The Short-Run Consequences of January 6*

Alberto Binetti

May 2024

Last version available here

Abstract

This paper studies politicians and voters' reaction to the attack to Capitol Hill on January 6, 2021. Using data from Members of Congress tweets, I document that, relative to Democrats, Republican politicians *i)* tweet less after the event, *ii)* talk about the events more in the immediate aftermath, and *iii)* they do so using a much more positive tone, consistently with a damage-control strategy. Proxying voters' reactions with positive engagement measures on Twitter, I find that capitol-related tweets from Republicans are much less popular than their Democratic counterpart. Finally, I leverage a large-scale nationally representative survey to investigate the immediate consequences of the event for public opinion. I find a sizeable decrease in Trump's popularity among Republican voters. Moreover, this decrease is almost entirely concentrated among those believing the official election results to be correct. This suggests that beliefs about the nature of the attack, legitimate protest vs. attack to democracy, play a large role in explaining voters' reaction to it.

*Binetti: alberto.binetti@studbocconi.it. I am extremely grateful to Tommaso Nannicini for his support and guidance throughout this project. I also thank Stefanie Stantcheva and Guido Tabellini for their continuous encouragement and suggestions. I thank Nunzio Fallico, Germain Gauthier, Alessandro Izzo, Rafael Jiménez-Durán, Christoph Pfeufer, Francesco Toti, and Jim Snyder for helpful comments.

1 Introduction

Despite being relatively "rare and recent practice" in most countries in the world (Przeworski, 2015), peaceful transitions of power have been the norm in the United States since the 19^{th} century. At least, until January 6, 2021. After months of Trump refusing to concede and invoking electoral fraud, his supporters breached police perimeters and entered the Capitol building demanding justice. It's difficult to understate the salience of this event in the short-run. Figure 1 plots Google trends in the US between November 11, 2020, and January 15, 2021. On the day of the attack, "Trump" is searched more than "Covid". "Capitol", a relatively unpopular term, is almost as searched as "Covid". This event has since then become an essential part of contemporary American politics, with its consequences still lingering after 4 years as Trump's participation to the 2024 election has been in doubt for months precisely because of his involvement with January 6.

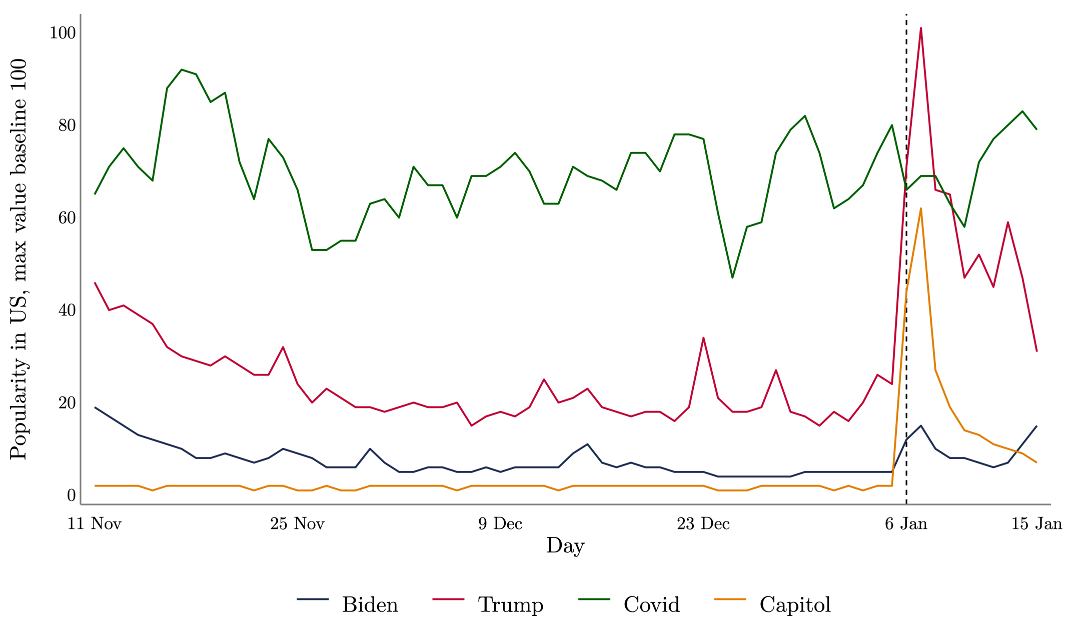


FIGURE 1: GOOGLE TRENDS IN THE US

As the "polarization of reality" increases (Alesina et al., 2020), investigating the short-run consequences of salient events and political scandals is useful to understand how this divergence of beliefs arises. At the same time, since voters do not form their beliefs in a vacuum, it's crucial to study the environment and tone set by politicians in the aftermath of such events to attempt to understand how they are related. Motivated by these questions, in this paper I study the short-run consequences of the capitol attack on politicians' communication strategies and voters attitudes.

In the first part of the paper, I use data from tweets of Members of congress from November 2020 to February 2021 to study how their communication strategy has changed in terms of activity, content, and sentiment.
I find that, compared to Democrats, Republicans start tweeting significantly less after the event, with each Republican user posting around 13 tweets less per week for almost a month. I also find that this drop is likely not related to Trump's ban from Twitter on January 8 (Müller and Schwarz, 2023), as their tweets mentioning Trump increase during the same period.
I then turn to the content of politicians' tweet and find that Republicans tweet relatively more about capitol than Democrats in the immediate aftermath, in contrast with previous findings of the literature regarding politicians' reactions to bad news such as mass shootings (Pfeufer, 2022). I then employ the semi-supervised machine learning algorithm introduced in Ash et al. (2024) to extract politicians' narratives from their tweets. I document how capitol-related narratives are the most prominent ones for both parties after January 6, but they differ greatly: Democrats say "trump incite capitol", while Republicans say "american tasked capitol". The interpretation of the event being unclear creates incentives for politicians to offer competing narratives, with Democrats doubling the blame and Republicans controlling the damage.
To quantify this qualitative intuition I compare partisan differences in the sentiment of tweets mentioning capitol or not. I estimate that, on average, Democratic tweets mentioning capitol are 42% more likely to be negative compared to non capitol-related tweets.

In the second part of the paper, I use both Twitter data and survey data to understand voters' reaction to politicians' communication and January 6 in general.
Focusing on positive engagement metrics, I show how capitol-related Republican tweets are much less popular than their Democratic counterpart compared to non capitol-related tweets. This effect is stronger for retweets, which, compared to likes, are associated higher image concerns related to publicly supporting January 6. This difference in popularity after the event is meaningful only for capitol-related tweets. Considering the nature of the self-selected Twitter sample, users engaging with their party's politicians on social media, these results suggest that the drop in popularity associated with capitol can be explained by motivated beliefs (Bénabou and Tirole, 2016). In line with D'Amico and Tabellini (2022), users may find more costly (less costly) to engage with bad news (good news) regarding their own politicians (their rival politicians).

I then turn to the large-scale nationally representative survey Nationscape (Holliday et al., 2021) to study the consequences of the event on public opinion. Leveraging the timing of the event and the (almost) weekly cadence of the survey, I employ a simple-difference specification to compare respondents of the same partisan affiliation who are interviewed before or after the event. I document a sizeable worsening in attitudes towards Trump among Republicans, whereas the effect is absent for Democrats. This first finding points out the accountability channel as a complement to the motivated beliefs one: the event has directly worsened, in the short-run, the favorability of both Trump and Republicans among their partisan supporters.

Similarly to how politicians found space to propose competing capitol-related narratives, voters as well have different interpretations of the event. I argue that the mechanism behind this worsening of attitudes has to do with how one interprets the event, either as a justified protest or an attack to democracy. I find that the negative effect is much stronger for Republicans who believe Biden to have won the election, while it's close to absent for those believing in electoral fraud. Using congress district civic capital as a proxy for standards of political accountability (Nannicini et al., 2013), I similarly find that the effect is stronger for respondents coming from places with higher levels of civic capital.

This paper relates to different strands of literature. First, it contributes to previous work directly examining the causes and consequences of January 6. Sonin et al. (2023) investigate the causes of participation to the March to Save America. They find that political isolation amplified the effect of partisanship on participation. Consistently with the results discussed above, participation is higher in counties where the electorate is more receptive to the "Big Steal" Hypothesis. Eady et al. (2021) show evidence of mass de-identification from the Republican party after January 6, while Bhatt et al. (2023) find a short-lived increase in polarization in Twitter discussions. Anderson and Coduto (2022) use survey data and find that the partisan divide in attitudes towards the riot persists after 6 months. Compared to those work, I combine different data sources to investigate politicians' communication and relate it to users' engagement, investigating the mechanisms linking the two. More broadly, this paper relates to the literature on the impact of protests on attitudes and public opinion (Wasow, 2020; Enos et al., 2019; Gethin and Pons, 2024) as well as to works documenting partisan reactions to politically salient events (Baysan, 2022; Bordalo et al., 2020; Djourelova et al., 2023; D'Amico and Tabellini, 2022).

Second, it relates to previous work studying strategic politicians' communication strategies (Djourelova and Durante, 2022; Kaplan et al., 2019; Lewandowsky et al., 2020) as well as to recent theoretical work modeling narratives as political tools of persuasion (Aina,

2021; Eliaz and Spiegler, 2020). I contribute to these literature by quantifying these strategies with a text-as-data approach and linking them with voters' reactions.
Finally, a nascent literature reviewed in Aridor et al. (2024) studies the causes and consequences of social media activity. Müller and Schwarz (2023) studies the effect of Trump's ban from Twitter on toxic content, while Beknazar-Yuzbashev et al. (2022) shows how an intervention targeted to reduce toxic content decreases overall engagement on the platform. I apply the production-consumption framework introduced in Aridor et al. (2024) to systematize and link results from activity, content, and sentiment analysis (production) to the consumption analysis.

The rest of the paper proceeds as follows. Section 2 describes in detail the data used, Section 3 investigates politicians' reactions to January 6, and Section 4 focuses on voters' reactions. Section 5 concludes.

2 Data

Twitter data The main dataset for this analysis consists of all tweets made by re-elected Members of Congress between November 11, 2020 and February 1, 2021. This information has been collected in two different ways. The sample for the analysis of politicians' activity comes from the GitHub repository *congresstweets*, available here. The dataset contains information about the account, text, and timing of each tweet. A subsample of this dataset, which is used in the consumption analysis, was obtained using the full-archive search functionality of Twitter API for academic research before its closure. For these tweets, I additionally collected a number of tweet-level metrics of engagement. This information is complemented with individual-level information such as party affiliation coming from ProPublica's API. I restrict my attention to original tweets, thus deleting duplicates and retweets.

Table 1 presents some summary statistics of the full sample, while Appendix Section A-2 discusses the differences between the two Twitter samples. The main (consumption) data has 86,328 (51,367) different tweets, of which 53,909 (32,157) were posted before the riot and 32,419 (19,210) afterwards, posted by 414 (321) different users, of which 224 (174) are from the Democratic Party and 190 (145) from the Republican Party. All the results presented in Section 3 are robust to using only the consumption subsample. Figure 6a shows the number of tweets per day per party, while Figure 6b shows the density of the length of each tweet, divided by party. Democrats consistently tweet more than Republicans.

The series are highly seasonal, displaying peaks during weekdays and low levels during weekends. Notably high peaks occur on January 6 and January 20. Tweet length is comparable across parties, although more left-skewed for Democrats, with a large number of tweets comprising of just less than 200 characters.

Survey data The main dataset for this analysis is the Nationscape survey, a weekly public-opinion survey conducted from July 18, 2019 to January 16, 2021. Holliday et al. (2021) provide an in-depth analysis of its methodology and representativeness. For the purposes of this paper, this survey represents a uniquely valuable source due to its fine-grained temporal dimension, set of questions asked, and timing of the last waves. Considering the scope of the analysis, I restrict my attention to all waves asked after the election results became official.

To identify political affiliation throughout the analysis, I use the standard 3-point partisan identity question. Table 2 reports a detailed summary of demographic characteristics for each wave, split by political affiliation. Crucially, considering the decrease in Republican affiliation caused by the capitol riot (Eady et al., 2021), there is no sharp difference in the number of Republican respondents relative to Democrats in the last waves.

Other data I use county-level measures of civic capital coming from Social Capital Project (2018) and Rupasingha et al. (2006). I aggregate this measures at the Congress District level using the methodology proposed in Ferrara et al. (2021). Specifically, I use the nearest census year methodology (in this case the last available in their dataset is 2020 for the 116^{th} Congress) and take the weighted average with population weights based on built-up property counts indicated in space, as they yield the highest correlation with official Congress District level data.

Socio-economic and demographic information for each Congress District is extracted using IPUMS (Ruggles et al., 2023). More precisely, I use: total population, share of male population, median age, share of college-educated population, share of population unemployed, share of population employed in manufacturing, and poverty rate. For electoral outcomes, I use the share of votes for Republicans in 2012, 2016, and 2020, from Daily Kos Elections (2020).

3 January 6 and politicians' communication

The question of which communication strategy Members of Congress chose to follow on Twitter after January 6 is interesting for at least two reasons. First, if one assumes that politicians are following the best strategy, it allows us to compare how differences in salience and content of the underlying events/scandals affects the optimal strategy. Is Republicans' reaction to the capitol events different from pro-gun politicians' to mass shootings? If yes, how? Second, tracking their activity on social media allows me to cleanly separate the most important dimensions of the "production-side" (Aridor et al., 2024) of social media: *i)* activity, namely how much politicians decide to tweet (or not), *ii)* content, namely the topics they decide to talk about, and *iii)* sentiment, how they talk about different topics. The next sections discuss in detail each of these dimensions.

3.1 Activity analysis

When investigating politicians' activity on Twitter, the sample consist of a balanced panel of all Members of Congress who are in the original sample (at least one tweet between November 11, 2020 and February 1, 2021) at the week level, so that each observation represents the activity associated with individual i in week t. I construct weeks so that January 5 is the last day of $t = 0$, leaving me with 11 time-windows of 7 days and one time-window (the last one) made up by six days. I estimate a regression of the form:

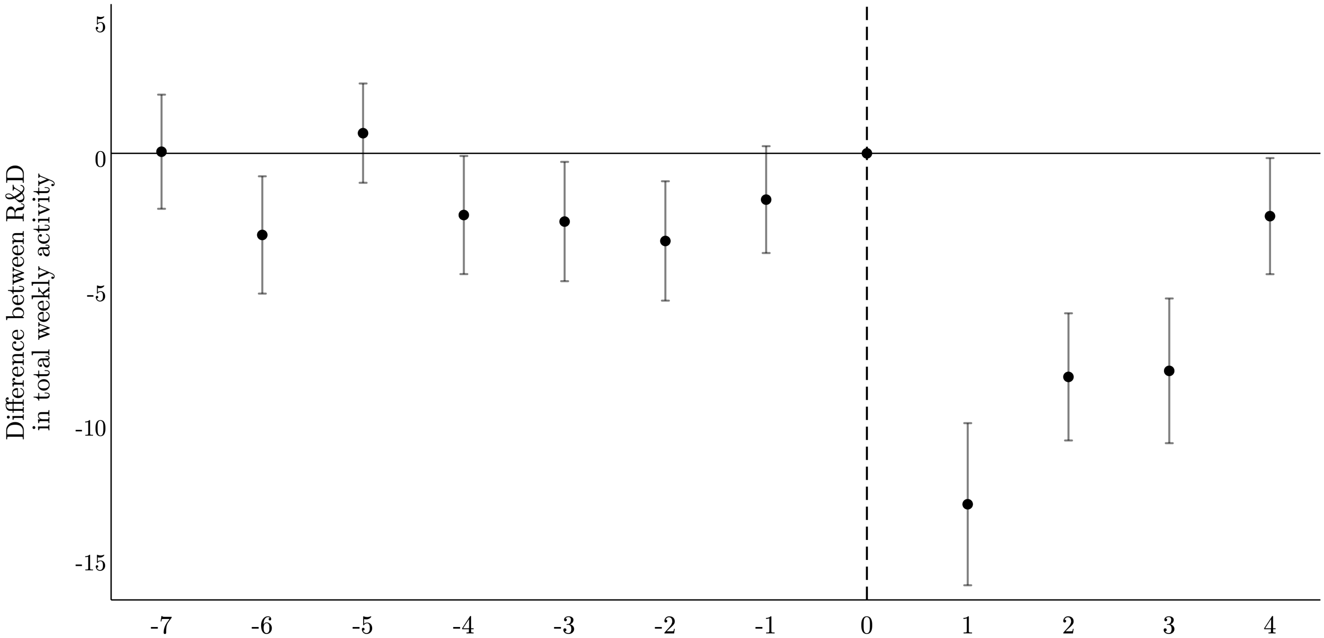
$$Y_{i,t} = \beta_0 + \alpha_i + \psi_t + \sum_{\substack{\tau=-7 \\ \tau \neq 0}}^{4} \mu_\tau \Big[\mathbb{1}(\text{Republican}_i) \times \mathbb{1}(t) \Big] + \varepsilon_{i,t} \tag{1}$$

Where $Y_{i,t}$ is the number of tweets that individual i has made in window t or an indicator for the extensive margin of activity in that week; α_i are individual FE; ψ_t are time-window FE; $\mathbb{1}(\text{Republican}_i)$ is an indicator equal to one if i is a Republican; $\mathbb{1}(t)$ is an indicator equal to 1 if we are in period t. Errors are clustered at the individual level.

There are two features of this specification that are worth highlighting. First, it collapses information at the week level instead of retaining it at the day level. This is to reduce noise from day-level observations as well as to deal with the high seasonality of activity within the same week. As it can be seen from Figure 6a, tweets tend to increase sharply during the weekdays to then decrease during the weekends. Second, $\{\beta_\tau\}_\tau$ tracks the evolution of the difference between Republicans and Democrats' posting activity similarly to a TWFE specification instead of a simple difference. However, both Democrats and Republicans are treated. Republicans are the direct protagonists of the scandal, but the scandal clearly affects Democrats' communication incentives as well. As such, one should interpret $\{\beta_\tau\}_\tau$ with caution, since it compounds the two effects. This choice is justified by the fact that seasonality is also present across weeks. Politicians tweet less often during Christmas or New Year's. Simply looking at within-group variation would pick up these seasonal effects. Comparing instead politicians across the aisle greatly diminishes this concern, assuming that holidays impact individual's propensity to tweet homogeneously between the two parties.

Figure 2 reports the results of the analysis on the intensive margin. The difference between Republicans and Democrats' weekly tweets is not significant up until the event, and then it becomes and remains negative and significant up until the last week of the sample. The shift is Republicans' activity is sizeable. For the week containing the event, it amounts to a decrease of around 13 tweets per week, approximately 0.7 standard deviations. Moreover, this effect remains similar in magnitude for the two subsequent weeks. Focusing on Figure 7, the difference in the probability of tweeting at least once per week is not affected. This makes sense, considering that the average number of tweets per week is 17. These results taken together suggest that, after the event, the difference in activity between Republicans and Democrats has increased (in absolute terms) by a sizeable amount, but it has done so at the margin. It's not that Republicans have stopped tweeting altogether, but that, compared to Democrats, they have tweeted less.

FIGURE 2: JANUARY 6 AND ACTIVITY ON THE INTENSIVE MARGIN



Notes: The figure reports point estimates and 95% robust confidence intervals for the β_τ in Equation 1. The outcome is the number of tweets that individual i has done in that week t. Errors are clustered at the individual level.

It could be that the banning of Trump's account on January 8, which happened for capitol-related reasons, decreased overall activity on Twitter for all accounts who followed Trump before the ban. This introduces the concern that the activity result is compounded by Trump's banning. It could be that fellow Republicans were scared of being banned themselves. Müller and Schwarz (2023) investigate the consequences of Trump's banning from Twitter on toxicity of tweets from Trump followers and a sample of Twitter users. They find that, after the account deletion, the overall number of tweets sent by his followers decreases by 0.05 standard deviation, and the effect rises to 0.08 when restricting to tweets that directly mention him. However, there are several reasons to think their mechanisms do not apply to politicians. First, compared to an average user, giving up social media use implies a much higher cost for public figures, such as politicians, who heavily rely on them to communicate with their audience. Second, Twitter's intervention was the first of its kind and did not happen to any other politician in that period, mitigating concerns about being banned. To further confirm this intuition, we can look at whether Republicans have stopped talking about Trump after January 8. If Republican members of Congress feared a ban and hence decided to decrease their Twitter activity in response to this, it would be reasonable to expect them to also decrease Trump's mentions, as indeed is shown in Müller and Schwarz (2023). Figure 8 shows the evolution of Republican activity that contains the word trump in it. We see that there is no noticeable change right after January 8 and, if anything, there is an increased number of tweets about Trump on, for instance, Inauguration Day on January 20th. Extending the analysis to trump-related words like president or 45 leaves the results unchanged, mitigating concerns that the results may be explained by Republicans referring to Trump with different terms. These findings support the hypothesis that the effect of Trump's ban on users' activity is markedly different between normal users and politicians.

3.2 Content analysis

I next turn to the content of politicians' tweets. First, I present some descriptive evidence directly measuring mentions of topics of interest in Figure 9. Figure 9a shows the share of tweets containing "trump" for each party and its evolution over time. Democrats consistently mention Trump more than Republicans, and even more so after January 6. Figure 9b shows the share of tweets containing "capitol". Reassuringly, the share of tweets mentioning "capitol" before the event is close to zero, suggesting that the analysis indeed captures the interest towards the event, and ruling out that it may be systematically used to address other issues. The share skyrockets on the day of the event and afterwards, reaching a peak on January 8 where more than 40% of Republican tweets mentioned it, against 30% of Democrats. The level fades gradually, remaining around 5-10% until January 20.

Descriptively, it seems that *both* parties have talked a lot about the event. To quantify partisan differences, I estimate Equation 1 using as an outcome both the number of tweets containing "capitol" and the daily share of tweets containing it. In this specification, $\{\beta_\tau\}_\tau$ tracks the evolution of politicians activity over time focusing solely on capitol-related tweets. Similarly to above, the coefficients of interest compound the changes in communication incentives of both Democrats, who may be more tempted to tweet about a scandal regarding the opposing party, and Republicans, who instead may want to avoid bad coverage, as in Pfeufer (2022). Figure 10 plots the results. Looking at the total number of tweets mentioning "capitol", the coefficients become negative and significant after the event until the last week of the sample. In the week of January 6, compared to Democrats, Republicans have made on average four and a half tweets less, around 0.7 standard deviation of the outcome in that week. However, considering the previous results on how Republicans have overall tweeted less when compared to Democrats, this result may be misleading. Focusing on the share of weekly tweets mentioning "capitol" reverses the picture, as the coefficient of the January 6 week is large and positive, while in the subsequent week is negative and then becomes close to zero. During the week of the event, Republicans' share of tweet referring to the event is 5 percentage points higher than Democrats', approximately 0.28 standard deviation of the outcome in that same week. If anything, proportionally, Republicans have talked *more* about the attack than Democrats in its immediate aftermath, although they have stopped doing so after a week. The reasons for this, and why it's different from the "usual" reaction of distraction from scandals, are potentially numerous. First, one explanation lies in its sheer salience, which would have made any attempt to shy away from it possibly useless. Second, contrary to events such as mass-shootings, January 6 did not have, at least for Republicans, an intrinsic negative connotation. Rather than a failed insurrection (or even worse coup d'état), there was space to describe it as a legitimate protest, or at least downplay some of its most negative sides and highlight other ones. Republican politicians, in the immediate aftermath of the event, had incentives to offer competing narratives.

To expand the description of Congressional narratives, I apply the `RELATIO`[1] algorithm described in Ash et al. (2024) to extract "narratives" from politicians' tweets. Narratives are semantic structures in which an agent (who) does something (what) to a patient (whom). This is achieved through an semi-surpevised machine learning algorithm combining named-entity recognition and k-means clustering. Compared to fully unsupervised methods such as Latent Dirichelet Allocation (LDA), this method provides much more interpretable output, which reduces the opportunity for post-hoc interpretations. I use it with the standard 100 clusters. Throughout the analysis, I focus on and present "low-dimensional narratives" that are complete, i.e., those that contain an agent, a verb, and a patient.[2] Appendix Figures A-1 and A-2 show the prevailing narratives, separate by party, over the whole period. In this representation, each agent is an edge, each verb is a node, the direction of the nodes represents the direction of the action undertaken, and their size is proportional to the frequency of the narrative. Even without focusing on January 6, it's clear that edges are very similar across parties. It's nodes that change. For the node "american", the most common Democratic narrative is "american need help". For Republicans, it's "american deserve integrity election".

To better isolate narratives about the events of January 6, I restrict the analysis to tweets

[1]This package is open-source and available at: `https://github.com/relatio-nlp/relatio`

[2]For more details on how the procedure works, see Ash et al. (2024).

that have been posted afterwards. The sample includes 22,728 tweets from Democratic Members of Congress and 9,550 tweets from Republican Members of Congress. Appendix Figures A-3 and A-4 show the most common 50 narratives estimated separately by party. "capitol" is the node with the highest in-degree centrality. Figure 3 shows only capitol-related narratives, obtained extracting narratives together for the two parties, classified by their partisan use. Narratives with odds ratio higher than 1 are classified as Democratic, while those with odds ratio smaller than 1 are classified as Republican. Partisan differences are stark. Democratic narratives (in blue) are mostly related to how Trump incited the event ("trump incite capitol") or how violent it was ("violence attack capitol"). By contrast, Republican narratives (in red) focus much more on the law-and-order aspect of January 6 ("capitol police support capitol"). Interestingly, one of the most common Republican narratives is "mob force capitol",in line with the initial Republican interpretation that the event was mostly peaceful and ruined by a handful of "rotten apples".

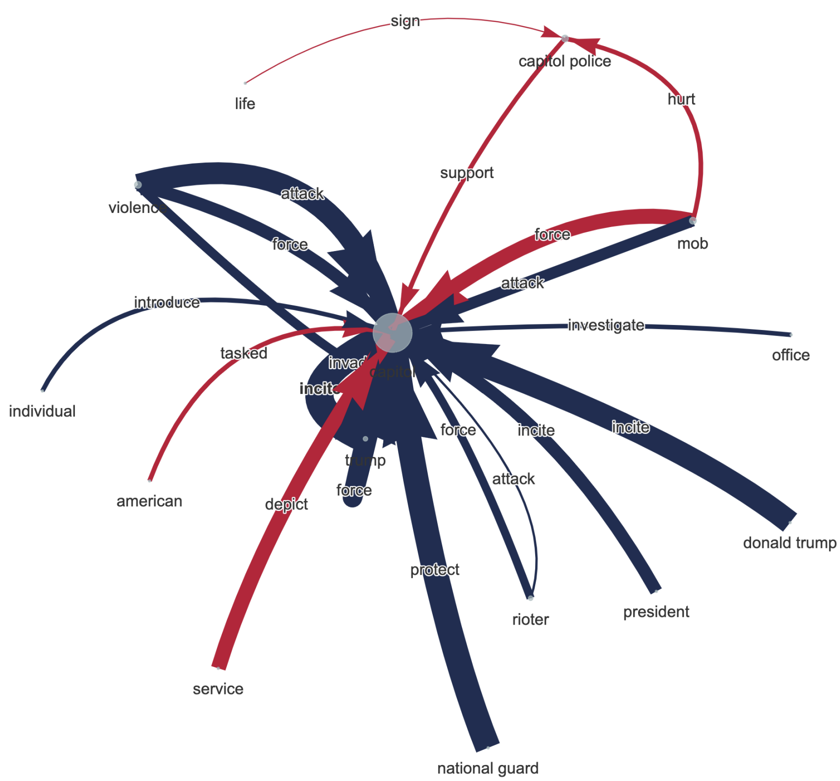


FIGURE 3: PARTISAN NARRATIVES ABOUT CAPITOL AFTER 6^{TH} OF JANUARY

Notes: The figure reports all low-dimensional and completes narratives including capitol as a node. The narratives are estimated for the two parties together on tweets posted after January 5. A narrative is classified as Democratic (blue) if it has odds ratio larger than 1 and Republican (red) if it has odds ratio lower than 1. The number of clusters is set to its default value, 100.

Table 3 reports the most common narratives split by party. Strikingly, all 10 narratives for the Democratic Party are directly or indirectly related to the events of January 6. On the other hand, consistently with the discussion above, Republican narratives are more heterogeneous: some contain vague messages of unity (rank 3, 5, 6), while others express dislike for the opposing party (rank 9). Moreover, narratives such as "open paycheckprotection progoram" and "ustreasury announce paycheck protection program", referring to other salient events during that period, suggest that Republicans attempted to shift the discourse to other points of their political agenda. Appendix Section A-3 investigates more systematically the evolution of topics' popularity over time.

3.3 Sentiment analysis

To conclude the analysis of politicians' communication surrounding January 6, I quantify partisan differences in the sentiment associated with each tweet. To estimate sentiment, I use the `XLM-T-Sent-Politics` model from Antypas et al. (2023). This is a fine-tuned version of the `twitter-roberta-base-sentiment` model with a focus on sentiment of politicians' tweets.[3] The model produces, for each tweet, a probability distribution over three states of the world (positive, neutral, negative). Starting from these probabilities, I build two measures: a compound sentiment, which is the difference between the probability of being positive and the probability of being negative, and a negative sentiment indicator equal to one whenever the probability assigned to negative is strictly larger than the one assigned to positive. Compared to traditional alternatives, this algorithm offers the advantage of being fine-tuned specifically on politicians' tweets, which are likely to have a different tone and overall dictionary compared to tweets from normal users. However, results are robust to using the standard `VADER` package (Hutto and Gilbert, 2014).

Figure 11a shows the 3-days moving average compound score by party. The compound score of tweets is generally positive and relatively similar across parties, especially at the start of the series. Average compound score sharply drops around January 6 for both parties, and the decrease is larger for Democrats than for Republicans. After January 6, the compound score of Democrats remains consistently lower than the one of Republicans until January 20, the day of Biden's inauguration. To explain these patterns, Figure 11b plots the 3-day moving average of compound score by party, distinguishing on whether the tweet contains the word capitol or not. The partisan difference in sentiment is much larger for tweets mentioning capitol than for tweets not mentioning it, echoing the pre-

[3] The model is publicly available on Hugging Face here.

vious qualitative results from narratives extraction. Although the sentiment for capitol tweets starts negative for both parties, it quickly becomes positive for Republicans and remains positive throughout the whole period. Democrat sentiment of capitol tweets becomes shortly positive after January 20, and overall Democrat sentiment becomes steadily higher than Republicans' once Biden takes office.

To quantify the hypothesis that capitol-related Democratic tweets are systematically more negative than Republican ones, I estimate the following regression:

$$\begin{aligned} Y_{t,i} = &\beta_0 + \beta_1 \mathbb{1}(\text{Democrat})_i + \beta_2 \mathbb{1}(\text{capitol} \in \text{tweet})_t + \\ &\beta_3 \mathbb{1}(\text{Democrat}) \times \mathbb{1}(\text{capitol} \in \text{tweet})_{t,i} + \delta_c + \gamma_i + \alpha_d + \varepsilon_{t,i} \end{aligned} \tag{2}$$

where Y_i is the compound score of tweet t posted by user i, δ_c are chamber FE, γ_i are individual FE, and α_d are day FE. Errors are clustered at the individual level. The main coefficient of interest is β_3, which estimates the impact of mentioning capitol on the sentiment of Democratic tweets vis-à-vis Republican tweets. In line with Enke (2020), observations are weighted by the square root of total non stop-words. I progressively add fixed effects to account for systematic cross-party differences in chamber composition, individual characteristics, and day-specific trends. Moreover, to dispel concerns that results are driven by a differential use of the word capitol across the two parties, I estimate Equation 2 both before and after the event separately. Table 4 reports the results. Column (1) reports baseline results, column (2) adds chamber FE, column (3) adds individual FE, and column (4) adds day FE.

Panel A shows that, before January 6, Democratic tweets were significantly more negative than Republican ones, consistently with Figure 11a, although this difference is only of 5 percentage points. Moreover, capitol is associated with a higher compound score, although, as shown in Figure 9b, the number of tweets mentioning it is almost zero. Finally, and crucially, β_3 is not significant, suggesting that the term capitol is not differentially used across parties before January 6. Panel B focuses on the period after January 6. The difference in sentiment between Democrats and Republicans is not significant, but now tweets that mention capitol are, on average, associated with higher sentiment scores. β_3 is negative, significant, and stable across all specifications. The size of the coefficient implies that, on average, Democratic tweets mentioning capitol have a compound score that is more than 42 percentage points lower than that of their Republican counterpart. The effect is sizeable, as it amounts to approximately 0.62 standard deviation of the outcome.

4 January 6 and voters' reaction

After having studied politicians' communication strategies after January 6, I turn to the event's consequences on voters. Using Twitter data, I focus on the consumption side of social media, namely how users have reacted to the communication strategies employed by politicians. This analysis aims to explain whether these strategies have been successful and to provide evidence as to the reason why they were (or not). Using survey data, I focus on changes in public opinion, what motivates them, and how they can help to interpret the engagement results from Twitter.

4.1 Consumption of social media

Similarly to Section 3.3, I start by reporting descriptive evidence about the consumption of social media during the period of interest. Figure 12a shows the evolution of the 3-days (moving) average retweets split by party. On average, Republicans are more retweeted than Democrats. The opposite is true only on January 6 and during the days right after, as Democrats' popularity experiences a significant increase while Republicans' decreases. Figure 12b presents a very similar picture for likes. To understand how these patterns relate to January 6, Figure 13 separates tweets containing the word capitol from the others from January 6 onward. Looking at both Figure 13a and 13b it becomes clear that Democrats' surge in popularity is entirely driven by tweets that mention capitol. The same applies to Republicans' slight decrease in retweets and likes. However, the trend appears to be short-lived, as it disappears almost entirely after January 15 to just pick up again briefly after Biden's inauguration.

To quantify partisan differences in the popularity of tweets mentioning word capitol or not, I estimate:

$$\begin{aligned} Y_{t,i} =& \beta_0 + \beta_1 \mathbb{1}(\text{capitol} \in \text{tweet})_t + \beta_2 \mathbb{1}(\text{Republican}) \times \mathbb{1}(\text{capitol} \in \text{tweet}) \\ &+ \delta \mathbb{1}(\text{Negative sentiment})_{t,i} + \gamma_i + \alpha_d + \psi_h + \varepsilon_{t,i} \end{aligned} \tag{3}$$

where Y_i is the popularity measure of tweet t posted by user i, γ_i are individual FE, α_d are day FE, and ψ_h are hour of the day FE. Errors are clustered at the individual level. The main coefficient of interest is β_2, which estimates the impact of mentioning capitol on the popularity of Republican tweets vis-à-vis Democratic tweets. As before, observations are weighted by the square root of total non stop-words. The fixed effects account for systematic cross-party differences in sentiment, individual characteristics, day and hour of the day specific trends. Moreover, for the same reasons reported in Section 3.3, I estimate Equation 3 both before and after the event separately.

As the main outcomes of these analyses, I focus on measures of positive engagement such as likes and retweets at the tweet-level. These measures are clearly limited, since they don't capture any individual-level information about the users reacting to politicians' tweets. This is the reason why I restrict my attention to positive attention metrics and ignore other ones, such as quotes, which may have a more ambivalent meaning. Under the assumption that these positive engagement measures capture partisan reactions, instead of noise coming from bots or unaffiliated accounts, they still provide useful insights into how, on average, followers of Democratic and Republican Members of Congress have perceived and reacted to politicians' narratives surrounding the capitol event. This assumption is less stringent than it seems, considering how many papers in the literature infer users' political affiliation through the accounts they follow (Barberá et al., 2019; Müller and Schwarz, 2023) or the accounts attracting most of their (positive or negative) activity (D'Amico and Tabellini, 2022), which may be ex-ante a more ambiguous indicator of partisan affiliation.

Table 5 reports the results. Focusing on the most stringent specifications, we see from the first panel that the word capitol per se is not associated, before the event, to differential engagement between Democrats and Republicans. This is no longer the case after the January 6. On average, whenever they mention capitol, Republicans get more than 700 likes less compared to Democrats, relative to all other tweets, although this effect is marginally not-significant. This represents around 0.081 standard deviations of the outcome, or around 50% of the mean. Looking instead at retweets, Republicans get on average 200 retweets less when mentioning capitol. This amounts to 0.12 of the standard deviation of the measure of engagement, around 70% of the mean of the outcome. Whenever they mention capitol in their tweets, Republicans get less engagement than Democrats. It's also interesting to note that the results differ both in size and significance across the two engagement measures, as it is stronger and more precisely estimated for retweets. A possible explanation has to do with social norms. If condoning or (somewhat) supporting capitol is not socially acceptable, then engaging with Republicans' tweets is costly in social terms. However, engagement through likes is not the same as through retweets, since likes do not appear on the user's personal page (retweets do) and are generally less visible than the latter. Hence, if users worry about this perceived break of social norms, the form of engagement that is reduced more should be the costlier one.

The results above may be interpreted through the lenses of accountability. After January 6, the favorability of Republican (Democrat) Members of Congress decreases (increased) when they mention capitol-related events. Alternatively, in line with the findings of D'Amico and Tabellini (2022), partisan users engage asymmetrically with consonant and not consonant scandals. Republican voters engage less with their politicians when they are talking about capitol not because their favorability has decreased, but because it's emotionally costly to engage with such a bad news. This mechanism would imply that, for Republican tweets mentioning capitol, engagement should be lower for negative tweets than for positive tweets. The opposite should hold for Democrats. At the same time, this pattern would also be relevant to interpret how communication strategies have been successful in doubling the blame for Democrats and controlling the damage for Republicans. To test these intuitions, I estimate the following regressions separately for each party only on the period after January 5:

$$\begin{aligned} Y_{t,i} = &\beta_0 + \beta_1 \mathbb{1}(\text{Negative sentiment})_t + \beta_2 \mathbb{1}(\text{capitol} \in \text{tweet})_t + \\ &\beta_3 \mathbb{1}(\text{Negative sentiment}) \times \mathbb{1}(\text{capitol} \in \text{tweet})_t + \delta_c + \gamma_i + \alpha_d + \varepsilon_{t,i} \end{aligned} \tag{4}$$

where the notation follows equation 3 and negative sentiment is an indicator equal to one whenever the tweet is strictly more likely to be negative than positive for the classification algorithm. The coefficient of interest, β_3, estimates the difference in engagement, within the same individual, between negative tweets mentioning capitol and non negative ones still mentioning it, compared to the difference between negative and non negative tweets not mentioning capitol.

Table 6 reports the results for Republican politicians in Panel A and Democratic ones in Panel B. Following a well established fact in the literature studying social media, negative content gets on average much more engagement, both in forms of likes and retweets. This holds true for both Republicans and Democrats, with negative tweets getting on average 800 likes and 200 retweets more. β_3 is negative but not significant for Republicans, presenting suggestive evidence that *i)* motivated beliefs for Republicans have no particular role on the sentiment margin and that *ii)* Republicans' strategy has not been entirely successful. On the other hand, the estimated coefficient for Democrats is positive and significant, although imprecisely estimated, when looking at retweets. On average, mentioning capitol in a negative tweet is associated with 233 more retweets, around 0.15 standard deviation. Differently from Republicans, this result is consistent with both the accountability and the motivated beliefs mechanisms.

To what extent is this drop in engagement associated with Trump's ban on January 8? Similarly to the discussion in Section 3.1, the ban of such a high-profile account within the same time-period may create concerns about the results presented in this section. Trump's ban could have had network effects discouraging Republican voters to use Twitter altogether, as shown in Müller and Schwarz (2023). Moreover, to the extent that Trump's ban is associated with a decrease in overall toxic content production, it could have had spillover effects on overall consumption in a similar fashion to targeted experiments (Beknazar-Yuzbashev et al., 2022). To mitigate these concerns, Appendix Tables A-1 and A-1 compare the differential change in engagement before and after January 6 and January 8 between Democrats and Republicans. Reassuringly, the results show that there is no such difference, as the coefficient is small and not significant for the whole sample and also excluding tweets that directly mention capitol. The partisan difference in change in engagement after the event is significant only for the tweets that directly refer to it. At the same time, this provides evidence that the mechanism of motivated beliefs could be at play here regarding the capitol topic as a whole, regardless of the sentiment associated with it. Since users in the sample self-select by engaging with this content, compared to the overall population of partisans, it's likely that they have a less malleable opinion regarding their party's politicians.

4.2 Survey evidence on public opinion

This section presents results using data from the Nationscape survey on the effect that January 6 had on Trump's favorability and public opinion in general.

4.2.1 Main results

I use data from a large and representative survey to test for the presence of an accountability channel in Republicans' reactions. Differently from the self-selected sample of Section 4.1, Nationscape's is more likely to be representative of the overall population of Democrats and Republicans in the US. Additionally, the stated preferences approach allows me to directly measure changes in attitudes towards Trump.

I estimate, separately for Democrats and Republicans, the following simple-differences specification:

$$Y_{i,t} = \alpha + \sum_{\substack{\tau=-6 \\ \tau\neq 0}}^{2} \beta_\tau \mathbb{1}(i,\tau) + \gamma X_{i,t} + \varepsilon_{i,t} \tag{5}$$

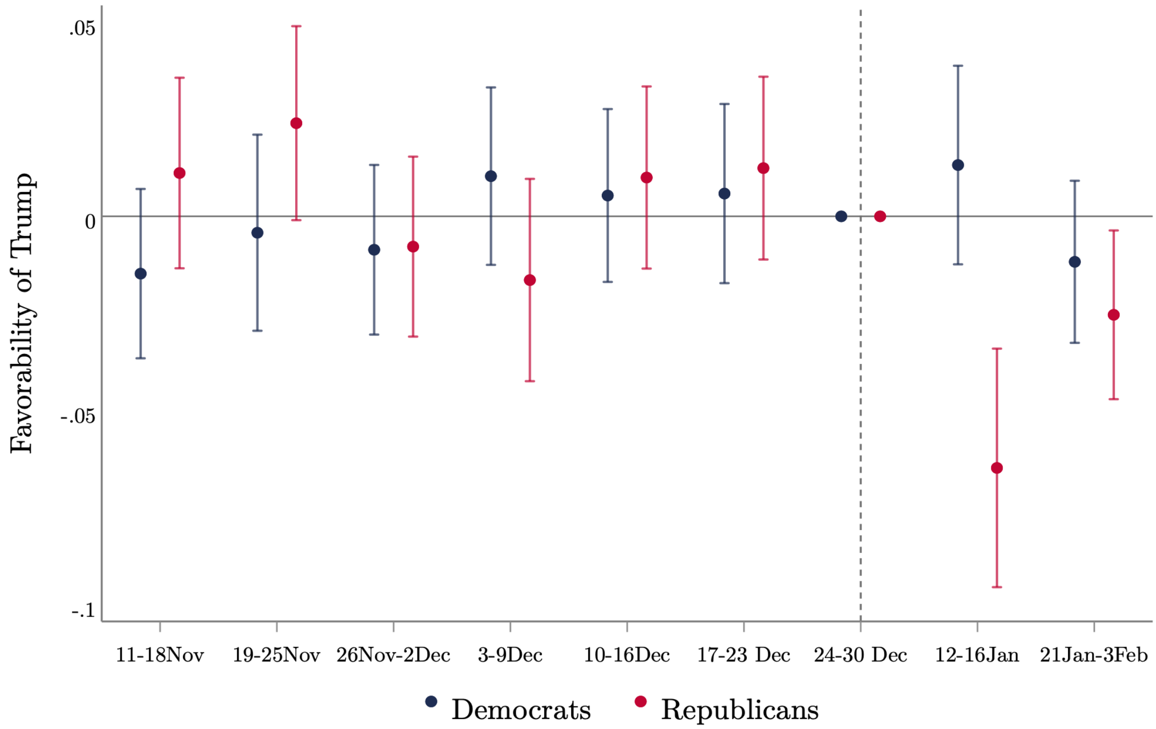
where $Y_{i,t}$ is the outcome for individual i at time t, $\mathbb{1}(i,\tau)$ is an indicator equal to one if individual i is interviewed in wave τ (whose timing is relative to the wave right before January 6), and $X_{i,t}$ is a vector of individual-level controls, including age, age squared, gender, employment, education, income, and race. Errors are clustered at the Congress district level. The coefficients of interest $\{\beta_\tau\}_\tau$ track the evolution of the outcome before and after January 6 for either Democrats or Republicans. I also estimate regression results comparing outcomes before and after the event replacing the dummies $\mathbb{1}(i,\tau)$ with a single dummy $After_{i,t}$ taking value zero before the event and one after:

$$Y_{i,t} = \alpha + \beta After_{i,t} + \gamma X_{i,t} + \varepsilon_{i,t} \tag{6}$$

The immediate identification assumption is that the events of January 6 are the *only relevant events* distinguishing our observations before from those after. There are other two important events happening in the same time-frame as the last two waves of Nationscape: Trump's ban from Twitter (January 8), and Biden's inauguration (January 20). I argue that neither of them is a concern for the identification of the effect of interest. Focusing on Trump's ban, it's more natural to interpret it as a *consequence* of the effect I estimate, rather than a cause of it. Trump was banned precisely for the events of January 6. While it's possible that being banned from Twitter has reflected negatively on his popularity, it's unlikely that this feedback effect is larger than the direct effect coming from his involvement in the capitol attack. Regarding Biden's inauguration, it does not pose a problem for the interpretation of β_1, which refers to a period ending on January 16. On the other hand, it could be that Biden's inauguration exogenously increased his salience and thus indirectly affected Trump's favorability as well. If popularity between the two is negatively correlated, then observing increased (decreased) Biden's favorability by Republicans could mechanically bias downward (upwards) estimates for Trump's favorability changes in the last wave. To account for this reasoning, I estimate Equation 5 using Biden's popularity as an outcome. Another common concern with this type of specification is that the evolution described by $\{\beta_\tau\}_\tau$ may be endogenous, as discussed for instance in Gethin and Pons (2024). There may be a third factor causing both the events of January 6 and a shift in attitudes towards Trump (or Republicans). Intuitively, this should not be a problem for the results. If anything, considering that the event was driven by people's increasing belief of fraudulent election results, which should be positively associated with attitudes towards Trump, then any estimate of the effect on attitudes towards Trump would represent at worst an upper bound for negative values of the coefficients. Considering the cross-sectional nature of Nationscape, another concern is that the timing of the survey interview is not random relative to the event. It could be that Republicans (Democrats) interviewed in the wave right before the event are systematically different from the other Republicans (Democrats) in the sample, and that this difference is driving the result. Table 2 reports sample means for different demographic and ideology-related variables, split by survey wave and by partisan affiliation. Reassuringly, there is no sizeable difference between the last wave before the event (23-30 December) and all of the other waves for both demographic and ideology-related factors, with the largest difference in the range of 8 percentage points.

Figure 4 plots the effects of the capitol attack starting from Equation 5 on Trump's favorability, estimated separately for Democrats and Republicans. For both political affiliations, no pre-trend is significant, mitigating concerns about anticipation effects. However, in the last two waves, the effect becomes negative and significant for Republicans. In the interviews carried out starting from 6 days after the event, Republicans are on average around 6.5 percentage points less likely to have a favorable impression of Donald Trump. This corresponds to roughly 0.2 standard deviations in the outcome. The effect remains significant but decreases to 2.5 percentage points in the very last wave of interviews, carried out from 15 days after the event. On the other hand, estimates for Democrats are not significant. These results suggest that the capitol attack worsened Republicans' attitudes towards Trump. The effect is absent for Democrats, plausibly because they already display an abysmal rate of approval for Trump (over all the waves after the election, the share of Democrats who approve of Trump is 14%) and thus were hardly surprised by what happened.

FIGURE 4: JANUARY 6 AND TRUMP FAVORABILITY



Notes: The figure reports point estimates and 95% robust confidence intervals for the β_τ in Equation 5. The outcome is a dummy equal to one if the respondent has a very favorable or somewhat favorable impression of Trump, 0 otherwise. Respondents saying that they have not heard enough about Trump are dropped from the sample.

To what extent did January 6 reflect badly on Trump relative to Republicans as a whole? Figure 14 plots the results using as an outcome Republicans' favorability. The absence of pre-trends is reassuring. However, compared to previous results, the effect is less precisely estimated. For Democrats, it remains not significant and very close to zero. Republicans are 3 percentage points less likely to have a favorable impression of Republicans in the immediate aftermath of the event but the effect vanishes in the subsequent wave. Comparing these results with the previous ones, it seems that there is a partial disconnection between attitudes towards Republicans and attitudes towards Trump. Only 50% of the effect estimated on Trump's favorability in the wave right after the event "passes-through" to Republicans, disappearing after a week.

Table A-3 reports the estimates of β from Equation 6 for both outcomes restricting the pre-event sample to different windows. Columns (1)-(3) focus on Trump's favorability, while columns (4)-(6) on Republicans'. In line with the graphical evidence presented above, the results are negative and significant for the Republican sample, while they remain not significant for the Democratic sample. With a 4-waves sample, Republicans interviewed after the event are, on average, four and a half (one and a half) percentage points less likely to have a favorable impression of Trump (Republicans), around 0.11 (0.04) standard deviations of the outcome. Similarly to above, the effect is larger for attitudes towards Trump.

Did January 20 impact Trump through Biden? Figure 15 reports the result using Biden's favorability as an outcome. For both political affiliations pre-trends are not significant. Two interesting patterns emerge. Focusing on Republicans, the effect becomes positive, although imprecisely estimated, and significant in the last wave. Compared to the wave before Janaury 6, Republicans improved their favorability of Biden by around three precentage points, around 0.075 standard deviation. It is possible then that the effect estimated for Trump's favorability in the last wave is downward biased by the negative correlation with Biden's. Second, the effect is not significant and null for Democrats. Combined with the results along the sentiment margin reported in Section 4.1, this presents evidence that the increase in Democrats' engagement on Twitter is mostly driven by behavioral reasons rather than changes in their opinion about Democratic leaders. Table A-4 confirms these results using the specification of Equation 6 restricting the pre-event sample to different time windows.

Was the effect among Republicans heterogeneous across demographic dimensions? figure 16 plots the results of Equation 5 estimated separately for each demographic group, with Panel A focusing on gender, B on education, and C on income. The effect is overall negative and significant for all demographic subgroups, without statistically significant differences in its size. Descriptively, the decrease in favorability seems more pronounced among female respondents, college educated respondents, and high income respondents.

4.2.2 Mechanism: justified protest or attack to democracy?

The previous section has provided evidence suggesting that there is an accountability channel for Republicans. In these section, I argue that the main mechanism behind this channel has to do with how the event is interpreted. According to a large survey conducted between January 8 and 12 (Hartig, 2021), only 27% of Republicans reported a strong and negative emotion when discussing the attack to capitol, as opposed to 50% of Democrats. Instead, 17% of Republicans doubted it was Trump supporters, 10% blamed Democrats and said the protest was fully justified, and 8% said it was nothing worse than

BLM-related protests.[4] I use different proxies of respondents' interpretation of January 6 and test whether perceiving it more negatively is associated with a larger decrease in Trump's favorability.

Beliefs in fraudulent election An intuitive proxy of the mechanism outlined above is related to respondents' beliefs about the 2020 election. If they believe that Biden won the election fairly, then they should be more likely to perceive the events of January 6 as an attack to democracy rather than a justified protest, at least relatively to those believing that Trump was the rightful winner. This implies that the effect should be stronger (i.e., more negative) for Republicans who believe the election results were correct. To test this mechanism, I exploit the presence of a question asking the respondent about the legitimate winner of the election. Then, I can estimate Equation 5 on the Republican sample separately for those believing that Biden won the election (32% of the sample) and those who don't believe that (68% of the sample).[5].

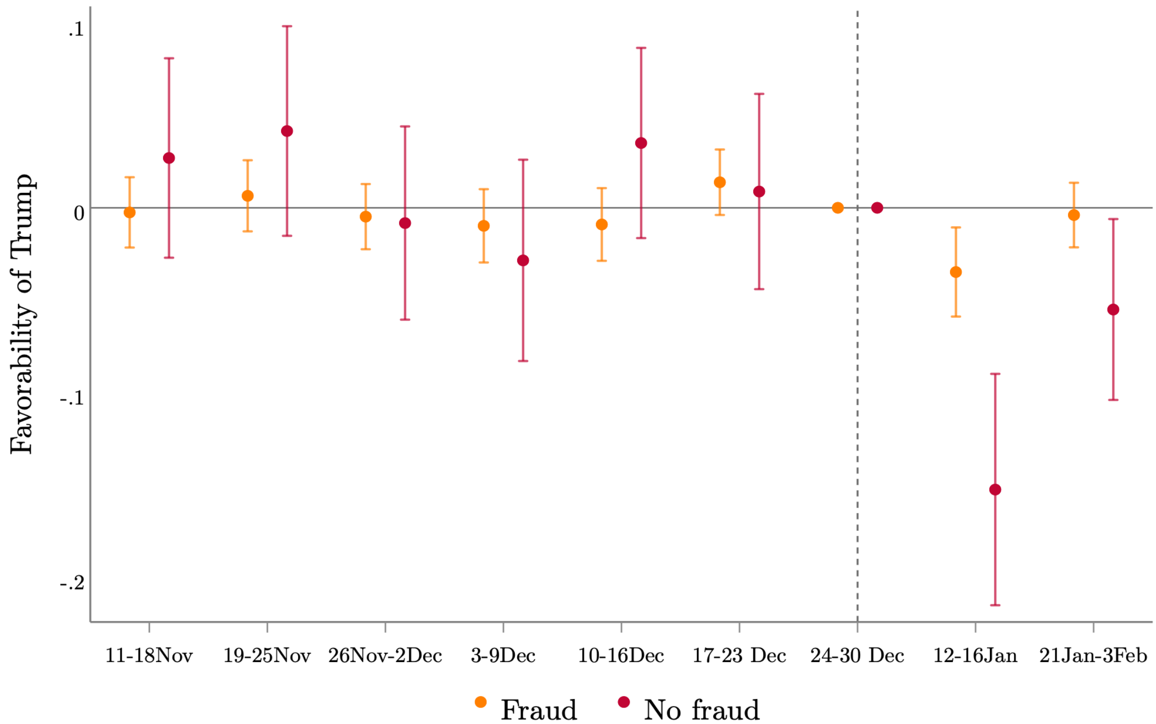
Figure 5 plots the results for those believing in fraud and those not believing in electoral fraud. Results are very similar with the pre-post specification as well. Pre-trends are not significant. Some interesting patterns emerge from the last periods. First, the estimates are negative for both groups, meaning that even those believing that Biden did not win the elections experienced a decrease in their favorability of Trump. However, the magnitude of the effect is completely different across the two groups, which have statistically different coefficients in the first wave after the event. For those believing in fraud, the associated decrease in favorability is around 3.5 percentage points, while for those not believing in fraud the decrease is more than 15 percentage points. While the first effect amounts to 0.16 standard deviations of the outcome, the latter amounts to 0.31 standard deviations of the outcome. Hence, on average, the associated worsening in attitudes towards Trump is twice as large for those not believing in the fraud hypothesis. Finally, for both types of Republicans, the effect sharply decreases in size already in the last wave. For those believing in fraud, it become close to zero and not significant, while for those not believing in fraud it remains significant and amounts to 0.1 standard deviation of the outcome. Results are robust to an additional specification in which the ideology-related variables of Table 2 are included and interacted with wave FE. Table A-5 confirms these results using the specification of Equation 6 restricting the pre-event sample to different

[4] For the full list, the article is available here.

[5] Results are robust to defining those who believe in fraud as those believing that Trump won, instead of those not believing that Biden won.

time windows.

FIGURE 5: ELECTIONS FRAUD AND TRUMP FAVORABILITY



Notes: The figure reports point estimates and 95% robust confidence intervals for the β_τ in Equation 5. See the notes of Figure 4 for a description of the outcome variable.

Civic capital The accountability channel should be stronger for individuals who have higher standards of political accountability. Unfortunately, there is no such question or proxy in the Nationscape survey. I leverage characteristics of the congress district respondents come from to separate them in those coming from places with above the median civic capital and below the median. This strategy follows Nannicini et al. (2013), who find that higher levels of civic capital are associated with higher levels of political accountability. Those coming from places with higher civic capital should have, on average, higher levels of political accountability and thus display a stronger decrease in Trump's favorability. The measures of civic capital employed are described in Section 2. I estimate Equation 5 only for Republicans separately on the above-the-median and below-the-median sample. To address systematic differences between congress districts, I control for the congress district level variables discussed in Section 2.[6]

Figure 17 (for the measure of Social Capital Project (2018)) and 18 (for the measure of Rupasingha et al. (2006)) show the results. Focusing on Figure 17, pre-trends are not significant. The coefficient becomes negative and significant for both groups in the first wave after January 6, with the effect being much more pronounced in the sample of respondents coming from above the median congress districts. They experience a decrease of eight percentage points, which amount to 0.23 standard deviation. For those below the median, the effect is less than four percentage points and around 0.1 standard deviation. The effect is twice as large for respondents coming from places with higher civic capital, and the difference is significant at 0.1. This discrepancy continues in the last wave, with above-the-median respondents experiencing a significant decrease of four percentage points, almost four times the size of the below-the-median respondents. These differences are still visible, although less precisely estimated, when looking at Figure 18. Tables A-6 and A-7 confirm these results using the specification of Equation 6 restricting the pre-event sample to different time windows.

5 Conclusion

I leverage the timing of the events of January 6 to study how they have affected politicians' narratives, voters' attitudes, and how the two are linked.

I first describe partisan differences in communication strategies along different dimensions. After the attack, Republicans post overall less than Democrats. However, when they do so, they focus on capitol relatively more. There are incentives to propose competing narratives. Democrats follow a double the blame strategy, while Republicans try to mitigate the damage. On the other side, Democratic (Republican) users engage more (less) with tweets discussing capitol. The fact that this pattern does not extend to other content suggest that their reaction is primarily driven by motivated reasoning. I then test for the presence of an accountability channel using stated preferences in a large survey. Republicans attitudes towards Trump worsen after January 6. I show that this heavily depends on the interpretation of the event, as the decrease in favorability is much more pronounced for Republicans believing that Biden won the election or Republicans coming from districts with higher civic capitol.

By focusing on both sides of the political equilibrium, these results paint a highly con-

[6] The results are unchanged if I use the continuous measure of civic capital and interact it with wave FE in a continuous difference-in-difference specification.

sistent picture of the aftermath of an essential part of contemporary American politics. Politicians offered competing narratives to rationalize the event. Since the scandal regarded only Republicans, Democrats reacted mostly through motivated reasoning, while Republicans displayed evidence of both motivated reasoning and a sizeable but short-lived worsening of their attitudes towards Trump. This paper's findings suggests that partisan belief divergence may mostly happen in the long run, as *i)* repeated interactions with persuading actors such as politicians or the media and *ii)* decreasing salience of the scandal slowly realign partisans with their priors. Simply, there is now a new controversial issue to argue about.

References

Aina, C. (2021). Tailored stories. Technical report, Mimeo.

Alesina, A., A. Miano, and S. Stantcheva (2020). The polarization of reality. In *AEA Papers and Proceedings*, Volume 110, pp. 324–328. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Anderson, J. and K. D. Coduto (2022). Attitudinal and emotional reactions to the insurrection at the us capitol on january 6, 2021. *American Behavioral Scientist*, 00027642221132796.

Antypas, D., A. Preece, and J. Camacho-Collados (2023). Negativity spreads faster: A large-scale multilingual twitter analysis on the role of sentiment in political communication. *Online Social Networks and Media 33*, 100242.

Aridor, G., R. Jiménez-Durán, R. Levy, and L. Song (2024). The economics of social media.

Ash, E., G. Gauthier, and P. Widmer (2024). Relatio: Text semantics capture political and economic narratives. *Political Analysis 32*(1), 115–132.

Barberá, P., A. Casas, J. Nagler, P. J. Egan, R. Bonneau, J. T. Jost, and J. A. Tucker (2019). Who leads? who follows? measuring issue attention and agenda setting by legislators and the mass public using social media data. *American Political Science Review 113*(4), 883–901.

Baysan, C. (2022). Persistent polarizing effects of persuasion: Experimental evidence from turkey. *American Economic Review 112*(11), 3528–3546.

Beknazar-Yuzbashev, G., R. Jiménez Durán, J. McCrosky, and M. Stalinski (2022). Toxic content and user engagement on social media: Evidence from a field experiment. *Available at SSRN 4307346*.

Bénabou, R. and J. Tirole (2016). Mindful economics: The production, consumption, and value of beliefs. *Journal of Economic Perspectives 30*(3), 141–164.

Bhatt, P., N. Vemprala, R. Valecha, G. Hariharan, and H. R. Rao (2023). Great divisions: The evolution of polarization during the man-made emergency of january 6, 2021.

Bordalo, P., M. Tabellini, and D. Y. Yang (2020). Issue salience and political stereotypes. Technical report, National Bureau of Economic Research.

Daily Kos Elections (2020). Election results by congress district. https://docs.google.com/spreadsheets/d/1XbUXnI9OyfAuhP5P3vWtMuGc5UJlrhXbzZo3AwMuHtk/edit#gid=0.

D'Amico, L. and G. Tabellini (2022). Disengaging from reality: Online behavior and unpleasant political news. *Available at SSRN 4305223*.

Djourelova, M. and R. Durante (2022). Media attention and strategic timing in politics: Evidence from us presidential executive orders. *American Journal of Political Science 66*(4), 813–834.

Djourelova, M., R. Durante, E. Motte, and E. Patacchini (2023). Experience, narratives, and climate change beliefs. *Available at SSRN 4680430*.

Eady, G., F. Hjorth, and P. T. Dinesen (2021). Do violent protests affect expressions of party identity? evidence from the capitol insurrection. *American Political Science Review*, 1–7.

Eliaz, K. and R. Spiegler (2020). A model of competing narratives. *American Economic Review 110*(12), 3786–3816.

Enke, B. (2020). Moral values and voting. *Journal of Political Economy 128*(10), 3679–3729.

Enos, R. D., A. R. Kaufman, and M. L. Sands (2019). Can violent protest change local policy support? evidence from the aftermath of the 1992 los angeles riot. *American Political Science Review 113*(4), 1012–1028.

Eshima, S., K. Imai, and T. Sasaki (2024). Keyword-assisted topic models. *American Journal of Political Science 68*(2), 730–750.

Ferrara, A., P. A. Testa, L. Zhou, et al. (2021). New area-and population-based geographic crosswalks for us counties and congressional districts, 1790-2020.

Gethin, A. and V. Pons (2024). Social movements and public opinion in the united states. Technical report, National Bureau of Economic Research.

Hartig, H. (2021). In their own words: How americans reacted to the rioting at the us capitol.

Holliday, D., T. Reny, A. R. Hayes, A. Rudkin, C. Tausanovitch, and L. Vavreck (2021). Democracy fund+ ucla nationscape methodology and representativeness assessment.

Hutto, C. and E. Gilbert (2014). Vader: A parsimonious rule-based model for sentiment analysis of social media text. In *Proceedings of the international AAAI conference on web and social media*, Volume 8, pp. 216–225.

Kaplan, E., J. L. Spenkuch, and H. Yuan (2019). Natural disasters, moral hazard, and special interests in congress. In *Moral Hazard, and Special Interests in Congress (September 2019)*.

Lewandowsky, S., M. Jetter, and U. K. Ecker (2020). Using the president's tweets to understand political diversion in the age of social media. *Nature communications 11*(1), 5764.

Müller, K. and C. Schwarz (2023). The effects of online content moderation: Evidence from president trump's account deletion. *Available at SSRN 4296306*.

Nannicini, T., A. Stella, G. Tabellini, and U. Troiano (2013). Social capital and political accountability. *American Economic Journal: Economic Policy 5*(2), 222–250.

Pfeufer, C. M. (2022). Essays in empirical political economics.

Przeworski, A. (2015). Acquiring the habit of changing governments through elections. *Comparative Political Studies 48*(1), 101–129.

Ruggles, S., S. Flood, M. Sobek, D. Brockman, G. Cooper, S. Richards, and M. Schouweiler (2023). Ipums usa: Version 13.0 [dataset]. minneapolis, mn: Ipums. https://doi.org/10.18128/D010.V13.0.

Rupasingha, A., S. J. Goetz, and D. Freshwater (2006). The production of social capital in us counties. *The journal of socio-economics 35*(1), 83–101.

Social Capital Project (2018). The geography of social capital in america. scp report no. 1-18. https://www.jec.senate.gov/public/index.cfm/republicans/sci/.

Sonin, K., D. Van Dijcke, and A. L. Wright (2023). Isolation and insurrection: How partisanship and political geography fueled january 6, 2021. *University of Chicago, Becker Friedman Institute for Economics Working Paper* (2021-13).

Wasow, O. (2020). Agenda seeding: How 1960s black protests moved elites, public opinion and voting. *American Political Science Review 114*(3), 638–659.

Table 1: Summary statistics for Twitter data

	N	Mean	SD	Min	Max
Democratic users	224				
Tweets per Democratic user		256.089	186.006	9.000	1459.000
Republican users	190				
Tweets per Republican user		153.289	185.767	1.000	1771.000
Number of words in tweet	86745	19.244	8.713	1.000	80.000
Share after January 5		0.375			
Share mentioning capitol		0.043			
Sentiment	86745	0.098	0.680	-0.943	0.986
Sentiment in capitol tweets	86745	-0.006	0.148	-0.930	0.980

TABLE 2: SUMMARY STATISTICS OF NATIONSCAPE

	Wave								
	11-18Nov	19-25Nov	26Nov-2Dec	3-9Dec	10-16Dec	17-23Dec	23-30Dec	12-15Jan	21Jan-3Feb
Panel A: Republicans									
Demographics									
Male	0.585	0.563	0.529	0.532	0.605	0.521	0.491	0.555	0.509
Employed	0.547	0.575	0.577	0.523	0.524	0.530	0.576	0.494	0.510
Age	46.354	47.667	46.998	49.979	49.213	51.115	49.110	51.270	50.286
White	0.877	0.875	0.909	0.904	0.887	0.899	0.884	0.893	0.879
Black	0.034	0.044	0.029	0.028	0.040	0.041	0.044	0.035	0.040
Income $<$ 25 K	0.293	0.247	0.263	0.242	0.263	0.250	0.236	0.237	0.253
Income $\leq$ 25K $<$ 75K	0.373	0.418	0.402	0.414	0.410	0.431	0.418	0.415	0.416
Income $\geq$ 75K	0.333	0.335	0.336	0.343	0.327	0.319	0.346	0.349	0.331
College	0.634	0.653	0.640	0.679	0.670	0.658	0.658	0.687	0.572
Ideology									
Liberal	0.088	0.108	0.086	0.081	0.094	0.071	0.076	0.067	0.074
Moderate	0.280	0.268	0.273	0.257	0.240	0.241	0.244	0.250	0.240
Conservative	0.656	0.642	0.665	0.678	0.684	0.701	0.694	0.692	0.702
Believes in election fraud	0.640	0.658	0.640	0.635	0.657	0.641	0.641	0.666	0.640
Seen the NYT last week	0.275	0.278	0.253	0.257	0.242	0.241	0.259	0.217	0.227
Seen Fox News last week	0.622	0.580	0.576	0.563	0.550	0.522	0.557	0.554	0.536
N	1838	1458	2232	1734	1861	1942	1919	1224	3049
Panel B: Democrats									
Demographics									
Male	0.628	0.595	0.597	0.624	0.639	0.596	0.615	0.635	0.576
Employed	0.583	0.598	0.596	0.560	0.559	0.562	0.589	0.560	0.555
Age	42.645	42.957	43.785	44.620	45.149	45.676	44.187	46.286	45.366
White	0.660	0.675	0.688	0.680	0.674	0.657	0.667	0.665	0.644
Black	0.195	0.199	0.194	0.187	0.204	0.204	0.189	0.213	0.205
Income $<$ 25 K	0.332	0.302	0.299	0.295	0.307	0.281	0.271	0.311	0.306
Income $\leq$ 25K $<$ 75K	0.353	0.352	0.367	0.371	0.359	0.379	0.387	0.369	0.353
Income $\geq$ 75K	0.315	0.346	0.335	0.334	0.334	0.340	0.342	0.320	0.341
College	0.667	0.694	0.698	0.686	0.716	0.717	0.714	0.707	0.621
Ideology									
Liberal	0.551	0.565	0.550	0.552	0.547	0.538	0.569	0.533	0.549
Moderate	0.360	0.337	0.355	0.354	0.340	0.364	0.351	0.357	0.357
Conservative	0.143	0.155	0.148	0.135	0.163	0.141	0.120	0.143	0.136
Believes in election fraud	0.046	0.045	0.042	0.048	0.053	0.045	0.049	0.047	0.058
Seen the NYT last week	0.435	0.467	0.433	0.415	0.418	0.424	0.427	0.371	0.393
Seen Fox News last week	0.469	0.445	0.392	0.371	0.383	0.362	0.362	0.371	0.374
N	2253	1956	2608	2124	2473	2481	2583	1654	3752

TABLE 3: MOST FREQUENT NARRATIVES AFTER 6TH OF JANUARY, BY PARTY

	Democratic Party		*Republican Party*	
Rank	Narrative	Frequency	Narrative	Frequency
1	penny invoke th amendment	72	open paycheckprotection program	40
2	fbi try washington dc	58	ustreasury announce paycheck protection program	22
3	trump incite capitol	50	hate attract hate	19
4	cabinet invoke th amendment	48	legislation stop legislation	18
5	individual incite violence	43	darkness attract darkness	18
6	senate convict donald trump	40	god sign america	18
7	senate support democracy	36	legislation break legislation	18
8	violence attack capitol	36	congress continue bill	17
9	trump incite violence	32	new radical left need change	17
10	president incite violence	32	colleague sign republican study	17

Notes: this table reports the most common low-dimensional and complete narratives extracted by `RELATIO` using 100 clusters and estimating it separately for Democrats and Republicans only on tweets posted after January 5.

TABLE 4: CAPITOL AND SENTIMENT: PARTISAN DIFFERENCES

	Dependent variable: compound score			
	(1)	(2)	(3)	(4)
Panel A: Before 6 Jan				
Democrat	-0.013	-0.008		
	(0.041)	(0.041)		
$\mathbf{1}$(capitol $\in$ tweet)	0.146*	0.149**	0.155**	0.147**
	(0.075)	(0.074)	(0.061)	(0.064)
Democrat $\times$ $\mathbf{1}$(capitol $\in$ tweet)	0.073	0.071	0.073	0.084
	(0.093)	(0.093)	(0.078)	(0.081)
Chamber FE		✓		
Individual FE			✓	✓
Day FE				✓
Observations	54051	54051	54048	54048
Adj. R^2	0.001	0.001	0.136	0.168
$\mathbb{E}$(Dependent variable)	0.124	0.124	0.124	0.124
Dependent variable std. dev.	0.684	0.684	0.684	0.684
Panel B: After 6 Jan				
Democrat	0.094***	0.104***		
	(0.033)	(0.033)		
$\mathbf{1}$(capitol $\in$ tweet)	0.084**	0.089**	0.052	0.188***
	(0.040)	(0.039)	(0.034)	(0.031)
Democrat $\times$ $\mathbf{1}$(capitol $\in$ tweet)	-0.496***	-0.497***	-0.421***	-0.421***
	(0.045)	(0.045)	(0.039)	(0.035)
Chamber FE		✓		
Individual FE			✓	✓
Day FE				✓
Observations	32278	32278	32275	32275
Adj. R^2	0.030	0.032	0.128	0.190
$\mathbb{E}$(Dependent variable)	0.036	0.036	0.036	0.036
Dependent variable std. dev.	0.679	0.679	0.679	0.679

Notes: this table reports estimates where the unit of observation is a tweet. Chamber FE refers to the chamber the Member of Congress belongs to. Errors are clustered at the individual level. *** **, and * indicate significance at the 1, 5, and 10 percent levels.

TABLE 5: CAPITOL AND POPULARITY

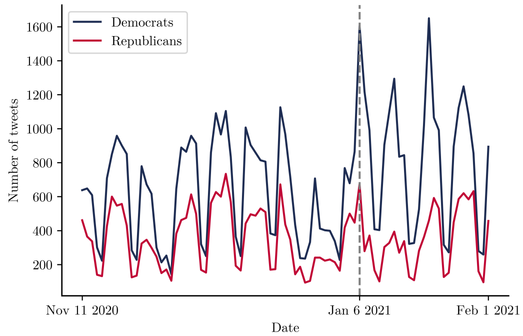
	Likes		Retweets	
	(1)	(2)	(3)	(4)
Panel A: Before 6 Jan				
$\mathbf{1}$(capitol $\in$ tweet)	-821.814	-953.690	-148.119	-171.798
	(531.224)	(644.849)	(107.687)	(106.747)
Republican $\times$ $\mathbf{1}$(capitol $\in$ tweet)	551.416	644.127	99.904	115.692
	(913.266)	(714.692)	(122.293)	(121.842)
Individual FE	✓	✓	✓	✓
Hour of the day FE	✓	✓	✓	✓
Day FE		✓		✓
Observations	32154	32154	32154	32154
Adj. R^2	0.273	0.273	0.228	0.232
$\mathbb{E}$(Dependent variable)	1045.511	1045.511	184.036	184.036
Dependent variable std. dev.	6196.444	6196.444	1125.166	1125.166
Panel B: After 6 Jan				
$\mathbf{1}$(capitol $\in$ tweet)	942.925**	431.941	189.492**	111.274
	(473.761)	(481.979)	(89.489)	(89.941)
Republican $\times$ $\mathbf{1}$(capitol $\in$ tweet)	-865.553	-796.243	-222.604**	-200.177**
	(533.696)	(492.561)	(105.197)	(97.129)
Individual FE	✓	✓	✓	✓
Hour of the day FE	✓	✓	✓	✓
Day FE		✓		✓
Observations	19208	19208	19208	19208
Adj. R^2	0.182	0.182	0.175	0.179
$\mathbb{E}$(Dependent variable)	1619.524	1619.524	287.024	287.024
Dependent variable std. dev.	9771.391	9771.391	1686.288	1686.288

Notes: this table reports estimates where the unit of observation is a tweet. Errors are clustered at the individual level. *** **, and * indicate significance at the 1, 5, and 10 percent levels.

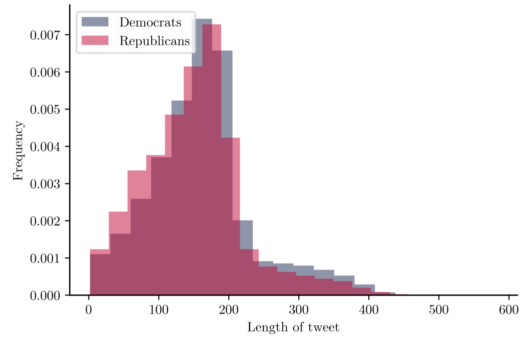
TABLE 6: CAPITOL AND POPULARITY: DIFFERENT STRATEGIES PAYING OFF?

	Likes		Retweets	
	(1)	(2)	(3)	(4)
Panel A: Republicans				
1(capitol ∈ tweet)	336.533	250.891	16.746	6.656
	(235.716)	(268.095)	(34.236)	(44.677)
Negative sentiment	867.220***	803.063***	265.572***	255.898***
	(182.501)	(178.177)	(52.293)	(49.776)
Negative sentiment × **1**(capitol ∈ tweet)	-596.852	-527.791	-127.449	-99.735
	(450.837)	(436.927)	(111.422)	(96.407)
Individual FE	✓	✓	✓	✓
Hour of the day FE	✓	✓	✓	✓
Day FE		✓		✓
Observations	5586	5586	5586	5586
Adj. R^2	0.294	0.294	0.271	0.274
$\mathbb{E}$(Dependent variable)	1784.793	1784.793	366.596	366.596
Dependent variable std. dev.	8228.140	8228.140	1671.322	1671.322
Panel B: Democrats				
1(capitol ∈ tweet)	597.073*	-125.471	58.774	-57.574
	(304.215)	(378.157)	(42.021)	(56.917)
Negative sentiment	1099.928***	847.249***	229.277***	189.095***
	(224.571)	(199.156)	(42.594)	(37.304)
Negative sentiment × **1**(capitol ∈ tweet)	495.560	681.594	202.980	233.016*
	(598.378)	(593.967)	(125.120)	(124.939)
Individual FE	✓	✓	✓	✓
Hour of the day FE	✓	✓	✓	✓
Day FE		✓		✓
Observations	13622	13622	13622	13622
Adj. R^2	0.155	0.155	0.138	0.143
$\mathbb{E}$(Dependent variable)	1551.751	1551.751	254.394	254.394
Dependent variable std. dev.	1.0e+04	1.0e+04	1691.367	1691.367

Notes: this table reports estimates where the unit of observation is a tweet. Errors are clustered at the individual level. *** **, and * indicate significance at the 1, 5, and 10 percent levels.



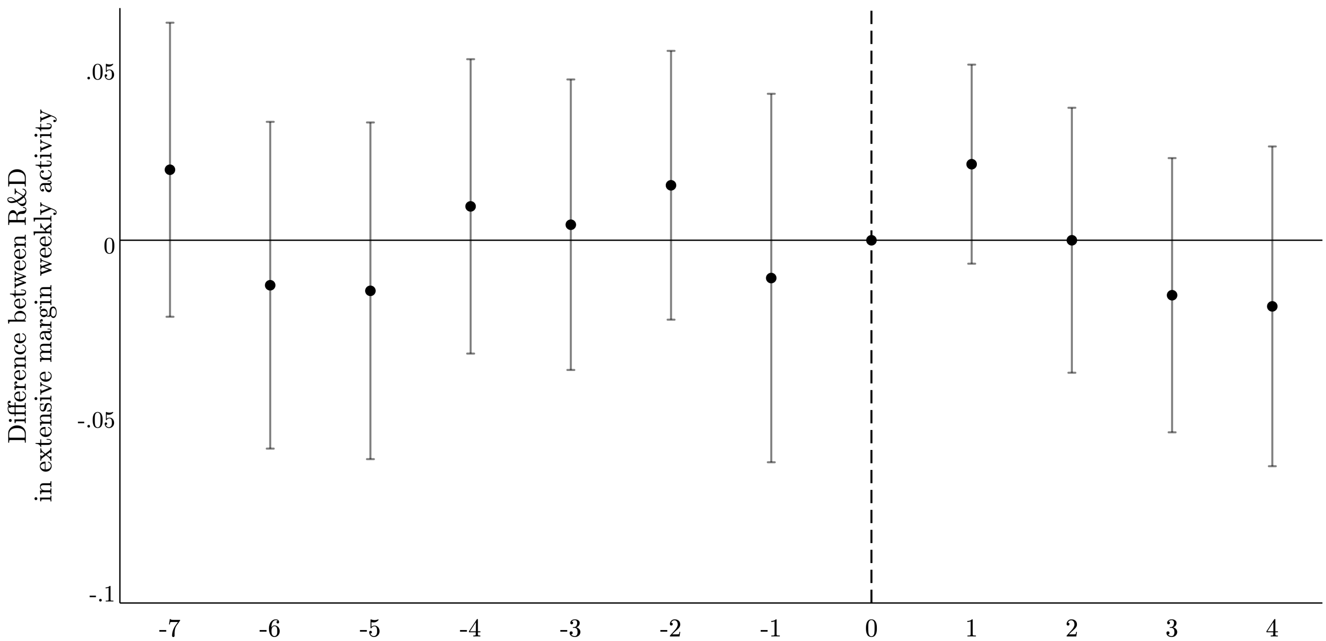
(A) NUMBER OF TWEETS



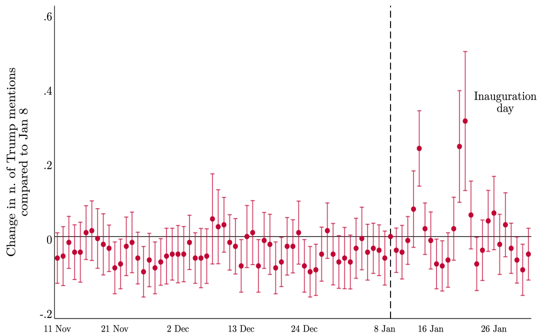
(B) LENGTH OF TWEETS

FIGURE 6: TWEETS BY PARTY

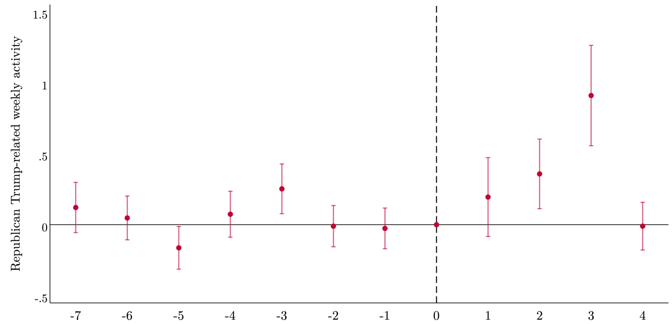
FIGURE 7: JANUARY 6 AND ACTIVITY ON THE EXTENSIVE MARGIN



Notes: The figure reports point estimates and 95% robust confidence intervals for the β_τ in Equation 1. The outcome is an indicator equal to one if individual i has tweeted in that week t. Errors are clustered at the individual level.



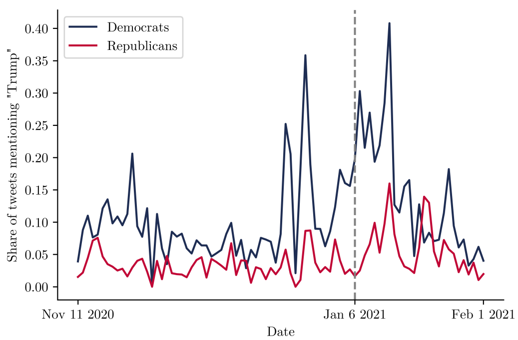
(A) DAY LEVEL



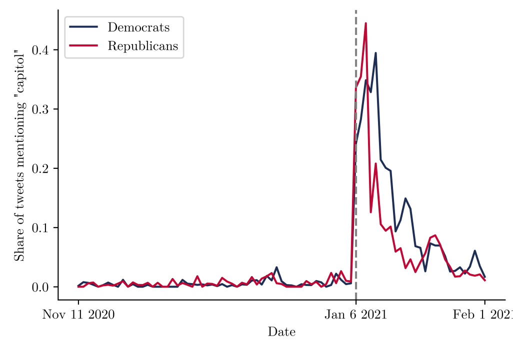
(B) WEEK LEVEL

FIGURE 8: ACTIVITY ANALYSIS: MENTIONING TRUMP AFTER JANUARY 8

Notes: The left panel reports point estimates and 95% robust confidence intervals for β_τ in Equation 1 estimated at the day level, using January 5 as baseline. The right reports point estimates and 95% robust confidence intervals for the β_τ in Equation 1. The outcome is the number of tweets mentioning Trump in that day (left) or week (right). Errors are clustered at the individual level.



(A) TRUMP



(B) CAPITOL

FIGURE 9: SHARE OF TWEETS MENTIONING EACH WORD BY PARTY

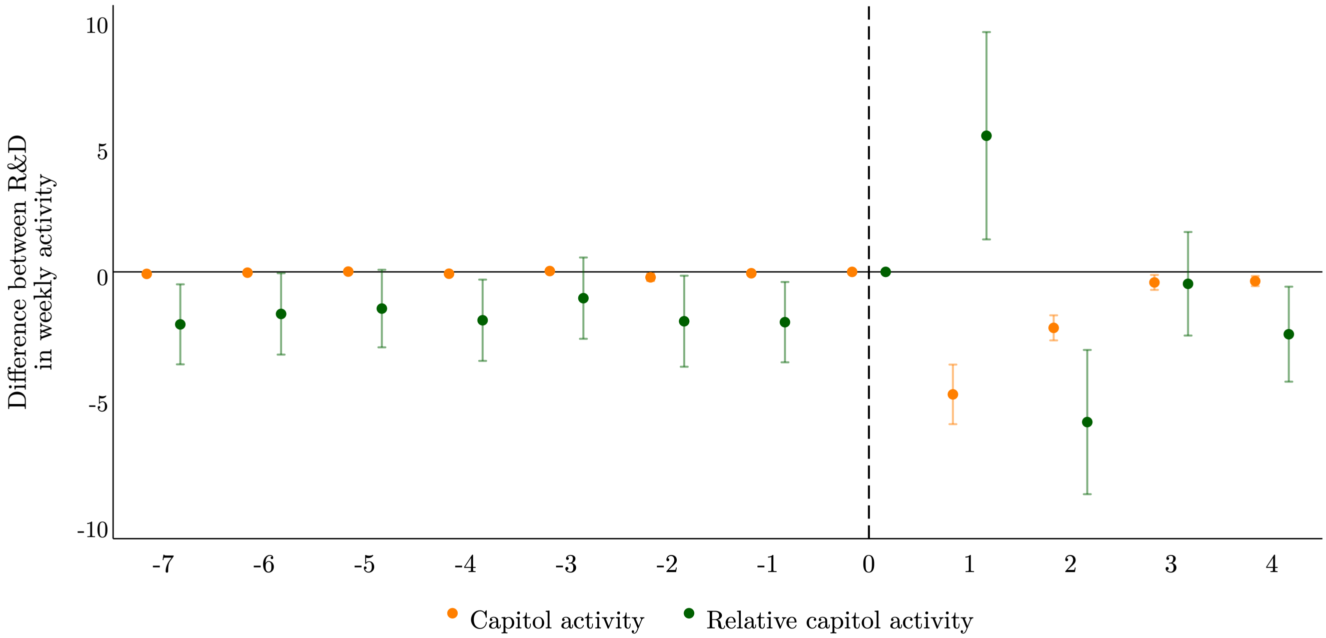
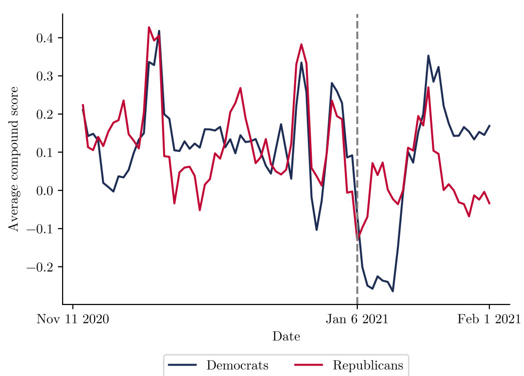
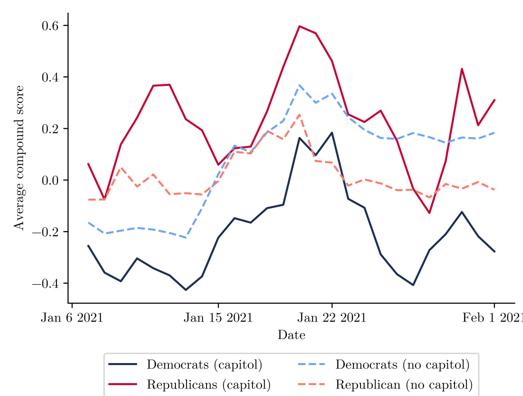


FIGURE 10: CAPITOL-RELATED ACTIVITY ANALYSIS

Notes: The orange dots report point estimates and 95% robust confidence intervals for β_τ in Equation 1 using as an outcome the number of tweets mentioning capitol in that week. The green dots report point estimates and 95% robust confidence intervals for the β_τ in Equation 1 using as an outcome the share of tweets of that week mentioning capitol. Errors are clustered at the individual level.

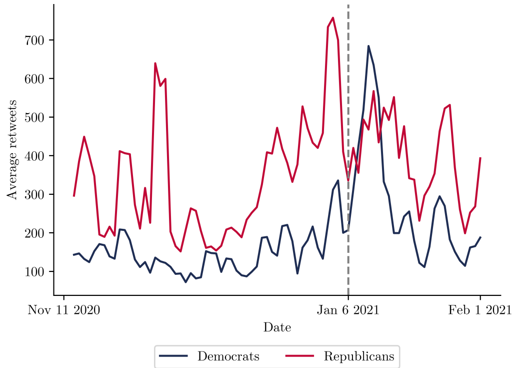


(A) OVER THE WHOLE PERIOD

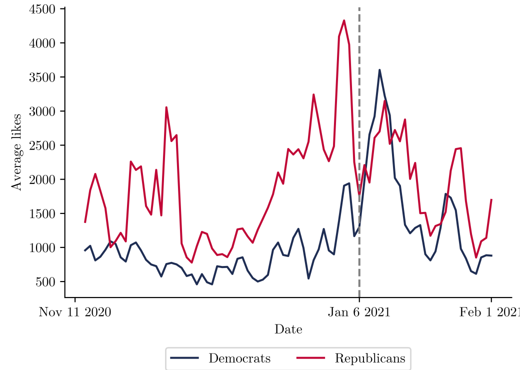


(B) CAPITOL AND NON-CAPITOL

FIGURE 11: EVOLUTION OF COMPOUND SCORE BY PARTY

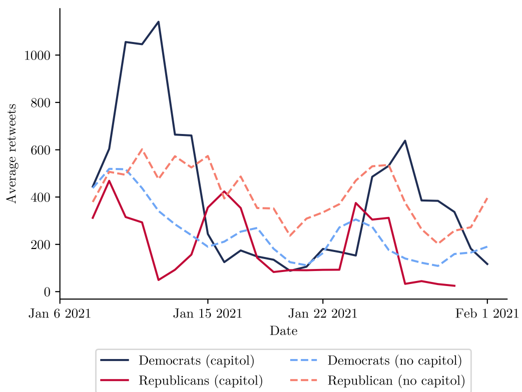


(A) DAILY AVERAGE OF RETWEETS

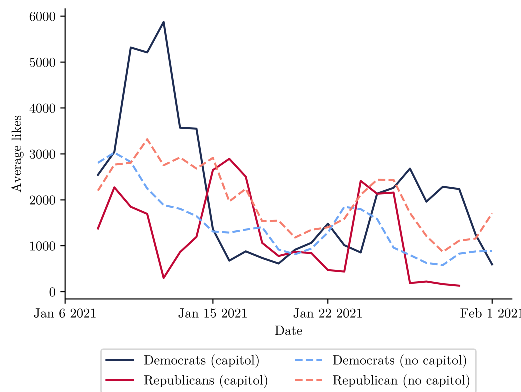


(B) DAILY AVERAGE OF LIKES

FIGURE 12: MEASURES OF POPULARITY BY DAY BY PARTY



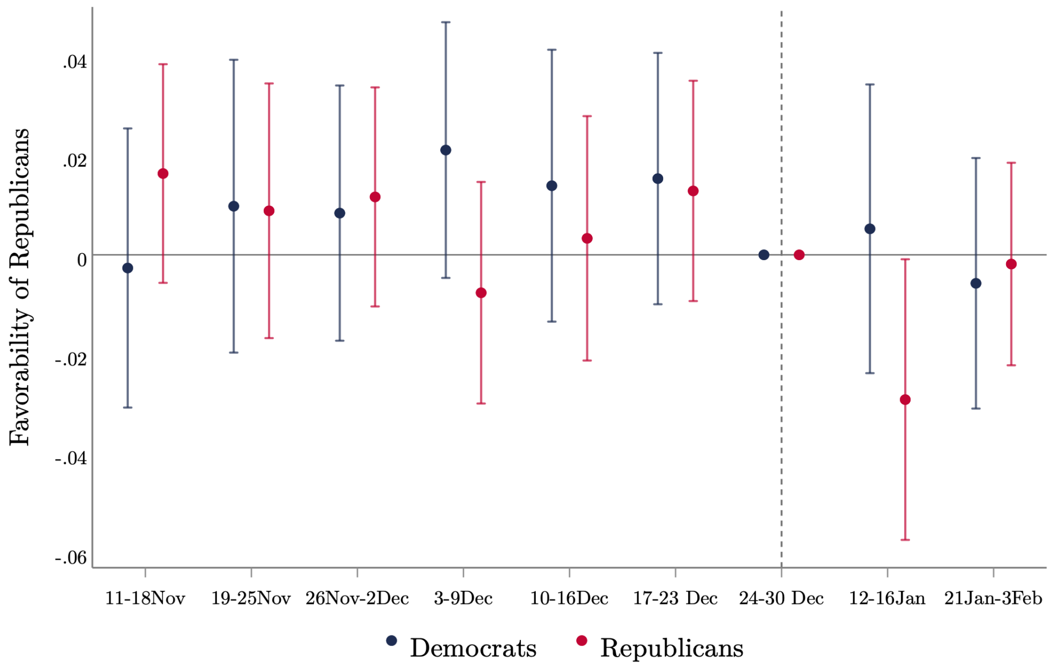
(A) MOVING AVERAGE OF RETWEETS BY TOPIC



(B) MOVING AVERAGE OF LIKES BY TOPIC

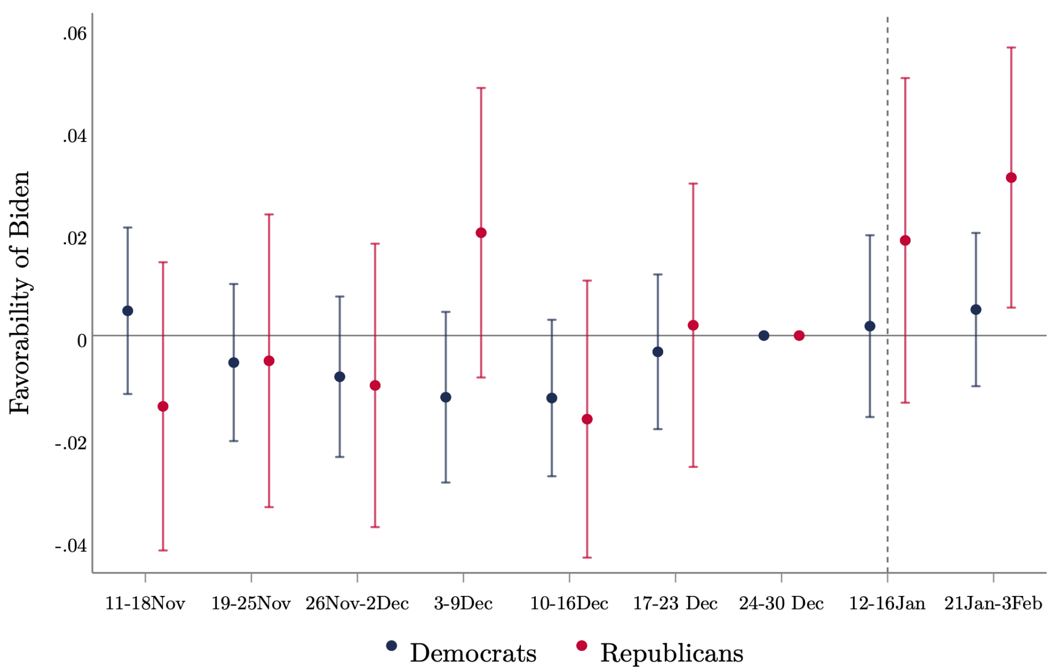
FIGURE 13: MEASURES OF POPULARITY BY DAY BY PARTY BY CAPITOL

FIGURE 14: JANUARY 6 AND REPUBLICAN'S FAVORABILITY

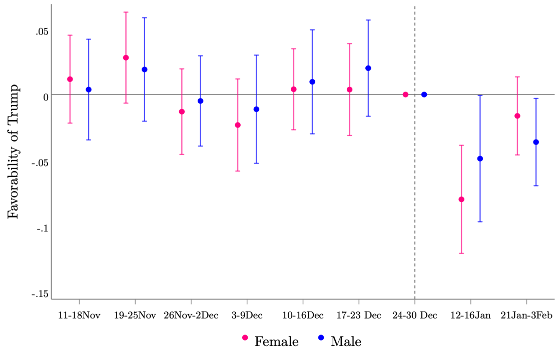


Notes: The figure reports point estimates and 95% robust confidence intervals for the β_τ in Equation 5. The outcome is a dummy equal to one if the respondent has a very favorable or somewhat favorable impression of Republicans, 0 otherwise. Respondents saying that they have not heard enough about Republicans are dropped from the sample.

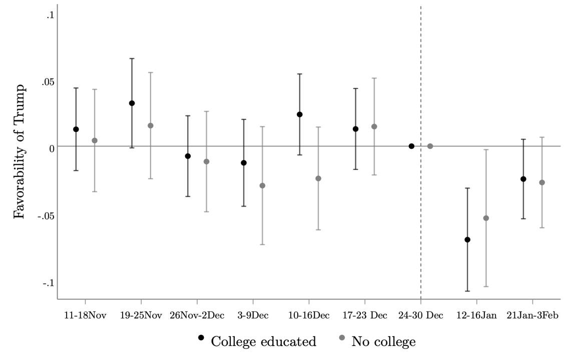
FIGURE 15: JANUARY 6 AND BIDEN'S FAVORABILITY



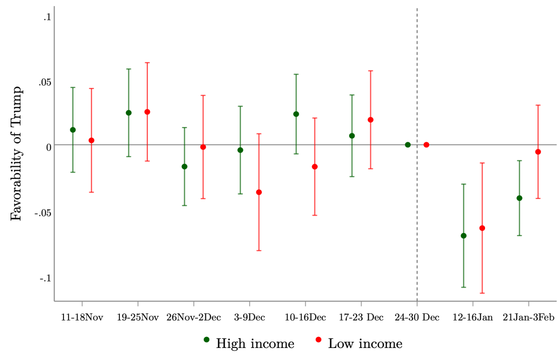
Notes: The figure reports point estimates and 95% robust confidence intervals for the β_τ in Equation 5. The outcome is a dummy equal to one if the respondent has a very favorable or somewhat favorable impression of Biden, 0 otherwise. Respondents saying that they have not heard enough about Biden are dropped from the sample.



(A) BY GENDER



(B) BY EDUCATION

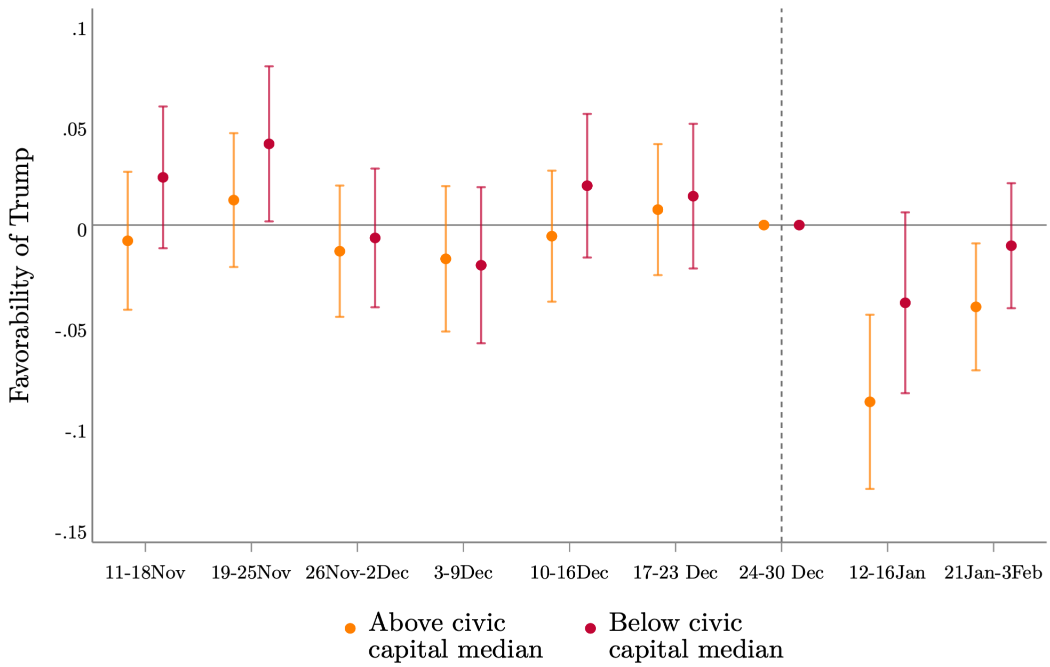


(C) BY INCOME

FIGURE 16: TRUMP FAVORABILITY AMONG REPUBLICANS AND DEMOGRAPHIC HETEROGENEITIES

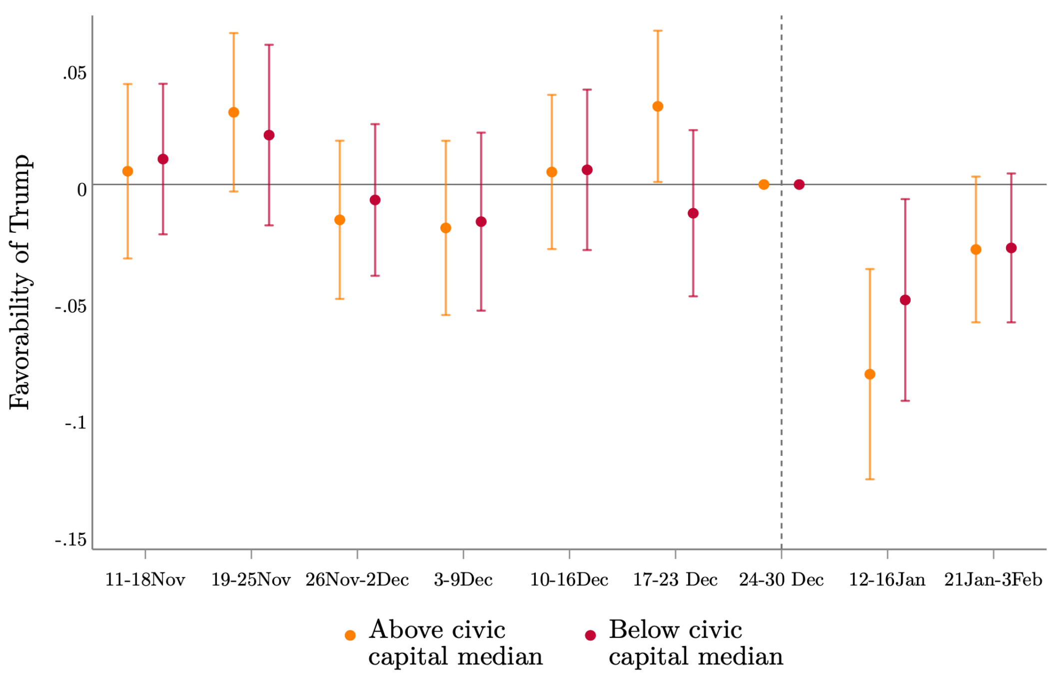
Notes: The figure reports point estimates and 95% robust confidence intervals for the β_τ in Equation 5 estimated only for Republican respondents split by the demographic characteristic in the relevant graph. Respondents are classified as high-income if they report income higher than the median and low-income if they report income below the median. See Figure 4 for a description of the outcome.

Figure 17: Civic capital I and Trump favorability



Notes: The figure reports point estimates and 95% robust confidence intervals for the β_τ in Equation 5. Respondents are classified as above the median civic capital if they report coming from a congress district whose level of civic capital (as measured in Social Capital Project (2018)) is higher than the national median. See Figure 4 for a description of the outcome.

Figure 18: Civic capital II and Trump favorability



Notes: The figure reports point estimates and 95% robust confidence intervals for the β_τ in Equation 5. Respondents are classified as above the median civic capital if they report coming from a congress district whose level of civic capital (as measured in Rupasingha et al. (2006)) is higher than the national median. See Figure 4 for a description of the outcome.

APPENDIX for

"The Short-Run Consequences of January 6" by Alberto Binetti

A-1 Additional Tables and Figures

TABLE A-1: OVERALL ENGAGEMENT AFTER JANUARY 6

	Likes		Retweets	
	(1)	(2)	(3)	(4)
Panel A: Full sample				
Democrat × After January 6	272.946	175.633	-8.374	-24.909
	(318.034)	(320.165)	(62.994)	(63.755)
Individual FE	✓	✓	✓	✓
Hour of the day FE	✓	✓	✓	✓
Day FE		✓		✓
Observations	51365	51365	51365	51365
Adj. R^2	0.203	0.203	0.182	0.187
$\mathbb{E}$(Dependent variable)	1261.123	1261.123	222.692	222.692
Dependent variable std. dev.	7736.383	7736.383	1363.457	1363.457
Panel B: Excluding capitol tweets				
Democrat × After January 6	95.989	9.235	-50.161	-63.065
	(308.906)	(312.516)	(63.856)	(64.932)
Individual FE	✓	✓	✓	✓
Hour of the day FE	✓	✓	✓	✓
Day FE		✓		✓
Observations	49226	49226	49226	49226
Adj. R^2	0.214	0.214	0.200	0.205
$\mathbb{E}$(Dependent variable)	1217.317	1217.317	214.314	214.314
Dependent variable std. dev.	7471.128	7471.128	1292.816	1292.816

Notes: this table reports estimates where the unit of observation is a tweet. Errors are clustered at the individual level. *** **, and * indicate significance at the 1, 5, and 10 percent levels.

TABLE A-2: OVERALL ENGAGEMENT AFTER JANUARY 8

	Likes		Retweets	
	(1)	(2)	(3)	(4)
Panel A: Full sample				
Democrat × After January 8	79.315	22.651	-39.650	-48.788
	(291.034)	(289.928)	(62.308)	(62.391)
Individual FE	✓	✓	✓	✓
Hour of the day FE	✓	✓	✓	✓
Day FE		✓		✓
Observations	51365	51365	51365	51365
Adj. R^2	0.203	0.203	0.181	0.187
$\mathbb{E}$(Dependent variable)	1261.123	1261.123	222.692	222.692
Dependent variable std. dev.	7736.383	7736.383	1363.457	1363.457
Panel B: Excluding capitol tweets				
Democrat × After January 8	-71.344	-96.832	-79.513	-82.896
	(289.325)	(293.508)	(63.866)	(64.832)
Individual FE	✓	✓	✓	✓
Hour of the day FE	✓	✓	✓	✓
Day FE		✓		✓
Observations	49226	49226	49226	49226
Adj. R^2	0.214	0.214	0.200	0.205
$\mathbb{E}$(Dependent variable)	1217.317	1217.317	214.314	214.314
Dependent variable std. dev.	7471.128	7471.128	1292.816	1292.816

Notes: this table reports estimates where the unit of observation is a tweet. Errors are clustered at the individual level. *** **, and * indicate significance at the 1, 5, and 10 percent levels.

TABLE A-3: PRE-POST RESULTS

	Dependent variable:					
	Favorability of					
	Trump			Republicans		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Republicans						
After	-0.041***	-0.044***	-0.037***	-0.017**	-0.014*	-0.008
	(0.008)	(0.009)	(0.011)	(0.006)	(0.007)	(0.010)
Observations	15540	9039	5630	15093	8769	5454
Adj. R^2	0.028	0.029	0.026	0.015	0.017	0.018
$\mathbb{E}$(Dependent variable)	0.828	0.823	0.810	0.869	0.865	0.859
Dependent variable std. dev.	0.377	0.381	0.393	0.338	0.341	0.348
Waves included	[-7,2]	[-2,2]	[0,2]	[-7,2]	[-2,2]	[0,2]
Panel B: Democrats						
After	-0.003	-0.008	-0.004	-0.012	-0.011	-0.003
	(0.006)	(0.007)	(0.010)	(0.007)	(0.009)	(0.012)
Observations	19349	11458	7105	18796	11125	6919
Adj. R^2	0.053	0.057	0.052	0.034	0.036	0.029
$\mathbb{E}$(Dependent variable)	0.137	0.137	0.134	0.246	0.242	0.236
Dependent variable std. dev.	0.344	0.344	0.341	0.430	0.428	0.425
Waves included	[-7,2]	[-2,2]	[0,2]	[-7,2]	[-2,2]	[0,2]

Notes: Errors are clustered at the Congress district level. Columns (1)-(3) report estimates of β from Equation 6 on Trump's favorability, while columns (4)-(6) on Republicans' favorability. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A-4: PRE-POST RESULTS AND BIDEN'S FAVORABILITY

	Dependent variable:		
	Favorability of Biden		
	(1)	(2)	(3)
Panel A: Republicans			
After	0.031***	0.030***	0.023*
	(0.008)	(0.009)	(0.012)
Observations	15420	8950	5562
Adj. R^2	0.068	0.067	0.052
$\mathbb{E}$(Dependent variable)	0.212	0.213	0.223
Dependent variable std. dev.	0.409	0.409	0.416
Waves included	[-7,2]	[-2,2]	[0,2]
Panel B: Democrats			
After	0.009*	0.009*	0.004
	(0.005)	(0.005)	(0.007)
Observations	19269	11399	7062
Adj. R^2	0.014	0.016	0.013
$\mathbb{E}$(Dependent variable)	0.918	0.921	0.924
Dependent variable std. dev.	0.274	0.270	0.265
Waves included	[-7,2]	[-2,2]	[0,2]

Notes: Errors are clustered at the Congress district level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A-5: PRE-POST RESULTS AND BELIEFS OF FRAUDULENT ELECTION

	Dependent variable: Favorability of Trump		
	(1)	(2)	(3)
Panel A: Believe in fraud			
After	-0.013**	-0.016**	-0.015*
	(0.006)	(0.006)	(0.009)
Observations	9737	5574	3368
Adj. R^2	0.024	0.028	0.023
$\mathbb{E}$(Dependent variable)	0.945	0.946	0.941
Dependent variable std. dev.	0.227	0.226	0.236
Waves included	[-7,2]	[-2,2]	[0,2]
Panel B: Don't believe in fraud			
After	-0.094***	-0.099***	-0.087***
	(0.016)	(0.018)	(0.023)
Observations	5346	3025	1833
Adj. R^2	0.030	0.027	0.025
$\mathbb{E}$(Dependent variable)	0.618	0.601	0.571
Dependent variable std. dev.	0.486	0.490	0.495
Waves included	[-7,2]	[-2,2]	[0,2]

Notes: Errors are clustered at the Congress district level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A-6: PRE-POST RESULTS AND CIVIC CAPITAL I

	Dependent variable:		
	Favorability of Trump		
	(1)	(2)	(3)
Panel A: Above civic capital median			
After	-0.051***	-0.057***	-0.056***
	(0.010)	(0.012)	(0.016)
Observations	8284	4834	3049
Adj. R^2	0.026	0.025	0.019
$\mathbb{E}$(Dependent variable)	0.831	0.825	0.809
Dependent variable std. dev.	0.375	0.380	0.393
Waves included	[-7,2]	[-2,2]	[0,2]
Panel B: Below civic capital median			
After	-0.027**	-0.027**	-0.015
	(0.011)	(0.012)	(0.016)
Observations	7141	4124	2538
Adj. R^2	0.034	0.038	0.039
$\mathbb{E}$(Dependent variable)	0.826	0.822	0.810
Dependent variable std. dev.	0.379	0.382	0.392
Waves included	[-7,2]	[-2,2]	[0,2]

Notes: Errors are clustered at the Congress district level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A-7: PRE-POST RESULTS AND CIVIC CAPITAL II

	Dependent variable:		
	Favorability of Trump		
	(1)	(2)	(3)
Panel A: Above civic capital median			
After	-0.048***	-0.058***	-0.044***
	(0.011)	(0.012)	(0.016)
Observations	8170	4770	2991
Adj. R^2	0.033	0.035	0.028
$\mathbb{E}$(Dependent variable)	0.828	0.825	0.807
Dependent variable std. dev.	0.377	0.380	0.394
Waves included	[-7,2]	[-2,2]	[0,2]
Panel B: Below civic capital median			
After	-0.032***	-0.029**	-0.031*
	(0.011)	(0.012)	(0.016)
Observations	7255	4188	2596
Adj. R^2	0.025	0.022	0.023
$\mathbb{E}$(Dependent variable)	0.829	0.822	0.813
Dependent variable std. dev.	0.377	0.383	0.390
Waves included	[-7,2]	[-2,2]	[0,2]

Notes: Errors are clustered at the Congress district level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

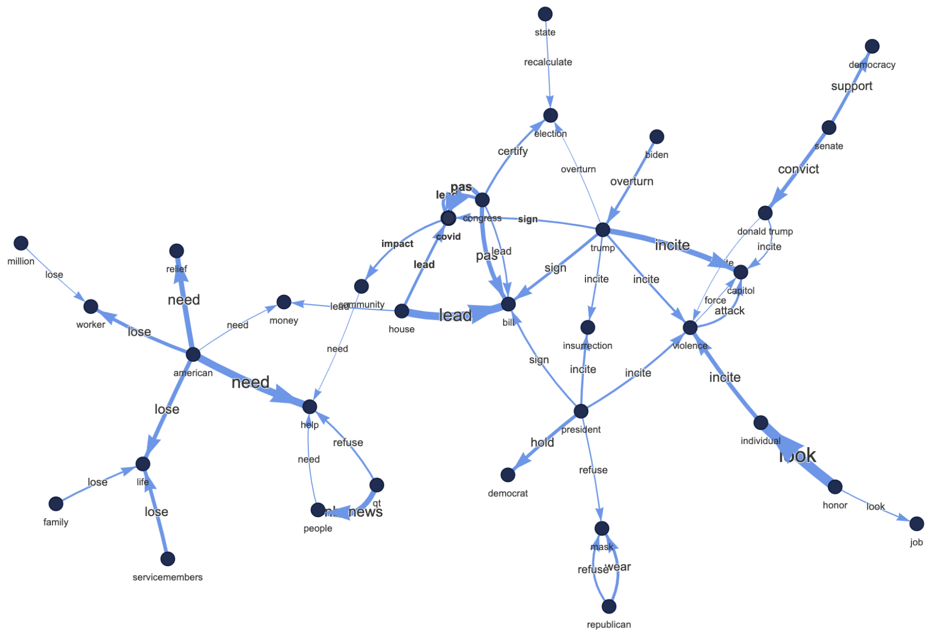


FIGURE A-1: DEMOCRATIC PARTY NARRATIVES OVER THE WHOLE PERIOD

Notes: The figure reports the top-50 low-dimensional and completes narratives estimated for Democrats on the whole sample. The number of clusters is set to its default value, 100. The network is pruned.

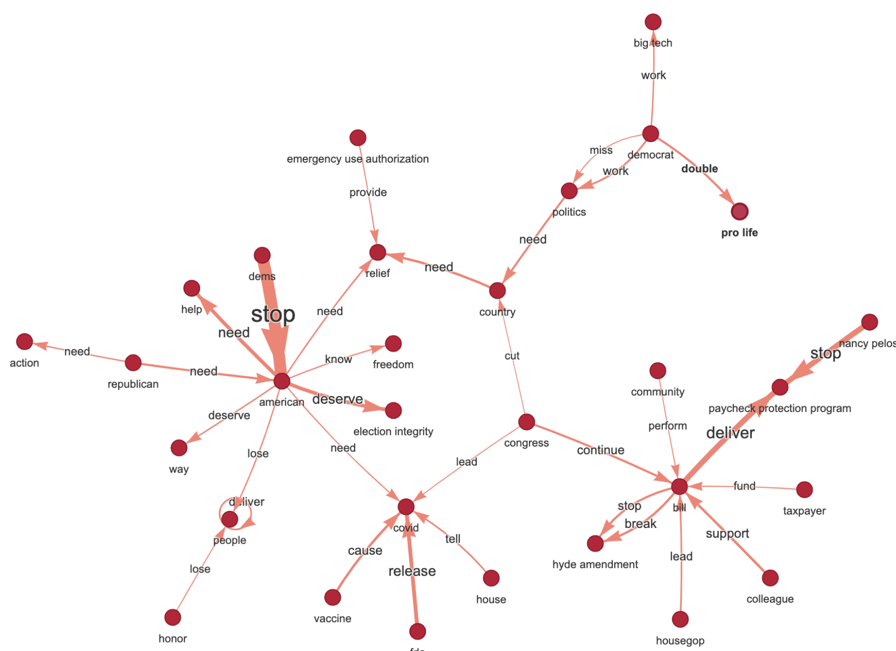


FIGURE A-2: REPUBLICAN PARTY NARRATIVES OVER THE WHOLE PERIOD

Notes: The figure reports the top-50 low-dimensional and completes narratives estimated for Republicans on the whole sample. The number of clusters is set to its default value, 100. The network is pruned.

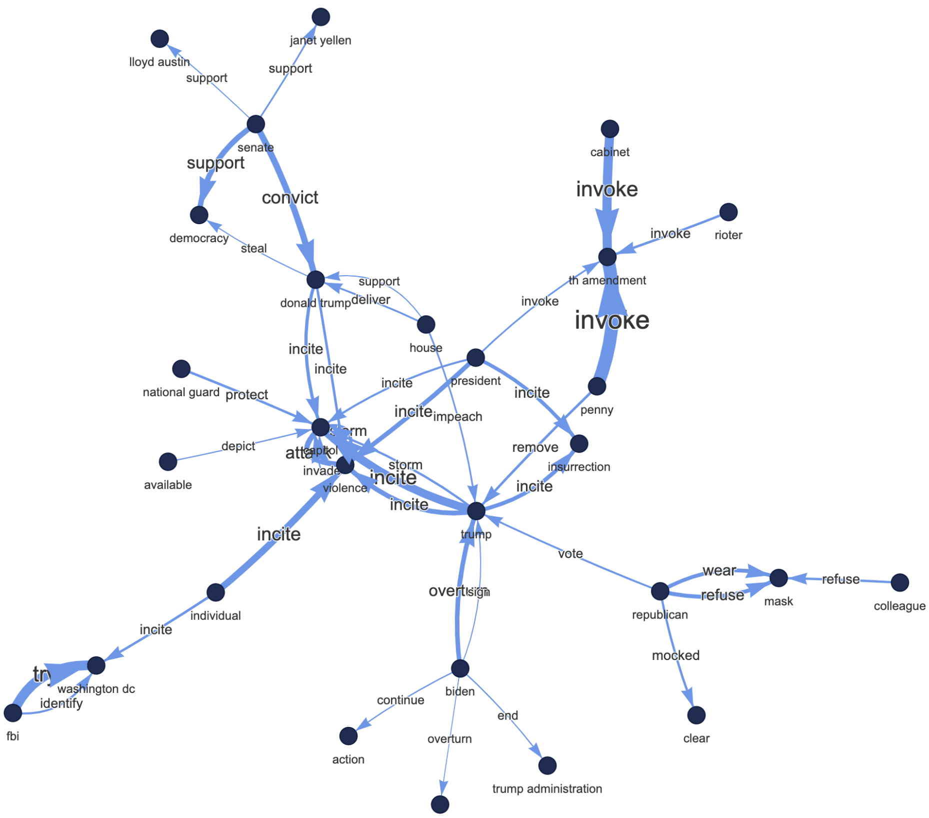


FIGURE A-3: DEMOCRATIC PARTY NARRATIVES AFTER JANUARY 6

Notes: The figure reports the top-50 low-dimensional and completes narratives estimated for Democrats on the tweets posted after January 5. The number of clusters is set to its default value, 100. The network is pruned.

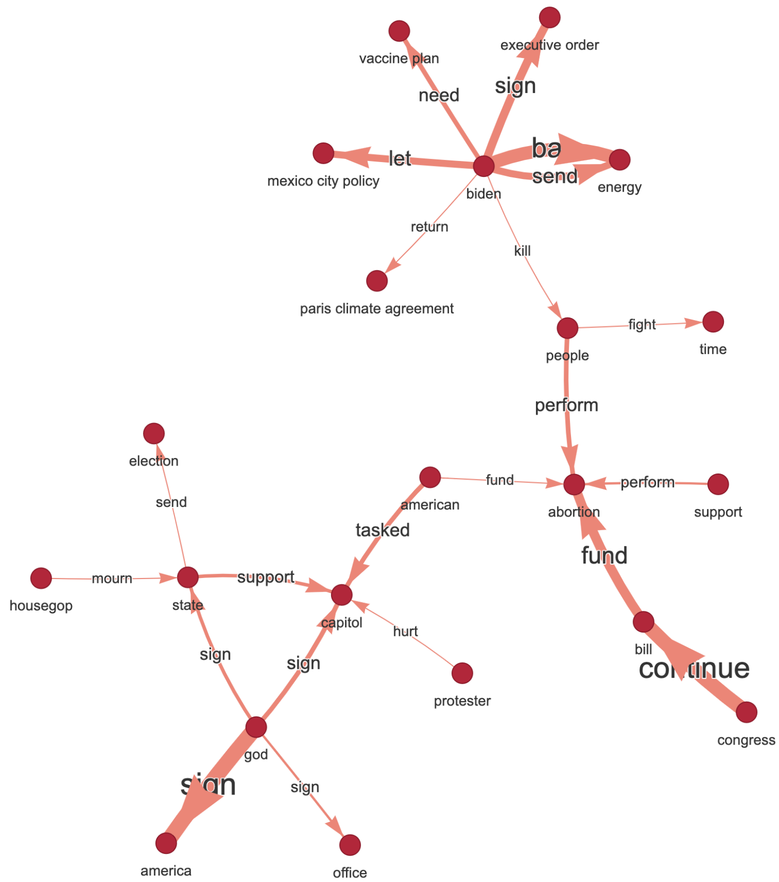


FIGURE A-4: REPUBLICAN PARTY NARRATIVES AFTER JANUARY 6

Notes: The figure reports the top-50 low-dimensional and completes narratives estimated for Republicans on the tweets posted after January 5. The number of clusters is set to its default value, 100. The network is pruned.

A-2 Differences between the two Twitter datasets

The dataset for the consumption analysis of Section 4.1 was obtained through Twitter's API only some days before Elon Musk closed it around early April 2023. As described in Section 2, it was obtained using the full-archive search functionality. However, the API query collected a maximum of 500 tweets per user and systematically excluded some. As a result, the consumption dataset is only a subsample of all tweets posted by Members of Congress during this time period, which is the main dataset for the politicians' analysis instead. As of now, academic access to Twitter data in the European Union is restricted to research about systemic and vital risk to the Union, which is outside the scope of this paper. As such, I'm unable to re-collect the data to obtain likes and tweets for the ≈

35k tweets not included in the consumption dataset. To understand how representative the results of the consumption analysis are, I compare the two datasets along different dimensions in Table A-8. The main difference seems to be in terms of activity, as those only in the *congresstweets* sample are on average less active than those in the consumption sample. Other than that, the samples are very much comparable in terms of number of words, share of tweets posted before the event, share of tweets mentioning capitol, sentiment, and sentiment in tweets mentioning capitol. Considering that the consumption analysis always includes individual FE, which absorb any time-invariant differences at the poster-level, these comparisons ensure the representativeness of the consumption analysis results.

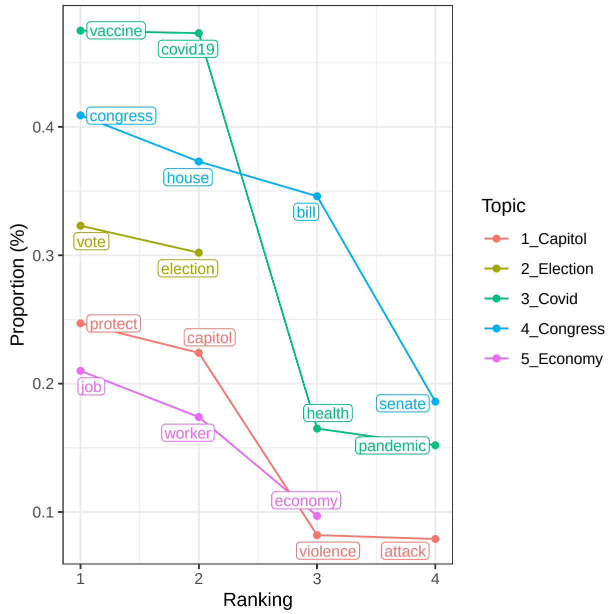
TABLE A-8: COMPARING THE TWO TWITTER DATASETS: SUMMARY STATISTICS

	N	Mean	SD	Min	Max
Panel A: Only *congresstweets*					
Democratic users	224				
Tweets per Democratic user		101.683	134.617	1.000	978.000
Republican users	185				
Tweets per Republican user		68.114	126.436	1.000	1271.000
Number of words in tweet	35378	21.220	9.932	1.000	80.000
Share after January 5		0.377			
Share mentioning capitol		0.046			
Sentiment	35378	0.062	0.669	-0.942	0.986
Sentiment in capitol tweets	35378	-0.009	0.149	-0.930	0.980
Panel B: Consumption sample					
Democratic users	174				
Tweets per Democratic user		197.972	111.465	5.000	500.000
Republican users	145				
Tweets per Republican user		113.959	104.213	1.000	500.000
Number of words in tweet	51367	17.884	7.464	1.000	51.000
Share after January 5		0.374			
Share mentioning capitol		0.042			
Sentiment	51367	0.122	0.687	-0.943	0.986
Sentiment in capitol tweets	51367	-0.005	0.148	-0.925	0.980

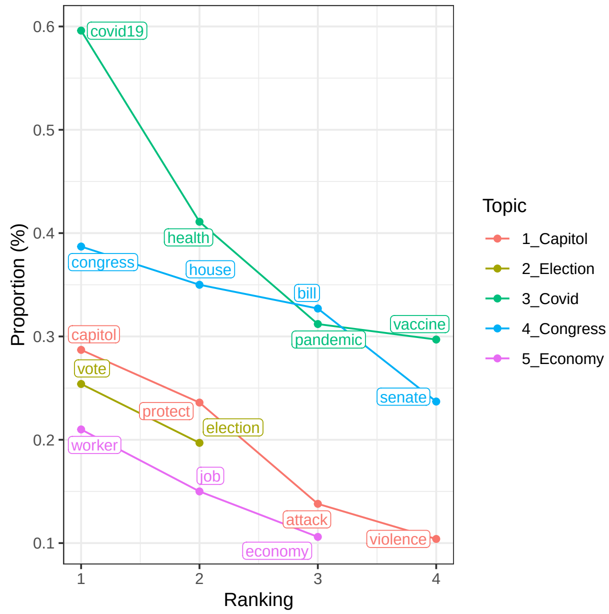
A-3 Dynamic evolution of topics

To complement the activity analysis focused on capitol-related tweets and the competing narratives approach extracted through `RELATIO`, I study the dynamic evolution of the discussion employing the semi-supervised dynamic topic model introduced in Eshima et al. (2024). This approach allows me to use the narratives extracted previously to choose some keyword assisted topics and leave instead the model unsupervised for the remaining topics, whose number must be chosen. I choose five key-word topics: capitol, election, covid, congress, and economy. The prevalence in the corpus of text of each key-word, split by party, is reported in Figure A-5. To fix the number of topics without assigned key-words, I estimate the model with 5, 10, 15, and 20 non-key-word topics, and find results to be almost identical, as it's shown in Figure A-6. This is consistent with Eshima et al. (2024) finding that the model is much less sensitive to the number of topics specified than a traditional LDA model.

Figure A-7 plots the evolution of the prevalence of each topic estimated separately for Democrats and Republicans. Several findings are worth highlighting. First, consistently with the results presented until now, the capitol topic jumps up in popularity on January 6 for both parties, and then gradually becomes less and less relevant. The election topic also increases in popularity concurrently with the capitol one, and has a subsequent spike for Republicans around January 20. However, both before and after the event this topic is much more prevalent in Republican tweets rather than in Democrats'. Both covid and economy show a gradual decrease in popularity leading to and right after January 6, to then increase again towards the end of the sample. Overall, there are no substantial partisan differences in terms of substitution over time across these topics.



(A) REPUBLICANS



(B) DEMOCRATS

FIGURE A-5: KEYWORD PREVALENCE BY PARTY

Notes: The figure reports the frequency the chosen keywords for each of the pre-established topics separately for Democrats and Republicans. Following the model's guidelines (available here) I selected keywords with a frequency larger than 0.1%.

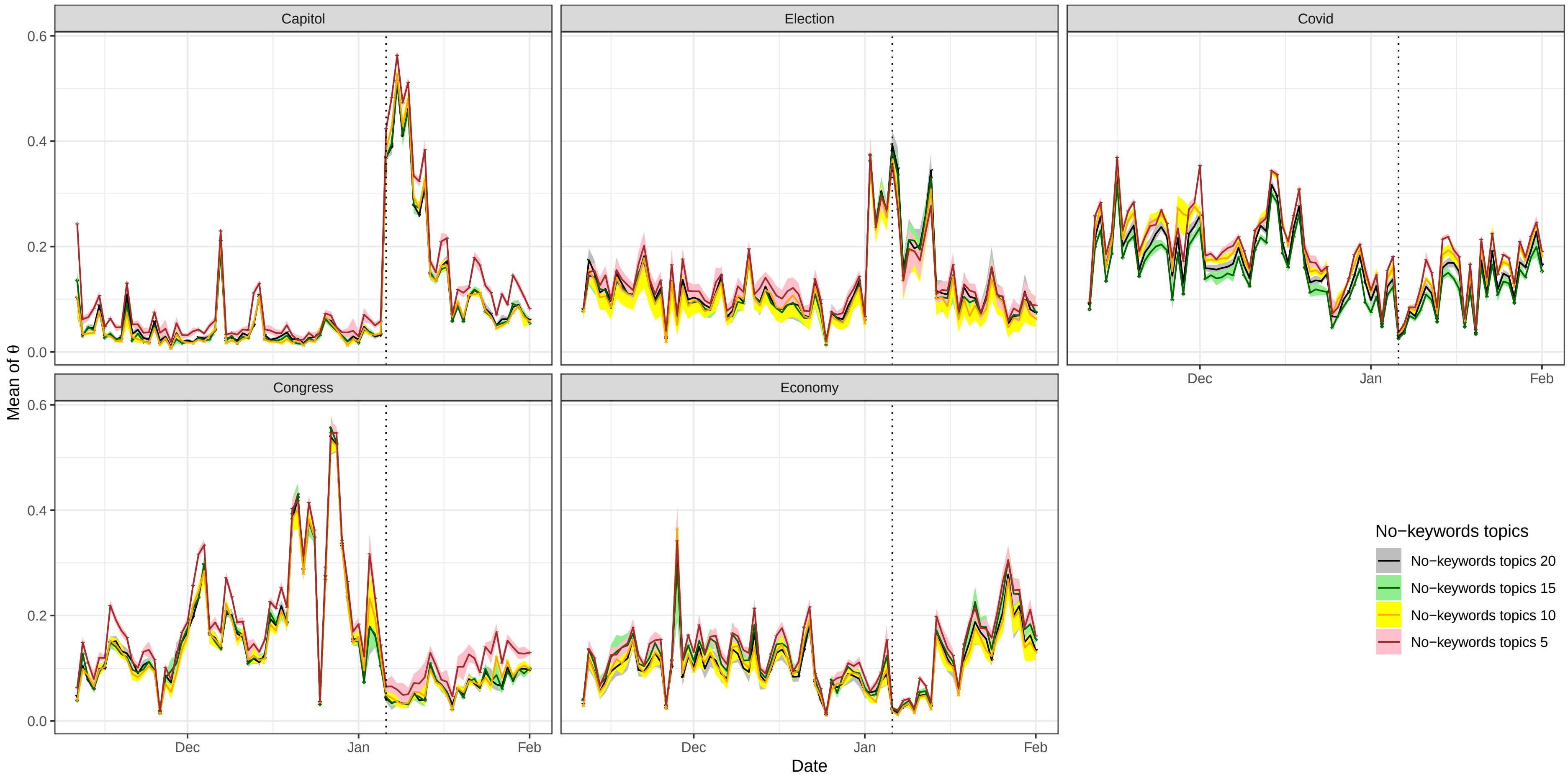


FIGURE A-6: TOPIC EVOLUTION WITH DIFFERENT NON-KEY-WORD TOPICS

Notes: dynamic `keyATM` model with 3,000 iterations with 5 states and thinning 5. Trend lines are reported alongside 90% credible intervals.

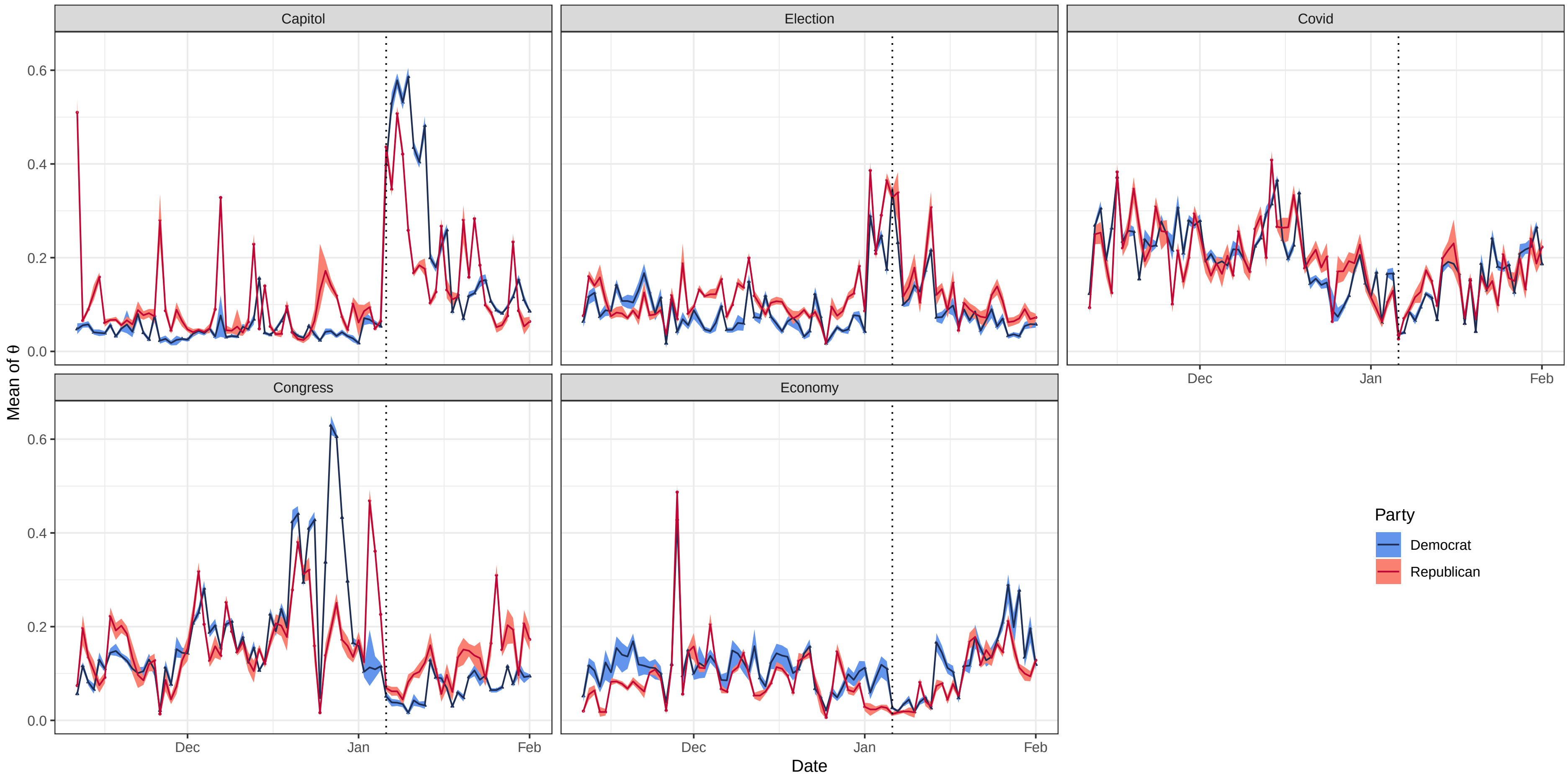


Figure A-7: Partisan topic evolution

Notes: dynamic `keyATM` model with 3,000 iterations with 5 states and thinning 5. Trend lines are reported alongside 90% credible intervals.