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Unmasking Partisanship: How Polarization Influences Public Responses to Collective Risk

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How Polarization Influences Public Responses to Collective Risk

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Abstract

Political polarization and competing narratives can undermine public policy implementation. Partisanship may play a particularly important role in shaping heterogeneous responses to collective risk during periods of crisis when political agents manipulate signals received by the public (i.e., alternative facts). 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 document four facts: (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 severity or local policies; (4) Trump's unexpected mask use at Walter Reed on July 11, 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 mask use.

JEL Classification: H12, I18.

Keywords: COVID-19, mask mandates, partisanship.

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Introduction

Political polarization can undermine effective public policy. This impact may be exacerbated during periods of substantial collective risk (crises) where uncertainty over optimal policy responses enables political agents to manipulate signals received by the public (Gitmez, Sonin and Wright, 2020). These signals 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 collective risk (Grossman et al., 2020). The promotion of alternative facts or disinformation may significantly impact public policy interventions 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 use of face masks to stem the spread of COVID-19. Prior work has demonstrated how partisanship (Allcott et al., 2020; Painter and Qiu, 2020; Gadarian, Goodman and Pepinsky, 2020), belief in science (Brzezinski, Kecht, Van Dijcke and Wright, 2020), social capital (Brzezinski, Deiana, Kecht and Van Dijcke, 2020; Barrios et al., 2020), and economic conditions (Wright et al., 2020) influence compliance with social distancing mandates during the ongoing pandemic. We advance this prior work by leveraging micro-level data on mask use collected during July 2020. The use of face masks is a cleaner setting to study the influence of political beliefs on public mandates as there is no trade-off between public health and the economy, whereas opponents of social distancing orders argue that social distancing has an adverse effect on economic growth. We supplement our mask use data with granular measures of local voting patterns, demographic characteristics, social and economic conditions, and COVID-19 cases and deaths.

Research Design and Findings

We implement and present evidence from four related studies.

Study I: 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 (a) for the pooled 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:

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

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 (i.e., local Trump support in the last election). We then collect, in the vector X_c^k , k local characteristics that might confound the correlation between mask use and voting patterns: demographic characteristics¹, COVID severity², local

¹Variables: 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.

²Variables: cumulative cases and cumulative deaths per capita.

mask mandates, economic characteristics³, social capital⁴, and comorbidity patterns⁵. We then vary the fixed effects used in each regression, including state and state-by-rural index fixed effects. This is parameterized as $\lambda_{s,r}$ in equation 1. Heteroskedasticity-robust standard errors are clustered by county.

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 remains 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 $\beta = .44$.

Study II: Flexibly Estimating the Marginal Effect of Policy Interventions

We study novel data on county-specific and state-wide mask mandates. We demonstrate that the effects of partisanship are similar even in the presence of government interventions. Enforceable mask mandates do not robustly offset the negative effects of partisanship. To study these dynamics, we estimate flexible (non-linear) marginal effects of partisanship in the presence of

³Variables: 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

⁴Variables: 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).

⁵Variables: 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.

a local mandate using the *interflex* approach introduced by Hainmueller, Mummolo and Xu (2019). These results are presented in Figure 2. In (a) we pool variation using the cross section and study flexibly estimated marginal effects with state and state-by-rural index fixed effects in (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. However, for the rest of the distribution (i.e., where GOP vote share exceeds .2), we observe no meaningful variation in the effect of partisanship on mask use, even in the presence of a government mandate to wear masks. Government policy interventions do not offset the impact of partisanship on mask use.

Study III: Machine Learning Approaches

Using several machine learning approaches, we examine which local factors most consistently predict mask use. We find compelling evidence that voting patterns in 2016 are the single most important factor predicting mask use. These results are presented in Figure 3, where we implement least absolute shrinkage and selection operator (LASSO) methods from the machine learning literature (Tibshirani, 1996) using the pooled cross section (a) as well as 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 the Figure 3). 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.

Study IV: Quasi-Experimental Design

We leverage 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, where President Trump wore 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. This gives our study consistent coverage around July 11. To collect only mask-related tweets we used 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 user’s location. We mine mask-related tweets on July 11, the day of the Walter Reed event, to identify *tweet*₀. We search in the time window around Trump’s visit to the hospital. While there is 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 4 (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 (positive versus negative language) around the identified temporal discontinuity. We notice a substantial shift in sentiment, equivalent to .94 standard deviations (see Figure 4 (e)).

In Figure 4 (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 4 (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 4 (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 Twitter 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 4 (d) and (h) (second and third estimated effects indicate deseason-

sonalized parameters).

Discussion and Interpretation of Results

Evidence from four related studies demonstrates that partisanship influences adoption of both public health recommendations and requirements (mask use) during an ongoing crisis in the United States. Mask use is significantly lower in areas where Trump vote shares are high. 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 attenuate the result significantly, 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). Evidence from a quasi-experimental design leveraging Trump’s unexpected mask use at Walter Reed indicates that partisan messaging, particularly if it counters a prevailing narrative, can increase public engagement with and sentiment towards mask use.

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Figure 1: Partisanship strongly correlated with local mask use.

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

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), state fixed effects are residualized in (b), and state-by-rural index (zip code-level) fixed effects are residualized in (c). Flexible marginal effects were estimated using the *interflex* package compiled by Hainmueller, Mummolo and Xu (2019). 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 3: Partisanship remains most important predictor of local mask use using machine learning methods.

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), state fixed effects are residualized in (b), and state-by-rural index (zip code-level) fixed effects are residualized in (c). Least absolute shrinkage and selection operator (LASSO) machine learning estimates presented. 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: 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 16:43 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.

Appendix

Data Overview and Links to Materials

We outline the sources 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. We study the 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** Economic and political measures are drawn from Fajgelbaum et al. (2019) and available for download here: <https://bit.ly/3aTo1SF>. 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. For more details see 'The Geography of Social Capital in America' <https://bit.ly/39HJUEy>. Additional data, including the social capital index, are drawn from an updated version of the data published by Rupasingha, Goetz and Freshwater (2006).
- **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 <https://bit.ly/3fn3BTH>.
- **COVID-19 cases and deaths** County-day level information about COVID-19 cases and related deaths are tracked and compiled by the New York Times from various government

sources. The tracker is available via their GitHub page <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 <https://bit.ly/2JU4ZQe>.