

# Partisanship and Fear are Associated with Resistance to COVID-19 Directives

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## Abstract

Ideological differences have had a large impact on individual and community response to the COVID-19 pandemic in the United States. Early behavioral research during the pandemic showed that conservatives were less likely to adhere to health directives, which contradicts a body of work suggesting that conservative ideology emphasizes a rule abiding, loss aversion, and prevention focus. We reconcile this contradiction by analyzing semantic content of local press releases, federal press releases, and localized tweets during the first month of the government response to COVID-19 in the United States. Controlling for factors such as COVID-19 confirmed cases and deaths, local economic indicators, and more, we find that online expressions of fear in conservative areas lead to an increase in adherence to public health recommendations concerning COVID-19, and that expressions of fear in government press releases are a significant predictor of expressed fear on Twitter.

## 1 Introduction

Over the last decade, politics in the United States have become increasingly polarized (Balz, 2019; Dimock et al., 2014; Lockhart et al., 2020). This phenomenon is manifest in the increasing politicization of historically non-partisan government agencies (Cooper, 2020; Mulgan, 2007; Peters, 2004), the divide on Ebola preparedness (Nyhhan, 2014), and most recently, reactions and responses to the COVID-19 pandemic (Rothwell and Makridis, 2020). A growing body of evidence suggests that, during the pandemic, conservatives in the United States have been less likely to restrict movement during shelter-in-place directives (van Holm et al., 2020; Clinton et al., 2021), less likely to engage in social distancing (Painter and Qiu, 2020), and less likely to search for information about COVID-19 (Barrios and Hochberg, 2020).

In addition, conservatives seem more likely to refuse to wear masks, view the pandemic as a hoax, and question or protest against health directives (Van Green and Tyson, 2020).

Though reactance to COVID-19 mitigation efforts among conservatives is well documented, it may have been difficult to predict from existing theory and research. Indeed, a sizeable body of literature suggests that, instead of reacting *against* state-suggested and mandated precautions, conservatives might instead be more inclined to comply than their liberal counterparts (Jost et al., 2003b, 2007; Sales, 1973). Indeed, in previous periods of crisis, conservatives have been more inclined to seek safety (Sales, 1973; Thorisdottir and Jost, 2011). This is associated with an increased likelihood among conservatives to respond to threats in the environment and appeals to fear (Block and Block, 2006; Jost et al., 2003a,b; Oxley et al., 2008; Pliskin et al., 2015).

In other words, both evidence from research and reports from the media suggest that conservatives demonstrate less compliance to COVID-19 directives than liberals while, at the same time, past research suggests conservatives might be more responsive if presented with an objective threat or when consumed by a sense of fear. That said, it is clear the divergent and partisan responses to mitigation efforts which have been observed to date pose a serious threat to communities in the United States (Rothwell and Makridis, 2020). Therefore, in this research we explore what might motivate conservatives to adhere to health directives. Empirically, we utilize community level mobility data to understand changes (or lack thereof) in behavior, analyze millions of tweets and a set of official press releases to measure expressed fear, and seek ways in which public health and other officials might responsibly and effectively apply fear appeals to motivate behavior. Analytically, we first measure

fear in press releases and tweets using word embeddings and distributed dictionaries, we identify the factors most likely to contribute to expressions of fear with gradient boosted trees, identify the words most common in press releases expressing fear, and explore the associations between expressions of fear and behavior changing with random effects models.

## 2 Background and related work

As stated in the previous section, recent work suggesting increased skepticism and reluctance to adhere to public health directives among conservatives (Barrios and Hochberg, 2020; Iyengar and Massey, 2019; Painter and Qiu, 2020; Rothwell and Makridis, 2020; Van Green and Tyson, 2020) is surprising. Indeed, a long stream of research has found conservatives to be more rule abiding, risk averse, and prevention focused (Jost et al., 2003a, 2007; Sales, 1973). In times of crisis, conservatives are more likely than liberals to seek safety (Sales, 1973; Thorisdottir and Jost, 2011). But given the current tug-of-war between political rhetoric and health risk (Barrios and Hochberg, 2020; Cruwys et al., 2020; Rothgerber et al., 2020; van der Linden et al., 2020) some work suggests conservatives have come to rely more on political identity (van Holm et al., 2020; Allcott et al., 2020; Gadarian et al., 2020; Painter and Qiu, 2020), which could be influenced or exacerbated by conservative officials downplaying the health risks of the coronavirus (Bursztyn et al., 2020; Peters, 2020). One specific attribute commonly associated with a conservative mindset may explain why some have diminished or ignored the importance of COVID-19 health directives. That attribute is fear.

Past research suggests that conservatives, more than liberals, display a reaction to fear in response to threats in the environment (Block and Block, 2006; Jost et al., 2003a,b; Oxley et al., 2008; Pliskin et al., 2015). That is, conservatives have a stronger reaction to threats and new experiences (Oxley et al., 2008) and express stronger emotional reactions to negative outcomes (Joel et al., 2014). Such a response could be driven by a greater need for control over the environment and greater impulse to reduce uncertainty (Jost et al., 2003a). Since conservatives generally respect authority and want the hierarchical structure to remain in place, they are more fearful of change to this structure (Adorno et al., 1950; Jurgert and Duckitt, 2009).

These conflicting streams of research can be reconciled if conservatives who do experience or express fear of coronavirus are more likely to adhere to health directives as compared to conservatives who do not experience fear of coronavirus. Such a pattern would not only explain the response of conservatives to COVID-19 directives and recommendations but would also suggest a path forward for policy makers intent on motivating greater adherence to health directives.

To explore this phenomenon, we utilize two sources of data representing community level expressions of sentiment. First, as a proxy for the attitudes of local and federal officials, we collect press releases. Press releases are a common communication method used to inform a large number of citizens of a problem. Similar to past public health crises, local and federal government offices and agencies have used press releases to communicate official information to the public. Press releases have been used in past research as representations of the overall attitude of government agencies and officials (Fairbanks et al., 2007; Grossman et al., 2020; Lee and Basnyat, 2013; Levi and Stoker, 2000; Mayhew, 1974). Second, to measure the fear expressed by citizens in each community, we collect tweets related to COVID-19.

## 3 Methodology

In this section we first present the press release, Twitter, and behavioral data sets. We then elaborate the method used to measure the degree of fear expressed in text data. Finally, we outline the modeling framework for assessing the factors influencing the expression of fear, the nature of observed communications, and the impact on behavior changes in response to state directives.

### 3.1 Press release data

All data was collected over a 30-day period between February 29, 2020 and March 29, 2020. February 29 was selected as the starting point of observation because the first COVID-related death in the United States was announced on this day (CDC, 2020). We collected press releases from federal government agencies and offices in addition to those from the local governments of the 53 most populous metropolitan areas in the United States. In total, we collected 166 national and 1232 local press releases across all metropolitan areas during the observation period. However, not every local

government issued a press release each day. In total, there were 291 observations which included both local and national press releases.

### 3.2 Twitter data

Using the Twitter API, tweets were collected which contained any occurrence (including but not limited to hashtags) of the words *coronavirus*, *covid*, *covid-19*, or *sars-cov2*. Tweets were filtered to include only those from authors whose profile indicated they reside in one of the 53 metropolitan areas. In total, more than two million relevant tweets were collected during the observation period.

### 3.3 Pandemic response data

To measure movement during the pandemic, we utilized mobility data provided by Google, aggregated at the level of the county and collected from individuals who have opted in to location sharing features in Android or Google services (Google, 2020). This data is subset into a variety of location types and represents the percent change in the number of visits and length of stay at each location as compared to an out of period baseline. We calculated the mean value for public locations (retail, grocery and pharmacy, workplaces, and transit stations) as our metric of local movement. County level data was aggregated to the level of the metropolitan area using a population-weighted mean.

To determine the aggregate political identity of the metropolitan area, we collected the results of presidential elections that occurred between 2000 and 2016 (MIT, 2018). Of course, it is possible that communities may have deviated from this baseline since 2016. We encourage future researcher to explore the ways in which community level political identification has changed since 2016. The average votes for Republican and Democrat candidates were calculated. If a metropolitan area cast more votes on average for Republican candidates over this period it was labelled *conservative*, otherwise it was classified as *liberal*. This categorical variable was then dummy coded for analysis. Across the 53 metropolitan areas, 17 were classified as conservative and 36 were classified as liberal.

In addition, we collected control variables including the number of COVID-19 cases and deaths reported for each metropolitan area, for each day, local income and poverty metrics, day of the week, and more. For the sake of parsimony, only variables that had a significant impact on the models are reported and discussed.

### 3.4 Measuring expressed fear

To measure expressed fear in press releases and tweets, we constructed a dictionary to represent the construct. First, we collected 35 common synonyms for the target word *fear*. Next, we extracted a vector representation for each word from a pre-trained language model (Pennington et al., 2014). The cosine similarity between each target-synonym pair was calculated and words were clustered based on these values. Finally, the synonyms forming the tightest cluster around the word *fear* were selected as the construct dictionary. This dictionary consisted of 25 words. Construct vectors were aggregated by taking the sum of individual vectors divided by their Euclidean norm (Garten et al., 2018), resulting in a single construct vector of 200 dimensions. Formally, a construct vector  $C$  is calculated as:

$$C = \frac{\sum_{w \in D_R} R(w)}{\|\sum_{w \in D_R} R(w)\|_2} \quad (1)$$

Where  $w$  is a word,  $R$  is an embedding representation for  $w$ , and  $D_R$  is the set of words in the construct dictionary representing  $C$  (Garten et al., 2018).

Next, press releases and tweets were normalized. Tweets and press release sentences were tokenized into word-grams, made lowercase, and single character words and stop words were removed (Bird et al., 2009; Symeonidis et al., 2018). Then, vectors for tweet and sentence tokens were aggregated as described in equation 1 (Garten et al., 2018; Pennington et al., 2014). Cosine similarity provided a measure of similarity between the construct vector and each aggregated tweet or sentence vector (Caliskan et al., 2017; Garten et al., 2018). Note that the method of aggregation described in equation 1 pre-normalizes the vector representation. As such, similarity  $S$  between a construct representation, say for fear,  $C_f$ , and a given document (e.g., a single tweet),  $T_i$ , is calculated as the dot product of the respective aggregate vectors:

$$S = C_f \cdot T_i \quad (2)$$

The resulting document-level similarity measures were aggregated to the level of the day and metropolitan area.

### 3.5 Identifying factors influencing fear

To identify the factors most closely associated with increases in expressed fear, we employed gradi-

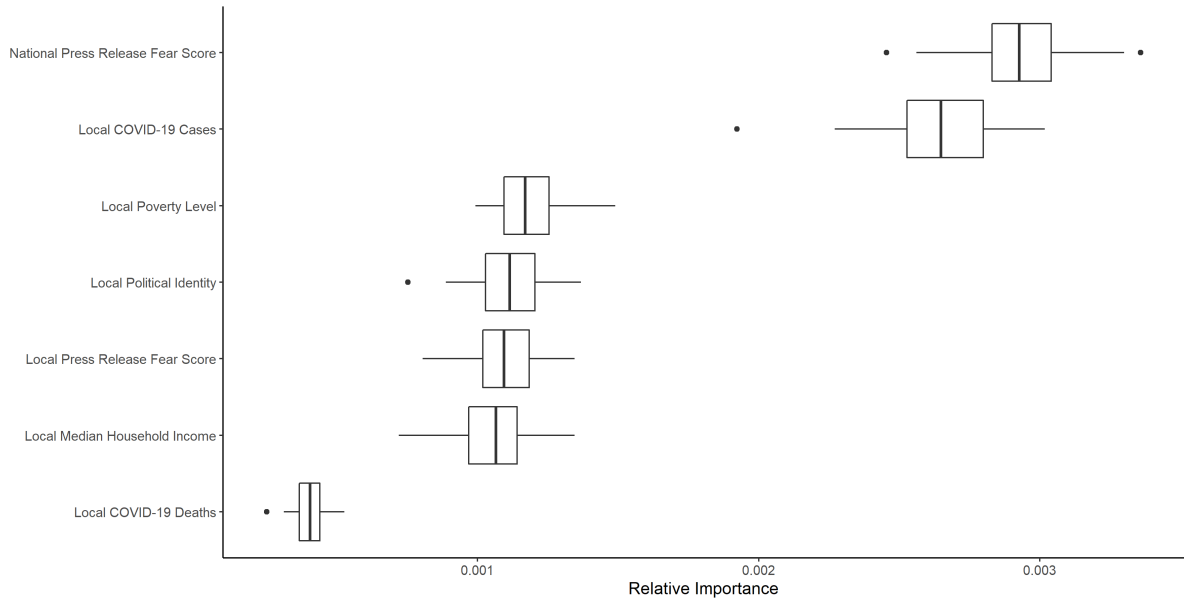


Figure 1: The relative importance of variables for predicting fear expressed in tweets, as determined by the XG-Boost model.

ent boosted trees (Chen and Guestrin, 2016; Friedman, 2001). Gradient boosted decision trees employ a series of shallow trees to predict an outcome variable (Quinlan, 1986). The assumption is that many weak learners will achieve a probably approximately correct (PAC) result (Valiant, 1984). Each tree is evaluated based on the gradient of the error with respect to the prediction via functional gradient descent (Ruder, 2017). Improvements in prediction accuracy for subtrees with a steeper gradient lead to larger overall improvements. Thus, gradient boosted trees result in the identification of variables that have the overall greatest influence on predictive accuracy. The method is amenable to analysis with relatively smaller sample sizes (Zhao and Duangsoithong, 2019), is not impacted by multicollinearity (Ding et al., 2016), and has been used in the past for prediction tasks involving social media in general and tweets in particular (Li et al., 2017; Ong et al., 2017). We implement gradient boosted decision trees via extreme gradient boosting or XGBoost (Chen and Guestrin, 2016).

### 3.6 Press release content analysis

To assess the type of language used in high- versus low-fear press releases, we counted each word in each press release (65,237 total words). Press releases were categorized based on their average cosine similarity (equation 2) with the fear construct (equation 1). Those that were on average more closely associated with fear than the median

measure (0.5713) were classified as *high fear* and those below the median were classified as *low fear*. A log-odds ratio was then calculated for each word in each category of high- or low-fear communications, indicating the probability of a word occurring in a press release. Words with a positive (negative) log-odds ratio are more likely to appear in a high (low) fear press release.

### 3.7 Modeling the impact on pandemic response

To model the impact of fear and political identity on pandemic responses, we utilized a random effects model. The data is panel in nature, with individual observations being made each day, for each subject or metropolitan area. Thus, a random effects specification assumes that time invariant variables are uncorrelated with the time varying predictors, which enables an examination of time invariant variables (such as political identity) on the outcome variable (local movement). Errors were clustered at the level of the metropolitan area, allowing us to control for community differences. We used a one-day lag for the expression of fear on Twitter, allowing us to assess the relationship between this expression and subsequent changes in movement behavior. Past work has also used a one-day lag when analyzing tweets (Kaminski, 2016; Li et al., 2017; Zhang et al., 2013) based on evidence that 75% of tweet replies are made within 17 minutes and the majority of twitter users are passive (Ye



and Wu, 2013; Romero et al., 2011).

## 4 Analyses

### 4.1 Factors influencing the expression of fear

The gradient boosted model predicts the next period (day) fear expression on Twitter based on the fear expressed in the current period in both local and national press releases, the number of confirmed COVID-19 cases and deaths in the current period, and the majority political identity, poverty rate, and median household income in a metropolitan area. Due to the sparsity in press release data described previously, the current analysis does not distinguish between metropolitan area and instead considers the influence of variables on the expression of fear across the entire data set. The model was trained on 80% of the available data and tested against the remaining 20% holdout sample, resulting in 235 training observations and 56 test observations. Each iteration was cross-validated with 10 folds for the purposes of hyperparameter tuning. After 700 iterations, the best performing model employed a learning rate of 0.025, a max tree depth of two, a minimum child weight of one, and a gamma of zero. The final model improves on the root mean square error (RMSE) of the untuned model from 0.0059 to 0.0055 and increases the  $R^2$  value from 0.3388 to 0.3931.

As shown in Figure 1, the most important variable for predicting the amount of fear expressed in tweets was the amount of fear expressed in national press releases the previous day, followed by the number of COVID-19 cases reported for a given metropolitan area on the previous day. The poverty rate, political identity, median household income, and amount of fear expressed in local press releases for each metropolitan area also contributed to the predictive accuracy, though to a lesser degree.

### 4.2 Language used to express fear

In considering the most likely words to appear in high-fear versus low-fear press releases from the local government, it is clear that the former tend to emphasize language directly related to COVID-19 like *fever*, *self-quarantine*, *flu*, *shortness*, *breath*, and *recover* while the latter lacks such a focus and contains words like *tax*, *loan*, *sales*, *bank*, *survey*, *art*, and *cultural* (see Figure 2). Similarly, in national press releases, those with higher expressions of fear are more likely to contain words like *tests*, *CDC*, *testing*, *spread*, *protect*, *support*, and *health*

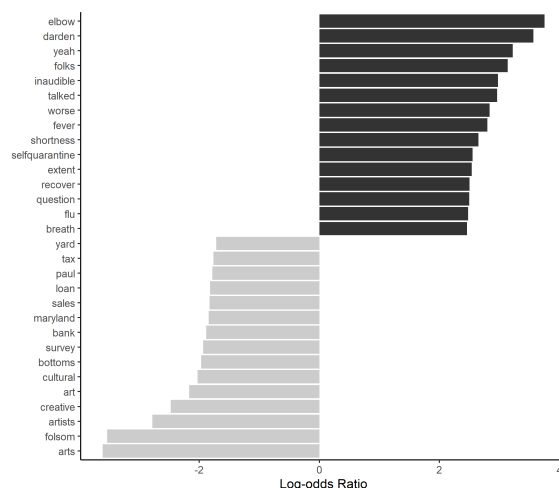


Figure 2: The most likely words to appear in high-fear (log-odds > 0) versus low-fear (log-odds < 0) local press releases.

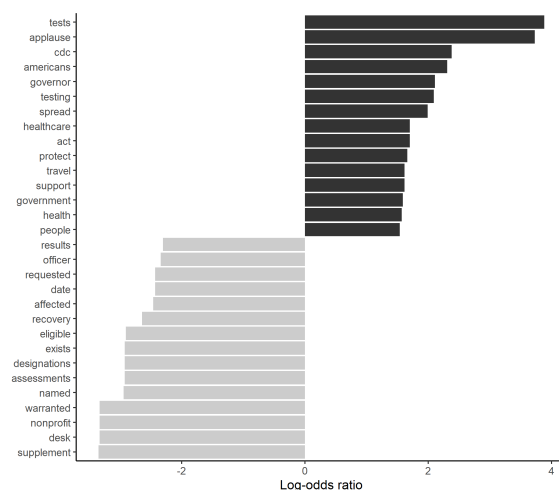


Figure 3: The most likely words to appear in high-fear (log-odds > 0) versus low-fear (log-odds < 0) national press releases.

as opposed to words like *eligible*, *nonprofit*, *office*, *designations*, and *assessments* (see Figure 3).

### 4.3 Relationship with behavior change

Finally, we consider whether an increase in expressed fear is associated with changes in behavior with a random effects model. When the base model is fit, we see both the previous day's fear as expressed on Twitter ( $b = 3.578, p < 0.01$ ) and classification of a community as conservative ( $b = 1.880, p < 0.01$ ) are associated with an increase in movement in public places over the pre-pandemic baseline (see Table 1). Importantly, however, the interaction between conservative identity and the expression of fear is significant and nega-

	Base Model	Covariates Model
	$b$	$b$
	( $SE$ )	( $SE$ )
Intercept	-2.113*** (0.521)	-1.959*** (0.507)
Confirmed COVID-19 cases		-0.0003*** (0.0001)
Confirmed COVID-19 deaths		0.005*** (0.002)
Fear expressed on Twitter (lagged 1-day)	3.578*** (0.832)	3.337*** (0.82)
Majority conservative identity	1.88*** (0.645)	1.573** (0.623)
Expressed fear (lagged 1-day) $\times$ Conservative identity	-2.464** (1.048)	
$F$	19.451***	72.933***
$R^2$	0.013	0.045

Table 1: Relative changes in movement in public place as compared to an out of sample baseline. For parsimony, only covariates that have a significant influence on the model are included. *Note:* \* $p < 0.1$ , \*\* $p < 0.05$ , \*\*\* $p < 0.01$ .

tive ( $b = -2.113, p < 0.01$ ), suggesting that for majority conservative communities an increase in expressed fear is associated with a subsequent decrease in movement in public places over the baseline.

Similarly, when control variables are added we see both the previous day’s fear as expressed on Twitter ( $b = 3.337, p < 0.01$ ) and classification of a community as conservative ( $b = 1.573, p = 0.012$ ) are associated with an increase in movement in public places over the pre-pandemic baseline (see Table 1). Again, the interaction between conservative identity and the expression of fear is significant and negative ( $b = -2.464, p = 0.019$ ), suggesting that for majority conservative communities an increase in expressed fear is associated with a subsequent decrease in movement in public places over the baseline.

## 5 Discussion

Past research suggests that conservatives are more likely to comply with authority (Jost et al., 2003a,b, 2007; Sales, 1973; Thorisdottir and Jost, 2011) and are likely to take preventative measures when they are fearful of a situation (Joel et al., 2014). However, a more recent stream of research argues the opposite (Barrios and Hochberg, 2020; Iyengar and Massey, 2019; Painter and Qiu, 2020; Rothwell and Makridis, 2020; Van Green and Tyson, 2020)

including evidence which suggests conservative non-adherence to COVID-19 health directives (Allcott et al., 2020; DeFranza et al., 2020; Gollwitzer et al., 2020). We offer evidence that may help to reconcile this contradiction. The present research suggests that while conservative communities in general ignore public health guidelines, this behavior is not monolithic. Instead, we see an association with the community’s expressions of fear when publicly discussing the pandemic and subsequent behaviors. When conservative communities express fear of the pandemic, subsequent movement in public places decreases as compared to pre-pandemic baselines. This is not the case in majority liberal communities, who exhibit no change in behavior in association with expressed fear. Moreover, we see that a dominant antecedent of local expressions of fear in conservative communities is the clear expression of fear from federal agencies and officials. Importantly, increasing confirmed COVID-19 case counts also predicted an increase in the expression of fear among members of majority conservative communities. This finding may be especially helpful in early phases of a pandemic when decisive action is essential.

Taken together, these results suggests that majority conservative communities might benefit from early regular updates from local and federal officials. Because discussions of COVID-19 have be-

come partisan (Allcott et al., 2020), the role of local governments cannot and should not be ignored. It is essential that official communications present details of the current situation clearly and honestly, but also that they emphasize the seriousness and severity of the pandemic (Wood and Schulman, 2021). At the same time, statements that work to diminish perceptions of risk or severity of the pandemic could be a detriment to efforts to manage infection rates in communities. The implications of these results extend beyond COVID-19 and help to inform policy communications at the local and federal level, specifically those targeted at majority conservative communities and for messages which may be unpopular but timely.

## 6 Conclusion

We have presented an analysis of the degree of fear expressed in association with COVID-19 in both official government press releases and by Twitter users in the 53 most populous metropolitan areas in the United States. In doing so, we have identified key factors that influence expressions of fear among members of communities: strong expressions of fear in national communications and increasing confirmed COVID-19 case counts. In addition, we have identified the words most likely to occur in both high- and low- fear official communications. Finally, we have provided evidence that expressions of fear are associated with different prophylactic behaviors in conservative and liberal communities. In the latter, increased expressions of fear are not associated with behavior change. However, in the former, increased expressions of fear are associated with an overall decrease in movement and activity in public spaces.

These results suggest that restricted testing and under-reporting case counts could be detrimental to safe individual behaviors and compliance with public health policy recommendations. Similarly, minimizing the severity or seriousness of COVID-19 poses a particular danger in majority conservative communities. Moving beyond COVID-19 mitigation, the present research emphasizes the importance of timely, relevant, and clear information capable of communicating the authentic seriousness of a situation, especially in majority conservative communities.

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