Low Government Performance and Uncivil Political Tweets:

Evidence from the COVID-19 Crisis in the U.S.*

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Abstract

Political expression through social media has already taken root as a form of political participation. Meanwhile, democracy seems to be facing an epidemic of incivility on social media platforms. With this background, online political incivility has recently become a growing concern in the field of political communication studies. However, it is less clear how a government’s performance is linked with people’s uncivil political expression on social media; investigating the existence of performance evaluation behavior through social media expression seems to be important, as it is a new form of non-institutionalized political participation. To fill this gap in the literature, the present study hypothesizes that when government performance worsens, people become frustrated and send uncivil messages to the government via social media. To test this hypothesis, the present study collected over 8 million tweets directed at U.S. state governors and classified them as

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uncivil or not, using a neural network-based machine learning method, and examined the impact of worsening state-level COVID-19 cases on the number of uncivil tweets directed at state governors. The results of the statistical analyses showed that increasing state-level COVID-19 cases significantly led to a higher number of uncivil tweets against state governors. Thereafter, the present study discusses the implications of the findings from two perspectives: non-institutionalized political participation and the importance of elections in democracies.

**Introduction**

Nowadays, many people use social media platforms, such as Twitter and Facebook, to express their political opinions. With this background, political expression through social media has already become a form of political participation (Theocharis, 2015), and related research has been rapidly advancing. Scholars have found, for example, that social media are prone to selective exposure and the echo chamber phenomenon (Bakshy et al., 2015; Cinelli et al., 2021; Mosleh et al., 2021). It has also been found that political engagement on social media enhances offline political participation (Bode, 2017; Conroy et al., 2012; Dimitrova et al., 2011; Holt et al., 2013). These findings suggest the importance of further research in this area for a better understanding of contemporary politics.

After the outbreak of the COVID-19 pandemic, people have had conversations about the pandemic on social media (Xiong et al., 2021; Xue et al., 2020). According to previous studies, communication about COVID-19 on social media is politicized (Jiang et al., 2020), and echo chambers can be observed therein (Jiang et al., 2021). In addition, conspiracy theories about COVID-19 and hate speech against Asians are prevalent on social media (Ahmed et al., 2020; He et al., 2021). Thus, research on social media communication is also
important in the context of the COVID-19 pandemic.

While previous studies have revealed the nature of political communication on social media from a variety of perspectives, few have examined how the worsening of government performance is linked with people’s political expression on social media. However, investigating the existence of performance evaluation behavior through social media expression, a form of non-institutionalized political participation (Michalski et al., 2021), is important from a political science perspective. The present study aims to fill this gap in the literature.

It hypothesizes that when government performance worsens, people feel frustrated and angry and thus post uncivil messages on social media to berate the government. The present study tested this hypothesis in the context of the COVID-19 pandemic by collecting a large number of tweets directed at U.S. state governors and classifying them as uncivil or not using a neural network machine learning method. Using these tweet data, it examined the impact of worsening state-level COVID-19 indicators on the number of uncivil tweets directed at state governors. The results showed that the number of state-level COVID-19 cases positively affected the number of uncivil tweets directed at state governors. This suggests that people evaluate the government’s performance through political expressions on social media, which is a new and growing form of non-institutionalized political participation.

**Political Communication on Social Media**

Social media seems to have played a significant role in real-world changes, such as the outbreak of the Arab Spring (Howard et al., 2015; Waechter, 2019) and the electoral victory of Donald Trump in the 2016 U.S. presidential election (Enli, 2017; Francia, 2017). With this
background, many scholars have studied political communication on social media from a variety of perspectives.

Some scholars have focused on what motivates people to express their political opinions on social media. For example, Bekafigo and McBride (2013) find that people with stronger partisanship levels and higher political engagement are more likely to tweet about politics. In terms of elections, it has been found that many people use social media during elections to persuade others to vote for the party that they support (Hosch-Dayican et al., 2016). In terms of social movement, it has been revealed that people participate in social media protests, such as the #MeToo movement, to change society (Mendes et al., 2018). Overall, these findings seem to suggest that people engage in political expression on social media to change other people’s opinions and social conditions.

In addition, online incivility has recently become a growing concern in the field of political communication studies (e.g., Borah, 2013; Jamieson et al., 2017; Kenski et al., 2017; Muddiman & Stroud, 2017; Papacharissi, 2004; Sobieraj & Berry, 2011; Theocharis et al., 2016). Previous studies have suggested that the prevalence of online political incivility leads to various consequences in democracies. For example, people’s exposure to incivility in discussions can lead to negative feelings toward the discussion partner (Hwang et al., 2018; Kim & Kim, 2019) and lower perceptions of the rationality of the opponent’s argument (Popan et al., 2019). These findings suggest that online incivility prevents the democratic society from reaching a consensus. People’s frequent exposure to online incivility has also been found to be negatively related to their levels of online and offline political participation (Yamamoto et al., 2020), hence suggesting that online incivility decreases people’s political participation. Thus, because online incivility affects various aspects of democratic politics, understanding the factors that contribute to online incivility is crucial to maintaining democracy. In this context, a growing body of the literature has investigated the factors
shaping online political incivility (e.g., Coe et al., 2014; Gervais, 2017; Rains et al., 2017; Rowe, 2015; Vargo & Hopp, 2017).

**Government Performance**

To understand political communication, it is also important to comprehend how people perceive their government, as this is a key actor in the political process. Political scientists have long investigated the relationships between people’s evaluations of their government’s performance and their voting behaviors (e.g., de Vries & Giger, 2014; Ecker et al., 2016; Fiorina, 1978; Fournier et al., 2003; Hobolt et al., 2013; Kinder & Kiewiet, 1979), showing that when government performance (such as the economy) is good, people vote for the government’s party to reward it; however, when the performance is bad, people vote for the opposition to punish the incumbent government. Such voting patterns are called retrospective voting.

While the concept of government performance has been frequently used to explain people’s voting behavior, few studies have examined whether government performance leads to people’s non-institutionalized political behaviors (i.e., political behaviors other than voting). However, it is crucial to investigate the relationships between government performance and non-institutionalized political participation because the latter is theoretically important as a tool for expressing political grievances and challenging authorities (Melo & Stockemer, 2012; Norris, 2002).

To address the issue, the present study argues that people’s evaluations of government performance lead to political expression on social media. More specifically, the present study hypothesizes that the worsening of government performance makes people frustrated and angry with the government and thus leads them to engage in uncivil political
expression against the government on social media.

Evidence from previous studies indirectly supports this argument. It has been shown that U.S. presidential approval ratings in public opinion polls correlate with the public sentiment expressed on Twitter (O’Connor et al., 2010). This suggests that people’s evaluations of their government lead to their political expression on social media. However, it is unclear whether the correlation shown by O’Connor et al. (2010) is in response to government performance. In addition, previous studies in social psychology have shown that frustration states lead to aggressive behavior toward the person causing the frustration (Berkowitz, 1989; Dill & Anderson, 1995; see also Breuer & Elson, 2017), which suggests that people’s political frustration may be a cause of online political incivility. The combination of these findings strengthens the present study’s argument.

The above mechanism should work as follows for the COVID-19 pandemic age. Throughout the pandemic, the number of COVID-19 cases has been considered an important indicator of government performance because people expect politicians to control the situation through policies related to lockdowns, masks, vaccines, and so on. Based on this assumption, when the number of COVID-19 cases increases (i.e., the COVID-19 indicator worsens), people should get frustrated and angry with the government, which is responsible for the worsening situation, and thus send uncivil messages to it on social media. Accordingly, the present study introduces the following hypothesis:

**Hypothesis**: An increase in COVID-19 cases leads to a higher number of uncivil messages on social media directed at governments.
Methods

To test the above-stated hypothesis, the present study constructed a state-level time series dataset that recorded some COVID-19-related indicators and the numbers of uncivil tweets directed at governors. Using the dataset, fixed effects regression models were estimated with ordinary least squares (OLS).

Collecting Tweets

The present study collected replies or mention tweets directed at the Twitter accounts of U.S. state governors and posted between April 1, 2020, and March 31, 2021, using Twitter API for Academic Research.\(^1\) In the case of Montana, Utah, and Rhode Island, where the governors changed in the middle of the data-collection period, the target accounts of the collection were switched on the inauguration day of the new governors. Through these procedures, 8,045,894 tweets were eventually collected.

Classifying the Tweets Using Machine Learning

The collected tweets were classified as uncivil or not using BERT (Devlin et al., 2019), a neural network machine learning method for language processing.

Supervised data for training the classification model were constructed via Lucid Marketplace as follows:\(^2\) First, 2,000 tweets were randomly extracted from the collected tweets. Then, U.S. respondents recruited via Lucid classified the 2,000 tweets as uncivil or civil in accordance with the following definition of incivility: “a disrespectful or insulting expression that attacks an individual or group.” One tweet was classified by 10 respondents.
on average. Tweets classified as uncivil by a majority of respondents were labeled as uncivil, while those classified as civil by a majority were labeled as civil in the supervised data.\(^3\)

With the supervised data, the present study trained the neural network machine learning model based on BERT to construct a classifier. BERTweet-base (Nguyen et al., 2020) was used as a pre-trained BERT model, and the outputs of the pre-trained layer were passed to a fully connected layer, and then a sigmoid function. Table 1 shows the classifier’s performance, calculated via five-fold cross-validation. The scores indicate the successful detection of incivility with high performance, compared to previous studies.\(^4\)

The present study used this classifier to classify the collected tweets as uncivil or not, and 2,172,839 out of 8,045,894 tweets (27.01\%) were classified as uncivil. This percentage of incivility is slightly higher than the ones reported by previous studies (Coe et al., 2014; Theocharis et al., 2020; Trifiro et al., 2021).

| Table 1: Classification Performance |
|-------------------------------------|
| Accuracy  | Precision | Recall  | F1-score |
| Score     | .84       | .65     | .75      | .70      |

**Counting Uncivil Tweets**

To count the daily numbers of uncivil tweets, it was necessary to identify the date and time when they were posted. Because the date and time of the tweets were originally recorded on Coordinated Universal Time (UTC), the present study converted them from UTC to the standard time of each state. In the case of states with multiple standard time zones, the standard time of the state capital was used. In addition, in the case of a daylight saving time period, the time was converted to daylight saving time.

Based on the identified date and time, the daily numbers of uncivil tweets were counted
for each state. As a rule, uncivil tweets posted by users who had sent uncivil tweets to multiple state governors were excluded from the count. When a user had sent uncivil tweets to several state governors, it meant that the user had sent the uncivil tweet to governors in states other than their own home state. However, in the present study’s theory, people send uncivil tweets as a result of evaluating their own government’s performance. In other words, sending uncivil tweets to multiple state governors does not align with the theory of the present study, and therefore, uncivil tweets by such users were excluded from the counts.

**Constructing a Dataset**

Combining the above data with other data from several sources, the present study constructed a state-level time series dataset. The dataset comprised 18,250 observations (50 states × 365 days) and included state-level daily numbers of uncivil tweets directed at state governors, tweets posted by state governors, COVID-19 cases, PCR tests, and dummy indicators for the presence of lockdown and mask policies. The numbers of tweets posted by state governors were retrieved via Twitter API. The numbers of COVID-19 cases and PCR tests were retrieved from the “COVID-19 Diagnostic Laboratory Testing (PCR Testing) Time Series” (U.S. Department of Health & Human Services [HHS], 2023). Indicators for lockdown and mask policies were retrieved from the “Oxford COVID-19 Government Response Tracker” (Hale et al., 2021, 2023). Table A1 presents the descriptive statistics for the dataset of the present study.
Estimation Strategies

Using the dataset, two-way fixed effects regression models were estimated. More specifically, the following four models were estimated:

\[
\text{UncivilTweets}_{st} = \beta_1 \text{COVID}_{st-1} + \beta_2 \text{PCR}_{st-1} + \beta_3 \text{GovTweets}_{st} + \beta_4 \text{Lockdown}_{st} + \beta_5 \text{Mask}_{st} + \text{StateFE}_s + \text{DayFE}_t + \epsilon_{st} \tag{1}
\]

\[
\text{UncivilTweets}_{st} = \beta_1 \text{COVID}_{st-1} + \beta_2 \text{PCR}_{st-1} + \beta_4 \text{Lockdown}_{st} + \beta_5 \text{Mask}_{st} + \text{StateFE}_s + \text{DayFE}_t + \epsilon_{st} \tag{2}
\]

\[
\text{UncivilTweets}_{st} = \beta_1 \text{COVID}_{st-1} + \beta_2 \text{PCR}_{st-1} + \beta_3 \text{GovTweets}_{st} + \text{StateFE}_s + \text{DayFE}_t + \epsilon_{st} \tag{3}
\]

\[
\text{UncivilTweets}_{st} = \beta_1 \text{COVID}_{st-1} + \beta_2 \text{PCR}_{st-1} + \beta_3 \text{GovTweets}_{st} + \beta_4 \text{Lockdown}_{st} + \beta_5 \text{Mask}_{st} + \text{StateFE}_s \times \text{Trend}_t + \epsilon_{st} \tag{4}
\]

where $\beta$ represents a coefficient, $s$ represents a state, $t$ represents a day, and $\epsilon$ represents an error term.

Model 1 was the main model. The independent variable was COVID, representing a log of 7-day moving average of the number of COVID-19 cases, and the dependent variable was UncivilTweets, denoting a log of the number of uncivil tweets directed at the state governor. In this model, COVID on a given day was assumed to affect UncivilTweets on the next day. This time delay was introduced because the number of COVID-19 cases on a given day should generally be reported on the next day or thereafter. Moving average is introduced
for COVID because people may evaluate the number of COVID-19 cases over the last few days rather than only on the previous day.

Model 1 includes StateFE (state fixed effects) and TimeFE (day fixed effects), which can remove the omitted variable bias caused by state-specific variables that do not vary across time and time-specific variables that do not vary across states (see Stock & Watson, 2020).

As a control variable, Model 1 included PCR (a log of 7-day moving average of the number of PCR tests). Considering that some people evaluate the number of COVID-19 cases based on the number of PCR tests and that an increase in the number of PCR tests leads to an automatic increase in the apparent number of COVID-19 cases, PCR may affect both COVID and UncivilTweets; thus, it should be controlled as a confounder.

Model 1 also included Lockdown (a dummy indicator for lockdown), Mask (a dummy indicator for strong mask requirement), and GovTweets (a log of 7-day moving average of the numbers of governor tweets). When the number of COVID-19 cases is high, lockdown and strong mask requirement are likely to be implemented, which may in turn stoke people’s frustration and thus increase the number of uncivil tweets. Moreover, when the number of COVID-19 cases is high, governors are likely to tweet a lot to call for attention, which may in turn lead to an automatic increase in the number of uncivil tweets to governors; in this sense, these two variables are considered mediator variables. Because the causal relationship via these mediator variables is not the present study’s interest, these variables should be controlled.

As already mentioned, all quantitative variables were converted into natural logarithm values in Model 1. The effect size of one increase in COVID-19 cases on the number of uncivil tweets might largely vary depending on the sizes of the states’ populations; hence, converting them into natural logarithm values was a better option, which allowed for the estimation of the relationship by which a 1% increase in the independent variable led to a
β% increase in the dependent variable (see Stock & Watson, 2020).

Models 2-4 were additional constructs. In Model 2, Lockdown and Mask were omitted, while in Model 3, GovTweets was omitted. As mentioned above, Model 1 controlled for Lockdown, Mask, and GovTweets because they were considered mediator variables, and the present study was not interested in the causal effect via these variables. However, it has been pointed out that when a variable U that affects both the mediator and dependent variables exists, controlling for the former can lead to a biased causal estimation, where the independent variable affects the dependent variable via the variable U (see Rohrer, 2018). As it was unknown whether such a variable U existed, the present study estimated Models 2 and 3, which did not include these mediator variables.

Model 4 additionally included StateFE × Trend, which represented state-specific time trends. This can capture regional characteristics that linearly evolve over time. 8

The linear regression models were estimated with OLS. Then, t-tests on the estimated $\beta_1$ were conducted at a significance level of $p = .05$.

### Results

Figure 1 presents the estimated $\beta_1$ for each model with 95% confidence intervals. The result of Model 1 shows that the estimated $\beta_1$ is 0.16, which is statistically significant ($t = 4.39, p < .001$). This means that a 1% increase in the 7-day moving average of the number of state-level COVID-19 cases leads to a 0.16% increase in the number of uncivil tweets directed at governors. Given that past tweets accumulate on Twitter, this effect size is considered not only statistically but also substantially meaningful. Furthermore, the results of the additional Models 2-4 show that the estimated $\beta_1$ values are 0.17, 0.16, and 0.15, respectively. These estimated values are similar to the one from Model 1, and they
hold statistical significance. Therefore, the present study concluded that the hypothesis was supported. More detailed results are presented in Table A2.

![Figure 1: Main Results](image)

**Robustness Check**

As a robustness check, the way of counting uncivil tweets was modified. More specifically, if a given user sent more than one uncivil tweet to the governor in a day, the number of uncivil tweets by that user in the day was counted as one. A user might have sent a large number of uncivil tweets; this could lead to the tendencies of a few such non-general people being overly reflected in the estimations; in this case, counting uncivil tweets in this modified way could be more appropriate. Using the new dataset, Models 1-4 were estimated.

Figure 2 shows the estimated $\beta_1$ for each model with 95% confidence intervals. The result of Model 1 shows that the estimated $\beta_1$ is 0.15, which is statistically significant ($t = 4.27, p < .001$) and similar to the estimated value in the main results. Furthermore, the results of Models 2-4 show that the estimated $\beta_1$ values are 0.17, 0.15, and 0.14, respectively. These estimated values are also similar to those from the main results, and
they hold statistical significance. Therefore, the results of the robustness check support the hypothesis. More detailed results are given in Table A3.

![Figure 2: Results of a Robustness Check](image)

**Discussion**

The present study investigated whether the worsening of government performance led to an increase in the number of uncivil tweets directed at the government. The present study collected tweets directed at U.S. state governors and classified them as uncivil or civil via a machine learning method. Two-way fixed effects regression models were estimated, which revealed that an increase in COVID-19 cases led to a statistically significant increase in the number of uncivil tweets against state governors.

Sophisticated methodologies were employed to provide solid evidence. Adopting a neural network machine learning method enabled to automatically classify many tweets as uncivil or civil. Furthermore, the introduction of the two-way fixed effects in the regression models allowed for the removal of a large part of omitted variable bias and thus provide causal evidence.

The present study makes significant contributions to the literature. First, it reveals
that people evaluate government performance through not only elections but also social media communication, a new form of non-institutionalized political participation. This suggests that people are interested in politics even outside the election period and try to influence the political process through social media to change the status quo. So far, the concept of government performance has been critical in the field of political science. However, although much attention has been paid to its impact on people’s voting behavior, few studies have examined the impact of government performance on people’s political behavior other than voting. As non-institutionalized political participation is theoretically important as a tool for expressing political grievances and challenging authorities (Melo & Stockemer, 2012; Norris, 2002), it is crucial to understand how government performance is linked to it. Non-institutionalized political participation has existed for a long time in the history of democracy, such as through street protest demonstrations and petitions. With the recent development of the Internet, political expression on social media has become an established form of participation (Theocharis, 2015). The growth of social media, coupled with its lack of costs, might be popularizing non-institutionalized political participation. Therefore, the contribution of the present study, which reveals the impact of government performance on non-institutionalized participation through social media, is extremely significant.

A second contribution is that the findings of the present study suggest the importance of elections in a democracy. When people elect a low-quality government, its performance would also be low. Low performance, according to the findings of the present study, increases uncivil behavior and worsens the environment of a discussion forum, and poor communication in a poor discussion forum would subsequently lead to increasingly low government performance. Through this process, a democratic society might fall into a negative spiral. This suggests that even one wrong choice in an election could be
irreversible, and therefore, every election is crucial for maintaining a healthy democracy.

Despite these contributions, the present study has several limitations. First, the present study focused on the U.S. Twitter sphere; thus, whether the findings of the present study apply to regions outside of the U.S. or to social media platforms other than Twitter has not been ascertained. Hence, validating the findings of the present study in various regions and platforms is an important future task. Second, although the tweet data in the present study are limited to replies and mentioned tweets directed at state governors, some people send uncivil tweets in ways other than replies and mentions. In addition, it is possible that people blame the worsening of COVID-19-related indicators not only on the governors but also on other actors, such as state health authorities, state legislators, and so on. Hence, a challenge for future scholars will be to analyze uncivil tweets directed at these actors. Third, the present study did not consider the presence of bots. It has been argued that bots are actively producing and spreading conspiracies and hate speech in the age of the COVID-19 pandemic (Ferrara, 2020; Uyheng & Carley, 2020). Although the second robustness check might have eliminated the influence of bots to some extent, future scholars should analyze data excluding bots through automated bot detection techniques. Because social media might become increasingly popular and play a progressively important role in society in the future, more research is needed on how people engage in democratic politics through social media communication.

Notes

1. The collection of tweets was mainly conducted on May 21 and 22, 2021. For Rhode Island’s new governor, the collection was conducted on April 24, 2023.

2. This was conducted after the review and approval by the research ethics committee (IRB) of the Graduate School of Law, Kobe University (approval ID 030013).
3. 300 U.S. citizens between the ages of 18 and 70 were recruited, which was conducted over five rounds. A quota sampling approach based on age and gender was employed to obtain a sample that closely resembled the composition of the U.S. population. For a technical reason, the number of participants exceeded the target numbers for some strata. Using all responses has the advantage of making the voting results closer to the true values in terms of the law of large numbers, but has the disadvantage of biasing the composition of the respondents. Conversely, excluding the responses of those who exceeded the target numbers of strata has the opposite advantage and disadvantage. The present study reports the analysis using the former approach in the main section and the latter in the appendix section.

4. The present study has a better F1-score than previous studies that have used machine learning methods to detect political incivility. For example, Trifiro et al. (2021) and Theocharis et al. (2020) obtained F1-scores of .65 and .66, respectively. Note that Theocharis et al. (2020) does not report F1-score itself, but recall and precision scores. Thus, the F1-score of Theocharis et al. (2020) here was obtained based on the reported precision and recall scores.

5. The present study used the numbers of positive cases from PCR tests as an indicator for the numbers of COVID-19 cases. This dataset has several versions. The present study used the version that was uploaded on May 30, 2023, which is archived by HHS (retrieved July 27, 2023, from https://us-dhhs-aa.s3.us-east-2.amazonaws.com/j8mb-icvb_2023-05-30T12-05-12.csv). This version is archived by not only HHS but also Internet Archive, which contributes to higher computational reproducibility. The data file of this version archived by Internet Archive is available at https://web.archive.org/web/20230530234829/https://healthdata.gov/api/views/j8mb-icvb/rows.csv?accessType=DOWNLOAD.

6. The present study used the file “OxCGRT_compact_subnational_v1.csv” (retrieved July 27, 2023, from https://github.com/OxCGRT/covid-policy-dataset/blob/main/data/OxCGRT_compact_subnational_v1.csv). Regarding lockdown, the dataset included the variable “C6M_Stay.at.home.requirements”, which was an ordinal scale ranging from 0 to 3. The present study re-codes this variable so that it takes value of 1 if the original value is 2 or 3, and otherwise takes value of 0, to create a dummy for lockdown. Regarding mask requirement, the dataset included the variable “H6M_Facial.Coverings”, which was an ordinal scale ranging from 0 to 4. The present study re-codes this variable so that it takes the value of 1 if the original value is 3 or 4, and otherwise takes the value of 0, to create a dummy for strong mask requirement.

7. As the minimum values of the variables were 0, the present study added one to them before converting them into natural logarithmic values.

8. A time trend is a quantitative variable that takes the values 1, 2, 3, ..., and 365, for day 1, day 2, day 3, ..., and day 365, respectively. A state-specific time trend is an interaction between a state dummy
and a time trend (see Angrist & Pischke, 2014; Carpenter, 2005; Friedberg, 1998).

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## Appendix

### Tables

**Table A1: Descriptive Statistics**

|                        | M     | SD    | Min   | Max    |
|------------------------|-------|-------|-------|--------|
| Uncivil tweets         | 54.18 | 269.86| 0.00  | 26,195.00 |
| Uncivil tweets (log)   | 2.48  | 1.68  | 0.00  | 10.17  |
| COVID-19 cases         | 1,777.70 | 3,279.55 | 0.00  | 59,712.00 |
| COVID-19 cases (log)   | 6.44  | 1.67  | 0.00  | 11.00  |
| PCR tests              | 20,850.28 | 31,252.62 | 0.00  | 371,033.00 |
| PCR tests (log)        | 9.14  | 1.45  | 0.00  | 12.82  |
| Governor tweets        | 3.64  | 5.63  | 0.00  | 98.00  |
| Governor tweets (log)  | 1.12  | 0.87  | 0.00  | 4.60   |
| Lockdown               | 0.18  | 0.38  | 0.00  | 1.00   |
| Strong mask requirement| 0.65  | 0.48  | 0.00  | 1.00   |
|                                | Model 1    | Model 2    | Model 3    | Model 4    |
|--------------------------------|------------|------------|------------|------------|
| **COVID-19 cases 7MA (log)**   | 0.16       | 0.17       | 0.16       | 0.15       |
|                                | [0.08, 0.23] | [0.10, 0.24] | [0.09, 0.23] | [0.05, 0.24] |
|                                | SE = 0.04  | SE = 0.04  | SE = 0.03  | SE = 0.05  |
|                                | t = 4.39   | t = 4.77   | t = 4.77   | t = 3.07   |
|                                | p < .001   | p < .001   | p < .001   | p = .003   |
| **PCR tests 7MA (log)**        | -0.09      | -0.09      | -0.09      | -0.06      |
|                                | [-0.19, 0.01] | [-0.18, 0.01] | [-0.19, 0.01] | [-0.19, 0.07] |
|                                | SE = 0.05  | SE = 0.05  | SE = 0.05  | SE = 0.06  |
| **Governor tweets 7MA (log)**  | 0.65       | 0.65       | 0.61       | 0.51, 0.78 |
|                                | [0.51, 0.78] | [0.52, 0.78] | [0.49, 0.73] |             |
|                                | SE = 0.07  | SE = 0.07  | SE = 0.07  | SE = 0.06  |
| **Lockdown**                   | 0.08       | 0.11       | -0.03      | -0.05, 0.21 |
|                                | [-0.05, 0.21] | [-0.03, 0.25] | [-0.14, 0.08] |             |
|                                | SE = 0.07  | SE = 0.07  | SE = 0.06  | SE = 0.06  |
| **Strong mask requirement**    | 0.01       | 0.04       | 0.11       | -0.16, 0.17 |
|                                | [-0.16, 0.17] | [-0.13, 0.22] | [-0.02, 0.23] |             |
|                                | SE = 0.08  | SE = 0.09  | SE = 0.06  | SE = 0.06  |
| **State fixed effect**         | Yes        | Yes        | Yes        | Yes        |
| **Day fixed effect**           | Yes        | Yes        | Yes        | Yes        |
| **Time trend**                 | No         | No         | No         | Yes        |
| **N of observations**          | 18,250     | 18,250     | 18,250     | 18,250     |

Numbers above blankets are regression coefficients for each variable. Numbers in blankets are 95% confidence intervals of the coefficients. Standard errors are clustered by state. 7MA means 7-day moving average. The dependent variable is the number of uncivil tweets (log).
Table A3: Results of a Robustness Check

|                          | Model 1     | Model 2     | Model 3     | Model 4     |
|--------------------------|-------------|-------------|-------------|-------------|
| COVID-19 cases 7MA (log) | 0.15        | 0.17        | 0.15        | 0.14        |
|                          | [0.08, 0.22]| [0.09, 0.24]| [0.09, 0.22]| [0.05, 0.24]|
|                          | SE = 0.04   | SE = 0.04   | SE = 0.03   | SE = 0.05   |
|                          | t = 4.27    | t = 4.63    | t = 4.64    | t = 3.00    |
|                          | p < .001    | p < .001    | p < .001    | p = .004    |
| PCR tests 7MA (log)      | -0.08       | -0.08       | -0.08       | -0.06       |
|                          | [-0.18, 0.02]| [-0.17, 0.01]| [-0.18, 0.01]| [-0.19, 0.07]|
|                          | SE = 0.05   | SE = 0.05   | SE = 0.05   | SE = 0.06   |
| Governor tweets 7MA (log)| 0.63        | 0.63        | 0.63        | 0.59        |
|                          | [0.50, 0.76]| [0.50, 0.76]| [0.48, 0.70]|             |
|                          | SE = 0.06   | SE = 0.06   | SE = 0.06   | SE = 0.06   |
| Lockdown                 | 0.07        | 0.10        |             | -0.04       |
|                          | [-0.06, 0.20]| [-0.04, 0.23]| [-0.15, 0.07]|             |
|                          | SE = 0.06   | SE = 0.07   | SE = 0.06   | SE = 0.06   |
| Strong mask requirement  | 0.00        | 0.04        |             | 0.11        |
|                          | [-0.17, 0.17]| [-0.13, 0.22]| [-0.02, 0.23]|             |
|                          | SE = 0.08   | SE = 0.22   | SE = 0.09   | SE = 0.23   |
| State fixed effect       | Yes         | Yes         | Yes         | Yes         |
| Day fixed effect         | Yes         | Yes         | Yes         | Yes         |
| Time trend               | No          | No          | No          | Yes         |
| N of observations        | 18,250      | 18,250      | 18,250      | 18,250      |

Numbers above blankets are regression coefficients for each variable. Numbers in blankets are 95% confidence intervals of the coefficients. Standard errors are clustered by state. 7MA means 7-day moving average. The dependent variable is the number of uncivil tweets (log).
Analysis with a Different Classifier

As mentioned in endnote 3, this section reports the results of the analysis using the supervised dataset based on responses from a sample close to the U.S. demographic composition. The supervised dataset was used to train a machine learning classifier with the exactly same hyper-parameter settings as when training the main classifier. This process produced a different classifier (accuracy = .81, precision = .63, recall = .67, F1 = .65), which yielded different classification results. Using the new dataset, Models 1-4 were estimated.

Figure A1 presents the estimated $\beta_1$ for each model with 95% confidence intervals. The result of Model 1 shows that the estimated $\beta_1$ is 0.16, which is statistically significant ($t = 4.63, p < .001$). This means that a 1% increase in the 7-day moving average of the number of state-level COVID-19 cases leads to a 0.16% increase in the number of uncivil tweets directed at governors. The estimated values of Models 2-4 are also similar to those from the main results. More detailed results are given in Table A4.

Figure A1: Results with a Different Classifier
| Model 1 | Model 2 | Model 3 | Model 4 |
|---------|---------|---------|---------|
| **COVID-19 cases 7MA (log)** | 0.16 | 0.18 | 0.17 | 0.16 |
|  | [ 0.09, 0.24] | [ 0.11, 0.25] | [ 0.10, 0.24] | [ 0.07, 0.26] |
|  | $SE = 0.04$ | $SE = 0.04$ | $SE = 0.03$ | $SE = 0.05$ |
|  | $t = 4.63$ | $t = 5.01$ | $t = 5.02$ | $t = 3.44$ |
|  | $p < .001$ | $p < .001$ | $p < .001$ | $p = .001$ |
| **PCR tests 7MA (log)** | -0.10 | -0.10 | -0.10 | -0.08 |
|  | [-0.20, 0.01] | [-0.19, 0.00] | [-0.20, 0.00] | [-0.20, 0.05] |
|  | $SE = 0.05$ | $SE = 0.05$ | $SE = 0.05$ | $SE = 0.06$ |
| **Governor tweets 7MA (log)** | 0.66 | 0.66 | 0.62 |
|  | [ 0.52, 0.79] | [ 0.53, 0.80] | [ 0.50, 0.74] |
|  | $SE = 0.07$ | $SE = 0.07$ | $SE = 0.06$ |
| **Lockdown** | 0.08 | 0.11 | -0.03 |
|  | [-0.05, 0.21] | [-0.02, 0.24] | [-0.14, 0.07] |
|  | $SE = 0.06$ | $SE = 0.07$ | $SE = 0.05$ |
| **Strong mask requirement** | 0.01 | 0.05 | 0.12 |
|  | [-0.16, 0.18] | [-0.13, 0.23] | [ 0.00, 0.24] |
|  | $SE = 0.08$ | $SE = 0.09$ | $SE = 0.06$ |
| **State fixed effect** | Yes | Yes | Yes | Yes |
| **Day fixed effect** | Yes | Yes | Yes | Yes |
| **Time trend** | No | No | No | Yes |
| **N of observations** | 18,250 | 18,250 | 18,250 | 18,250 |

Numbers above blankets are regression coefficients for each variable. Numbers in blankets are 95% confidence intervals of the coefficients. Standard errors are clustered by state. 7MA means 7-day moving average. The dependent variable is the number of uncivil tweets (log).