



Short communication

# Unmasking partisanship: Polarization undermines public response to collective risk <sup>☆</sup>



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## ARTICLE INFO

### Article history:

Received 29 April 2021

Revised 12 October 2021

Accepted 14 October 2021

### Keywords:

Partisanship

Polarization

COVID-19

## 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 U.S., focusing on how partisanship has influenced the use of face masks to stem the spread of COVID-19. Using a variety of approaches, we find partisanship is the single most important predictor of mask use and local policy interventions do not offset this relationship.

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## 1. Introduction

Political economists 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 et al., 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 et al., 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 et al., 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 et al., 2020) and job losses (Friedson et al., 2020; Chudik et al., 2020; Gupta et al., 2020; Beland et al., 2020) and is itself influenced by economic conditions (Wright et al., 2020). Hence, partisan divides in mask wearing are likely to more strongly reflect politicization effects rather than differences in underlying views on societal priorities during a health crisis. Moreover, mask use appears to be the primary non-pharmaceutical intervention that has the potential for widespread adoption as the pandemic continues and different variants of coronavirus emerge, as evidenced by the changing mask guidance issued by the Center for Disease Control.<sup>1</sup> Analysis of heterogeneity in mask use is therefore relevant for policy makers who are continuing to implement these tools.

<sup>☆</sup> We thank Alex Engler, Thomas Pepinsky, Thomas Fujiwara, and an anonymous referee for comments. All errors remain our own.

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<sup>1</sup> "A timeline of the CDC's advice on face masks." Los Angeles Times. July 27, 2021.

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 implement three related research designs. Each design enables us to assess a distinct aspect of the impact of partisan polarization on policy implementation. We start with an evaluation of the association between partisanship and mask use. Leveraging a combination of zipcode- and county-level data, this approach begins with documenting 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. As a second design, we use the technique described in Oster (2019) to confirm the main effect is robust to extremely conservative specifications of positive and negative selection on unobservable characteristics. Overall, these first two designs reveal that the association between partisanship and mask use is large, statistically precise, and highly unlikely to be explained by observed or unobserved confounding factors.

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) method (Tibshirani, 1996), we find that partisanship remains the most robust and effective predictor of mask use across numerous alternative machine learning models. 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.

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 et al., 2020; Mitze et al., 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). Notably, a large-scale randomized control trial of mask use in Bangladeshi villages during the COVID-19 pandemic found that a 29 pp increase in mask wearing during an 8-week intervention period in treated villages decreased symptomatic seroprevalence of COVID-19 by 9.3% (Abaluck et al., 2021). Moreover, due to the particular nature of the coronavirus disease, with its high rate of asymptomatic transmission (Gandhi et al., 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 non-pharmaceutical mitigation strategy that can reduce the transmission rate without undermining economic activities (Howard et al., 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.<sup>2</sup> 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 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 or discourage mask use can depend on their social welfare preferences (Cohen and Werker, 2008), their incentives towards corruption (Yamamura, 2014), or the local political landscape (Ono, 2017).<sup>3</sup> 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.<sup>4</sup> Second, we assess the plausibility of some unknown confounding factor driving the observed relationship between partisanship and mask use. Third, we establish the predictive power of local partisanship with respect to mask wearing using machine learning approaches.

### 3.1. Data

#### 3.1.1. Mask use

We obtain our measure of mask use from Dynata, an online market research firm. Dynata was commissioned by the New York Times<sup>5</sup> to implement an online survey where 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: the probability that, if one has five random encounters within a zip code, all people encountered are wearing masks. The normalization assumes that people from any response category

<sup>2</sup> See, 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."

<sup>3</sup> At the same time, US counties that were hit harder by the 2020 pandemic have been found to exhibit larger decreases in electoral support for Republican candidates (Warshaw et al., 2020).

<sup>4</sup> Note that the goal here is not to estimate the causal effect of partisanship on mask-wearing in a potential-outcomes setting, but rather to document the robust correlations that appeared between both in this pandemic. This more modest endeavor does not face the so-called "commensurability problem" that affects causal estimates of the effect of behavior on behavior (De Mesquita and Tyson, 2020).

<sup>5</sup> A Detailed Map of Who Is Wearing Masks in the U.S. Josh Katz, Margot Sanger-Katz and Kevin Quealy. The New York Times. July, 2020.

can be encountered with equal probability, and that the probability that the person from each category is wearing a mask is 0, 0.2, 0.5, 0.8, 1, respectively. The survey was conducted between July 2<sup>nd</sup> and July 14<sup>th</sup> and includes 250,000 survey responses across the U.S.<sup>6</sup> We present a map of the data in Fig. 1, which shows heterogeneity in mask use both across and within states. We find the average probability that a person would exclusively encounter mask wearers if they encountered five random people in July 2020 is 41.1% with a standard deviation of 21.5%, which aligns closely with a study that hand-counted shoppers who wore masks in grocery stores across Wisconsin in May 2020 (Arp et al., 2020).

### 3.1.2. Demographic and economic data

We supplement the survey data with various local statistics that may also influence the tendency to wear a face mask. The following economic and political measures are drawn from Fajgelbaum et al., 2019<sup>7</sup>: 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. 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 age 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.<sup>8</sup> 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 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 of people without health insurance, and average commute time to work. We also employ a county-level social capital index, drawn from an updated version of the data published by Rupasingha et al. (2006).

### 3.1.3. Local mask mandates

We are able to control for county- and state-level mask mandates using data that was hand collected by research assistants in the IPAL Lab at the Harris School of Public Policy at the University of Chicago.<sup>9</sup> Lastly, we collect the county-day level information on COVID-19 cases and deaths compiled by the New York Times. The union of these datasets allows us to study nearly 20,000 U.S. zip codes (out of 41,692 total) that collectively are inhabited by 288 million Americans.

<sup>6</sup> Though our dataset is not a recurring panel, we do note that at the time of the survey 136,941 deaths in the U.S. were attributed to COVID-19 and it was commonly believed that wearing a face mask reduced the potential to spread the virus. Source: Our World in Data

<sup>7</sup> <https://bit.ly/3aTo1SF>

<sup>8</sup> For more details see United States Joint Economic Committee (2018).

<sup>9</sup> 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 et al. (2020). Data is available for download here: <https://bit.ly/30vjCh7>.

## 3.2. 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 two-party county-level vote shares to Donald Trump in the 2016 presidential election. This result is presented in Fig. 2 panel (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 percentage point swing) is associated with a decrease in mask use by 13.1 percentage points ( $p < .001$ ), which represents a 31.9% deviation from the mean mask use level of 41.1%. In panel (b), we residualize mask use and voting patterns using state fixed effects.<sup>10</sup> The correlation remains consistent in magnitude and the explanatory power of voting patterns remains large (25%).

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 and  $GOP\_voteshare_{c,2016}$  indicates the GOP vote share in the 2016 presidential election. The  $\beta$  coefficient can therefore be interpreted as the percentage point change in mask use associated with a one percentage point increase in the GOP vote share. We then collect, in the vector  $X_c^k$ ,  $k$  local characteristics that might confound the correlation between mask use and voting patterns: demographic characteristics, COVID severity, local mask mandates, economic characteristics, social capital, and comorbidity patterns.<sup>11</sup> 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 Eq. 1. Heteroskedasticity-robust standard errors are clustered by county.

We stagger the introduction of covariates in the regression results in Fig. 3. 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  $\beta = -.40$  (panel (a) of Fig. 3). Using state-level fixed effects in panel (b), the introduction of covariates does not cause attenuation in the association between partisanship and mask use. The estimated effect size is approximately  $\beta = -.52$ .<sup>12</sup> The table output presented in panels (c) and (d) show that variation explained in the fully saturated model is 63.2% for the pooled cross section and 70.5% for the state fixed effects model.

## 3.3. Plausible bounds on partisanship

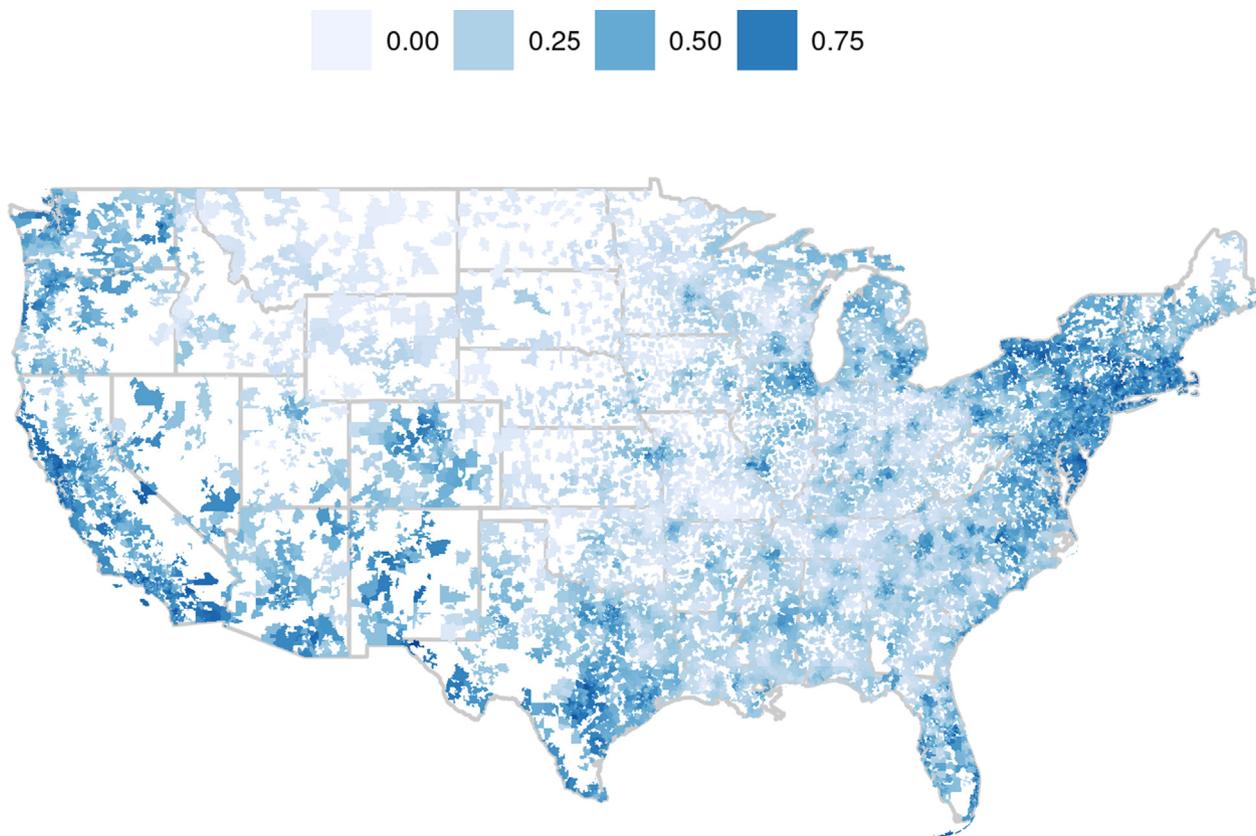
We next estimate bounds for the main effect of vote share on local mask use using the Oster coefficient stability test (Oster, 2019).<sup>13</sup> These results are depicted in Fig. 4. This method enables us to evaluate how selection on unobservables relative to the observable covariates included in our within-state model specification

<sup>10</sup> We present similar results using state-by-rural index fixed effects (Gadarian et al., 2020) in Fig. A-1. We thank Thomas Pepinsky for sharing the zip code version of the rural index data. For more details, see here: <https://bit.ly/3fn3BT8>.

<sup>11</sup> The specific variables included in each grouping along with their summary statistics are shown in Table A-1

<sup>12</sup> In Fig. A-2, we account for state-by-rural index fixed effects and find the association between partisanship and mask use stabilizes at  $\beta = -.44$ .

<sup>13</sup> Note that, while the original paper is framed in the context of causal estimation, the approach generalizes to the estimation of any coefficient of interest.



**Fig. 1.** Descriptive statistics: mask use by zip code, July 2020. *Note:* This figure shows cross-sectional zip code level data of mask use across the United States. In a survey carried out by Dynata for the New York Times between July 2 and July 14, 2020, 250,000 people were asked with which frequency they wear masks: never, rarely, sometimes, often, always. The chance that all 5 people wear masks in 5 random encounters in a zip code is constructed by weighting the frequency of each response by 0%, 20%, 50%, 80% and 100%, respectively. Blue colors indicate degree of mask wearing by increasing darkness. White color indicates not enough sample variation in zip code.

could influence the estimated correlation between partisanship and mask use. This approach allows us to account for positive and negative selection on unobservables (relative to observables) conditional on state fixed effects. To visualize the results of this test, we leverage a series of maximum  $R^2$  values and alternative thresholds for selection (1.1, 1.5, 2, 3). This yields 1048 alternative combinations. We present these estimates in Fig. 4. Notice that the range of estimates varies from approximately  $-.455$  to  $-.485$  and stabilizes at roughly  $-.475$ , indicating that a 10 pp increase in Trump support in 2016 corresponds to a 4.75 pp decrease in mask use. These magnitudes are consistent with the results in Fig. 3.

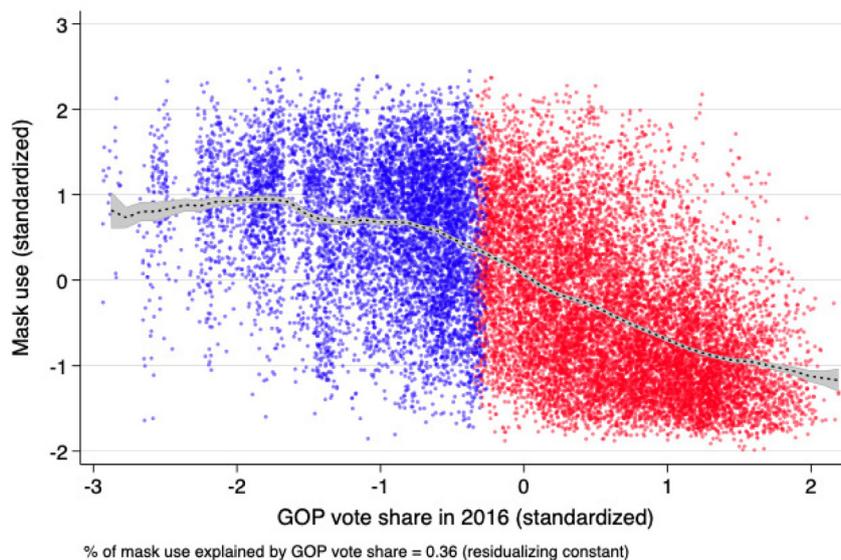
In the appendix, we present several additional bounding exercises. In Fig. A-3, we plot several potential solutions when the  $\delta$  parameter (selection on observables) is set to one. This allows us to consider whether the unique solutions under varying selection thresholds map on to the most plausible parameter values when selection on unobservable factors matches selection on observable factors. Indeed, the plausible bounds in Fig. A-3 are consistent with Fig. 4. In Figures A-4 and A-5 we repeat this exercise for a more demanding baseline, focusing on state-by-rural index variation, and find a similar result. In Figures A-6 and A-7 we relax the baseline specification in Fig. 4, allowing for calibration of the bounds with respect to first-order selection on unobservables otherwise partialled out through the use of either state or state-by-rural index fixed effects. Likewise, we estimate bounds that remain distinct from zero and consistent with the plausible bounds exercise, as in Fig. A-3.

### 3.4. Machine learning approaches

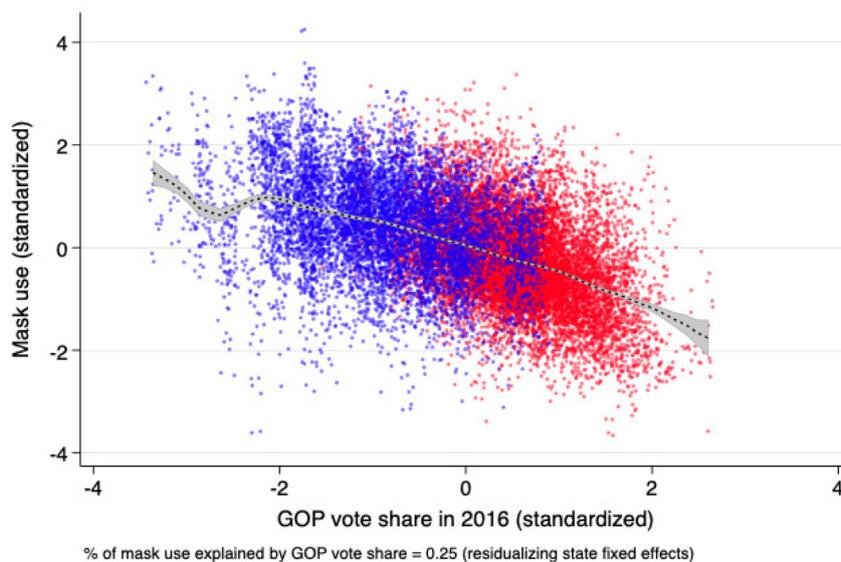
Using several machine learning approaches, we examine which local factors most consistently predict mask use. We find

compelling evidence that voting patterns in 2016 is the single most important factor predicting mask use. These results are presented in Fig. 5, 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 fixed effects (panel (b)). As shown in the top row, 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 Fig. 5). 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 Fig. 2. In the bottom row, we re-estimate the LASSO 1,000 times for each penalty  $\lambda$  based on repeatedly drawn random subsamples. Then, we estimate the probability that a given regressor is selected as an important predictor by the LASSO as the frequency with which that regressor is selected in the 1,000 re-estimations, as in Meinshausen and Bühlmann (2010). GOP vote share is selected in every single one of the estimations, that is, its estimated probability of being selected as an important predictor is always 1, and it is the only variable for which this is consistently the case. As the figure shows, the other regressors (grey lines) only start getting selected by the LASSO as the penalty term decreases (the L1 norm increases), and their selection probabilities only gradually approach 1. Thus, LASSO estimation robustly selects GOP vote share as the single most important predictor of mask wearing.

To get an idea of how much of the variation in mask wearing is predicted by GOP vote share, in the right panel of Fig. 5, we



(a) Pooled Cross Section.



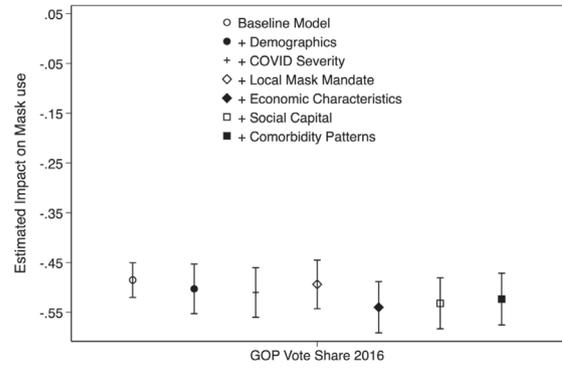
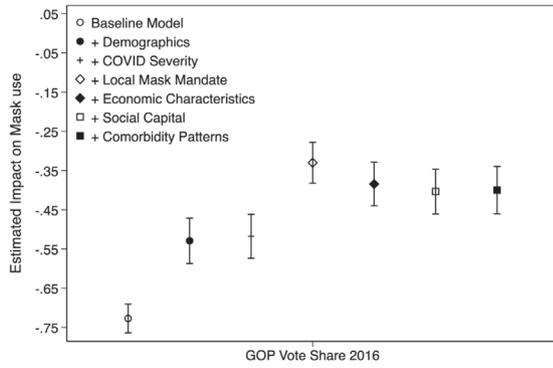
(b) Within State Variation.

**Fig. 2.** 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), state fixed effects are residualized in (b). Residuals are standardized (mean of zero, scaled in standard deviations). Mask use measures compiled by Dynata from zip code-level surveys from July 2, 2020 to July 14, 2020.

decompose the  $R^2$  of the specification selected by the LASSO for the model with state fixed effects partialled out. To determine the optimal penalty  $\lambda$ , we use the data-driven penalty estimation procedure proposed by Belloni et al. (2012). That way, the LASSO selects 19 out of 51 variables to be included in the regression model. Subsequently, we decompose the  $R^2$  of this residualized model using Shapley Value Regression (Lindeman, 1980). This decomposition involves re-estimating the model for each possible combination of regressors and calculating the average marginal contribution of each regressor to the  $R^2$ , which equals the average increase in the  $R^2$  due to adding a given variable to a given model specification. The second column in the table gives the contribution of each variable to the total  $R^2$  of the model. GOP vote share contributes 31% of the model's explanatory power, while the next

most important regressor, the share of the county population that graduated from college, only contributes 12%, nearly one-third the magnitude of GOP vote share. GOP vote share thus explains the lion's share of the variation in mask use, even as several of the included variables capture health conditions of the counties' populations (diabetes and premature mortality rate).<sup>14</sup> These findings further underscore the regression-based results: among a large set of potentially relevant predictors of local mask wearing, GOP vote share consistently is the single most important predictor and accounts for 30% of all explained variation in mask wearing.

<sup>14</sup> COVID cases and deaths are not selected by the LASSO. This is likely either due to these alternative measures of population health being better predictors of the variation in mask wearing that is driven by health concerns, or due to the inclusion of state fixed effects. Indeed, in the non-residualized model, the LASSO does select COVID deaths as an important predictor of mask wearing.



(a) Coefficient on  $\beta$ : Pooled Cross Section.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GOP Vote Share	-0.73*** (0.02)	-0.53*** (0.04)	-0.52*** (0.03)	-0.33*** (0.03)	-0.38*** (0.03)	-0.40*** (0.03)	-0.40*** (0.04)
Demographics	No	Yes	Yes	Yes	Yes	Yes	Yes
Covid Severity	No	No	Yes	Yes	Yes	Yes	Yes
Mask Mandate	No	No	No	Yes	Yes	Yes	Yes
Economic Char.	No	No	No	No	Yes	Yes	Yes
Social Capital	No	No	No	No	No	Yes	Yes
Comorbidity	No	No	No	No	No	No	Yes
$R^2$	0.365	0.475	0.485	0.578	0.606	0.628	0.632
Observations	19,720	19,109	19,109	19,033	18,943	18,943	18,935

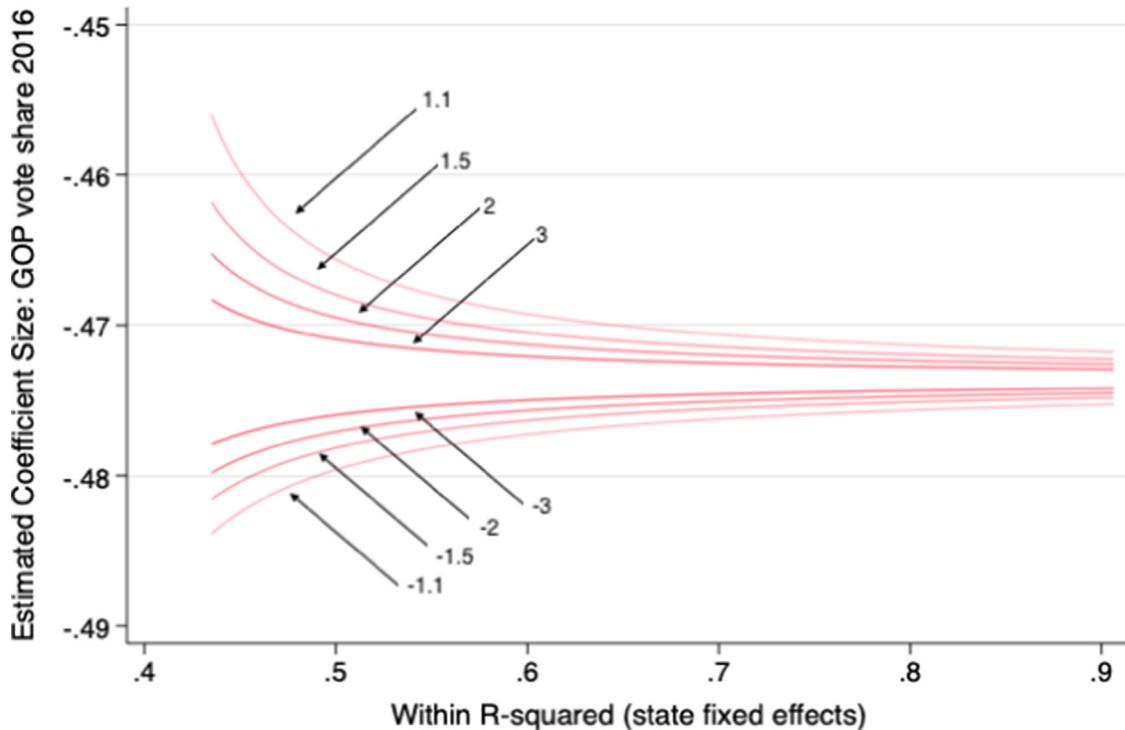
(c) Pooled Cross Section Estimates.

(b) Coefficient on  $\beta$ : Within State Variation.

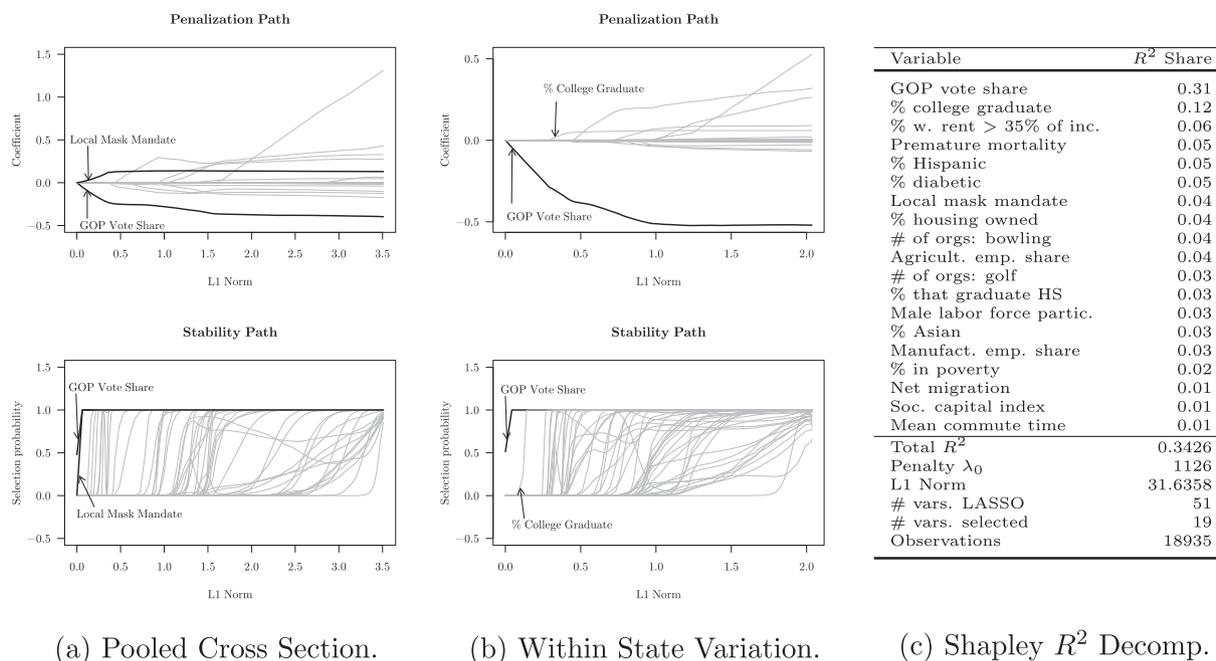
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GOP Vote Share	-0.49*** (0.02)	-0.50*** (0.03)	-0.51*** (0.03)	-0.49*** (0.03)	-0.54*** (0.03)	-0.53*** (0.03)	-0.52*** (0.03)
Demographics	No	Yes	Yes	Yes	Yes	Yes	Yes
Covid Severity	No	No	Yes	Yes	Yes	Yes	Yes
Mask Mandate	No	No	No	Yes	Yes	Yes	Yes
Economic Char.	No	No	No	No	Yes	Yes	Yes
Social Capital	No	No	No	No	No	Yes	Yes
Comorbidity	No	No	No	No	No	No	Yes
$R^2$	0.661	0.685	0.685	0.689	0.698	0.705	0.705
Observations	19,720	19,109	19,109	19,033	18,943	18,943	18,935

(d) Within State Variation Estimates.

**Fig. 3.** Partisanship and local mask use: Multivariate correlations. Notes: Panel (a) studies cross sectional variation while panel (b) introduces results with state fixed effects (within state variation). The sequence of estimates presented in panels (c) and (d) correspond to the models used in (a) and (b) respectively.



**Fig. 4.** 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 Fig. 3 (d): 1.1, 1.5, 2, 3 (as well as negative selection at these thresholds). The within-fixed effect (state-level) variation explained by the most saturated model is 3625. The corresponding  $R_{max}$  value is allowed to vary continuously (x axis). The coefficient of vote share converges to approximately  $-0.475$ . Fig. 3 (d) 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 (rather than diverge).



**Fig. 5.** Partisanship selected as most important predictor of local mask use using machine learning methods. *Notes:* Panel (a)-(b) top row presents least absolute shrinkage and selection operator (LASSO) estimates are plotted against the L1 Norm to show which variables most consistently predict mask use. All regressors are standardized to have unit variance and mean 0 (standardization incorporated into the penalty loadings). The constant is residualized in (a), state fixed effects are residualized in (b). Mask use measures compiled by Dynata from zip code-level surveys from July 2, 2020 to July 14, 2020. Panel (a)-(b) bottom row plots frequency with which each variable is selected (“selection probability”) in 1,000 re-estimations of LASSO for a given λ and random subsamples of size 0.632 · n against the L1 norm, as in Meinshausen and Bühlmann (2010). Panel (c) notes contribution of each regressor to R<sup>2</sup> in regression of measure of mask wearing on regressors selected by LASSO with data-driven penalty (Belloni et al., 2012), with state fixed effects residualized. Variable contributions are calculated by Shapley Value Regression. Note that total R<sup>2</sup> does not include variance explained by state fixed effects.

#### 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 U.S. 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), where mask use is mixed and vaccination rates remain low. More broadly, our findings contribute to the academic literature on the dynamics of partisan public responses to the COVID-19 pandemic.

#### Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at <https://doi.org/10.1016/j.jpube.2021.104538>.

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