Attention to the COVID-19 pandemic on Twitter: Partisan differences among U.S. state legislators

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Abstract

Subnational governments in the United States have taken the lead on many aspects of the response to the COVID-19 pandemic. Variation in government activity across states offers the opportunity to analyze responses in comparable settings. We study a common and informative activity among state officials—state legislators' attention to the pandemic on Twitter. We find that legislators' attention to the pandemic strongly correlates with the number of cases in the legislator's state, the national count of new deaths, and the number of pandemic-related public policies passed within the legislator's state. Furthermore, we find that the degree of responsiveness to pandemic indicators differs significantly across political parties, with Republicans exhibiting weaker responses, on average. Lastly, we find significant differences in the content of tweets about the pandemic by Democratic and Republican legislators, with Democrats focused on health indicators and impacts, and Republicans focused on business impacts and opening the economy.

Keywords: *COVID-19, Twitter, Legislators, U.S. states, Partisanship*

Introduction

State governments in the United States have played, and continue to play, substantial roles in shaping the management of the COVID-19 pandemic (Adolph et al., 2021). Initial state policy considerations concerned the scope and timing of lockdowns (Ng, 2020), restrictions on intra- and interstate travel (Studdert, Hall and Mello, 2020), and ongoing pandemic management regulations regarding policies such as masking and indoor gathering capacity (Fraser, Juliano and Nichols, 2021). More recently, states have developed policies to disseminate COVID-19 vaccines (Grünebaum et al., 2021). Much of the existing research on states' responses to the pandemic has focused on aggregate, state-level activity. We contribute a micro-level perspective, analyzing how individual policymakers (state legislators) respond to pandemic dynamics in their public rhetoric.

Analyzing variation in pandemic management activity across states and individual policymakers is useful for effectively drawing insights from past experiences and projecting the trajectory of state responses going forward. Though it is feasible to conduct cross-state comparisons of governors' management of the pandemic in terms of policy enactments (Baccini and Brodeur, 2020); due to cross-state differences in resources, powers, and organization (see, e.g., Gerber, Maestas and Dometrius, 2005; Barber, Bolton and Thrower, 2019), it is more challenging to compare reactions to the pandemic in the legislative branch of state governments. We build and analyze a database of over 5,000 U.S. state legislators on Twitter—a platform through which we can track timely and comparable measures of attention to the pandemic among state lawmakers. We analyze the degree to which lawmakers' attention to the pandemic correlates with pandemic indicators at the national and state levels, and study how these relationships differ based on the legislators' partisanship.

Though public policy is not made directly on social media, public officials' social media activity serves several significant functions in the policy and political processes. Public officials' activities on social media have been found to influence public policy diffusion (Schuster, Jörgens and Kolleck, 2021), the effectiveness of policy implementation (Kavanaugh et al., 2012; Graham, Avery and Park, 2015), political engagement among young citizens (Marquart, Ohme and Möller, 2020), and media coverage (Broersma and Graham, 2012; Von Nordheim, Boczek and Koppers, 2018). Indeed, several of the tweets in the data that we report on below appear in recent news articles (e.g., Coleman, 2020; Sobey, 2020). Overall, social media use serves as a direct and cost-effective mechanism through which politicians at all levels of government can engage the public's interest agenda (Conway, Kenski and Wang, 2015; Barberá et al., 2019). The state legislators who we study have a substantial following on social media—approximately 3.7 million unique followers, which is, e.g., more than the number of followers of U.S. Senator (and Majority Leader) Chuck Schumer (D-NY) as of March 23, 2021.

Given the relatively novel nature of data on state legislators' social media use, we seek to understand the broad factors that drive state legislators' activity on Twitter, within the focused and salient context of COVID-19 discourse. We focus on two categories of factors. First, we know from the literature that public officials regularly use Twitter to discuss and respond to contemporary policy problems (Jörgens, Kolleck and Saerbeck, 2016; Russell, 2021). We therefore expect legislators' discussion of the pandemic to be directly related to the severity of the pandemic in their states, and the degree to which their state governments are involved in policymaking related to the pandemic.

Second, in past research on U.S. elected officials' social media use, partisanship has been found to be the primary factor in explaining the nature of officials' social media engagement. For example, U.S. Senators engage in highly partisan rhetoric on Twitter (Russell, 2018). Partisanship was one of the primary determinants of how U.S. Congress members' framed the confirmation hearings of Supreme Court nominee Brett Kavanaugh in their tweets (Wright, Clark and Evans, 2021). In the 115th Congress, the average legislator devoted 22% of their tweets to partisan rhetoric (Gelman and Wilson, 2021). Given the highly politicized nature of the pandemic (Pickup, Stecula and Van Der Linden, 2020; Green et al., 2020), and the partisan dynamics of U.S. national politics (Burke, 2021; Zingher and Richman, 2019), we hypothesize that partisanship moderates the frequency and content of legislators' online engagement with the pandemic. Our contributions are threefold. First, we offer one of the only analyses of state legislators' online communications—covering what we believe to be every U.S. state legislator on Twitter. Second, we contribute to our understanding of how partisanship shapes legislative rhetoric at the state level. Third, we contribute a large-scale analysis of the factors that drive individual state legislators to engage publicly on issues related to the COVID-19 pandemic.

Data Collection

In order to investigate state legislators' attention to the pandemic and their responses, we (1) hand-collected relevant Twitter accounts, (2) identified tweets about the pandemic, (3) gathered data on pandemic indicators as well as state legislators, and (4) gathered data on COVID-19 related policies in the states.

State Legislators' Twitter Accounts

To identify the Twitter accounts belonging to state legislators, we relied on existing data (Cook, 2017), searches on Google, Twitter, and Wikipedia, state legislators' official legislative and campaign websites, and Ballotpedia. Out of the population of 7,383 state legislators in the U.S., there are 5,376 for which we identified at least one account. This amounts to 72.8% of the population of state legislators, an increase from 65.1% recorded in September 2015 (Cook, 2017). For the analysis in the subsequent sections, we focus on 4,092 accounts that posted at least one tweet during the period from Mar 30 and Oct 25 2020. We have two reasons for limiting our focus to this timeline. First, the week of March

30 (March 30–April 5) is approximately when the pandemic started to spread nationwide in that both the number of states without new cases and the number of states without new deaths converged to zero (see Figure S7 in the Supplementary Information (SI)). Second, we chose to end the timeline we analyze right before the 2020 U.S. Election because state legislators' use of Twitter substantially destabilizes in the period following the election. Compared to the population of U.S. state legislators, the sample of 4,092 accounts slightly over-represent women and Democrats (for detailed information, see the SI). Since the population of legislators with active Twitter accounts differs slightly from the overall population of state legislators, we note that our findings can only be generalized to state legislators on Twitter.

Tweets about the Pandemic

To gather tweets about the pandemic, we first retrieved all the tweets published on the timeline of each of the identified accounts (as of Oct 25, 2020, the number of retrieved tweets was over six million). A total of 1,326,220 tweets was posted between Mar 30 and Oct 25, 2020. We took a machine learning approach to identifying tweets that are relevant to the COVID-19 pandemic. For detailed information about our coding and machine learning classification, see the SI. We found a total of 270,103 tweets about the pandemic, which is 20.4% of all tweets posted during the period of study.

Public Policy Data for the Pandemic

We captured state public policy activity with daily counts of policy actions drawn from the COVID-19 US State Policy Database (CUSP) compiled by researchers at Boston University (Raifman et al., 2020). CUSP tracks orders, mandates, and official governor press releases, including only policies that apply to the whole state. We included all policy entries from CUSP that had action dates within our study period. This produced a list of 79 distinct policies with 1,894 state actions during the study period.

Partisan Differences in COVID-19 Pandemic Attention

Our core theoretical question regards how state legislators' communications about the pandemic have differed based on partisanship. In our empirical analysis we consider two dimensions of legislators' pandemic-related communication—content and frequency. The analysis of content provides insight into the topics emphasized in legislators' discussion of the pandemic, and the analysis of frequency provides insight into the factors that drive the timing and overall intensity of legislators' discussion of the pandemic.

The Content of Pandemic Discussion

To analyze the partisan differences in pandemic discussion content, we focus on identifying the terms that effectively differentiate Democrats' and Republicans' pandemic-relevant tweets. In Figure 1 we use the "fightin' words" (FW) measure and visualization (Monroe, Colaresi and Quinn, 2008) to illustrate the textual features that best differentiate Democratic and Republican tweets about the pandemic. The x-axis in this plot depicts the relative frequency with which the term occurs in the respective group. The y-axis depicts the strength with which the term correlates with group membership. Terms located higher on the y-axis signal a stronger association with the tweet belonging to the respective group. Each plot includes (up to) the 100 top words that discriminate between the two groups. The FW measure produces a z-score that quantifies the significance with which the use of a term differs between the two groups of documents. We only plot terms for which the z-score exceeds 1.96 in magnitude.

We see clear differences in the ways Democratic and Republican legislators discuss the pandemic. Republicans emphasize the business and state political environments, with a focus on re-opening. Democrats emphasize the health indicators and policies aimed at slowing the spread of COVID-19. These differences in content across parties are largely in line with previous work on the differences in COVID-19 relevant tweet content between Democratic and Republican members of the U.S. Congress (Green et al., 2020). Note that in the top-left of the plot, we see that one of the 'terms' that disproportionately appears in Democrat tweets is a bullet point. This indicates that Democrats are more likely than Republicans to make lists when discussing the pandemic.

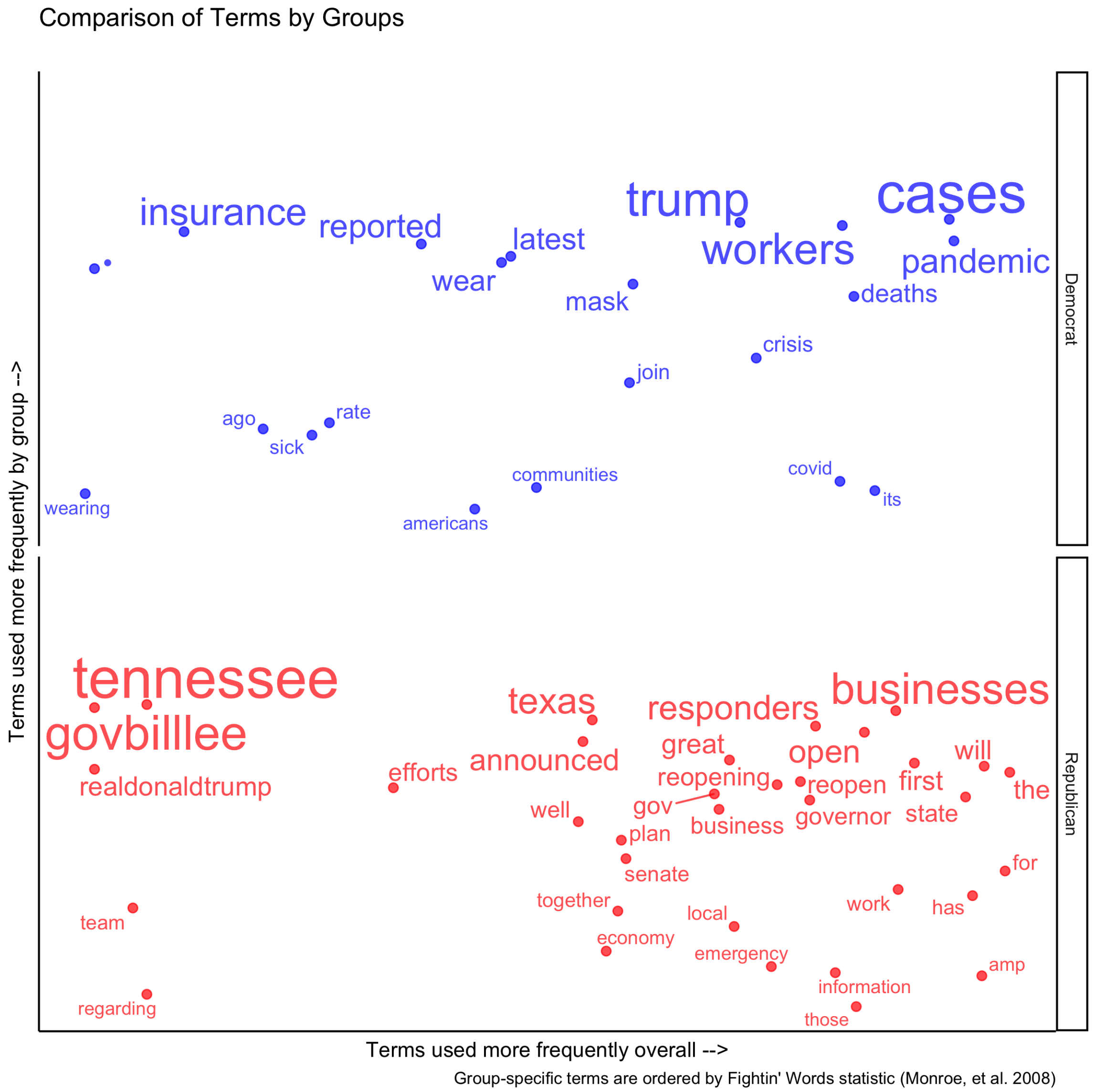

Figure 1: Words that differentiate between the content of tweets by Republican and Democrat legislators, identified using fightin' words (Monroe, Colaresi and Quinn, 2008).

The Frequency of Pandemic Attention

We now study how state legislators' attention to the pandemic on Twitter responds to public health indicators and reflects pandemic-related public policy activities. Specifically, we regressed the weekly count of legislators' pandemic-related tweets (measured on the natural log scale to limit the influence of outliers (Xiao et al., 2011)) on a number of independent variables. To study the effects of public health indicators, we included weekly state- and national-level new cases and deaths. Though we expect partisan patterns to follow the national-level party divide, it appears that the content of discussion is more state-focused. As a simple proxy, we looked at the relative prevalence of mentions of former President Trump's Twitter handle to the mention of any active state governor's Twitter handle—see the SI for details. On average, governors' handles (in 7.4% of tweets) are mentioned more than ten times as frequently as are Trump's handle (in 0.9% of tweets). COVID-19 national and state health indicators come from Johns Hopkins University (Dong, Du and Gardner, 2020).

To understand the relationship between online discourse and policymaking activity, we included the count of weekly pandemic-related public policies adopted in legislators' states from CUSP. We expect that legislators will engage more heavily with pandemic-relevant discussion on Twitter in the time leading up to and immediately following pandemic policy adoptions in their states.

We normalized all the pandemic indicator variables to indicate the count per 10,000 residents. To understand how the effects are conditioned on legislators' political parties, we interact, via multiplicative terms (Brambor, Clark and Golder, 2006), the pandemic health indicator variables and the policymaking variable with indicator variables for the party of the legislator (Republican, Democrat, and other). We excluded the observations from Nebraska because its state legislature is nonpartisan.

The data are cross-sectional time series, with legislators within states tweeting over time. We model possible dependencies via fixed effects for states, two-way random effects for legislators and weeks, and autocorrelation-robust standard errors.[1] To account for time trends in the discussion of the pandemic on Twitter (see Figure S8 in the SI), we

[1]We used the `plm` package (Croissant and Millo, 2008) in `R`. Standard errors are computed using the methods proposed by Arellano (1987).

	Coefficient (S.E.)
State New Cases (per 10k)	0.00643^{***}
	(0.00090)
State New Deaths (per 10k)	-0.00963
	(0.01854)
State COVID-19 Policies	0.01091^{***}
	(0.00168)
National New Cases (per 10k)	0.00850^{*}
	(0.00374)
National New Deaths (per 10k)	0.35427^{*}
	(0.15275)
Other	0.01137
	(0.22458)
Republican	-0.26369^{***}
	(0.02236)
Other * State New Cases (per 10k)	-0.00399
	(0.01047)
Republican * State New Cases (per 10k)	-0.00386^{***}
	(0.00102)
Other * State New Deaths (per 10k)	0.06943
	(0.29646)
Republican * State New Deaths (per 10k)	-0.00581
	(0.02742)
Other * State COVID-19 Policies	-0.02338
	(0.01529)
Republican * State COVID-19 Policies	-0.01009^{***}
	(0.00222)
Other * National New Cases (per 10k)	-0.01967
	(0.01552)
Republican * National New Cases (per 10k)	-0.00063
	(0.00149)
Other * National New Deaths (per 10k)	0.16271
	(0.53586)
Republican * National New Deaths (per 10k)	-0.31286^{***}
	(0.06427)
Week	-0.07510^{***}
	(0.01381)
Week (quadratic)	0.00316^{***}
	(0.00085)
Week (cubic)	-0.00005^{**}
	(0.00002)
(Intercept)	0.69797^{***}
	(0.09590)
S.D. (observation)	0.49177
S.D. (legislator)	0.63501
S.D. (week)	0.03821
R^2	0.01601
Adj. R^2	0.01547
Num. obs.	122760

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 1: Regression model results. Model includes state fixed effects (unreported), as well as legislator and week random effects. Regression coefficients reported, with standard errors in parentheses. Standard errors are adjusted for serial correlation in the residuals.

include a cubic polynomial of time in the regression model. The polynomial includes three variables—the week number, week number squared, and week number cubed. Plümper, Troeger and Manow (2005) note that time effects can be used to absorb the effects of unmeasured variables on the time trend in panel data. The SI includes alternative specifications of the regression model, including different functional forms of the dependent variable and additional control variables. It also reports split sample models based on (1) gubernatorial partisanship, and (2) whether legislators are of the same party as the governor. The results are robust to these alternative specifications

The complete set of regression estimates is reported in Table 1.[2] The most notable findings from our analysis are that, compared to legislators from other parties, (1) Republican legislators tweet less about the pandemic overall, and (2) Republicans' frequencies of tweeting about the pandemic are driven less by pandemic health indicators and pandemic-related policymaking. These results emerge from the negatively-signed main and interaction effects for variables involving Republican Party members.

To aid interpretation of the interaction effects Figure 2 presents visual representations of the party-conditional effects of pandemic indicators on legislators' attention to the pandemic. In each plot, the y-axis gives the expected count of pandemic-related tweets per week for a legislator with median, or modal, values of the covariates not visualized in the plots. .

Among Democrats, three of the four health indicators exhibit positive and statistically significant (at the 0.05 level, two-tailed) relationships with the number of weekly pandemic-related tweets: state cases, national cases, and national deaths. Statistical significance is not an indicator of effect strength, especially given our large sample size, but we would not want to substantively interpret effects for which we fail to reject the null hypothesis of no effect. In terms of COVID-19 related policies, we find that, among Democrats, for each additional pandemic-related policy passed in a state in a given week, the expected number of tweets that week increases by 1.1% for legislators in that state—a relationship that is statistically significant. The largest effect by magnitude for Democrats is that of the

[2] The Adjusted R^2, at 0.015, is relatively low, which could be due to the inherently "bursty" nature of social media usage. As a robustness check, in the SI we report estimates with legislator fixed effects. These estimates are based only on within-legislator variation, and the overall Adjusted R^2 is higher (0.11 for Republicans and 0.13 for Democrats). We use split samples in this robustness check because party intercepts cannot be estimated along with legislator fixed effects in a pooled sample. The results are nearly the same, except the effect of national deaths is positive and significant for each party in the within-legislator models.

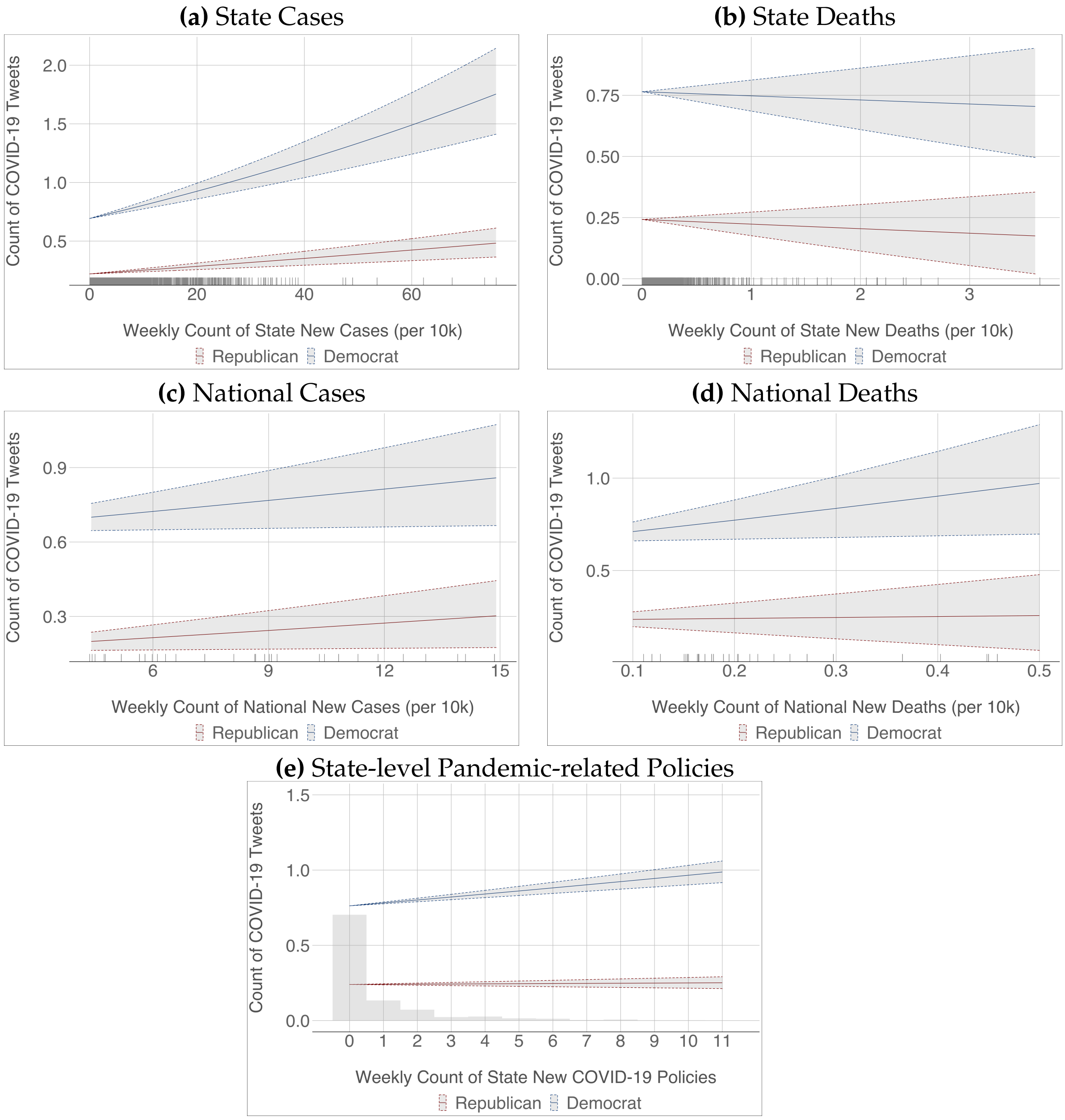

Figure 2: y-axis gives the predicted value for a legislator/week with median values of the variables not depicted in the plot. Grey bounds depict the 95% confidence intervals for the predicted value. The distribution of the respective independent variable is depicted in each plot. For the pandemic indicator variables, we use rug plots. For the number of policies passed, which takes on integer values 0–11, we use a histogram.

number of new cases. Shifting from a relatively low state case week to a relatively high state case week increases the expected number of tweets by approximately one full tweet.

The public health indicators and policy adoption counts have generally weaker effects among Republicans. While no statistically significant difference is found between Republicans and Democrats in terms of national cases, Republicans' discussion of the pandemic is statistically significantly less strongly associated with three of the other variables: state cases, national deaths, and policy adoption counts. In particular, Republicans' discussion of the pandemic on Twitter hardly correlates with national death count and pandemic-related policymaking. Among Republicans only state and national cases are associated with the weekly count of tweets. As with Democrats, state cases has the highest magnitude effect for Republicans. A shift from a relatively low state case week to a relatively high state case week increases the expected count of tweets by approximately 0.25 tweets. Given that Republicans, in their discussion of the pandemic on Twitter, focus more on keeping businesses and other institutions open than on health indicators, it is not surprising that their discussion is less reliably tied to health indicators.

Discussion

Especially early on in the pandemic, state governments were clear leaders in the majority of public policy issues that made up the response to the COVID-19 pandemic in the United States. Given the importance of elected officials' public discourse about major public policy issues, we analyzed the content and frequency of state legislators' discussion of the pandemic on Twitter. Relative to Republicans, Democratic and Independent legislators are focused heavily on the public health context of the pandemic and the intensity of their attention to the pandemic on Twitter increases when common health indicators—both at the national level, and within their states—spike. Republican legislators' attention to the pandemic, however, exhibits less systematic relationships with public health indicators, and is less frequent overall.

Our results regarding the relative lack of responsiveness of Republican state legislators' online discourse to pandemic indicators fits with the pattern of state politicians adopting partisan stances from the national political setting. From early in the pandemic, former president Donald Trump and other national Republican politicians, downplayed the health impacts of the COVID-19 pandemic (Hatcher, 2020). Our findings indicate that state legislators quickly fell into the national partisan divide among political elites.

Our results have two important implications for researchers and practitioners going forward. First, in general, state policymakers' public discourse regarding a public health crisis is responsive to the severity of that crisis. Second, there is an elite partisan divide in both the framing and frequency of public discourse related to the COVID-19 pandemic—a divide that is likely to continue to shape the management of COVID-19 in the United States. In future work, the partisan dynamics of legislators' communication on social media could be further studied by analyzing the degree to which their discussions are directed at each other, as well as other political figures. For example, do state legislators use Twitter to publicly engage with other legislators, and/or governors of the opposite party? Such relational analyses are beyond the scope of the current paper, but could advance our understanding of how partisanship shapes public officials' communications on social media.

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Supplementary Information for:
Attention to the COVID-19 pandemic on Twitter: Partisan differences among U.S. state legislators

Manual Labeling. Because the number of tweets to be labeled for COVID-19 relevance is huge (N = 1,326,220), we take a supervised learning approach where we manually label a small subset of tweets from the entire data, train a machine learning classifier, and predict the label for the rest of the data. For the training set, we randomly sampled 2,000 tweets from the entire data set. We excluded tweets published prior to March 1, 2020 because they are unlikely to be related to the COVID-19 pandemic given the timeline of the spread of the COVID-19 in the U.S. We also did not include retweets to prevent duplicated texts in our training set.

Two independent coders labeled each of the 2,000 tweets for the relevance to the COVID-19 pandemic. For retweets with a comment, the comment was treated as an independent tweet. For such tweets, the coders were presented with the text of a tweet (the comment) along with the text of quoted content (the original tweet). The meaning of the former is much clearer with the latter than without. For any external links (images, news articles, websites, and so on), we did not consider the content. Rather, we only took into account the text of the URL (e.g., "https://www.nytimes.com/interactive/2020/us/coronavirus-us-cases.html"). We labeled a tweet relevant to the pandemic only when the tweet can be read as relevant without knowing the publication date. By doing so, we were able to rule out generating false positives where authors discuss things that can be related *both* to the pandemic *and* to other events (e.g., helping local businesses by placing take-out orders).

For 300 of the 2,000 tweets, the two coders labeled the tweets together, meaning that each of the 300 tweets got a label from each coder. After the labeling of the initial 300 tweets, we updated specific labeling rules—as described in the above paragraph—and set out to label another 200 tweets, again, together. The level of inter-coder reliability achieved on the 200 tweets is 0.88 (both for Cohen's Kappa and for Krippendorff's Alpha). For the initial 300 and 200 tweets for which the coders had disagreement, they discussed about their disagreement and agreed upon a common labeling decision. Based on the coding rules, the two coders labeled the remaining 1500 tweets separately with each coder labeling 750 tweets. As a result, 24.4% (N = 488) were coded as relevant to the pandemic among the 2,000 tweets.

Classifier. To label the rest of the tweets in the entire data, we experimented with various classifiers: Random Forest, XGBoost, and BERT (Bidirectional Encoder Representations from Transformers). We relied exclusively on text-related information for features. For the feature matrix for the first two, we used count vectorization, TF-IDF vectorization, and 200-dimensional GloVe word embeddings (1). To estimate the performance of our models reliably, we conducted 5-fold cross-validation. Table S2 reports the precision, recall, and the harmonic mean of the two (i.e., F-1) of the classifiers from 5-fold cross-validation. Since the BERT-based fine-tuned model achieves the best performance, we used it to label the rest of the tweets.

In Figure S1, we illustrate the textual attributes that differentiate pandemic relevant and non-relevant tweets. Specifically, we use the "fightin' words" (FW) measure and visualization (2) to illustrate the textual features that best differentiate pandemic-related tweets and non-pandemic tweets. The x-axis in this plot depicts the relative frequency with which the term occurs in the respective group. The y-axis depicts the strength with which the term correlates with group membership. Terms located higher on the y-axis signal a stronger association with the tweet belonging to the respective group. Each plot includes (up to) the 100 top words that discriminate between the two groups. The FW measure produces a z-score that quantifies the significance with which the use of a term differs between the two groups of documents. We only plot terms for which the z-score exceeds 1.96 in magnitude.

The words that effectively identify tweets about COVID-19 are largely intuitive, with the most prominent being words that are clearly on the topic of the pandemic (e.g., coronavirus, pandemic, testing, cases). An interesting result regarding terms that best identify tweets that are not relevant to the pandemic is that they are generally positive words (e.g., happy, great, thank, love). The highly intuitive nature of the terms differentiating pandemic from non-pandemic tweets underscores why we were able to so effectively machine-classify pandemic relevance based on the text of the tweets.

Descriptive Statistics. Table S1 compares the sample used for our regression analysis (4,092 accounts) and the population of state legislators in terms of political party, gender, and chamber. Gender data for state legislators in our sample were generated mainly using `gender` R package that infers gender categories from first names. For 91 state legislators whose gender the automated approach failed to infer, we manually collected relevant information. In terms of political party, the sample slightly over-represent Democrats relative to Republicans and independents. Also, women and upper-chamber legislators are over-represented in the sample. Although the sample generally resembles the population of state legislators with respect to these key attributes, any findings based on the sample should only be generalized to state legislators on Twitter, and not to the full population of state legislators.

Table S3 reports the descriptive statistics for categorical variables: political party and majority status in the chamber. Note that non-Republican legislators involve the members of other parties and independents as well as Democrats. The majority status indicates whether the legislator belongs to the majority party in the chamber. Note that this variable is not used in the model in the main text but included in the models for robustness check.

Table S4 provides the descriptive statistics for all the other variables included in the regression analysis. The statistics are recorded at different units of analysis to summarize the distribution effectively. The data involve 4,092 state legislators, 30 weeks, and 49 states. Nebraska's non-partisan legislature is excluded. The number of COVID-19 relevant tweets are log-transformed. The pandemic indicator variables are presented both with and without standardization based on population (per 10k). The legislator ideology variable is a quantitative measure of conservatism based on legislators' roll call votes (3, 4) and, like the majority status variable in Table S3, is only included in the models for robustness check. While all the other variables have no missing values, this variable has 1,170 missing observations.

Figure S2 depicts the distributions of the number of pandemic-related tweets that of all tweets recorded at the legislator-week level (without log-transformation). Note that both of the distributions are right-skewed and so the x-scale is condensed for more effective visualization. Figure S3 illustrates the distribution of the two categorical variables (see Table S3 as well): the political party of state legislators and the majority status in the chamber. Figure S4 shows the distributions for continuous and discrete variables (see Table S4 as well). The pandemic indicators, (a)–(d), are standardized based on population (per 10k). For the plot for the legislator ideology variable, grater numbers indicate greater conservatism.

Figure S5 illustrates the timeline of new cases and deaths at the national-level. Each dot in the plots represents the relevant statistic per week. Figure S6 shows two heat maps for the number of new cases and that of new deaths, at the state level. The state in the x-scale is ordered alphabetically and the statistics are standardized based on population (per 10k). Figure S7 depicts the state-level timeline of the number of states with zero new cases (a) and with zero new deaths (b). The timelines show why we exclude the early months of the pandemic from our analysis. As seen in the two plots, it was not until the week of March 30 (March 30–April 5) when the pandemic started to spread nationwide. Figure S8 depicts the timelines for the number of pandemic-related tweets (a) and for the number of all tweets (b), with each dot indicating the tweet count per week. The states in the plots are the five most populous states. As discussed in the main text, we see the general diminishing trend in panel (a), which is consistent with the novelty fading dynamic (5, 6). In contrast, the trend in panel (b) does not exhibit a consistent trend over time.

Regression Analysis. In Tables S5–S7, we assess whether the results of our regression analysis are robust to alternative forms of the dependent variable. The first three columns in each of the tables model state legislators' attention as homogeneous across political parties, at the state-level, nation-level, and both, respectively (Models 1–3). The next four columns take partisan heterogeneity into account (Models 4–7). Model 7 incorporates two additional variables to account for the influence of state legislators' ideology and the majority status in their respective chamber. We run Model 7 to assess whether our conclusions are robust to including more variables related to individual legislators. The ideology measure is not available for legislators who started in the legislature in 2020, so the sample size is lower in Model 7. In each model we include legislator and week random effects as well as state fixed effects (unreported). Note that we cannot include legislator or time fixed effects—an alternative approach to accounting for unit and/or time heterogeneity—as partisanship varies only by legislator, and national pandemic indicators vary only with time.

In Table S5, we log-transform (natural log) the linear-scale dependent variable after adding 1 (Model 6 in Table S5 is the model reported in the main text). To assess whether our results are robust to the constant value added to the linear-scale dependent variable, we added 0.01, instead of 1, for the models in Table S6. Also, Table S7 reports models where the dependent variable is the proportion of pandemic-related tweets, out of the total number of tweets per week for the respective legislature. The results are consistent across the two transformations, in that the effects of the pandemic variables are generally positive and significant for Democrats, and either negative and significant, or not statistically significant, for Republicans. We also note that one additional form of regression model that we considered was a hierarchical count model (e.g., (7)). However, we had convergence problems with several alternative implementations of hierarchical count models. This is likely due to the fact that approximately 10% of the legislators in our data never tweet about the pandemic—a feature of the data that poses challenges for fitting legislator heterogeneity within count model functional forms.

To evaluate the how gubernatorial partisanship might factor into our results in the main text, we fit two sets of additional models in Tables S8–S11. First, Tables S8 and S9 replicate our main analysis (Table S5) on two subsets of data based on the partisanship of governors. Table S8 is for observations with a Republican governor and Table S9 is for observations with a Democratic governor. Second, Tables S10 and S11 show models for observations that share partisanship with the governor and observations that do not share partisanship with the governor, respectively. Note that we cannot fit state fixed effect for these two sets of models because the party variable only varies across states. The results across all four of these models are highly consistent with the main results that do not account for gubernatorial partisanship (see Figures S9–12 for effect plots).

To assess whether our findings are robust to any unobserved legislator-level attributes, Tables S12-13 model Republican and Democratic legislators separately and include legislator fixed effects. This is a within-legislator model of legislator change over time, rather than a comparison across legislators or states. The findings are similar to those in the our models and the R^2 is higher by an order of magnitude. This also alleviates concerns about omitted variable bias. Note that social media usage is inherently "bursty" (i.e., heavy-tailed), which can lead to a relatively low signal-to-noise ratio and a low R^2, in general.

Drivers of Pandemic-related Discussion. Trump was a pivotal actor in the formation of the discourse about the pandemic, at least for the period under our study (Mar 2020 – Oct 2020). It is possible that state legislators' discussions reflect their responses to Trump's actions/remarks related to the pandemic. To evaluate the extent to which state legislators' discussions are driven by Trump, we use the relative frequency of the mentions of Trump's account (@realDonaldTrump) to the mentions of governors' accounts in pandemic-related tweets as a proxy. Table S14 reports a) the proportion of tweets mentioning Trump's account to all pandemic-related tweets, b) the proportion of tweets mentioning any of the governors' accounts to all pandemic tweets, c) the proportion of a) relative to b). We can see that Trump is not overly prominent in state legislators' pandemic discussion in general, with governors mentioned much more frequently than Trump. The table also reveals some partisan differences where Trump is more prominent in Republican state legislators' pandemic discussion than non-Republicans'. Also, Figure S13 depicts the timeline of the relative frequency. It shows that the relative frequency increases over time. We believe that this is likely because Trump received more attention as the election came closer (in addition to his COVID-19 infection and hospitalization in October). Note that, although the relative frequency of Trump mentions rapidly increases after August, it remains low in general due to the decline in the total number of all mentions in pandemic related tweets over time.

Figures S1 - S13

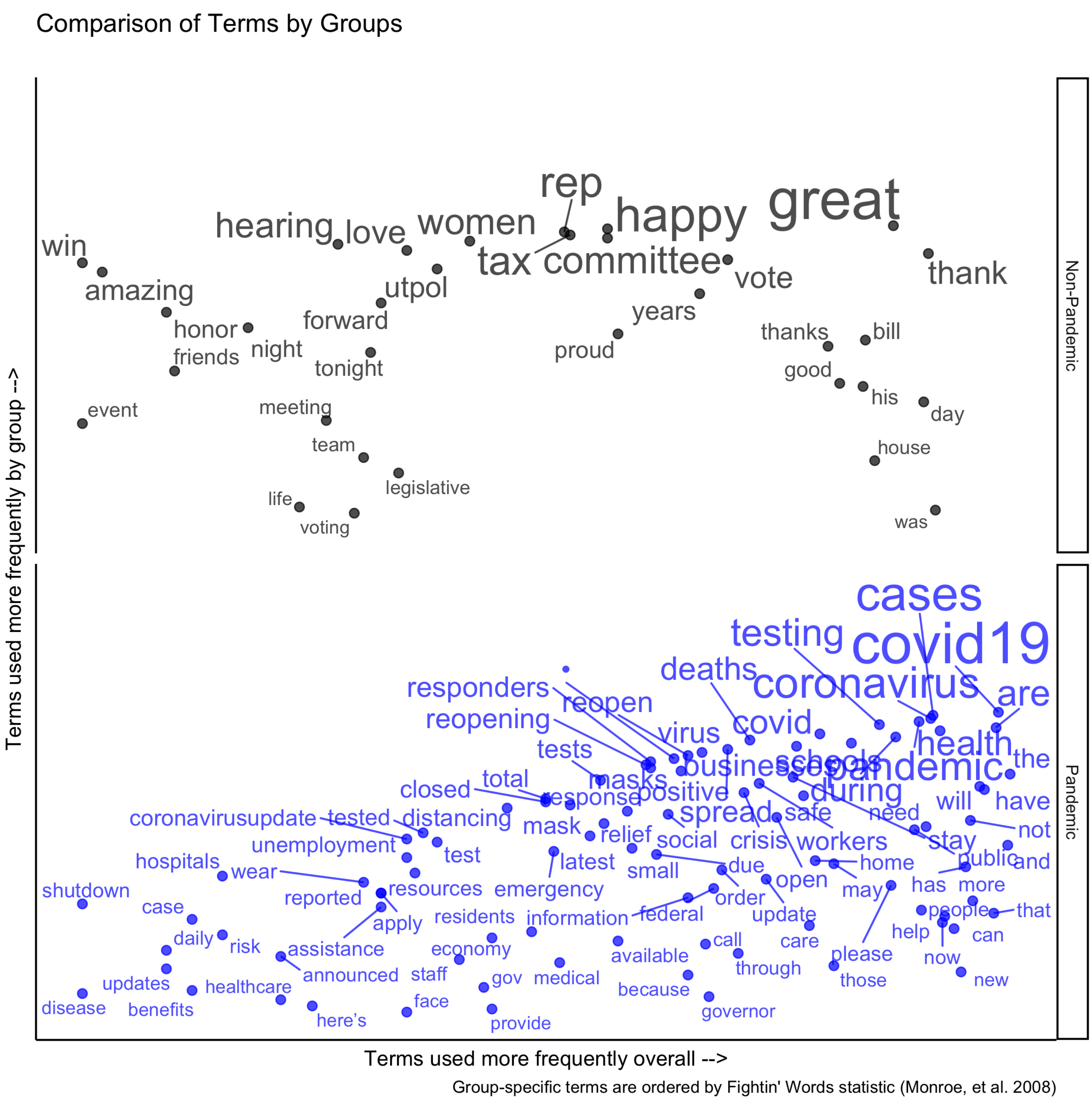
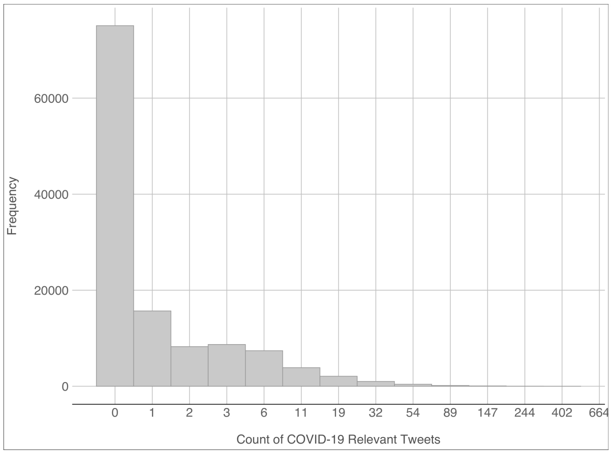
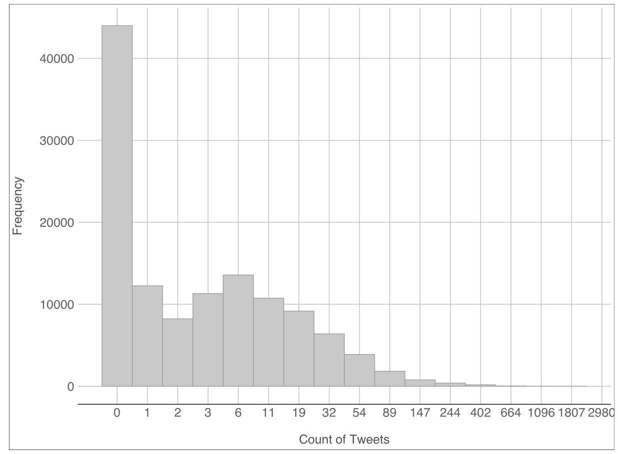


Fig. S1. Words that differentiate between the content of tweets by COVID-19 relevance, identified using fightin’ words (2).

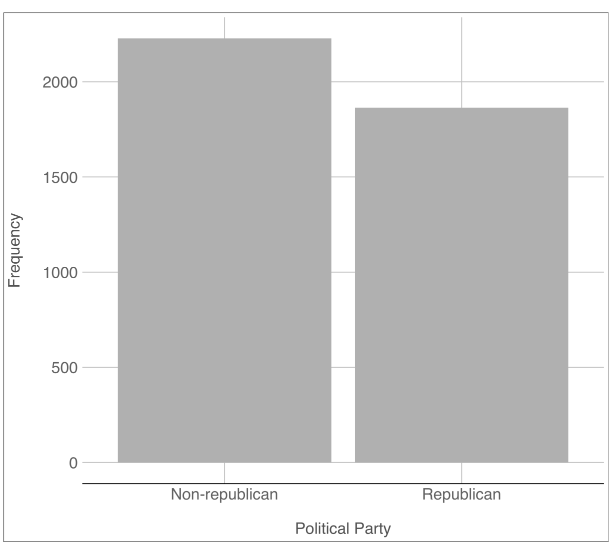


(a) Pandemic-related Tweets (per legislator-week)

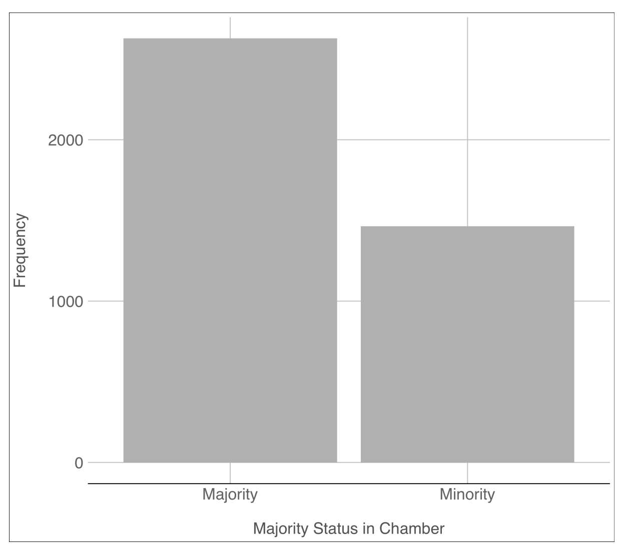


(b) All Tweets (per legislator-week)

Fig. S2. Distribution of Tweet Count Variables

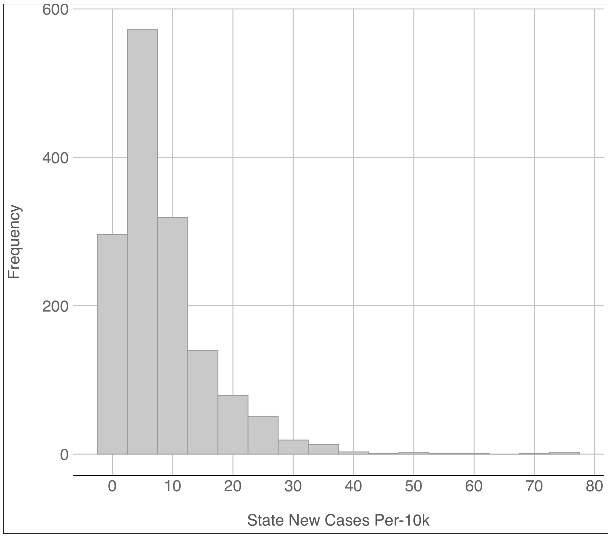


(a) Political Party

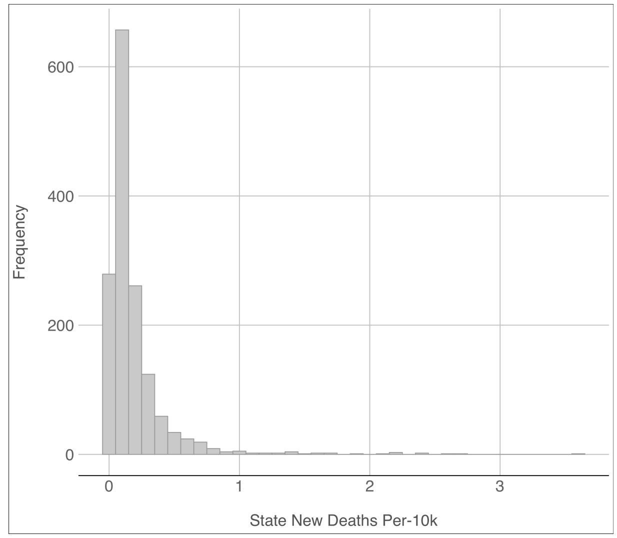


(b) Majority Status in Chamber

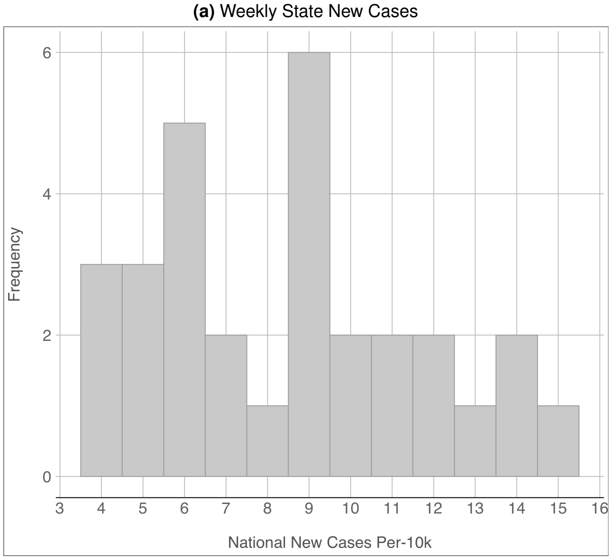
Fig. S3. Distribution of Categorical Variables



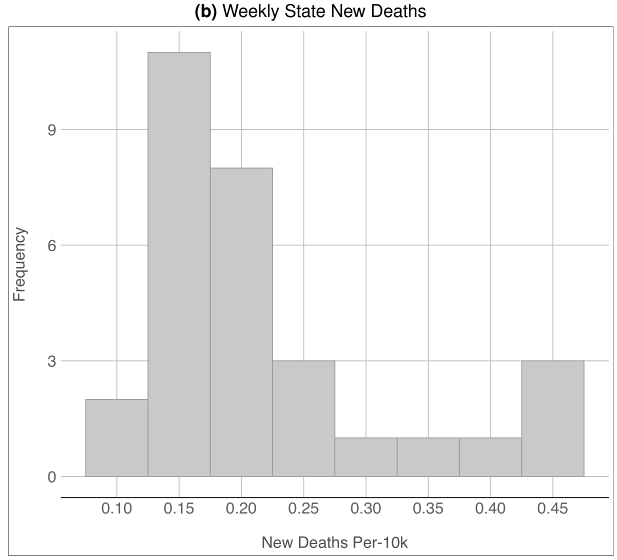
(a) Weekly State New Cases



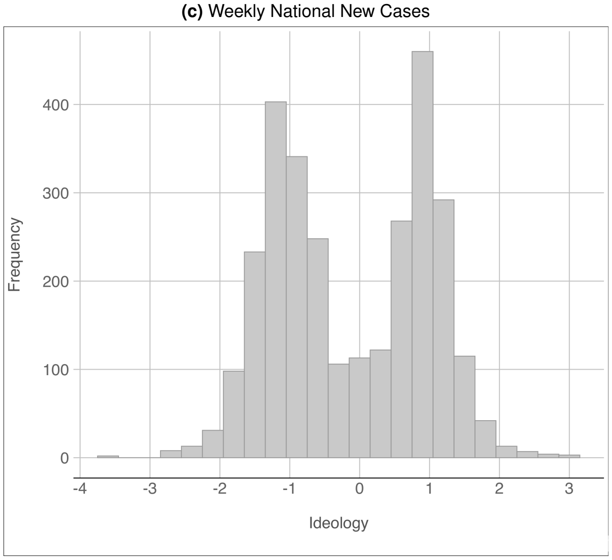
(b) Weekly State New Deaths



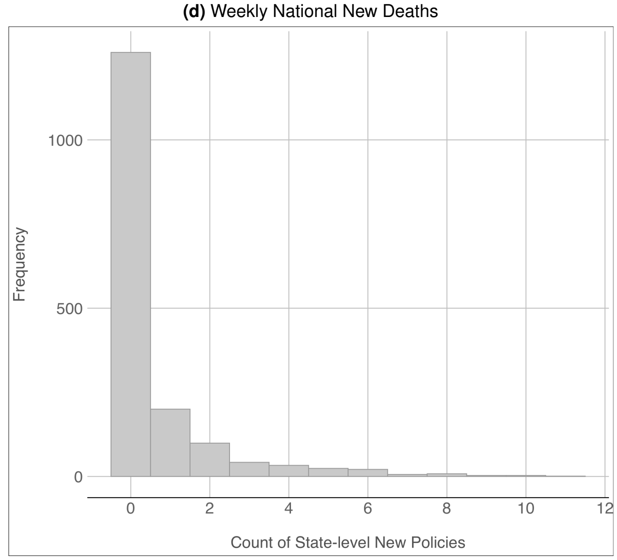
(c) Weekly National New Cases



(d) Weekly National New Deaths

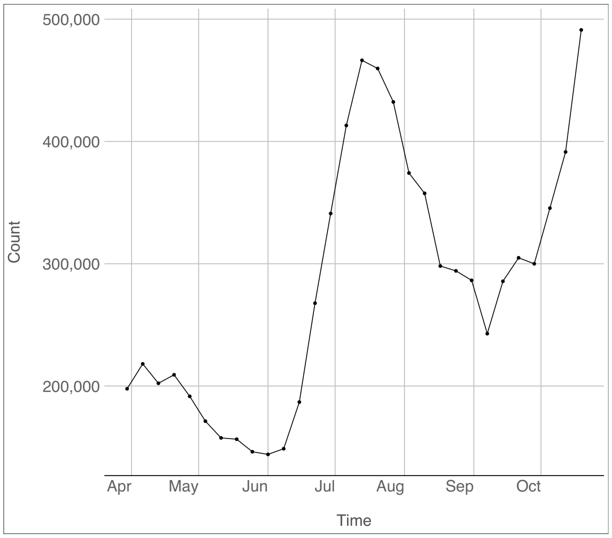


(e) Legislator Ideology

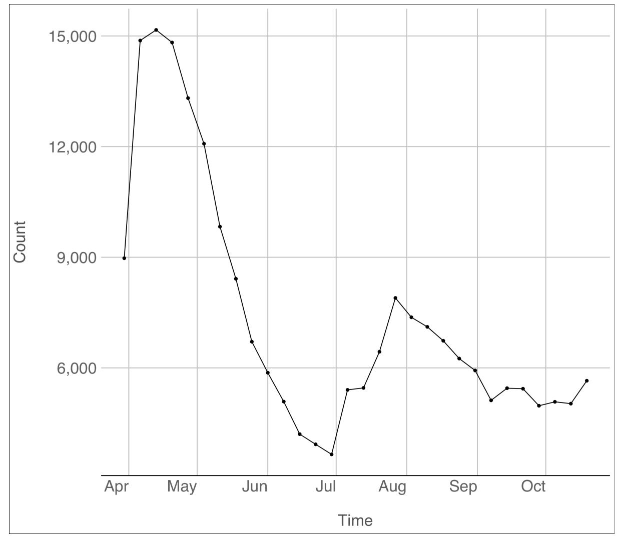


(f) Weekly State-level COVID-19 Policies

Fig. S4. Distribution of Discrete and Continuous Variables

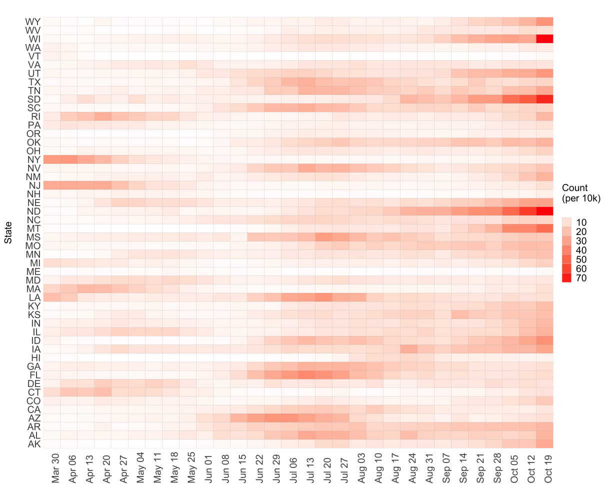


(a) National New Cases

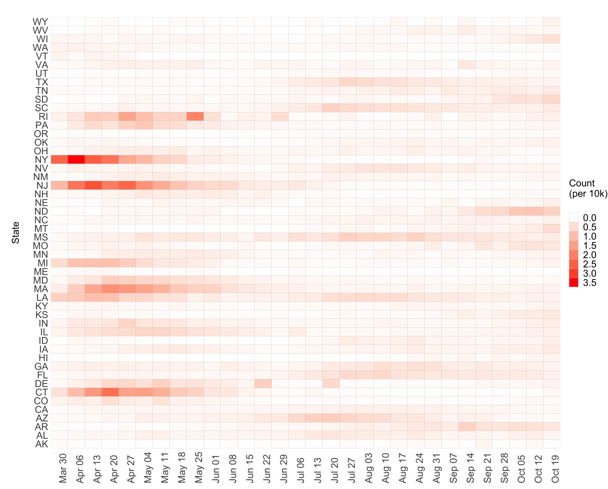


(b) National New Deaths

Fig. S5. Weekly Trend of Pandemic: National-level New Cases and Deaths

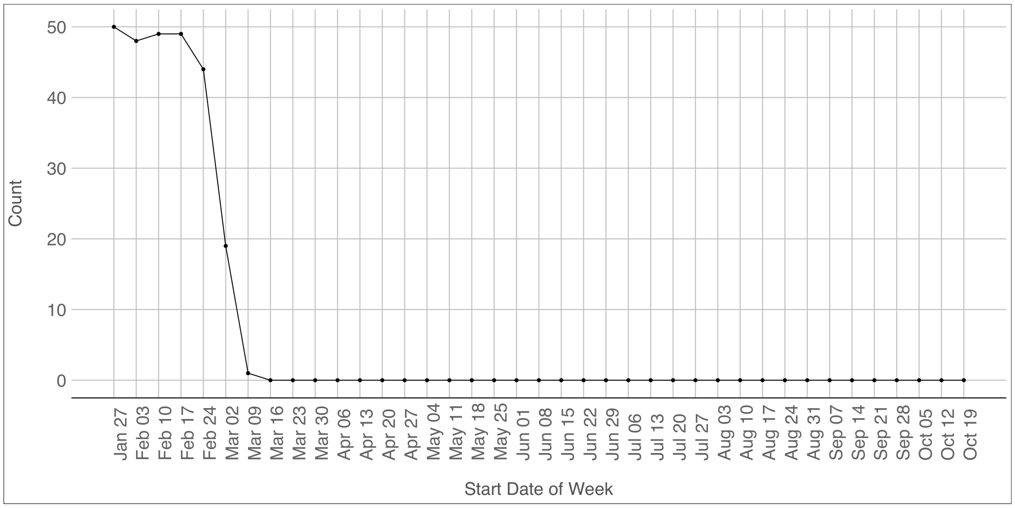


(a) State New Cases

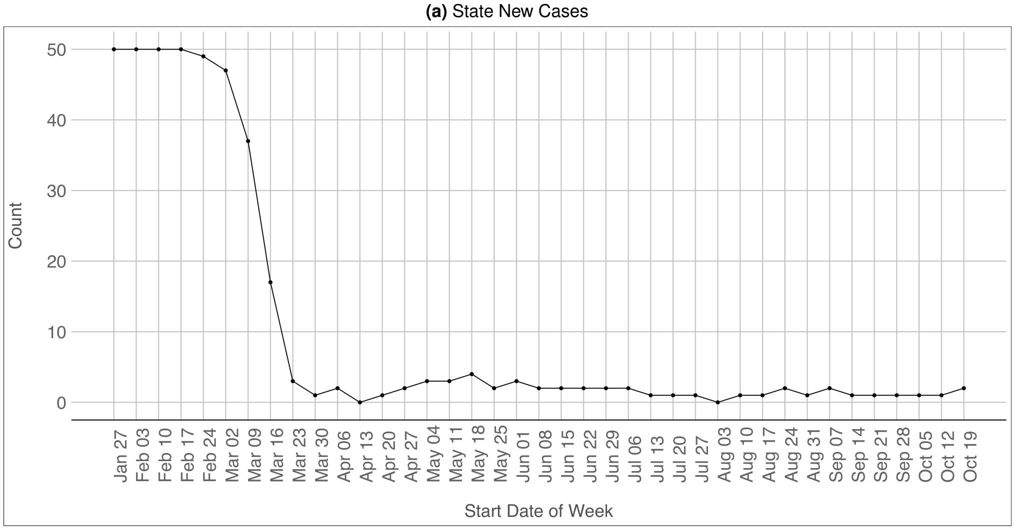


(b) State New Deaths

Fig. S6. Weekly Trend of Pandemic: State-level New Cases and Deaths

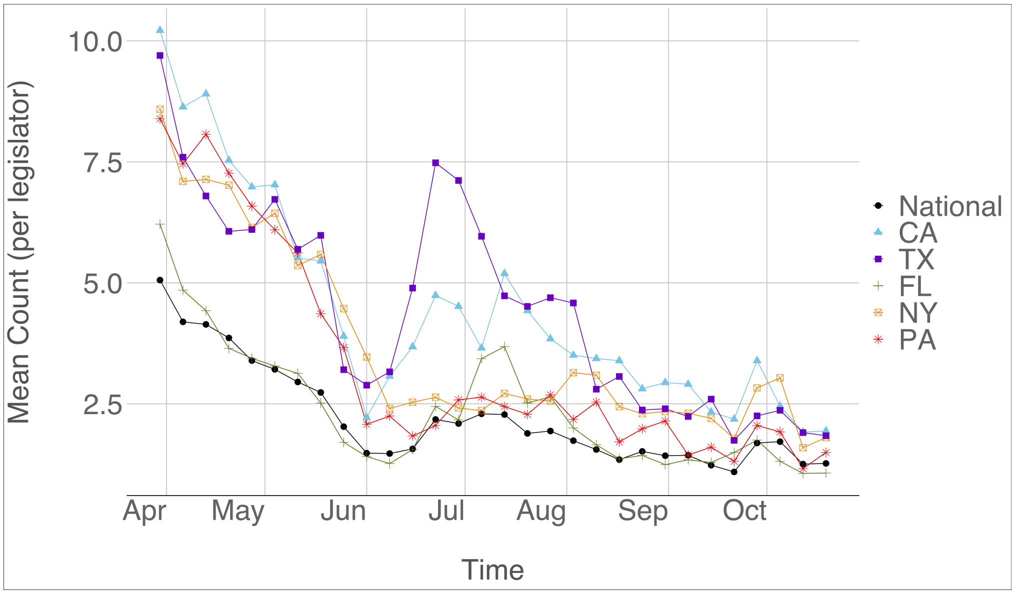


(a) State New Cases

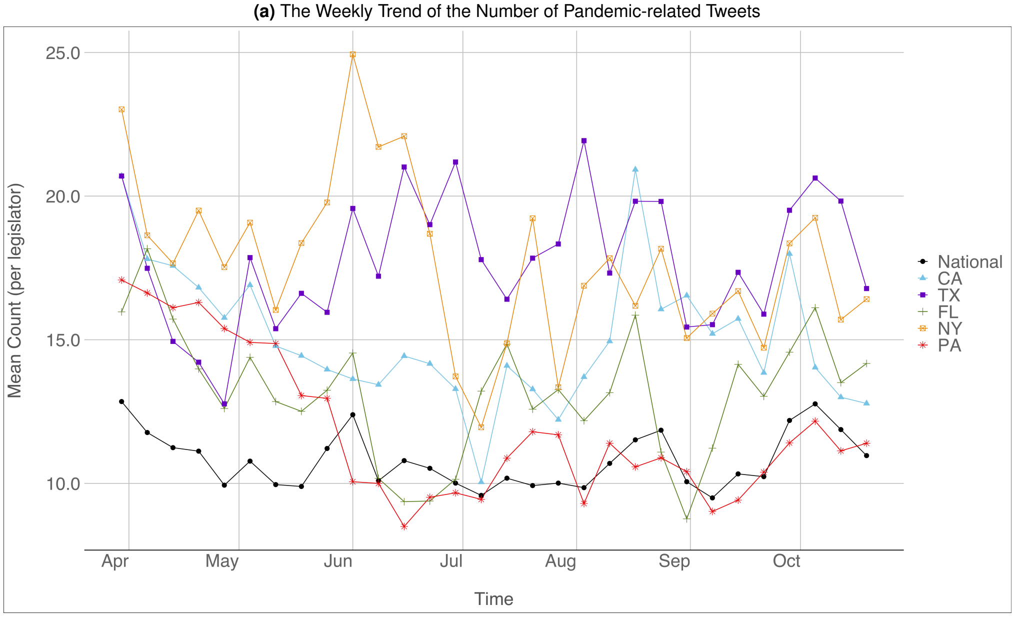


(b) State New Deaths

Fig. S7. Weekly Trend of Pandemic: Count of States with Zero New Cases and Zero New Deaths



(a) The Weekly Trend of the Number of Pandemic-related Tweets



(b) The Weekly Trend of the Number of All Tweets

Fig. S8. The Weekly Trend of the Number of Tweets

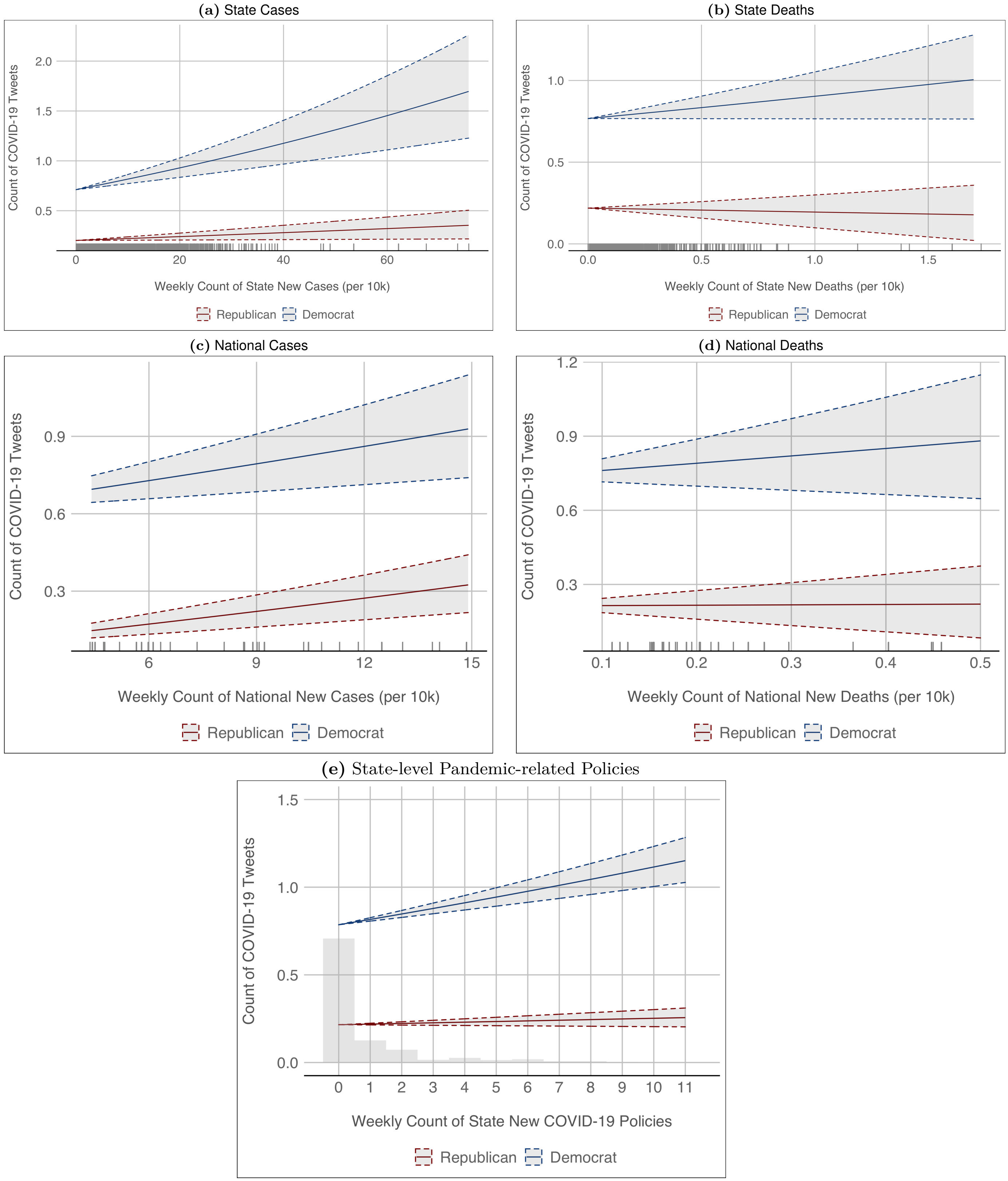


Fig. S9. Relationships estimated with regression on Rep-governor observations. y-axis gives the predicted value for a legislator/week with median values of the variables not depicted in the plot. Grey bounds depict the 95% confidence intervals for the predicted value. The effects for Democratic, Republican, and independents/other parties are estimated but only the first two groups are reported because there are so few other-party observations that the confidence intervals are too big to visualize clearly. The distribution of the respective independent variable is depicted in each plot. For the pandemic indicator variables, we use rug plots. For the number of policies passed, which takes on integer values 0–11, we use a histogram.

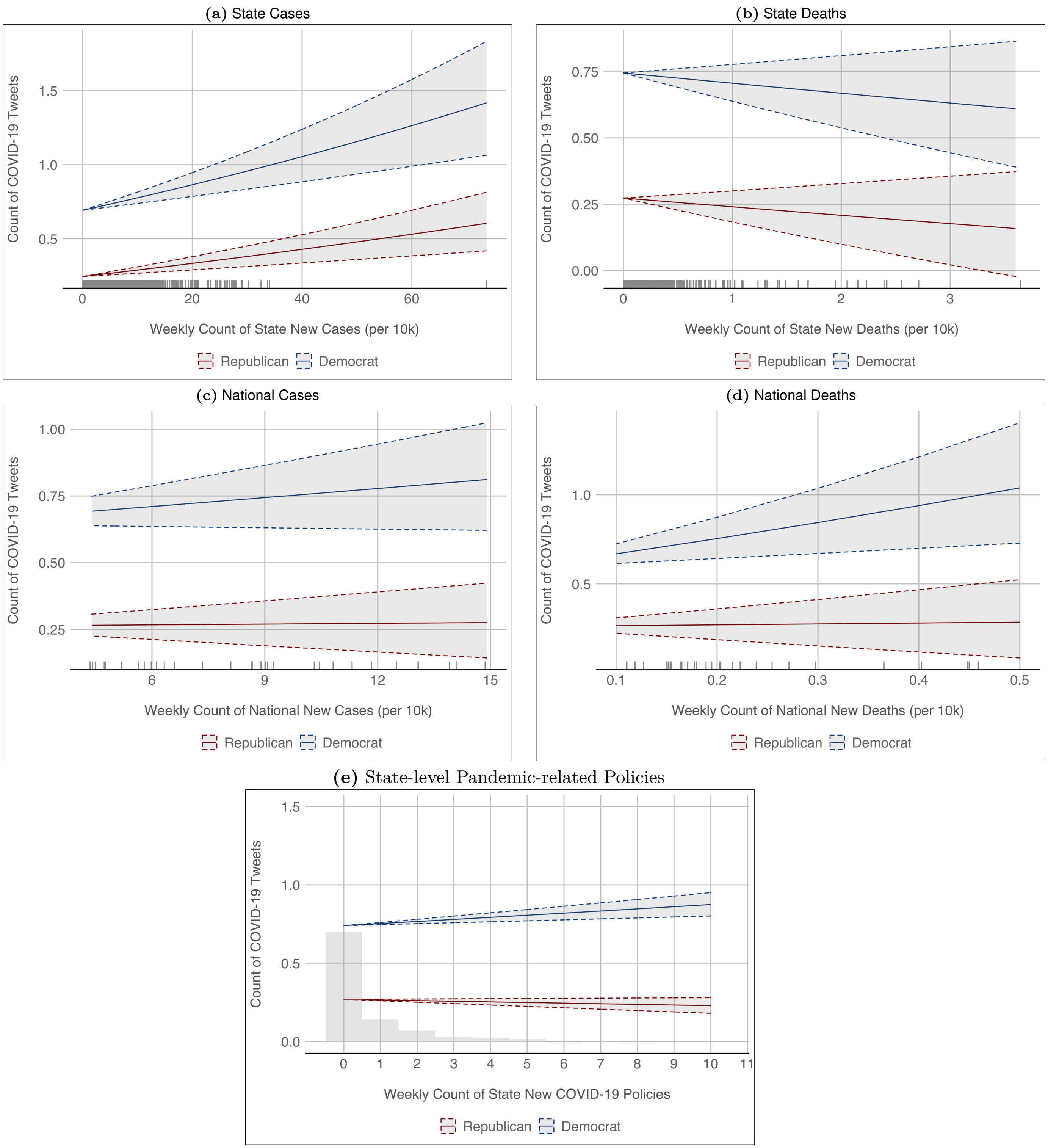


Fig. S10. Relationships estimated with regression on Dem-governor observations. y-axis gives the predicted value for a legislator/week with median values of the variables not depicted in the plot. Grey bounds depict the 95% confidence intervals for the predicted value. The effects for Democratic, Republican, and independents/other parties are estimated but only the first two groups are reported because there are so few other-party observations that the confidence intervals are too big to visualize clearly. The distribution of the respective independent variable is depicted in each plot. For the pandemic indicator variables, we use rug plots. For the number of policies passed, which takes on integer values 0–11, we use a histogram.

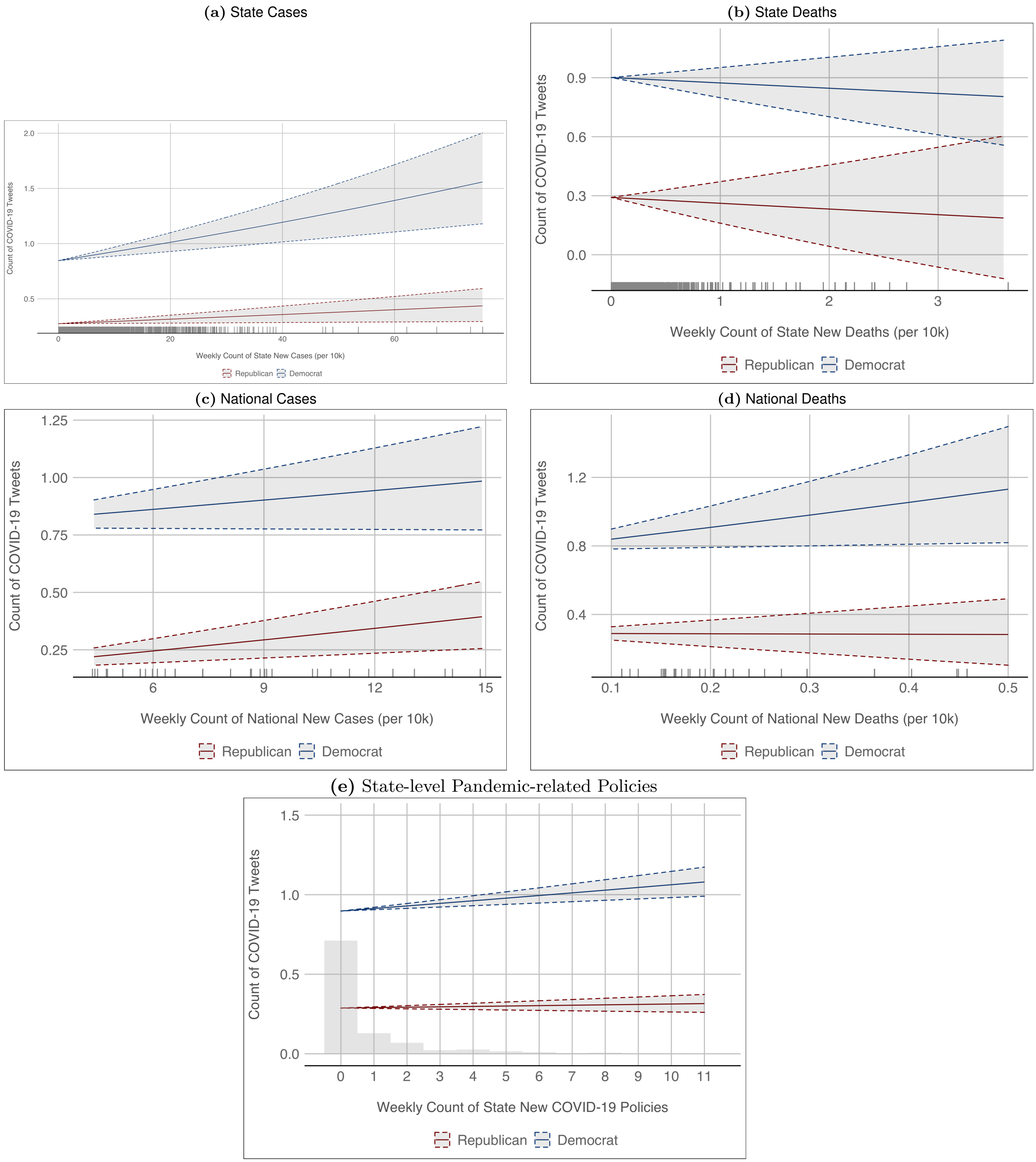


Fig. S11. Relationships estimated with regression on legislator-governor partisanship-match observations. y-axis gives the predicted value for a legislator/week with median values of the variables not depicted in the plot. Grey bounds depict the 95% confidence intervals for the predicted value. The effects for Democratic, Republican, and independents/other parties are estimated but only the first two groups are reported because there are so few other-party observations that the confidence intervals are too big to visualize clearly. The distribution of the respective independent variable is depicted in each plot. For the pandemic indicator variables, we use rug plots. For the number of policies passed, which takes on integer values 0–11, we use a histogram.

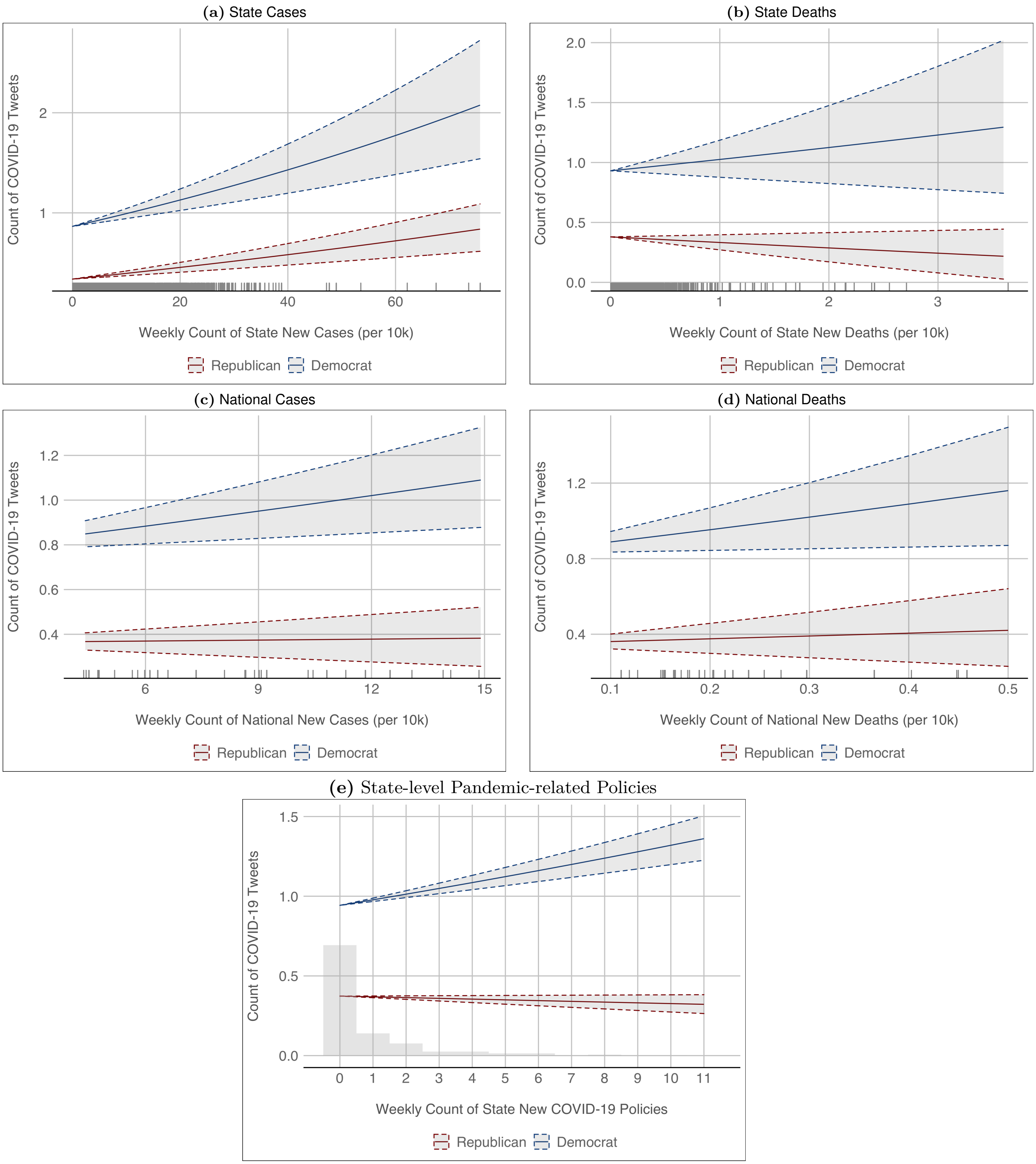


Fig. S12. Relationships estimated with regression on legislator-governor partisanship-mismatch observations. y-axis gives the predicted value for a legislator/week with median values of the variables not depicted in the plot. Grey bounds depict the 95% confidence intervals for the predicted value. The effects for Democratic, Republican, and independents/other parties are estimated but only the first two groups are reported because there are so few other-party observations that the confidence intervals are too big to visualize clearly. The distribution of the respective independent variable is depicted in each plot. For the pandemic indicator variables, we use rug plots. For the number of policies passed, which takes on integer values 0–11, we use a histogram.

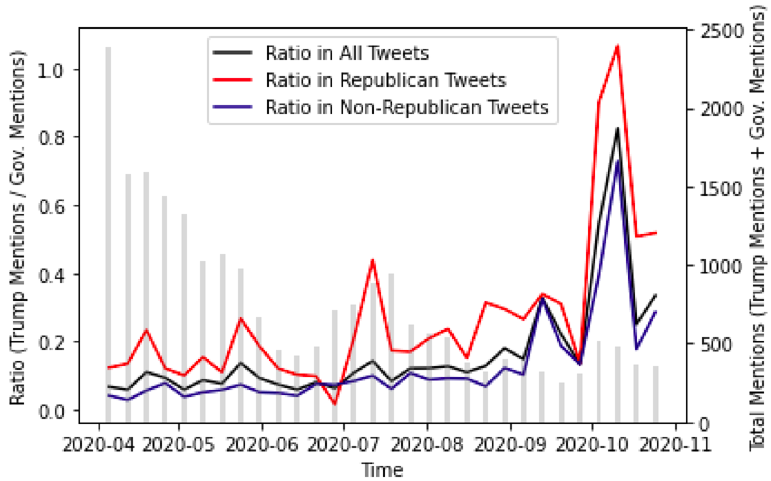


Fig. S13. Weekly Trend of the Frequency of the Mentions of Trump's Account Relative to the Mentions of Governors' Accounts

Tables S1 - S14

Variable	Category	Population Proportion	Sample Proportion
Political Party	Republican	0.520	0.455
	Democrat	0.460	0.542
	Independent/other	0.020	0.003
Gender	Men	0.710	0.654
	Women	0.290	0.346
Chamber	Lower	0.730	0.719
	Upper	0.270	0.281

Table S1. Comparison between the State Legislator Population and the Sample for Regression Analysis

* Sources for the population proportion: https://www.ncsl.org/research/about-state-legislatures/state-legislator-demographics.aspx and https://www.ncsl.org/research/about-state-legislatures/number-of-legislators-and-length-of-terms.aspx

	Precision	Recall	F-1
RF + Count	98.05 (0.02)	36.59 (0.04)	53.11 (0.05)
RF + TFIDF	97.94 (0.02)	35.84 (0.04)	52.33 (0.04)
RF + GloVe	83.07 (0.09)	24.97 (0.05)	38.30 (0.06)
XGB + Count	93.85 (0.04)	65.74 (0.02)	77.27 (0.02)
XGB + TFIDF	93.55 (0.03)	63.46 (0.03)	75.56 (0.02)
XGB + GloVe	77.13 (0.03)	47.03 (0.07)	58.22 (0.06)
BERT Fine Tuned	87.20 (0.02)	82.40 (0.04)	84.60 (0.01)

Table S2. Performance of Classifiers

	Republican	Non-Republican	Total
Party	1864	2228	4092
	Majority	Minority	Total
Majority in Chamber	2628	1464	4092

Table S3. Descriptive Statistics for Categorical Variables

	COVID tweet (log)	State Case	State Case (per 10k)	State Death	State Death (per 10k)	National Case	National Case (per 10k)	National Death	National Death (per-10k)	State COVID Policy	Legislator Ideology
Unit	legislator-week	state-week	state-week	state-week	state-week	week	week	week	week	state-week	legislator
Min.	0.0	4	0.04	0.0	0.0	144106	4.35	3655	0.11	0.0	-3.7
1st Q.	0.0	921.2	3.10	17.0	0.06	193126	5.84	5191	0.15	0.0	-1.1
Med.	0.0	2982.5	6.18	54.0	0.12	286048	8.65	6092	0.18	0.0	-0.3
Mean	0.6	5620.0	8.49	147.7	0.19	282742	8.55	7409	0.22	0.6	-0.1
3rd Q.	1.1	6208.8	11.17	139.2	0.21	354538	10.72	8287	0.25	1.0	0.9
Max.	6.0	80236.0	75.73	7114.0	3.64	491180	14.85	15164	0.46	11.0	3.0

Table S4. Descriptive Statistics for Discrete and Continuous Variables

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
State New Cases (per 10k)	0.005^{***}		0.004^{***}	0.006^{***}		0.006^{***}	0.007^{***}
	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)
State New Deaths (per 10k)	0.001		0.002	0.013		-0.010	-0.020
	(0.014)		(0.014)	(0.017)		(0.019)	(0.022)
State COVID-19 Policies	0.006^{***}	0.005^{***}	0.006^{***}	0.012^{***}	0.010^{***}	0.011^{***}	0.010^{***}
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
National New Cases (per 10k)		0.012^{**}	0.008^{*}		0.013^{***}	0.008^{*}	0.008^{*}
		(0.004)	(0.004)		(0.004)	(0.004)	(0.004)
National New Deaths (per 10k)		0.218	0.205		0.386^{*}	0.354^{*}	0.388^{**}
		(0.145)	(0.147)		(0.151)	(0.153)	(0.148)
Other	-0.147	-0.147	-0.147	-0.113	0.017	0.011	0.261
	(0.200)	(0.200)	(0.200)	(0.184)	(0.225)	(0.225)	(0.244)
Republican	-0.380^{***}	-0.380^{***}	-0.380^{***}	-0.339^{***}	-0.272^{***}	-0.264^{***}	0.122^{*}
	(0.021)	(0.021)	(0.021)	(0.022)	(0.023)	(0.022)	(0.060)
Other * State New Cases (per 10k)				-0.012		-0.004	-0.008
				(0.009)		(0.010)	(0.009)
Republican * State New Cases (per 10k)				-0.002^{*}		-0.004^{***}	-0.005^{***}
				(0.001)		(0.001)	(0.001)
Other * State New Deaths (per 10k)				0.209		0.069	0.879^{***}
				(0.309)		(0.296)	(0.234)
Republican * State New Deaths (per 10k)				-0.060^{*}		-0.006	0.012
				(0.025)		(0.027)	(0.031)
Other * State COVID-19 Policies				-0.011	-0.025	-0.023	-0.023
				(0.021)	(0.016)	(0.015)	(0.013)
Republican * State COVID-19 Policies				-0.013^{***}	-0.009^{***}	-0.010^{***}	-0.010^{***}
				(0.003)	(0.002)	(0.002)	(0.003)
Other * National New Cases (per 10k)					-0.023	-0.020	-0.021
					(0.012)	(0.016)	(0.016)
Republican * National New Cases (per 10k)					-0.002	-0.001	-0.002
					(0.001)	(0.001)	(0.002)
Other * National New Deaths (per 10k)					0.240	0.163	-0.043
					(0.553)	(0.536)	(0.494)
Republican * National New Deaths (per 10k)					-0.366^{***}	-0.313^{***}	-0.327^{***}
					(0.058)	(0.064)	(0.078)
Legislator Ideology							-0.196^{***}
							(0.030)
Chamber Majority Status							0.003
							(0.026)
Week	-0.085^{***}	-0.074^{***}	-0.075^{***}	-0.085^{***}	-0.074^{***}	-0.075^{***}	-0.073^{***}
	(0.012)	(0.014)	(0.014)	(0.012)	(0.014)	(0.014)	(0.013)
Week (quadratic)	0.004^{***}	0.003^{***}	0.003^{***}	0.004^{***}	0.003^{***}	0.003^{***}	0.003^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Week (cubic)	-0.000^{***}	-0.000^{**}	-0.000^{**}	-0.000^{***}	-0.000^{**}	-0.000^{**}	-0.000^{**}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
(Intercept)	0.903^{***}	0.750^{***}	0.758^{***}	0.884^{***}	0.699^{***}	0.698^{***}	0.466^{***}
	(0.075)	(0.095)	(0.096)	(0.073)	(0.096)	(0.096)	(0.106)
S.D. (observation)	0.492	0.493	0.492	0.492	0.493	0.492	0.490
S.D. (legislator)	0.635	0.635	0.635	0.635	0.635	0.635	0.631
S.D. (week)	0.038	0.038	0.039	0.036	0.038	0.038	0.035
R^2	0.014	0.011	0.014	0.016	0.013	0.016	0.021
Adj. R^2	0.014	0.011	0.014	0.015	0.013	0.015	0.020
Num. obs.	122760	122760	122760	122760	122760	122760	87660

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table S5. Panel Regression Model (State Fixed Effect and Legislator-week Random Effect): Population Normalized + Three-fold Party Variable + Week Polynomial + Logged DV (1 added)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
State New Cases (per 10k)	0.010^{***}		0.010^{***}	0.016^{***}		0.014^{***}	0.016^{***}
	(0.002)		(0.002)	(0.003)		(0.003)	(0.003)
State New Deaths (per 10k)	-0.042		-0.041	-0.078		-0.058	-0.062
	(0.039)		(0.039)	(0.047)		(0.050)	(0.060)
State COVID-19 Policies	0.021^{***}	0.019^{***}	0.021^{***}	0.029^{***}	0.029^{***}	0.032^{***}	0.030^{***}
	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.006)	(0.007)
National New Cases (per 10k)		0.029^{**}	0.021		0.034^{**}	0.025^{*}	0.023^{*}
		(0.011)	(0.011)		(0.011)	(0.011)	(0.011)
National New Deaths (per 10k)		0.889^{*}	0.903^{*}		0.951^{*}	0.922^{*}	1.001^{*}
		(0.412)	(0.417)		(0.421)	(0.418)	(0.410)
Other	-0.679	-0.679	-0.679	-0.568	-0.294	-0.318	0.517
	(0.557)	(0.557)	(0.557)	(0.513)	(0.633)	(0.627)	(0.696)
Republican	-1.264^{***}	-1.264^{***}	-1.264^{***}	-1.177^{***}	-1.117^{***}	-1.099^{***}	-0.003
	(0.066)	(0.066)	(0.066)	(0.069)	(0.080)	(0.079)	(0.190)
Other * State New Cases (per 10k)				-0.040		-0.018	-0.028
				(0.033)		(0.036)	(0.034)
Republican * State New Cases (per 10k)				-0.010^{***}		-0.007^{*}	-0.009^{*}
				(0.003)		(0.003)	(0.004)
Other * State New Deaths (per 10k)				0.653		0.224	2.252^{**}
				(0.876)		(0.854)	(0.847)
Republican * State New Deaths (per 10k)				0.037		-0.002	0.031
				(0.076)		(0.083)	(0.092)
Other * State COVID-19 Policies				-0.004	-0.041	-0.041	-0.037
				(0.073)	(0.055)	(0.055)	(0.057)
Republican * State COVID-19 Policies				-0.019^{*}	-0.021^{**}	-0.022^{**}	-0.021^{*}
				(0.008)	(0.008)	(0.008)	(0.009)
Other * National New Cases (per 10k)					-0.066^{*}	-0.052	-0.057
					(0.032)	(0.036)	(0.037)
Republican * National New Cases (per 10k)					-0.012^{**}	-0.009	-0.013^{*}
					(0.004)	(0.005)	(0.006)
Other * National New Deaths (per 10k)					0.946	0.787	0.325
					(1.730)	(1.731)	(1.775)
Republican * National New Deaths (per 10k)					-0.138	-0.040	-0.134
					(0.169)	(0.187)	(0.224)
Legislator Ideology							-0.534^{***}
							(0.089)
Chamber Majority Status							0.010
							(0.080)
Week	-0.233^{***}	-0.189^{***}	-0.191^{***}	-0.233^{***}	-0.190^{***}	-0.191^{***}	-0.189^{***}
	(0.033)	(0.037)	(0.037)	(0.032)	(0.037)	(0.036)	(0.035)
Week (quadratic)	0.010^{***}	0.007^{**}	0.008^{**}	0.010^{***}	0.008^{**}	0.008^{**}	0.008^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Week (cubic)	-0.000^{***}	-0.000^{*}	-0.000^{*}	-0.000^{***}	-0.000^{*}	-0.000^{*}	-0.000^{**}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
(Intercept)	-1.487^{***}	-2.061^{***}	-2.052^{***}	-1.530^{***}	-2.128^{***}	-2.132^{***}	-2.800^{***}
	(0.244)	(0.304)	(0.305)	(0.242)	(0.307)	(0.303)	(0.351)
S.D. (observation)	1.805	1.805	1.805	1.805	1.805	1.804	1.796
S.D. (legislator)	1.934	1.934	1.934	1.934	1.934	1.934	1.913
S.D. (week)	0.116	0.118	0.119	0.112	0.119	0.116	0.108
R^2	0.013	0.012	0.013	0.013	0.012	0.013	0.017
Adj. R^2	0.012	0.011	0.012	0.013	0.012	0.013	0.017
Num. obs.	122760	122760	122760	122760	122760	122760	87660

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table S6. Panel Regression Model (State Fixed Effect and Legislator-week Random Effect): Population Normalized + Three-fold Party Variable + Week Polynomial + Logged DV (0.01 added)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
State New Cases (per 10k)	0.001^{***}		0.004^{***}	0.006^{***}		0.006^{***}	0.007^{***}
	(0.000)		(0.001)	(0.001)		(0.001)	(0.001)
State New Deaths (per 10k)	-0.006		0.002	0.014		-0.010	-0.020
	(0.003)		(0.014)	(0.017)		(0.019)	(0.022)
State COVID-19 Policies	0.002^{***}	0.005^{***}	0.006^{***}	0.012^{***}	0.010^{***}	0.011^{***}	0.010^{***}
	(0.000)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
National New Cases (per 10k)		0.008	0.008^{*}		0.013^{***}	0.005	0.008^{*}
		(0.006)	(0.004)		(0.004)	(0.004)	(0.004)
National New Deaths (per 10k)		0.782^{***}	0.205		0.386^{*}	0.897^{***}	0.388^{**}
		(0.220)	(0.147)		(0.151)	(0.154)	(0.148)
Other	-0.048^{*}	-0.147	-0.147	-0.113	0.017	0.011	0.261
	(0.021)	(0.200)	(0.200)	(0.185)	(0.225)	(0.225)	(0.244)
Republican	-0.053^{***}	-0.380^{***}	-0.380^{***}	-0.339^{***}	-0.272^{***}	-0.264^{***}	0.122^{*}
	(0.003)	(0.021)	(0.021)	(0.022)	(0.023)	(0.022)	(0.060)
Other * State New Cases (per 10k)				-0.012		-0.004	-0.008
				(0.009)		(0.011)	(0.009)
Republican * State New Cases (per 10k)				-0.002^{*}		-0.004^{***}	-0.005^{***}
				(0.001)		(0.001)	(0.001)
Other * State New Deaths (per 10k)				0.209		0.070	0.879^{***}
				(0.305)		(0.293)	(0.234)
Republican * State New Deaths (per 10k)				-0.060^{*}		-0.006	0.012
				(0.025)		(0.027)	(0.031)
Other * State COVID-19 Policies				-0.011	-0.025	-0.023	-0.023
				(0.021)	(0.016)	(0.015)	(0.013)
Republican * State COVID-19 Policies				-0.013^{***}	-0.009^{***}	-0.010^{***}	-0.010^{***}
				(0.003)	(0.002)	(0.002)	(0.003)
Other * National New Cases (per 10k)					-0.023	-0.020	-0.021
					(0.012)	(0.016)	(0.016)
Republican * National New Cases (per 10k)					-0.002	-0.001	-0.002
					(0.001)	(0.001)	(0.002)
Other * National New Deaths (per 10k)					0.240	0.162	-0.043
					(0.553)	(0.536)	(0.494)
Republican * National New Deaths (per 10k)					-0.366^{***}	-0.313^{***}	-0.327^{***}
					(0.058)	(0.064)	(0.078)
Legislator Ideology							-0.196^{***}
							(0.030)
Chamber Majority Status							0.003
							(0.026)
Week	-0.022^{***}	-0.014^{***}	-0.075^{***}	-0.019^{***}	-0.074^{***}	-0.014^{***}	-0.073^{***}
	(0.004)	(0.003)	(0.014)	(0.002)	(0.014)	(0.002)	(0.013)
Week (quadratic)	0.001^{***}		0.003^{***}		0.003^{***}		0.003^{***}
	(0.000)		(0.001)		(0.001)		(0.001)
Week (cubic)	-0.000^{***}		-0.000^{**}		-0.000^{**}		-0.000^{**}
	(0.000)		(0.000)		(0.000)		(0.000)
(Intercept)	0.231^{***}	0.346^{***}	0.758^{***}	0.624^{***}	0.699^{***}	0.302^{***}	0.466^{***}
	(0.021)	(0.083)	(0.096)	(0.054)	(0.096)	(0.064)	(0.106)
S.D. (observation)	0.131	0.493	0.492	0.492	0.493	0.492	0.490
S.D. (legislator)	0.085	0.635	0.635	0.635	0.635	0.635	0.631
S.D. (week)	0.012	0.038	0.039	0.036	0.038	0.039	0.035
R^2	0.016	0.011	0.014	0.016	0.013	0.016	0.021
Adj. R^2	0.015	0.011	0.014	0.015	0.013	0.015	0.020
Num. obs.	122760	122760	122760	122760	122760	122760	87660

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table S7. Panel Regression Model (State Fixed Effect and Legislator-week Random Effect): Population Normalized + Three-fold Party Variable + Week Polynomial + Proportion DV

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
State New Cases (per 10k)	0.003^{***}		0.003^{***}	0.006^{***}		0.006^{***}	0.008^{***}
	(0.001)		(0.001)	(0.001)		(0.001)	(0.002)
State New Deaths (per 10k)	0.069^{*}		0.075^{**}	0.089^{*}		0.074	0.055
	(0.029)		(0.029)	(0.035)		(0.038)	(0.044)
State COVID-19 Policies	0.009^{***}	0.007^{***}	0.009^{***}	0.018^{***}	0.014^{***}	0.017^{***}	0.016^{***}
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
National New Cases (per 10k)		0.016^{***}	0.013^{***}		0.017^{***}	0.012^{***}	0.011^{**}
		(0.004)	(0.003)		(0.004)	(0.004)	(0.004)
National New Deaths (per 10k)		0.115	0.058		0.234	0.164	0.189
		(0.140)	(0.134)		(0.151)	(0.135)	(0.151)
Other	-0.310^{**}	-0.310^{**}	-0.310^{**}	-0.383^{***}	-0.174	-0.262^{**}	-0.078
	(0.109)	(0.109)	(0.109)	(0.093)	(0.091)	(0.097)	(0.117)
Republican	-0.417^{***}	-0.417^{***}	-0.417^{***}	-0.349^{***}	-0.345^{***}	-0.324^{***}	0.063
	(0.032)	(0.032)	(0.032)	(0.033)	(0.032)	(0.032)	(0.095)
Other * State New Cases (per 10k)				-0.002		-0.003	-0.002
				(0.005)		(0.008)	(0.008)
Republican * State New Cases (per 10k)				-0.003^{*}		-0.004^{**}	-0.007^{***}
				(0.001)		(0.001)	(0.002)
Other * State New Deaths (per 10k)				0.548^{***}		0.643^{***}	0.630^{***}
				(0.127)		(0.111)	(0.125)
Republican * State New Deaths (per 10k)				-0.132^{*}		-0.094	-0.064
				(0.052)		(0.057)	(0.066)
Other * State COVID-19 Policies				-0.027	-0.028	-0.018	-0.018
				(0.021)	(0.015)	(0.018)	(0.020)
Republican * State COVID-19 Policies				-0.017^{***}	-0.011^{***}	-0.014^{***}	-0.014^{***}
				(0.004)	(0.003)	(0.003)	(0.004)
Other * National New Cases (per 10k)					-0.011	-0.002	-0.008
					(0.010)	(0.009)	(0.010)
Republican * National New Cases (per 10k)					-0.002	0.001	0.002
					(0.002)	(0.002)	(0.003)
Other * National New Deaths (per 10k)					-0.106	-0.521	-0.356
					(0.589)	(0.510)	(0.587)
Republican * National New Deaths (per 10k)					-0.219^{**}	-0.152	-0.171
					(0.082)	(0.090)	(0.112)
Legislator Ideology							-0.181^{***}
							(0.045)
Chamber Majority Status							-0.039
							(0.050)
Week	-0.085^{***}	-0.078^{***}	-0.082^{***}	-0.086^{***}	-0.078^{***}	-0.082^{***}	-0.079^{***}
	(0.012)	(0.014)	(0.013)	(0.010)	(0.013)	(0.011)	(0.013)
Week (quadratic)	0.004^{***}	0.003^{***}	0.004^{***}	0.004^{***}	0.003^{***}	0.004^{***}	0.003^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Week (cubic)	-0.000^{***}	-0.000^{**}	-0.000^{***}	-0.000^{***}	-0.000^{**}	-0.000^{***}	-0.000^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
(Intercept)	0.913^{***}	0.772^{***}	0.815^{***}	0.876^{***}	0.732^{***}	0.751^{***}	0.538^{***}
	(0.074)	(0.094)	(0.090)	(0.065)	(0.095)	(0.084)	(0.110)
S.D. (observation)	0.490	0.491	0.490	0.489	0.491	0.489	0.484
S.D. (legislator)	0.641	0.641	0.641	0.641	0.641	0.641	0.635
S.D. (week)	0.035	0.036	0.034	0.028	0.036	0.030	0.031
R^2	0.020	0.016	0.021	0.027	0.017	0.026	0.031
Adj. R^2	0.019	0.016	0.020	0.026	0.017	0.025	0.030
Num. obs.	62670	62670	62670	62670	62670	62670	43380

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table S8. Panel Regression Model (State Fixed Effect and Legislator-week Random Effect): Rep-governor Observations, Population Normalized + Three-fold Party Variable + Week Polynomial + Logged DV (1 added)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
State New Cases (per 10k)	0.004^{***}		0.004^{***}	0.005^{***}		0.005^{***}	0.005^{***}
	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)
State New Deaths (per 10k)	-0.021		-0.022	-0.005		-0.022	-0.027
	(0.016)		(0.016)	(0.020)		(0.021)	(0.025)
State COVID-19 Policies	0.003^{*}	0.003^{*}	0.003^{*}	0.007^{***}	0.008^{***}	0.007^{***}	0.007^{**}
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
National New Cases (per 10k)		0.007	0.004		0.009^{*}	0.006	0.007
		(0.004)	(0.004)		(0.004)	(0.004)	(0.004)
National New Deaths (per 10k)		0.332	0.327		0.520^{**}	0.501^{**}	0.531^{**}
		(0.171)	(0.178)		(0.167)	(0.168)	(0.162)
Other	0.157	0.157	0.157	0.332	0.326	0.266	0.987
	(0.516)	(0.516)	(0.516)	(0.484)	(0.579)	(0.645)	(0.535)
Republican	-0.343^{***}	-0.343^{***}	-0.343^{***}	-0.318^{***}	-0.174^{***}	-0.172^{***}	0.222^{**}
	(0.029)	(0.029)	(0.029)	(0.029)	(0.032)	(0.032)	(0.081)
Other * State New Cases (per 10k)				-0.034^{***}		-0.002	0.004
				(0.006)		(0.009)	(0.009)
Republican * State New Cases (per 10k)				-0.001		-0.001	-0.001
				(0.001)		(0.001)	(0.002)
Other * State New Deaths (per 10k)				0.248		-0.404^{***}	0.648^{***}
				(0.203)		(0.114)	(0.184)
Republican * State New Deaths (per 10k)				-0.060^{*}		-0.004	-0.010
				(0.029)		(0.032)	(0.035)
Other * State COVID-19 Policies				0.034	0.014	0.007	0.008
				(0.018)	(0.012)	(0.010)	(0.017)
Republican * State COVID-19 Policies				-0.010^{**}	-0.011^{***}	-0.011^{***}	-0.010^{**}
				(0.003)	(0.003)	(0.003)	(0.003)
Other * National New Cases (per 10k)					-0.049^{*}	-0.054	-0.076^{***}
					(0.024)	(0.030)	(0.021)
Republican * National New Cases (per 10k)					-0.006^{**}	-0.006^{**}	-0.008^{**}
					(0.002)	(0.002)	(0.002)
Other * National New Deaths (per 10k)					1.091	2.211^{*}	1.246
					(0.973)	(0.952)	(0.686)
Republican * National New Deaths (per 10k)					-0.500^{***}	-0.462^{***}	-0.436^{***}
					(0.084)	(0.095)	(0.114)
Legislator Ideology							-0.202^{***}
							(0.041)
Chamber Majority Status							0.048
							(0.035)
Week	-0.084^{***}	-0.069^{***}	-0.069^{***}	-0.084^{***}	-0.069^{***}	-0.069^{***}	-0.068^{***}
	(0.015)	(0.016)	(0.016)	(0.014)	(0.015)	(0.015)	(0.013)
Week (quadratic)	0.004^{***}	0.003^{**}	0.003^{**}	0.004^{***}	0.003^{**}	0.003^{**}	0.003^{**}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Week (cubic)	-0.000^{**}	-0.000^{*}	-0.000^{*}	-0.000^{**}	-0.000^{*}	-0.000^{*}	-0.000^{*}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
(Intercept)	1.690^{***}	1.514^{***}	1.505^{***}	1.682^{***}	1.449^{***}	1.439^{***}	1.111^{***}
	(0.106)	(0.123)	(0.125)	(0.102)	(0.119)	(0.119)	(0.129)
S.D. (observation)	0.494	0.494	0.494	0.494	0.494	0.493	0.495
S.D. (legislator)	0.628	0.628	0.628	0.627	0.628	0.627	0.626
S.D. (week)	0.044	0.044	0.046	0.040	0.041	0.041	0.036
R^2	0.016	0.014	0.015	0.018	0.018	0.020	0.028
Adj. R^2	0.015	0.014	0.015	0.018	0.018	0.019	0.027
Num. obs.	60090	60090	60090	60090	60090	60090	44280

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table S9. Panel Regression Model (State Fixed Effect and Legislator-week Random Effect): Dem-governor Observations, Population Normalized + Three-fold Party Variable + Week Polynomial + Logged DV (1 added)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
State New Cases (per 10k)	0.003^{***}		0.003^{***}	0.003^{**}		0.004^{***}	0.004^{**}
	(0.001)		(0.001)	(0.001)		(0.001)	(0.001)
State New Deaths (per 10k)	0.016		0.017	0.026		−0.014	−0.019
	(0.018)		(0.018)	(0.020)		(0.021)	(0.025)
State COVID-19 Policies	0.004^{*}	0.003	0.004^{**}	0.010^{***}	0.008^{***}	0.008^{***}	0.008^{***}
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
National New Cases (per 10k)		0.012^{**}	0.009^{*}		0.010^{*}	0.007	0.007
		(0.004)	(0.004)		(0.004)	(0.004)	(0.004)
National New Deaths (per 10k)		0.185	0.163		0.392^{*}	0.368^{*}	0.404^{*}
		(0.143)	(0.149)		(0.153)	(0.162)	(0.174)
Republican	-0.415^{***}	-0.405^{***}	-0.414^{***}	-0.394^{***}	-0.346^{***}	-0.347^{***}	0.027
	(0.026)	(0.026)	(0.026)	(0.028)	(0.027)	(0.027)	(0.087)
Republican * State New Cases (per 10k)				0.001		-0.003^{*}	-0.003^{*}
				(0.001)		(0.001)	(0.002)
Republican * State New Deaths (per 10k)				-0.104^{*}		−0.009	0.016
				(0.045)		(0.048)	(0.057)
Republican * State COVID-19 Policies				-0.013^{***}	-0.007^{*}	-0.006^{*}	-0.007^{*}
				(0.003)	(0.003)	(0.003)	(0.003)
Republican * National New Cases (per 10k)					0.005^{**}	0.006^{**}	0.005^{*}
					(0.002)	(0.002)	(0.002)
Republican * National New Deaths (per 10k)					-0.431^{***}	-0.379^{***}	-0.454^{***}
					(0.076)	(0.084)	(0.101)
Legislator Ideology							-0.169^{***}
							(0.039)
Chamber Majority Status							−0.003
							(0.045)
(Intercept)	1.307^{***}	1.175^{***}	1.178^{***}	1.310^{***}	1.144^{***}	1.140^{***}	0.952^{***}
	(0.073)	(0.090)	(0.093)	(0.073)	(0.091)	(0.095)	(0.112)
Week	-0.097^{***}	-0.088^{***}	-0.089^{***}	-0.099^{***}	-0.089^{***}	-0.089^{***}	-0.088^{***}
	(0.013)	(0.014)	(0.015)	(0.013)	(0.014)	(0.015)	(0.015)
Week (quadratic)	0.005^{***}	0.004^{***}	0.004^{***}	0.005^{***}	0.004^{***}	0.004^{***}	0.004^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Week (cubic)	-0.000^{***}	-0.000^{***}	-0.000^{***}	-0.000^{***}	-0.000^{***}	-0.000^{***}	-0.000^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
S.D. (observation)	0.482	0.483	0.482	0.482	0.482	0.481	0.483
S.D. (legislator)	0.631	0.632	0.631	0.627	0.628	0.627	0.633
S.D. (week)	0.038	0.038	0.039	0.037	0.038	0.040	0.040
R^2	0.015	0.013	0.014	0.016	0.016	0.016	0.020
Adj. R^2	0.015	0.013	0.014	0.015	0.016	0.016	0.019
Num. obs.	70110	70110	70110	70110	70110	70110	50070

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table S10. Panel Regression Model (Legislator-week Random Effect): Legislator-governor Partisanship Match, Population Normalized + Three-fold Party Variable + Week Polynomial + Logged DV (1 added)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
State New Cases (per 10k)	0.006^{***}		0.006^{***}	0.008^{***}		0.007^{***}	0.009^{***}
	(0.001)		(0.001)	(0.001)		(0.001)	(0.002)
State New Deaths (per 10k)	-0.022		-0.022	0.036		0.048	0.025
	(0.021)		(0.021)	(0.036)		(0.039)	(0.044)
State COVID-19 Policies	0.008^{***}	0.007^{***}	0.008^{***}	0.017^{***}	0.015^{***}	0.018^{***}	0.017^{***}
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
National New Cases (per 10k)		0.011^{**}	0.007		0.017^{***}	0.012^{**}	0.010^{**}
		(0.004)	(0.004)		(0.004)	(0.004)	(0.004)
National New Deaths (per 10k)		0.263	0.264		0.387^{*}	0.336^{*}	0.364^{*}
		(0.156)	(0.152)		(0.155)	(0.147)	(0.154)
Other	-0.254	-0.267	-0.255	-0.201	-0.094	-0.080	0.133
	(0.228)	(0.228)	(0.228)	(0.219)	(0.262)	(0.266)	(0.319)
Republican	-0.382^{***}	-0.386^{***}	-0.382^{***}	-0.319^{***}	-0.200^{***}	-0.187^{***}	0.265^{**}
	(0.032)	(0.032)	(0.032)	(0.032)	(0.034)	(0.034)	(0.084)
Other * State New Cases (per 10k)				-0.013		-0.004	-0.008
				(0.009)		(0.011)	(0.010)
Republican * State New Cases (per 10k)				-0.004^{**}		-0.002	-0.004^{*}
				(0.001)		(0.001)	(0.002)
Other * State New Deaths (per 10k)				0.191		0.013	0.823^{***}
				(0.308)		(0.294)	(0.245)
Republican * State New Deaths (per 10k)				-0.068		-0.083	-0.069
				(0.041)		(0.046)	(0.050)
Other * State COVID-19 Policies				-0.015	-0.029	-0.030	-0.029^{*}
				(0.021)	(0.015)	(0.015)	(0.013)
Republican * State COVID-19 Policies				-0.019^{***}	-0.018^{***}	-0.021^{***}	-0.020^{***}
				(0.004)	(0.003)	(0.003)	(0.004)
Other * National New Cases (per 10k)					-0.027^{*}	-0.023	-0.024
					(0.013)	(0.016)	(0.016)
Republican * National New Cases (per 10k)					-0.013^{***}	-0.011^{***}	-0.012^{***}
					(0.002)	(0.002)	(0.003)
Other * National New Deaths (per 10k)					0.369	0.284	0.116
					(0.556)	(0.538)	(0.502)
Republican * National New Deaths (per 10k)					-0.279^{**}	-0.229^{*}	-0.156
					(0.090)	(0.101)	(0.123)
Legislator Ideology							-0.244^{***}
							(0.044)
Chamber Majority Status							-0.033
							(0.038)
(Intercept)	1.205^{***}	1.042^{***}	1.037^{***}	1.169^{***}	0.952^{***}	0.953^{***}	0.687^{***}
	(0.070)	(0.092)	(0.089)	(0.064)	(0.088)	(0.081)	(0.092)
Week	-0.069^{***}	-0.056^{***}	-0.057^{***}	-0.068^{***}	-0.054^{***}	-0.057^{***}	-0.053^{***}
	(0.012)	(0.014)	(0.013)	(0.011)	(0.013)	(0.012)	(0.012)
Week (quadratic)	0.003^{***}	0.002^{*}	0.002^{*}	0.003^{***}	0.002^{*}	0.002^{**}	0.002^{*}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Week (cubic)	-0.000^{**}	-0.000	-0.000	-0.000^{**}	-0.000	-0.000^{*}	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
S.D. (observation)	0.505	0.506	0.505	0.504	0.506	0.504	0.497
S.D. (legislator)	0.694	0.696	0.694	0.692	0.696	0.692	0.682
S.D. (week)	0.037	0.039	0.038	0.033	0.037	0.033	0.032
R^2	0.018	0.013	0.018	0.023	0.016	0.024	0.033
Adj. R^2	0.018	0.013	0.018	0.022	0.016	0.023	0.032
Num. obs.	52650	52650	52650	52650	52650	52650	37590

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table S11. Panel Regression Model (Legislator-week Random Effect): Legislator-governor Partisanship Mismatch, Population Normalized + Three-fold Party Variable + Week Polynomial + Logged DV (1 added)

	Model 1	Model 2	Model 3
State New Cases (per 10k)	0.010^{***}		0.007^{***}
	(0.001)		(0.001)
State New Deaths (per 10k)	-0.049^{**}		-0.019
	(0.017)		(0.019)
State COVID-19 Policies	0.006^{***}	0.007^{***}	0.008^{***}
	(0.002)	(0.002)	(0.002)
National New Cases (per 10k)		0.018^{***}	0.013^{***}
		(0.001)	(0.001)
National New Deaths (per 10k)		0.142^{***}	0.122^{**}
		(0.043)	(0.047)
Week	-0.088^{***}	-0.081^{***}	-0.081^{***}
	(0.004)	(0.004)	(0.004)
Week (quadratic)	0.004^{***}	0.003^{***}	0.003^{***}
	(0.000)	(0.000)	(0.000)
Week (cubic)	-0.000^{***}	-0.000^{***}	-0.000^{***}
	(0.000)	(0.000)	(0.000)
R^2	0.129	0.128	0.132
Adj. R^2	0.099	0.098	0.102
Num. obs.	66480	66480	66480

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table S12. Panel Regression Model (Legislator Fixed Effect): Democratic Legislators, Population Normalized + Three-fold Party Variable + Week Polynomial + Logged DV (1 added)

	Model 1	Model 2	Model 3
State New Cases (per 10k)	0.002^{***}		0.002^{***}
	(0.001)		(0.001)
State New Deaths (per 10k)	0.006		-0.008
	(0.019)		(0.020)
State COVID-19 Policies	0.008^{***}	0.009^{***}	0.009^{***}
	(0.001)	(0.001)	(0.001)
National New Cases (per 10k)		0.004^{***}	0.002^{*}
		(0.001)	(0.001)
National New Deaths (per 10k)		0.324^{***}	0.332^{***}
		(0.038)	(0.042)
Week	-0.081^{***}	-0.066^{***}	-0.066^{***}
	(0.004)	(0.004)	(0.004)
Week (quadratic)	0.004^{***}	0.003^{***}	0.003^{***}
	(0.000)	(0.000)	(0.000)
Week (cubic)	-0.000^{***}	-0.000^{***}	-0.000^{***}
	(0.000)	(0.000)	(0.000)
R^2	0.113	0.114	0.115
Adj. R^2	0.082	0.084	0.084
Num. obs.	55920	55920	55920

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table S13. Panel Regression Model (Legislator Fixed Effect): Republican Legislators, Population Normalized + Three-fold Party Variable + Week Polynomial + Logged DV (1 added)

	Mention Trump	Mention Governors	Mention Trump / Mention Governors
All	0.9%	7.4%	12.0%
Republican	1.8%	9.3%	19.9%
Non-Republican	0.6%	6.8%	.890%

Table S14. Percentage of Tweets Mentioning Trump's and Governors' Accounts

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