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**UNMASKING PARTISANSHIP:
POLARIZATION UNDERMINES PUBLIC
RESPONSE TO COLLECTIVE RISK**

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UNMASKING PARTISANSHIP: POLARIZATION UNDERMINES PUBLIC RESPONSE TO COLLECTIVE RISK

Abstract

Political polarization may undermine public policy response to collective risk, especially in periods of crisis, when political actors have incentives to manipulate public perceptions. We study these dynamics in the United States, focusing on how partisanship has influenced the use of face masks to stem the spread of COVID-19. Using a wealth of micro-level data, machine learning approaches, and a novel quasi-experimental design, we establish the following: (1) mask use is robustly correlated with partisanship; (2) the impact of partisanship on mask use is not offset by local policy interventions; (3) partisanship is the single most important predictor of local mask use, not COVID-19 severity or local policies; (4) president Trump's unexpected mask use at Walter Reed on July 11, 2020 and endorsement of masks on July 20, 2020 significantly increased social media engagement with and positive sentiment towards mask-related topics. These results unmask how partisanship undermines effective public responses to collective risk and how messaging by political agents can increase public engagement with policy measures.

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Unmasking Partisanship: Polarization Undermines Public Response to Collective Risk

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Abstract

Political polarization may undermine public policy response to collective risk, especially in periods of crisis, when political actors have incentives to manipulate public perceptions. We study these dynamics in the United States, focusing on how partisanship has influenced the use of face masks to stem the spread of COVID-19. Using a wealth of micro-level data, machine learning approaches, and a novel quasi-experimental design, we establish the following: (1) mask use is robustly correlated with partisanship; (2) the impact of partisanship on mask use is *not* offset by local policy interventions; (3) partisanship is the single most important predictor of local mask use, not COVID-19 severity or local policies; (4) president Trump's unexpected mask use at Walter Reed on July 11, 2020 and endorsement of masks on July 20, 2020 significantly increased social media engagement with and positive sentiment towards mask-related topics. These results unmask how partisanship undermines effective public responses to collective risk and how messaging by political agents can increase public engagement with policy measures.

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*We thank Alex Engler and Thomas Pepinsky for comments. All errors remain our own.

Introduction

Political scientists have long recognized that increased polarization can undermine effective public policy via lack of accountability, diminished trust in government, divisive use of rules and tactics within Congress, and gridlock on issues of national importance (McCarty, 2007; Brady, Ferejohn and Harbridge, 2008; Iyengar et al., 2019). As the 2020 pandemic has demonstrated, partisanship might have more direct, immediate policy consequences. During periods of substantial collective risk, uncertainty over optimal policy responses enables political agents to manipulate signals received by the public (Gitmez, Sonin and Wright, 2020) and create competing narratives over the extent of the crisis (Eliaz and Spiegler, 2020), who has been or will be impacted, and how members of the public should respond to the collective risk (Grossman et al., 2020). The promotion of distorted facts or disinformation may significantly impact public policy interventions and public health outcomes by undermining compliance with government recommendations and enforceable mandates (Bursztyn et al., 2020; Ash et al., 2020).

We study these dynamics in the United States, focusing on how partisanship has influenced the use of face masks to stem the spread of COVID-19. Prior work has demonstrated how partisanship influences public perceptions of and responses to the ongoing pandemic (Allcott et al., 2020; Painter and Qiu, 2020; Gadarian, Goodman and Pepinsky, 2020). Leveraging cellphone trace data and repeated surveys, this work has linked partisanship with voluntary social distancing, compliance with local shelter-in-place mandates, and beliefs about the severity of the pandemic as well as individual-level behavioral responses (e.g., staying home from work). These findings clarify how economically costly behaviors shift to government interventions and public information. The advantage of our focus on the public use of face masks is that it provides a clearer assessment of how partisanship influences responses to collective risk since there is no trade-off between mask use and economic activity. By contrast, social distancing has had an adverse effect in terms of consumer activity (Goolsbee and Syverson, 2020; Chetty et al., 2020; Coibion, Gorodnichenko and Weber, 2020) and job losses (Friedson et al., 2020; Chudik, Pesaran and Rebucci, 2020; Gupta et al., 2020; Beland et al., 2020) and is itself influenced by economic conditions (Wright, Sonin, Driscoll and Wilson, 2020). Partisan divides in mask wearing are more likely to reflect pure politi-

cization effects, rather than differing underlying views about how to balance economic and societal priorities during a health crisis.

Our empirical work leverages rich, micro-level survey data from 250,000 respondents on mask use collected during July 2020. We supplement the mask use data with granular measures of local voting patterns, demographic characteristics, social and economic conditions, and COVID-19 cases and deaths. Further, we use hand-collected data on county- and state-level mask mandates to study whether these policies alleviate any differences in mask use by political affiliation. We also collect millions of mask-related tweets surrounding both President Trump’s visit to Walter Reed Medical Center on July 11, 2020 and Trump’s endorsement of masks on July 20, 2020. The social media data enables real-time analysis of whether the public’s engagement and sentiment towards mask use is affected by the cues of America’s top elected official.

We implement four related research designs. Each design enables us to assess a distinct aspect of the impact of partisan polarization on policy implementation. We start with evaluation of the association between partisanship and mask use. Leveraging a combination of zipcode- and county-level data and variation, this approach begins with the simple bivariate correlation and then adds dozens of covariates as well as alternative fixed effects specifications to account for potential confounding factors. We are able to convincingly rule out a number of plausible explanations for a potential link and find robust evidence of an association between political preferences and mask use. We also use the technique described in [Oster \(2019\)](#) to assess the potential biases from unobservable characteristics. Taking advantage of this test, we are able to bound the estimated effects of partisanship using our most demanding fixed effects approach. We find that the main effect is robust to extremely conservative specifications of positive and negative selection on unobservable characteristics. Overall, the first design reveals that the association between partisanship and mask use is large, statistically precise, and highly unlikely to be explained by observed or unobserved confounding factors.

Next, we gather novel data on local mask use mandates and assess whether the correlation between mask use and mask mandates varies across levels of partisanship. We leverage the flexible estimation approach described in [Hainmueller, Mummolo and Xu \(2019\)](#) to investigate these differential effects across counties. We find no evidence that mask mandates

increase mask use in Republican areas, though these mandates do increase mask use in heavily Democratic counties.

Our third design addresses important questions that our first design cannot address: can local political preferences be used to effectively predict mask use? How does the predictive power of partisanship compare with other factors that could reasonably influence the decision to use a mask in public, such as local COVID-19 severity or prevalence of comorbidity risk in the surrounding area? Using the least absolute shrinkage and selection operator (LASSO) methods ([Tibshirani, 1996](#)), we find that that partisanship remains the most robust and effective predictor of mask use across numerous alternative machine learning approaches. This finding suggests that the result uncovered in the first design is not just a statistically precise effect with little real-world relevance; indeed, partisanship is *the* primary factor influencing variation in local mask use across a broad array of potential model specifications.

Our fourth design leverages social media data and President Trump’s unexpected public appearance in a mask to investigate how leadership, even among partisans, can influence attention and sentiment towards a polarized issue or topic. The president’s tweet serves as a quasi-experimental shock to partisan messaging, following the event study design approach in [Benton and Philips \(2020\)](#). We find that engagement with and attitudes towards mask use online increases and becomes more positive after each of these events. A second event, Trump’s unexpected praise of mask use as patriotic, allows us to produce a nearly identical out-of-sample replication of our baseline event study design. We find comparably scaled effects of presidential messaging on social media engagement and sentiment. In the Appendix, we provide a theoretical model that explains the non-monotonic impact of a message sent by a biased source in a polarized polity: an increase in the signal’s bias has a low impact when the bias is relatively low, but jump to significant levels when the source is heavily biased.¹

The results from these research designs provide compelling evidence regarding the relationship between partisanship and mask use. We find that the vote share for Donald Trump in the 2016 election is negatively correlated with mask use and is the single most important predictor of mask use. Local policy interventions do not attenuate the relationship between partisanship and mask use, but natural experiments surrounding Trump’s mask use and

¹Compared to the classic model of the “Nixon goes to China” phenomenon by [Cukierman and Tommasi, 1998](#), in our model the channel of changing beliefs is information provision rather than a policy choice.

endorsement show that both attention and positive sentiment towards masks do increase with the President’s involvement.² In addition to documenting the immediate impact of partisanship on public policy, our results speak to the debate on whether voters can affect policies (Lee, Moretti and Butler, 2004) and demonstrate the importance of national leadership (Jones and Olken, 2005).

The rest of the paper is organized as follows. The short Section 2 describes the existing evidence on masks usage. Section 3 contains the empirical analysis. Section 4 concludes.

2 The Science and Politics of Mask Usage

By the half-year mark of the pandemic, mask mandates emerged as a cornerstone of the COVID-19 policy response. Recent medical and epidemiological research suggests that face coverings are effective in reducing viral transmission loads and slowing or even stopping the pandemic’s trajectory, while involving minimal downsides (Schünemann et al., 2020; Chernozhukov, Kasahara and Schrimpf, 2020). Several studies have shown that the cloth and medical masks typically worn by the general population offer various degrees of protection against viral respiratory infection and reduce the transmission of viral load through respiratory droplets and aerosol (Fischer et al., 2020; Chu et al., 2020; Leung et al., 2020). Moreover, due to the particular nature of the coronavirus disease, with its high rate of asymptomatic transmission (Gandhi, Yokoe and Havlir, 2020; Bai et al., 2020; Nishiura et al., 2020) and its transmission through droplets (Stadnytskyi et al., 2020), widespread mask use currently appears to be one of if not the only effective mitigation strategy that can reduce the transmission rate without undermining economic activities (Gandhi and Rutherford, 2020).

There was, however, no such academic consensus on the efficacy of widespread mask use in the initial stages of the pandemic, clearing the way for its subsequent politicization.³ This was likely the combined result of the paucity of knowledge about the novel coronavirus (WHO, 2020), as well as the international community’s historical focus on vaccine development

²Given our focus on immediate policy consequences of partisanship and polarization in these experiments, we do not address the potential effect of President’s action on polarization itself. Given the existing results on the effect of information provision on polarization (Levendusky and Malhotra, 2016), it is natural to expect a significant impact.

³See, e.g., Klompas et al. 2020, published May 2020: “In many cases, the desire for widespread masking is a reflexive reaction to anxiety over the pandemic.”

instead of alternative pandemic mitigation strategies such as mask use (Kamradt-Scott, 2012). The academic literature on the politicization of public symbols and natural disasters suggests several potential explanations for the partisan divide in mask use that developed out of this initial uncertainty: devoid of unequivocal medical purpose, masks can become signals of co-partisanship (Posner, 1998; Cornelson and Miloucheva, 2020; Goldstein and Wiedemann, 2020); symbols of individual autonomy vs. social responsibility (Taylor, 2019) or of competing electoral narratives (Eliaz and Spiegler, 2020). Leaders’ decisions to encourage mask use (or not) can depend on their social welfare preferences (Cohen and Werker, 2008), their incentives towards corruption (Yamamura, 2014), or the local political landscape (Ono, 2017).⁴ The observed polarization might also be influenced by the early geographic spread of COVID-19 in predominantly Democratic counties, reducing the perceived necessity of mask use in Republican areas (Barrios and Hochberg, 2020).

3 Empirical Analysis

We explore several research designs to assess the impact of partisan polarization on policy implementation. First, we statistically isolate and estimate the association between partisanship and mask use starting with the simple bivariate correlation and then adding numerous potential covariates as well as alternative fixed effects specifications to account for potential confounding factors. Second, we use data on local mask use mandates to investigate their differential effects across counties. Third, we further establish robustness of our findings using machine learning approaches. Finally, we use President Trump’s unexpected public appearance in a mask as a quasi-experiment to investigate how leadership, even among partisans, can influence attention and sentiment towards a polarized issue or topic.

3.1 Robust Regression-Based Evidence

Using a regression-based framework, we evaluate the correlation between voting patterns in the 2016 presidential election and local mask use. We begin by studying the simple bivariate correlation between zip code-level mask use and county-level vote shares to Donald Trump in the 2016 presidential election. This result is presented in Figure 1 panel (a) for the pooled

⁴At the same time, harder-hit counties have been found to exhibit larger decreases in electoral support for Republican candidates (Warshaw, Vavreck and Baxter-King, 2020).

cross section. We find that voting patterns alone explain more than 36% of variation in mask use. A one standard deviation shift in votes in favor of Donald Trump (=18% swing) decreases mask use by 13.1% ($p < .001$). In panels (b) and (c) we residualize mask use and voting patterns using state and state-by-rural index fixed effects (Gadarian, Goodman and Pepinsky, 2020). Even under such demanding specifications, the correlation remains consistent in magnitude and the explanatory power of voting patterns remains large (25% and 12%, respectively).

This correlation between mask use and partisanship may, however, be driven by a number of confounding factors including local mask mandates and the economic and demographic characteristics of the given area. To address these concerns, we consider a more saturated regression approach. We estimate several variations of the following regression specification:

$$maskuse_z = \alpha + \beta GOP_voteshare_{c,2016} + \sum_{i=1}^k \phi_i X_c^k + \lambda_{sr} + \epsilon_c \quad (1)$$

where $maskuse_z$ is the measure of mask use by zip code. $GOP_voteshare_{c,2016}$ indicates the GOP vote share in the 2016 presidential election. We then collect, in the vector X_c^k , k local characteristics that might confound the correlation between mask use and voting patterns⁵: demographic characteristics⁶, COVID severity⁷, local mask mandates, economic characteristics⁸, social capital⁹, and comorbidity patterns.¹⁰ We then vary the fixed effects used in each regression, including state and state-by-rural index fixed effects. This is parameterized as λ_{sr} in equation 1. Heteroskedasticity-robust standard errors are clustered by county.

⁵We outline each data source in the appendix

⁶Variables: population, adult college graduation rate; high school graduation rate; on-time graduation rate; percentage of the population that is 65 and above; percentage of white, black, Hispanic, indigenous, and Asian individuals in the county population; black-white segregation index; percentage of the local population that is foreign born; percentage of the population that resides in a rural area of the surrounding county; net migration; average commute time to work.

⁷Variables: cumulative cases and cumulative deaths per capita.

⁸Variables: average income in 2016, unemployment rate in 2016, share of the local economy due to agriculture and manufacturing, male labor force participation, poverty rate, percentage of the local population with debts in collection, percentage of the population that spends more than 35% of income on housing, Gini coefficient, relative immobility, and percentage of the housing stock that is resident-owned

⁹Variables: number of organizations: religious, civic, business, political, professional, labor, bowling, recreational, golf, and sporting; mail-back US census response rate; social capital index. For additional details on the social capital index, see Rupasingha, Goetz and Freshwater (2006).

¹⁰Variables: percentage of adults with poor or fair health; premature mortality; percentage that are disabled, diabetic, obese, and smoke (distinct categories); percentage of babies born with low birth-weight; percentage with no health insurance coverage.

We stagger the introduction of covariates in the regression results presented in Figure 1 panels (d) through (f). Using the pooled cross section, the main effect of voting patterns is attenuated with the introduction of additional control variables but remains highly statistically significant ($p < .001$) and stable at approximately $\beta = -.39$. Using state-level fixed effects in panel (e), the introduction of covariates does not cause attenuation in the association between partisanship and mask use. The estimated effect size is approximately $\beta = -.53$. Once we account for state-by-rural index fixed effects in panel (f), the association between partisanship and mask use stabilizes at $\beta = -.44$. In Figure 2, we estimate bounds for the main effect of vote share on local mask use using the Oster coefficient stability test (Oster, 2019). This method enables us to evaluate how selection on unobservables relative to the observable covariates included in our most demanding model specification could influence the estimated correlation. This approach allows us to account for positive and negative selection on unobservables (relative to observables). It is important to recall that bias caused by omitted variables itself can be either positive or negative, which slightly changes the interpretation of the direction of selection in the test. In Figure 1 panel (f), notice that the magnitude of the effect of partisanship is increasing in magnitude (becoming more negative) as additional covariates are added. The main effect, in this case, is biased towards zero from below. Accounting for positive selection will increase the magnitude of the estimated effect (in absolute terms) while accounting for negative selection will decrease the magnitude (in absolute terms). Because of these case-specific sources of bias, the range of bounded effects estimated by the test narrows rather than widens. Results from 1048 alternative combinations of selection thresholds and model fit suggest the range of potential coefficients is approximately $-.32$ to $-.34$, a substantively large reduction in mask use due to partisanship that is consistent in magnitude with the baseline result in Figure 1 panel (f).

3.2 The Marginal Effect of Policy Interventions

Mask-related policy interventions play an important role in the prevalence of mask use and the spread of COVID-19 (Cheng et al. (2020); Lyu and Wehby (2020)). Next, we study novel data on county-specific and state-wide mask mandates. We demonstrate that the government interventions do not close the partisan gap in mask use. To study these dynamics, we

estimate flexible (non-linear) marginal effects of a local mask mandate under varying levels of partisanship using the approach described in [Hainmueller, Mummolo and Xu \(2019\)](#). These results are presented in Figure 3. In panel (a), we pool variation using the cross section. Flexibly estimated marginal effects with state and state-by-rural index fixed effects are presented in panels (b) and (c). Results are consistent across specifications. In areas with strong Democratic support in 2016 (i.e., GOP vote shares between 0 and .2), we observe large marginal effects: government mandates significantly increase mask use among subjects where mask use is already pervasive. For the rest of the distribution, however (i.e., where GOP vote share exceeds .2), we observe no meaningful variation in the marginal effect of government mask mandates on mask use. Stated differently, government policy interventions do not increase mask use at moderate to high levels of Republican vote share and, as such, do not close the partisan gap in mask wearing.

3.3 Machine Learning Approaches

Using several machine learning approaches, we examine which local factors most consistently predict mask use. That way, we find compelling evidence that voting patterns in 2016 is the single most important factor predicting mask use. These results are presented in Figure 4, where we implement least absolute shrinkage and selection operator (LASSO) methods from the machine learning literature ([Tibshirani, 1996](#)) using the pooled cross section (panel (a)) as well as when residualizing state and state-by-rural index fixed effects (panels (b) and (c) respectively). Across all specifications, the first factor loading is GOP vote share in 2016. The second loading is either local mask mandates or the percentage of adults that have graduated from college. As the L1 Norm is relaxed, the magnitude of the GOP vote share coefficient immediately increases and remains stable (the slope of the convex solid line noted in Figure 4). K-fold cross-validation (using 10 folds) suggests the coefficient magnitude for vote share in the optimal specification is approximately identical to the baseline regression estimates in Figure 1.

3.4 Quasi-Experimental Design

Our fourth design leverages the unexpected news that President Trump wore a face mask for the first time in public as a quasi-experimental shock to partisan messaging. We use mask-related engagement and sentiment on Twitter, a large social media platform, to estimate a series of interrupted time series models using the exact timing of the Walter Reed event. This event consisted of President Trump wearing a face mask while visiting wounded members of the military at Walter Reed National Military Medical Center. We began by compiling the universe of mask-related tweets between July 6 and July 19 to get consistent coverage around July 11. To collect only mask-related tweets, we focused on the key words “mask” and “face covering”. The resulting tweets are in English language but are not necessarily written by American users, since it was not possible to restrict the search by users’ location. To identify $tweet_0$, we mine mask-related tweets on July 11 in the time window around Trump’s visit to the hospital. While there was some discussion about Trump potentially wearing a mask to the hospital from the morning onward, the first tweet confirming it as a fact was sent at 16:34 Eastern Standard Time. We use this minute of the day as the temporal discontinuity in our analysis. Within approximately five minutes of this event, the volume of mask-related tweets had increased by 2.13 standard deviations (see Figure 5, (a)).

Next, we classify the tweets by sentiment using the sentiment lexicon from [Hu and Liu \(2004\)](#). The lexicon classifies certain words as positive or negative, which allows us to find the share of each class in a list of tweets. This enables us to study changes in mask-related sentiment around the identified temporal discontinuity. There is a substantial shift in sentiment, equivalent to .94 standard deviations (see Figure 5, (e)).

In Figure 5, panels (d) and (h), we report results from a series of interrupted time series models. These models reveal that the level shift in volume and sentiment is substantively large and statistically precise ($p < .001$), even after accounting for the temporal autocorrelation of activity on Twitter.

In Figure 5, panels (b) and (f), we find similar patterns at the temporal discontinuity after deseasonalizing trends in volume and sentiment using hour-of-day fixed effects. In Figure 5, panels (c) and (g), we repeat this exercise using quarter-of-hour-of-day fixed effects for a more refined deseasonalization of the raw volume and sentiment data. For the shift in mask-related tweet volume, we find evidence of an even larger overall effect at the discontinuity after

removing trends (4.24 standard deviation increase, $p < .001$). For mask-related sentiment, we find consistent, though slightly larger, effects at the discontinuity (1.02 standard deviation increase, $p < .001$). These results are displayed in Figure 5, panels (d) and (h) (second and third estimated effects indicate deseasonalized parameters).

We replicate this result using a secondary natural experiment: President Trump’s unexpected use of Twitter to promote mask use as patriotic. This event occurred at 14:43 Eastern Standard Time on July 20, 2020. The results are shown in Figure 6 (presentation is equivalent to Figure 5). We find evidence of a large, 2.6 standard deviation increase in the volume of mask-related tweets, as well as a substantial .6 standard deviation increase in positive sentiment in these tweets.

4 Conclusion

Our paper provides robust evidence that partisanship has influenced adoption of both public health recommendations and requirements during an ongoing crisis in the United States. These findings are consistent with the emergence of competing narratives that have politicized pandemic response in the United States. Accounting for numerous alternative mechanisms that potentially confound the correlation between partisanship and mask use does not significantly attenuate the result, suggesting a robust link. Even when accounting for the effect of local mask mandates, partisanship remains the most consistent predictor of mask use. These results address important and time-sensitive concerns about how to stem the spread of COVID-19 in polarized contexts, including the United States and Brazil (Ricard and Medeiros, 2020). Our findings contribute to the academic literature on the dynamics between voters and policies, and the dynamic effects of messaging by political or social leaders. Evidence from a quasi-experimental design that leverages Trump’s unexpected mask use at Walter Reed Medical Center and later endorsement of mask use indicates that partisan messaging, particularly if it counters a prevailing narrative, can increase public sentiment towards and engagement with mask use.

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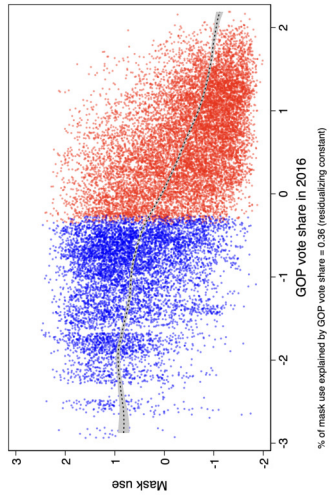
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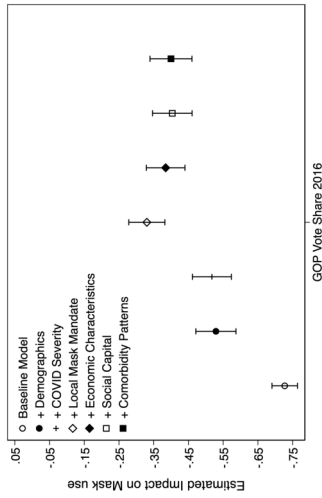
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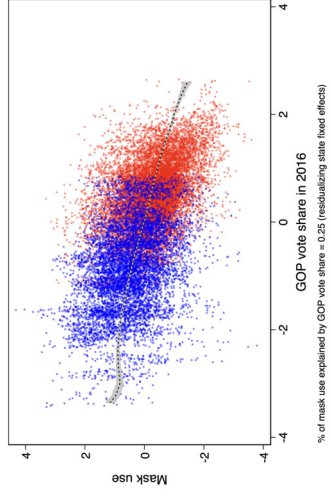
Figure 1: Partisanship strongly correlated with local mask use.



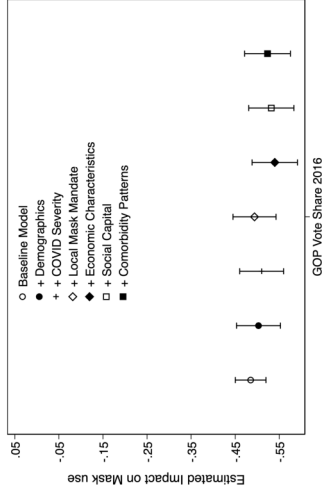
(a) Pooled Cross Section.



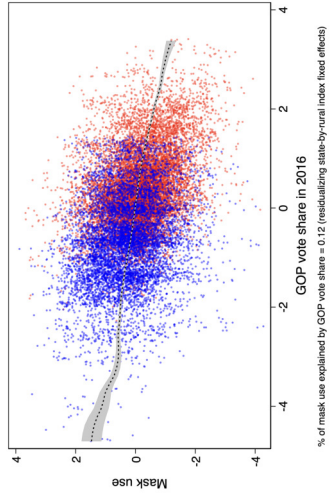
(d) Pooled Cross Section.



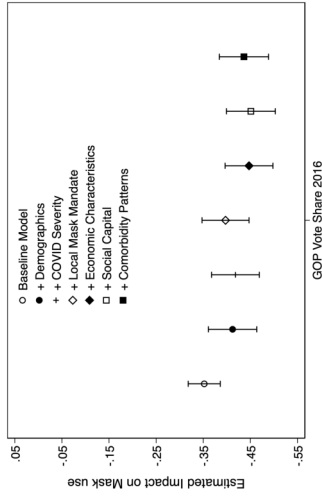
(b) Within State Variation.



(e) Within State Variation.



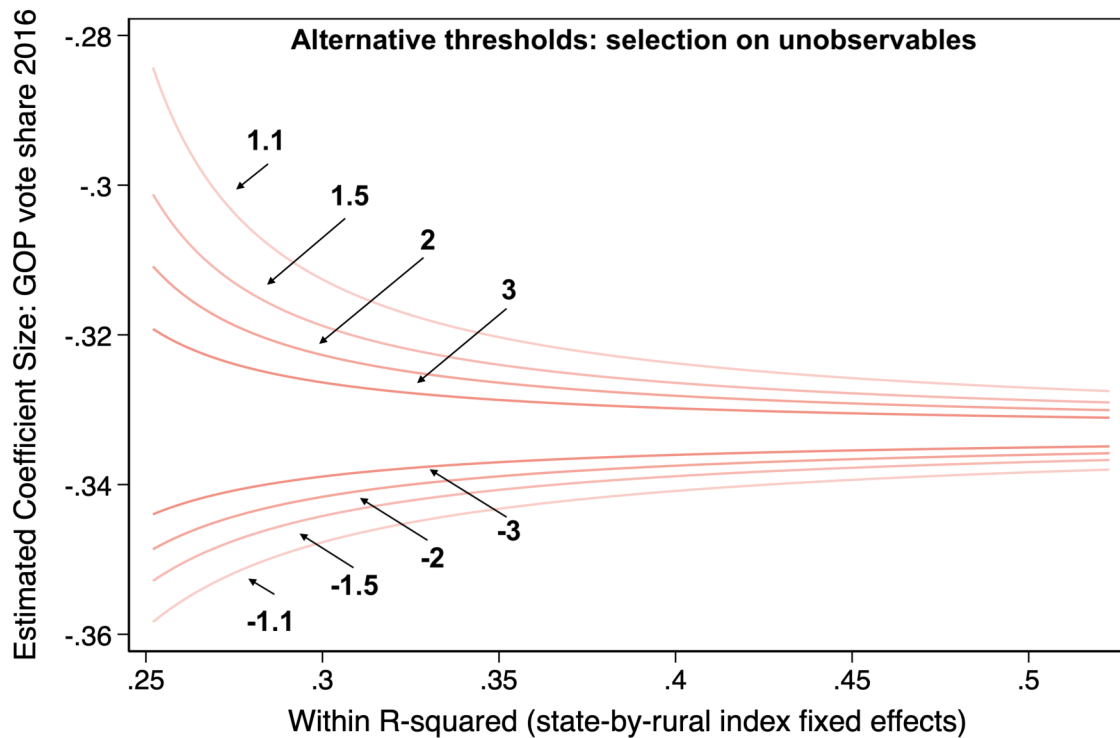
(c) Within State-by-Rural Index Variation.



(f) Within State-by-Rural Index Variation.

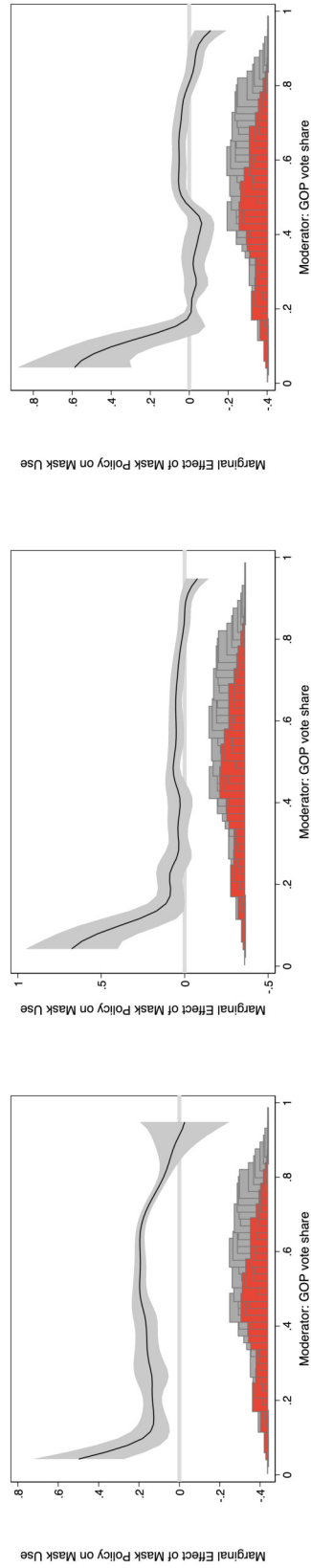
Notes: zip code-level measure of mask use prevalence is strongly correlated with county-level GOP vote share in 2016 election. The constant is residualized in (a/d), state fixed effects are residualized in (b/e), and state-by-rural index (zip code-level) fixed effects are residualized in (c/f). Subpanels (d), (e), and (f) present results from multivariate linear regressions as detailed in the text. Mask use measures compiled by Dynata from zip code-level surveys from July 2, 2020 to July 14, 2020. Rural index is compiled by the United States Census Bureau and is a nine point scale. Each element of the index is allowed to have a state-specific effect.

Figure 2: Unobservables are unlikely to explain observed relationship between partisanship and local mask use.



Notes: Bounds for treatment effects are estimated using the Oster coefficient stability test (Oster, 2019). The relative degree of selection on unobservables (compared to observables) is allowed to vary in the most saturated model specification in Figure 1 (f): 1.1, 1.5, 2, 3 (as well as negative selection at these thresholds). The within-fixed effect (state-by-rural index) variation explained by the most saturated model is .21. The corresponding R_max value is allowed to vary continuously (x axis). The coefficient of vote share converges to approximately -0.33. Figure 1 (f) suggests the estimated magnitude of the main effect is *increasing* as additional covariates are added to the regression, explaining why the corresponding positive and negative proportional selection bounds converge (instead of diverge).

Figure 3: Government interventions do not consistently reduce partisan gap in mask use.



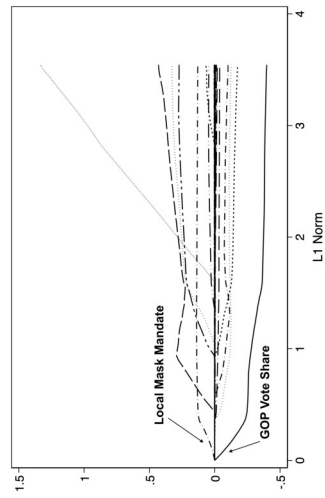
(a) Pooled Cross Section.

(b) Within State Variation.

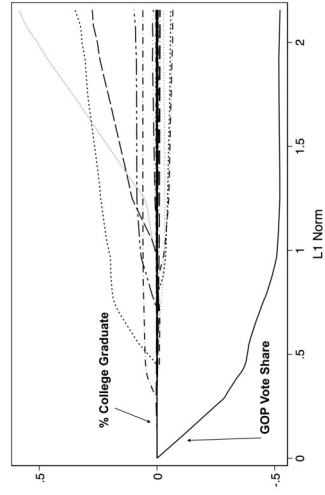
(c) Within State-by-Rural Index Variation.

Notes: The partisan gap in mask use is not consistently reduced by government interventions. Flexible marginal effects of mask policies were estimated using the *interflex* package compiled by [Hainmueller, Mummolo and Xu \(2019\)](#). The constant is residualized in (a), state fixed effects are residualized in (b), and state-by-rural index (zip code-level) fixed effects are residualized in (c). Mask use measures compiled by Dynata from zip code-level surveys from July 2, 2020 to July 14, 2020. Rural index is compiled by the United States Census Bureau and is a nine point scale. Each element of the index is allowed to have a state-specific effect.

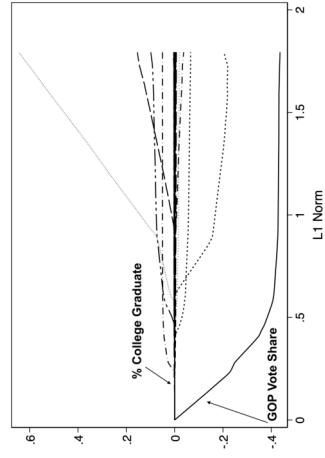
Figure 4: Partisanship remains most important predictor of local mask use using machine learning methods.



(a) Pooled Cross Section.



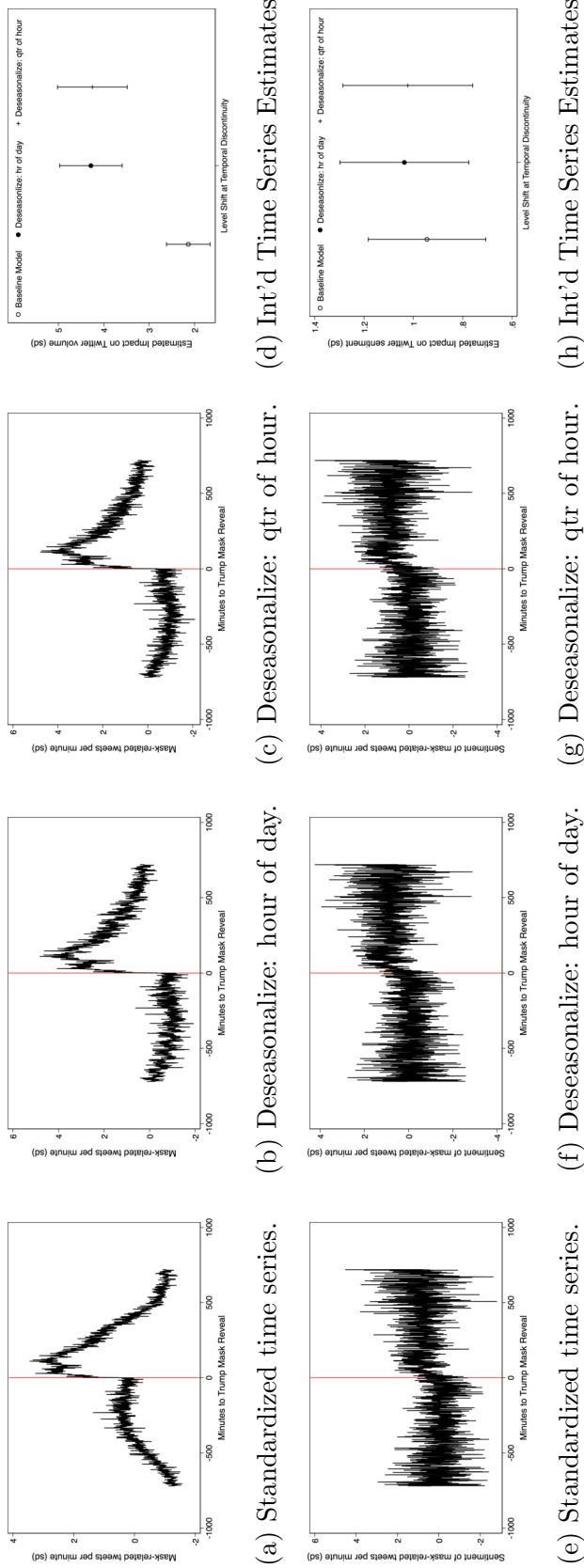
(b) Within State Variation.



(c) Within State-by-Rural Index Variation.

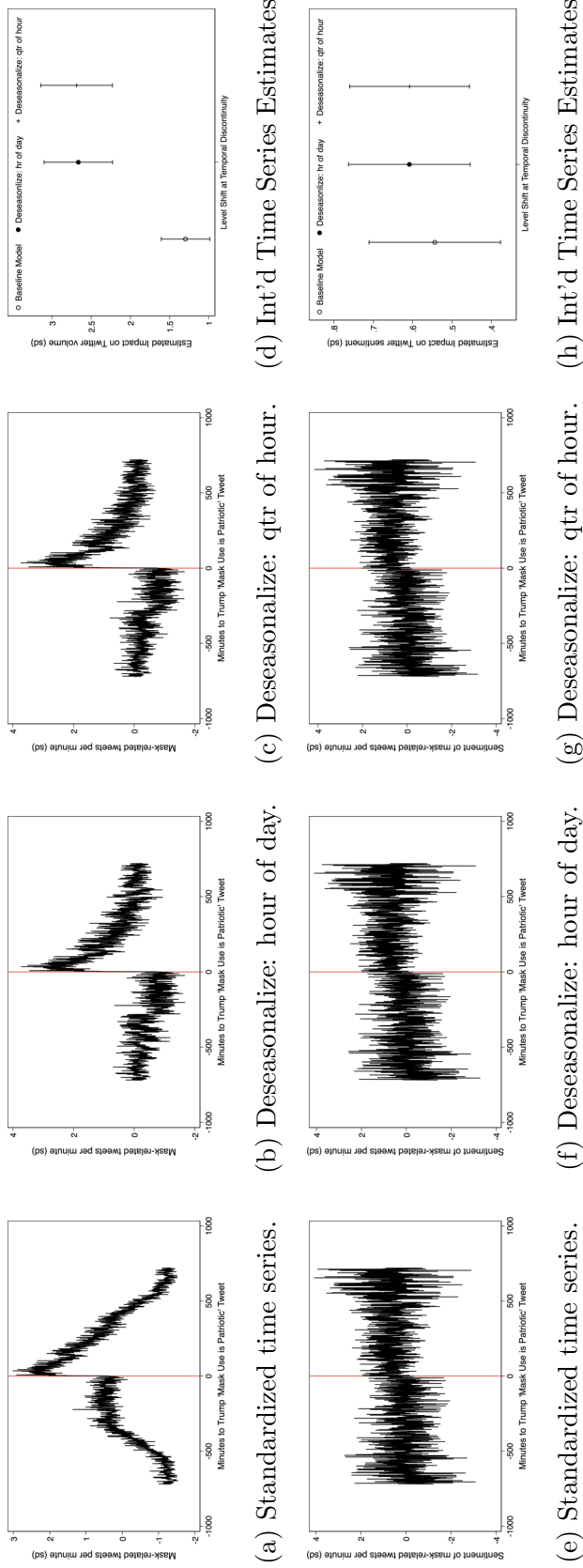
Notes: Least absolute shrinkage and selection operator (LASSO) machine learning estimates presented to show which factors most consistently predict mask use. The constant is residualized in (a), state fixed effects are residualized in (b), and state-by-rural index (zip code-level) fixed effects are residualized in (c). Mask use measures compiled by Dynata from zip code-level surveys from July 2, 2020 to July 14, 2020. Rural index is compiled by the United States Census Bureau and is a nine point scale. Each element of the index is allowed to have a state-specific effect.

Figure 5: Trump mask use increases mask-related social media engagement and positive sentiment.



Notes: (a)-(d) focus on level changes in mask-related content on Twitter (intensive margin of tweets per minute). (e)-(h) focus on composition changes in sentiment (positive versus negative language) in mask-related content on Twitter (intensive margin of sentiment share per minute). Sample cutoff around treatment discontinuity is twelve hours pre/post. Treatment discontinuity is 16:34 Eastern Standard Time, when news of Trump mask use at Walter Reed Hospital breaks. Interrupted time series analysis is implemented in (d) and (h) using autocorrelation-robust standard errors with a lag structure of 60 minutes.

Figure 6: Trump support for mask use on Twitter increases mask-related social media engagement and positive sentiment.



Notes: (a)-(d) focus on level changes in mask-related content on Twitter (intensive margin of tweets per minute). (e)-(h) focus on composition changes in sentiment (positive versus negative language) in mask-related content on Twitter (intensive margin of sentiment share per minute). Sample cutoff around treatment discontinuity is twelve hours pre/post. Treatment discontinuity is 14:43 Eastern Standard Time, when Trump sent tweet about mask use being patriotic (<https://bit.ly/3kAFg0a>). Interrupted time series analysis is implemented in (d) and (h) using autocorrelation-robust standard errors with a lag structure of 60 minutes.

Appendix

Data

We outline the sources and construction of each component of our data below.

Mask use by zip code: The New York Times commissioned Dynata, an online market research firm, to collect a large scale survey in the United States about mask use. The survey was conducted online between July 2 and July 14 and includes 250,000 survey responses. Each participant was asked “How often do you wear a mask in public when you expect to be within six feet of another person?” with answer options of “Never,” “Rarely,” “Sometimes,” “Frequently,” and “Always.” These responses are then normalized to create our primary outcome of interest described in The New York Times’s introduction of the data: the probability (chance) that, if one has five random encounters, all people encountered are wearing masks. Zip code level measures are produced using the geographic location of survey responses. Data was retrieved using a web crawling approach. For additional information, see: ‘A Detailed Map of Who Is Wearing Masks in the U.S.’ By Josh Katz, Margot Sanger-Katz and Kevin Quealy. July 17, 2020. *The New York Times*.

County-level administrative covariates: The following economic and political measures are drawn from [Fajgelbaum et al. \(2019\)](#)¹¹: population, adult college graduation rate, mean income, unemployment rate, GOP share of the vote in the 2016 presidential election, the share of agriculture workers, and the share of manufacturing workers (all 2016 measurements). Data on social capital and demographic information are derived from a collection of measures published by the United States Census Bureau and collated by the United States Congress Joint Economic Committee. These variables include prime-age male labor force participation, share of men 25-54 who worked at some point over the previous 12 months, the share of families and people whose income in the past 12 months is below the poverty level, the percent with debt in collections, the percent with housing costs exceeding income by 35%, Gini coefficient, and the share of household income received by the top 5 percent. For more details see ‘The Geography of Social Capital in America’ (<https://bit.ly/39HJUEy>). We also collect the following measures from [Chetty et al. \(2014\)](#): relative immobility, high school graduation rate, on-time HS graduation rate, percentage of the population that is 65

¹¹<https://bit.ly/3aTo1SF>

and above, percentage of white, black, Hispanic, indigenous, and Asian individuals in the county population, black-white segregation index, percentage of the local population that is foreign born, percentage of the population that resides in a rural area of the surrounding county, net migration, the share of adults in fair or poor health, the age-adjusted premature mortality, the share of people who are disabled, diabetic, obese, and smokers, the percent of babies born with low birth weight, the share without health insurance, and average commute time to work. The social capital index is drawn from an updated version of the data published by [Rupasingha, Goetz and Freshwater \(2006\)](#).

County-level mask mandates: County and state level mask mandates were hand collected by research assistants in the IPAL Lab at the Harris School of Public Policy at the University of Chicago. Every data point was cross-validated by assigning multiple RA's to each state who then performed independent research to ensure accuracy. This data collection went through a second cross-validation by research assistants in the DPSS Lab at Harris. For more information on the data collection, see [Wright, Chawla, Chen and Farmer \(2020\)](#). Data is available for download here: <https://bit.ly/30vJCh7>.

Zip code-level administrative covariates: The rural index is based on a rural classification system established by the United States Department of Agriculture Economic Research Service. Whole numbers (1-10) delineate metropolitan, micropolitan, small town, and rural commuting areas. We thank Thomas Pepinsky for sharing the zip code version of this data, which is used in work on partisanship and COVID-19 behaviors ([Gadarian, Goodman and Pepinsky, 2020](#)). For more details, see here: <https://bit.ly/3fn3BTH>.

COVID-19 cases and deaths: County-day level information about COVID-19 cases and related deaths is tracked and compiled by the New York Times from various government sources. The tracker is available via their GitHub page here: <https://bit.ly/2wrK0RB>.

Administrative shapefiles: We visualize county-level variation in policy changes and economic and political measures using the 2016 TIGER/Line shapefile made available by the US Census Bureau (Department of Commerce) via the DATA.GOV initiative. Data is available for download here: <https://bit.ly/2JU4ZQe>.

Theoretical Model

Our model considers an environment, in which there is a threat of pandemics, the severity of which is unknown, and agents have to decide whether or not wear masks. Agents have heterogeneous prior about the severity of the threat. Then, agents receive information about the severity of the threat. This information is imperfect: probability to get infected if they do not comply. The information is provided with a slant, which is known to the audience. Our main comparative statics is with respect to the slant: it allows to see the differential impact of announcements coming from different sources.

Setup There is a society that consists of a unit continuum of agents with preferences heterogeneous alongside the one-dimensional policy space, the real line \mathbb{R} . We parameterize political polarization as follows. We assume that the share $\frac{1}{2}\alpha$ of agents has bliss points $q_i = \mathbf{L} = \frac{1}{4}$, another share $\frac{1}{2}\alpha$ has bliss points $q_i = \mathbf{R} = \frac{3}{4}$, and the rest (share $1 - \alpha$) has their bliss points distributed uniformly over $[0, 1]$.¹² With such parameterization, $\alpha = 0$ corresponds to no polarization, while $\alpha = 1$ corresponds to fully polarized society, in which every citizen has the bliss point of either $\frac{1}{4}$ or $\frac{3}{4}$.

Agents' optimal decision about the mask-wearing depends on their assessment of risk probabilities. There are two possible states of the world, $s \in \{C, N\}$, for “serious threat” and “no serious threat”; the *ex ante* probabilities are $P(S) = \theta \leq \frac{1}{2}$ and $P(N) = 1 - \theta$. Agent i 's utility depends on both the action and the state of the world as follows.

$$\begin{aligned} q_i \text{ if } a_i &= m, & s &= S, \\ 0 \text{ if } a_i &= m, & s &= N, \\ 1 - q_i \text{ if } a_i &= n, & s &= N, \\ 0 \text{ if } a_i &= n, & s &= S. \end{aligned}$$

Before making the decision, agents get additional information from a source of information (media, government official, etc), which operates as follows. The source receives a signal $\omega \in [0, 1]$, which is conditional on the true state of the world, and is committed to report

¹²Alternatively, one might assume that instead of shares of $\frac{\alpha}{2}$ with bliss points $\frac{1}{4}$ and $\frac{3}{4}$, the probability density distributions of ideal points for these shares are given by $\mathcal{N}(\frac{1}{4}, \sigma^2)$ and $\mathcal{N}(\frac{3}{4}, \sigma^2)$ for some $\sigma > 0$, respectively.

a recommendation $\hat{s} \in \{\widehat{M}, \widehat{N}\}$ for “comply” and “go”.¹³ If $s = C$, then signal ω is drawn with c.d.f. $F_C(x) = x^2$; if $s = N$, then ω is drawn with c.d.f. $F_N(x) = 2x - x^2$. The source outlet with slant $\beta \in [0, 1]$ reports $\hat{s} = \widehat{M}$ if $\omega > \beta$ and $\hat{s} = \widehat{N}$ otherwise. Thus, a source with low β is putting more emphasis on dangers of the virus, while high β corresponds to the desire to downplay the danger.

Analysis Suppose that citizen i watched the news with the media threshold β . If the report is $\hat{s} = \widehat{M}$, then citizen i infers that the probability to get the virus is

$$\begin{aligned} P(s = C|\hat{s} = \widehat{M}) &= \frac{P(\hat{s} = \widehat{M}|s = C)P(C)}{P(\hat{s} = \widehat{M}|s = C)P(C) + P(\hat{s} = \widehat{M}|s = N)P(N)} \\ &= \frac{\theta}{\theta + \frac{1-\beta}{1+\beta}(1-\theta)}, \end{aligned}$$

which is an increasing function of θ , the *ex ante* probability of danger, and β , the information source’s slant.

Similarly, if the report is $\hat{s} = \widehat{N}$,

$$P(s = N|\hat{s} = \widehat{N}) = \frac{1-\theta}{\frac{\beta}{2-\beta}\theta + 1-\theta}.$$

In what follows, we will focus on the case $\hat{s} = \widehat{M}$; the other case, $\hat{s} = \widehat{N}$ is similar.

Agent i chooses wearing mask, m , over not wearing, n , when the signal is $\hat{s} = \widehat{M}$ if and only if

$$Eu_i(m|\hat{s} = \widehat{M}) \geq Eu_i(n|\hat{s} = \widehat{M}).$$

Start with the expected utility of wearing a mask when the signal is $\hat{s} = \widehat{M}$:

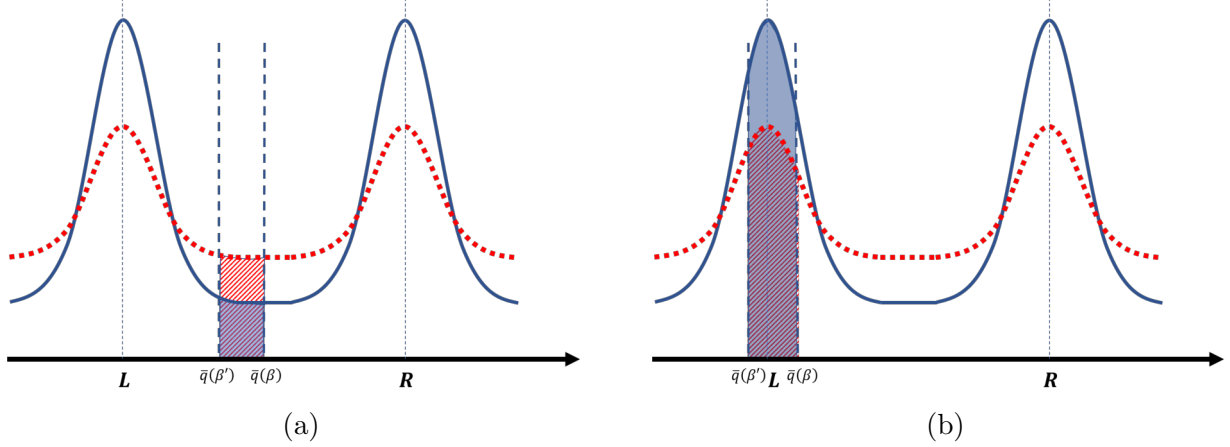
$$\begin{aligned} Eu_i(m|\hat{s} = \widehat{M}) &= P(s = C|\hat{s} = \widehat{M}) \times q_i + P(s = N|\hat{s} = \widehat{M}) \times 0 \\ &= \frac{\theta}{\theta + \frac{1-\beta}{1+\beta}(1-\theta)} q_i. \end{aligned}$$

The expected utility of not wearing a mask is

$$\begin{aligned} Eu_i(n|\hat{s} = \widehat{M}) &= P(s = C|\hat{s} = \widehat{M}) \times 0 + P(s = N|\hat{s} = \widehat{M}) \times (1 - q_i) \\ &= \frac{\frac{1-\beta}{1+\beta}(1-\theta)}{\theta + \frac{1-\beta}{1+\beta}(1-\theta)} (1 - q_i). \end{aligned}$$

¹³See [Gentzkow and Shapiro \(2006, 2008\)](#) for the basics of this approach to modeling media.

Figure A-1: The Effect of Change in Messaging Slant for Different Degrees of Polarization.



(a) When the pro-danger slant increases from β to β' , the increase in share of mask-wearers (shaded area) is higher in the less polarized society (red dotted line) than in a more polarized one (blue solid line). (b) The same change in slant results in a higher effect in the more polarized society when the change from β to β' comes close to the bliss point of those who did not wear masks under β .

Now, agent i wears a mask upon receiving signal $\hat{s} = \widehat{M}$ if and only if

$$q_i > \bar{q}(\beta) = 1 - \frac{\theta}{\theta + \frac{1-\beta}{1+\beta}(1-\theta)}.$$

Therefore, the share of mask-wearers conditional on $\hat{s} = \widehat{M}$ is $M^{\widehat{M}}(\alpha, \beta)$. (We assume that $\frac{1}{4} < \theta < \frac{1}{2}$.)

$$M^{\widehat{M}}(\alpha, \beta) = \begin{cases} \alpha + \frac{\theta}{\theta + \frac{1-\beta}{1+\beta}(1-\theta)}(1-\alpha), & \text{if } \beta > \bar{\beta} = \frac{1}{2\theta-3}(4\theta-3). \\ \frac{1}{2}\alpha + \frac{\theta}{\theta + \frac{1-\beta}{1+\beta}(1-\theta)}(1-\alpha), & \text{otherwise.} \end{cases}$$

The comparative statics is as follows. $M^{\widehat{M}}(\alpha, \beta)$ is increasing in β - when the media is slanted to downplay the danger, the share of mask wearers, conditional on $\hat{s} = \widehat{C}$ is higher. If $\beta < \bar{\beta} = \frac{1}{2\theta-3}(4\theta-3)$, then the second cross-derivative of $M^{\widehat{M}}(\alpha, \beta)$ w.r.t. to α and β is negative, which means that for a higher level of polarization (α), an increase in slant (β) reduces the share of mask-wearers.

With β increasing past $\bar{\beta}$, $M^{\widehat{M}}(\alpha, \beta)$ jumps discontinuously. (Figure A-1 illustrates the jump in the case of the probability density distributions of share α of ideal points given by $\mathcal{N}(\frac{1}{4}, \sigma^2)$ and $\mathcal{N}(\frac{3}{4}, \sigma^2)$ for some $\sigma > 0$, respectively.) The size of jump is $\frac{1}{2}\alpha$, which

is increasing in polarization. This is the “Trump mask effect”: the signal to wear masks by someone whose perspective is credibly slanted towards downplaying the danger has a disproportional effect in a polarized environment.