
Reps. in Network (1) X Partisanship (0)	0
	(.)
Reps. in Network (1) X Partisanship (1)	-2.006
	(1.203)
Reps. in Network (2) X Partisanship (0)	0
	(.)
Reps. in Network (2) X Partisanship (1)	-1.291
	(1.202)
Reps. in Network (3) X Partisanship (0)	0
	(.)
Reps. in Network (3) X Partisanship (1)	-3.649***
	(0.889)
Reps. in Network (4) X Partisanship (0)	0
	(.)
Reps. in Network (4) X Partisanship (1)	-3.611***
	(0.932)
Dems. in Network (0) X Reps. in Network (0) X Partisanship (0)	0
	(.)
Dems. in Network (0) X Reps. in Network (0) X Partisanship (1)	0
	(.)
Dems. in Network (0) X Reps. in Network (1) X Partisanship (0)	0
	(.)
Dems. in Network (0) X Reps. in Network (1) X Partisanship (1)	0
	(.)
Dems. in Network (0) X Reps. in Network (2) X Partisanship (0)	0
	(.)
Dems. in Network (0) X Reps. in Network (2) X Partisanship (1)	0
	(.)
Dems. in Network (0) X Reps. in Network (3) X Partisanship (0)	0
	(.)

Dems. in Network (0) X Reps. in Network (3) X Partisanship (1)	0 (.)
Dems. in Network (0) X Reps. in Network (4) X Partisanship (0)	0 (.)
Dems. in Network (0) X Reps. in Network (4) X Partisanship (1)	0 (.)
Dems. in Network (1) X Reps. in Network (0) X Partisanship (0)	0 (.)
Dems. in Network (1) X Reps. in Network (0) X Partisanship (1)	0 (.)
Dems. in Network (1) X Reps. in Network (1) X Partisanship (0)	0 (.)
Dems. in Network (1) X Reps. in Network (1) X Partisanship (1)	2.598 (1.467)
Dems. in Network (1) X Reps. in Network (2) X Partisanship (0)	0 (.)
Dems. in Network (1) X Reps. in Network (2) X Partisanship (1)	2.128 (1.478)
Dems. in Network (1) X Reps. in Network (3) X Partisanship (0)	0 (.)
Dems. in Network (1) X Reps. in Network (3) X Partisanship (1)	4.329*** (1.219)
Dems. in Network (1) X Reps. in Network (4) X Partisanship (0)	0 (.)
Dems. in Network (1) X Reps. in Network (4) X Partisanship (1)	4.348*** (1.296)
Dems. in Network (2) X Reps. in Network (0) X Partisanship (0)	0 (.)
Dems. in Network (2) X Reps. in Network (0) X Partisanship (1)	0 (.)

Dems. in Network (2) X Reps. in Network (1) X Partisanship (0)	0 (.)
Dems. in Network (2) X Reps. in Network (1) X Partisanship (1)	-4.624 (218.8)
Dems. in Network (2) X Reps. in Network (2) X Partisanship (0)	0 (.)
Dems. in Network (2) X Reps. in Network (2) X Partisanship (1)	-4.812 (218.8)
Dems. in Network (2) X Reps. in Network (3) X Partisanship (0)	0 (.)
Dems. in Network (2) X Reps. in Network (3) X Partisanship (1)	-2.056 (218.7)
Dems. in Network (2) X Reps. in Network (4) X Partisanship (0)	0 (.)
Dems. in Network (2) X Reps. in Network (4) X Partisanship (1)	0 (.)
Dems. in Network (3) X Reps. in Network (0) X Partisanship (0)	0 (.)
Dems. in Network (3) X Reps. in Network (0) X Partisanship (1)	0 (.)
Dems. in Network (3) X Reps. in Network (1) X Partisanship (0)	0 (.)
Dems. in Network (3) X Reps. in Network (1) X Partisanship (1)	0.890 (1.599)
Dems. in Network (3) X Reps. in Network (2) X Partisanship (0)	0 (.)
Dems. in Network (3) X Reps. in Network (2) X Partisanship (1)	-0.131 (1.624)
Dems. in Network (3) X Reps. in Network (3) X Partisanship (0)	0 (.)
Dems. in Network (3) X Reps. in Network (3) X Partisanship (1)	2.578

	(1.405)
Dems. in Network (3) X Reps. in Network (4) X Partisanship (0)	0 (.)
Dems. in Network (3) X Reps. in Network (4) X Partisanship (1)	0 (.)
Dems. in Network (4) X Reps. in Network (0) X Partisanship (0)	0 (.)
Dems. in Network (4) X Reps. in Network (0) X Partisanship (1)	0 (.)
Dems. in Network (4) X Reps. in Network (1) X Partisanship (0)	0 (.)
Dems. in Network (4) X Reps. in Network (1) X Partisanship (1)	1.662 (1.373)
Dems. in Network (4) X Reps. in Network (2) X Partisanship (0)	0 (.)
Dems. in Network (4) X Reps. in Network (2) X Partisanship (1)	1.873 (1.755)
Dems. in Network (4) X Reps. in Network (3) X Partisanship (0)	0 (.)
Dems. in Network (4) X Reps. in Network (3) X Partisanship (1)	-2.945 (218.8)
Dems. in Network (4) X Reps. in Network (4) X Partisanship (0)	0 (.)
Dems. in Network (4) X Reps. in Network (4) X Partisanship (1)	-3.520 (203.1)
Male	0.0831* (0.0392)
Age	0.00506*** (0.00151)
White	0.176*** (0.0469)

Education Level	0.0566**
	(0.0202)
Attention to Politics	0.00433
	(0.0226)
Attention to News	0.00549
	(0.0259)
Ideology	-0.152***
	(0.0153)
Income Level	-0.00319
	(0.00555)
Employed	-0.0477
	(0.0435)
Married	-0.0350
	(0.0439)
Covered by Health Insurance	0.218**
	(0.0750)
Self-Identified General Health	-0.0351
	(0.0197)
# of People in Household	-0.00294
	(0.0139)
Know Someone with Covid	-0.120**
	(0.0383)
State Deaths (divided by 1000)	-0.151
	(0.250)
Rep. Governor	0.0329
	(0.0496)
Statewide Mask Mandate During Survey	0.0202
	(0.0583)
Statewide Mask Mandate Implemented During Survey	-0.0855
	(0.105)

Cutpoint 1	-0.505
	(0.475)
Cutpoint 2	0.450
	(0.475)
Cutpoint 3	1.466**
	(0.475)
Cutpoint 4	2.386***
	(0.476)
N	3390
AIC	9269.5
BIC	9692.4
PCP	36.70
PRE	8.330

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Two-tailed statistical test reported
Data gathered from American National Election Study's 2020 Social Media Study and replication data from "Political partisanship influences behavioral responses to governors' recommendations for COVID-19 prevention in the United States" by Guy Grossman, Soojong Kim, Jonah M. Rexer, and Harsha Thirumurthy

Appendix Figure 3: Ordered Probit Regression of Support for Mask Requirements on Covariates

	Covariates
Dems. in Network (0)	0
	(.)
Dems. in Network (1)	0.341
	(0.751)
Dems. in Network (2)	-0.178
	(0.673)
Dems. in Network (3)	-0.146
	(0.540)
Dems. in Network (4)	0.130
	(0.521)
Reps. in Network (0)	0
	(.)
Reps. in Network (1)	-1.153
	(0.968)

Reps. in Network (2)	3.985 (405.6)
Reps. in Network (3)	-0.838 (0.709)
Reps. in Network (4)	-1.353 (0.760)
Dems. in Network (0) X Reps. in Network (0)	0 (.)
Dems. in Network (0) X Reps. in Network (1)	0 (.)
Dems. in Network (0) X Reps. in Network (2)	0 (.)
Dems. in Network (0) X Reps. in Network (3)	0 (.)
Dems. in Network (0) X Reps. in Network (4)	0 (.)
Dems. in Network (1) X Reps. in Network (0)	0 (.)
Dems. in Network (1) X Reps. in Network (1)	0.686 (1.125)
Dems. in Network (1) X Reps. in Network (2)	-4.507 (405.6)
Dems. in Network (1) X Reps. in Network (3)	0.407 (0.918)
Dems. in Network (1) X Reps. in Network (4)	5.338 (188.8)
Dems. in Network (2) X Reps. in Network (0)	0 (.)
Dems. in Network (2) X Reps. in Network (1)	1.309 (1.083)

Dems. in Network (2) X Reps. in Network (2)	-3.917 (405.6)
Dems. in Network (2) X Reps. in Network (3)	0.324 (0.887)
Dems. in Network (2) X Reps. in Network (4)	2.525 (1.611)
Dems. in Network (3) X Reps. in Network (0)	0 (.)
Dems. in Network (3) X Reps. in Network (1)	1.376 (0.987)
Dems. in Network (3) X Reps. in Network (2)	-3.817 (405.6)
Dems. in Network (3) X Reps. in Network (3)	1.174 (0.781)
Dems. in Network (3) X Reps. in Network (4)	1.267 (1.056)
Dems. in Network (4) X Reps. in Network (0)	0 (.)
Dems. in Network (4) X Reps. in Network (1)	1.149 (0.984)
Dems. in Network (4) X Reps. in Network (2)	-0.176 (477.6)
Dems. in Network (4) X Reps. in Network (3)	4.754 (573.9)
Dems. in Network (4) X Reps. in Network (4)	5.296 (284.1)
Partisanship (0)	0 (.)
Partisanship (1)	0.142 (0.879)
Dems. in Network (0) X Partisanship (0)	0

	(.)
Dems. in Network (0) X Partisanship (1)	0 (.)
Dems. in Network (1) X Partisanship (0)	0 (.)
Dems. in Network (1) X Partisanship (1)	-2.591* (1.263)
Dems. in Network (2) X Partisanship (0)	0 (.)
Dems. in Network (2) X Partisanship (1)	-1.926 (1.415)
Dems. in Network (3) X Partisanship (0)	0 (.)
Dems. in Network (3) X Partisanship (1)	-2.103 (1.353)
Dems. in Network (4) X Partisanship (0)	0 (.)
Dems. in Network (4) X Partisanship (1)	-1.053 (1.035)
Reps. in Network (0) X Partisanship (0)	0 (.)
Reps. in Network (0) X Partisanship (1)	0 (.)
Reps. in Network (1) X Partisanship (0)	0 (.)
Reps. in Network (1) X Partisanship (1)	0.344 (1.374)
Reps. in Network (2) X Partisanship (0)	0 (.)
Reps. in Network (2) X Partisanship (1)	-5.144 (405.6)

Reps. in Network (3) X Partisanship (0)	0 (.)
Reps. in Network (3) X Partisanship (1)	-0.498 (1.029)
Reps. in Network (4) X Partisanship (0)	0 (.)
Reps. in Network (4) X Partisanship (1)	-0.0723 (1.049)
Dems. in Network (0) X Reps. in Network (0) X Partisanship (0)	0 (.)
Dems. in Network (0) X Reps. in Network (0) X Partisanship (1)	0 (.)
Dems. in Network (0) X Reps. in Network (1) X Partisanship (0)	0 (.)
Dems. in Network (0) X Reps. in Network (1) X Partisanship (1)	0 (.)
Dems. in Network (0) X Reps. in Network (2) X Partisanship (0)	0 (.)
Dems. in Network (0) X Reps. in Network (2) X Partisanship (1)	0 (.)
Dems. in Network (0) X Reps. in Network (3) X Partisanship (0)	0 (.)
Dems. in Network (0) X Reps. in Network (3) X Partisanship (1)	0 (.)
Dems. in Network (0) X Reps. in Network (4) X Partisanship (0)	0 (.)
Dems. in Network (0) X Reps. in Network (4) X Partisanship (1)	0 (.)
Dems. in Network (1) X Reps. in Network (0) X Partisanship (0)	0 (.)

Dems. in Network (1) X Reps. in Network (0) X Partisanship (1)	0 (.)
Dems. in Network (1) X Reps. in Network (1) X Partisanship (0)	0 (.)
Dems. in Network (1) X Reps. in Network (1) X Partisanship (1)	1.358 (1.658)
Dems. in Network (1) X Reps. in Network (2) X Partisanship (0)	0 (.)
Dems. in Network (1) X Reps. in Network (2) X Partisanship (1)	6.733 (405.6)
Dems. in Network (1) X Reps. in Network (3) X Partisanship (0)	0 (.)
Dems. in Network (1) X Reps. in Network (3) X Partisanship (1)	1.874 (1.384)
Dems. in Network (1) X Reps. in Network (4) X Partisanship (0)	0 (.)
Dems. in Network (1) X Reps. in Network (4) X Partisanship (1)	-3.212 (188.8)
Dems. in Network (2) X Reps. in Network (0) X Partisanship (0)	0 (.)
Dems. in Network (2) X Reps. in Network (0) X Partisanship (1)	0 (.)
Dems. in Network (2) X Reps. in Network (1) X Partisanship (0)	0 (.)
Dems. in Network (2) X Reps. in Network (1) X Partisanship (1)	0.482 (1.799)
Dems. in Network (2) X Reps. in Network (2) X Partisanship (0)	0 (.)
Dems. in Network (2) X Reps. in Network (2) X Partisanship (1)	6.240 (405.6)
Dems. in Network (2) X Reps. in Network (3) X Partisanship (0)	0

	(.)
Dems. in Network (2) X Reps. in Network (3) X Partisanship (1)	2.103 (1.554)
Dems. in Network (2) X Reps. in Network (4) X Partisanship (0)	0 (.)
Dems. in Network (2) X Reps. in Network (4) X Partisanship (1)	0 (.)
Dems. in Network (3) X Reps. in Network (0) X Partisanship (0)	0 (.)
Dems. in Network (3) X Reps. in Network (0) X Partisanship (1)	0 (.)
Dems. in Network (3) X Reps. in Network (1) X Partisanship (0)	0 (.)
Dems. in Network (3) X Reps. in Network (1) X Partisanship (1)	0.938 (1.724)
Dems. in Network (3) X Reps. in Network (2) X Partisanship (0)	0 (.)
Dems. in Network (3) X Reps. in Network (2) X Partisanship (1)	6.387 (405.6)
Dems. in Network (3) X Reps. in Network (3) X Partisanship (0)	0 (.)
Dems. in Network (3) X Reps. in Network (3) X Partisanship (1)	1.908 (1.502)
Dems. in Network (3) X Reps. in Network (4) X Partisanship (0)	0 (.)
Dems. in Network (3) X Reps. in Network (4) X Partisanship (1)	0 (.)
Dems. in Network (4) X Reps. in Network (0) X Partisanship (0)	0 (.)
Dems. in Network (4) X Reps. in Network (0) X Partisanship (1)	0

	(.)
Dems. in Network (4) X Reps. in Network (1) X Partisanship (0)	0 (.)
Dems. in Network (4) X Reps. in Network (1) X Partisanship (1)	-0.396 (1.528)
Dems. in Network (4) X Reps. in Network (2) X Partisanship (0)	0 (.)
Dems. in Network (4) X Reps. in Network (2) X Partisanship (1)	1.417 (477.6)
Dems. in Network (4) X Reps. in Network (3) X Partisanship (0)	0 (.)
Dems. in Network (4) X Reps. in Network (3) X Partisanship (1)	-3.991 (573.9)
Dems. in Network (4) X Reps. in Network (4) X Partisanship (0)	0 (.)
Dems. in Network (4) X Reps. in Network (4) X Partisanship (1)	-10.51 (537.5)
Male	-0.0797 (0.0473)
Age	0.0170*** (0.00187)
White	-0.0253 (0.0581)
Education Level	0.0576* (0.0244)
Attention to Politics	-0.0275 (0.0266)
Attention to News	0.0910** (0.0304)
Ideology	-0.244*** (0.0190)

Income Level	0.00131
	(0.00668)
Employed	-0.0742
	(0.0526)
Married	-0.0392
	(0.0535)
Covered by Health Insurance	0.104
	(0.0855)
Self-Identified General Health	-0.0313
	(0.0240)
# of People in Household	-0.00306
	(0.0165)
Know Someone with Covid	-0.156***
	(0.0458)
State Deaths (divided by 1000)	-0.106
	(0.316)
Rep. Governor	0.0509
	(0.0602)
Statewide Mask Mandate During Survey	0.138*
	(0.0690)
Statewide Mask Mandate Implemented During Survey	-0.0888
	(0.117)
Cutpoint 1	-2.184***
	(0.537)
Cutpoint 2	-1.686**
	(0.537)
Cutpoint 3	-1.183*
	(0.536)
Cutpoint 4	-0.609
	(0.536)
N	3391

AIC	6649.4
BIC	7072.3
PCP	63.05
PRE	8.205

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Two-tailed statistical test reported
Data gathered from American National Election Study's 2020 Social Media Study and replication data from "Political partisanship influences behavioral responses to governors' recommendations for COVID-19 prevention in the United States" by Guy Grossman, Soojong Kim, Jonah M. Rexer, and Harsha Thirumurthy