**Supplemental Appendix for:**

**Congressional support for democratic norms on January 6th (Research Note)**

**Identifying Congressional Twitter Accounts**

 We begin by identifying all of the official accounts for members of Congress who were in office on January 6th (the 117th Congress), using the UCSD database (Smith, 2023). As some members tweeted from a campaign or personal account, we enlisted a team of research assistants to search for each member and identify the “secondary” accounts for all members of Congress. We limited our search to accounts that were verified, and every account was manually reviewed for accuracy. The expansive approach to gathering Twitter handles was appropriate because we were interested in capturing members’ first reactions, and non-official accounts can have high numbers of followers. Our search yielded 2,336 tweets from 993 accounts.

**Text Preprocessing**

 Once we identified the relevant tweets, we applied several basic preprocessing steps. First, we removed all links, punctuation, and capitalization. Relevant numbers (e.g. 25, in reference to the 25th amendment) were converted to text, and all numerals were removed. Using the quanteda package (Benoit et al., 2023), we converted the tweets into tokens and transformed each token into its base word form, or lemma. This lemmatization process is similar to stemming in that it reduces the amount of noise in the corpus but still preserves parts of speech. For example, “protests,” “protesting,” and “protested” are all reduced to the lemma “protest,” while “protesters” is reduced to “protester.” We accomplish this lemmatization using a dictionary of 41,531 English-language words and their lemmas (Měchura, 2018).

Next, we removed English and Spanish-language stop words using a modified version of the Python NLTK dictionary (Benoit et al., 2021). We preserved a series of common stop words that might change the meaning of another token or have meaning in the context of political tweets. For example, we preserved all negations, such as “not” and “isnt,” as well as “down,” as in “stand down,” and “from,” as in “from office.” We then generated a list of all text collocations using the quanteda package (Benoit et al., 2023), which identifies word combinations that tend to appear together in the text and the likelihood of their cooccurrence. With this list, we identified the word combinations that included at least one of our preserved stop words and created bigrams and trigrams to preserve the combinations. This included 29 word combinations:

"urge\_all", "any\_form", "any\_kind", "any\_violence", "not\_who\_we\_be", "this\_be\_not\_we", "both\_side", "but\_violence", "back\_down", "lock\_down", "stand\_down", "tear\_down", "vote\_down", "call\_for", "fight\_for", "stand\_for", "vote\_for", "work\_for", "from\_office", "im\_safe", "end\_now", "right\_now", "stop\_now", "right\_of", "vote\_of", "will\_of", "call\_off", "good\_than\_this", and "right\_to".

It also included 35 negations:

"against\_law", "violence\_against", "vote\_against", "make\_no\_mistake", "no\_evidence", "no\_matter", "no\_mistake", "no\_one", "no\_place", "not\_accept\*", "not\_allow", "not\_america\*", "not\_answer", "not\_change", "not\_condone", "not\_deserve", "not\_deter", "not\_happen", "not\_intimidate", "not\_peaceful\*", "not\_protest\*", "not\_stop", "not\_succeed", "not\_sufficient", "not\_tolerate", "not\_true", "not\_violence", "not\_way", "not\_win", "violence\_against", "vote\_against", "never\_acceptable", "never\_answer", "never\_imagine", and "never\_think".

Once this initial set of compound words was created, we removed the remaining stop words in the nltk dictionary and generated a new list of text collocations using only the substantive words. Any word pairs appearing in the collocation list with a z-score greater than 3 were combined into a compound term. This resulted in the addition of 436 bigrams such as “staff\_safe”, “shelter\_place”, “domestic\_terrorist”, “attempt\_coup”, and “certify\_election”. Importantly, this procedure maintains the individual tokens in addition to the bigrams: “staff” and “safe” both appear in the list of tokens in addition to “staff\_safe”.

Our initial corpus consisted of 1,863 tweets and 4,599 unique tokens. After preprocessing, we are left with 1861 tweets and 3,932 unique tokens, which we organize into a document-feature matrix. **Figure S1** displays the 100 most frequently used words (excluding common stop words) as a proportion of all words used by Democrats and Republicans. (Labels are included for the top 20 words as well as all dictionary words.) The figure illustrates clear differences in each party’s vocabulary. Neutral terms, such as “country” and “safe” are used equally by both parties, while the words in our lawless protest dictionary are a larger proportion of Republican vocabulary, and the words in our attack on democracy dictionary are a larger proportion of Democratic vocabulary.

**Dictionary Creation**

 To create our “attack on democracy” and “lawless protest” dictionaries, we used an iterative procedure developed by King, Roberts, and Lam (King et al., 2017) to account for limitations in the ability of humans to create dictionaries.

 We began by defining reference and search sets of tweets based on keywords that cleanly identify the concept of interest. In the case of the attack on democracy dictionary, we began with the words “insurrect\*,” “coup”, and “seditio\*” and identified all tweets that used one of these three terms (or their variants). A review of the resulting 150 tweets confirmed that they all successfully captured our concept of interest: that January 6th was a threat to democracy. These tweets became our reference set, and all other tweets (those that did not include the three keywords) were the search set.

 With the initial seed words determined, we then divide the tweets into training and test sets. The training set, which comprises 70% of the documents, consists of all tweets in the reference set and a random sample of tweets from the search set. We then apply seven different supervised learning models to classify each tweet into either the search or reference set. The classifiers used are naïve Bayes, support vector machine (SVM), scaled linear discriminant analysis (SLDA), classification tree, gradient boosting, random forest, and bagging. From each classification algorithm, we obtain the probability that a given tweet is in the reference set. The probabilities from all seven classifiers are combined so that each tweet is assigned a single probability – the maximum probability that a tweet belongs in the reference set across all seven classifiers.

 Next, we split our search set into two groups: those tweets for which at least one model classified it into the reference set with a probability of at least 0.5 and those tweets that were not identified as potentially belonging to the reference set. We identify all tokens that appear in at least five tweets and calculate the proportion of tweets that contain each token within the two groups. Finally, we take all tokens that are more prevalent in the predicted reference group and calculate a statistical likelihood score for each token that measures how well it discriminates between the two groups.

 In our initial iteration, we identified 150 tweets that contained the words “insurrect\*,” “coup,” or “seditio\*” and an additional 409 tweets that were classified as likely belonging to that same group based on at least one classification algorithm. Of the 1,160 tokens that appeared in at least five tweets, 349 were more likely to be associated with the insurrection/coup/sedition group. This included tokens such as “remove\_from\_office,” “realdonaldtrump,” and “domestic\_terrorist.” After ranking the 349 tokens by their discrimination index, we reviewed the list ourselves and identified those that we think belong in the attack on democracy dictionary. For example, “domestic\_terrorist” is a clear recognition of the political nature of the attack. We also include “remove\_from\_office” in our attack on democracy dictionary, as it recognizes President Trump’s involvement as a threat to democracy. However, “realdonaldtrump” is excluded, as it does not capture our concept of interest. Once we finish reviewing the rank-ordered list of tokens, we add all of the relevant keywords to our initial dictionary and repeat the process until we generate a token list that does not include any relevant keywords. The final list of words in our attack on democracy dictionary and the frequency of their usage are provided in **Table S1**.

 The creation of the lawless protest dictionary proceeded according to the same process, independent of the creation of the attack on democracy dictionary. For the lawless protest dictionary, we began with the keywords “law\_order,” “lawless\*,” and “rule\_law” to reflect the idea that January 6th was a protest that got out of hand. This generated 111 tweets for our lawless protest reference set. The initial run of the classification algorithms identified an additional 301 tweets that were likely to belong to the lawless protest set. Of the 1,194 tokens that appeared in at least five tweets, 394 were more likely to be associated with the law\_order/lawless/rule\_law group. This included tokens such as “restore\_order,” “peaceful\_protest,” and “condemn\_action.” We reviewed the 394 ranked tokens and identified the words that best captured the idea of a protest gone too far, which included “restore\_order” and “peaceful\_protest.” Those that did not capture our concept of interest, like “condemn\_action,” were excluded. We add all relevant keywords to our initial dictionary and repeat the same iterative procedure as we used to create the attack on democracy dictionary. The final list of words in our lawless protest dictionary and the frequency of their usage are provided in **Table S2**.

 **Figure S2** displays two sample tweets to illustrate the different language used to discuss the January 6th attacks. Representative Seth Moulton’s (D-MA) tweet invoked the attack on democracy frame by describing events as a “domestic coup attempt” which recognizes the attack on democracy. In contrast, Bill Hagerty’s (R-TN) tweet is an illustration of the lawless protest frame in which he defended the right to protest peacefully before condemning the violence because “we are a nation of laws.”

**“Neither” Tweets**

 Due to the significant number of tweets classified as using neither the attack on democracy nor the lawless protest frame, we conducted basic descriptive analyses to identify other narratives that were prevalent on Twitter among members on January 6th. To identify topics within the category of “neither” tweets, we estimated a series of models using Latent Dirichlet Allocation (LDA) to identify the number of topics in these tweets. We tested models with between two and 30 topics and found that the models with between 4 and 6 topics produced the highest Jensen-Shannon divergence scores.

 After reviewing the terms associated with each topic in the 4-, 5-, and 6-topic models, we identified four clear topics: Status Updates, General Condemnations, Floor Proceedings, and Miscellaneous. Because we have limited text for the LDA algorithm to learn from, we used these four identified topics to hand-code the 925 “neither” tweets. This allowed us to review the tweets for additional topics and identify subcategories of each topic, as follows:

* Status Updates
	+ *I’m Safe:* Members marking themselves and their staff as safe.
		- *Example:* “I am currently sheltering in place and safe.”
	+ *Other Updates:* Updates about events in the Capitol building.
		- Example: "On House floor. Capitol Police have sealed the chamber."
* General Condemnations
	+ *Generic Disapproval:* Any tweet expressing disapproval of events without using the language in either the attack on democracy or lawless protest frames.
		- Example: “I condemn any kind of violence and intimidation. This is unacceptable.”
	+ *Blame Trump:* Tweets attributing responsibility for the attack to Trump.
		- Example*:* “Donald Trump can end this with one tweet.”
* Floor Proceedings
	+ *Pro-Certification* – Support for certifying the election results.
		- Example: “The Amerian people decide elections, not @GOP sore losers.”
	+ *Anti-Certification* – Opposition to certifying the election results.
		- Example: “It’s an honor to stand with @tedcruz and object to electors that were chosen by fraud, certified by knaves and proffered mendaciously.”
	+ *Generic Certification* – Other discussion of certification with no obvious position
		- Example: “The Senators are going to get their steps in today.”
	+ *Return to Business* – Members pledging to return to the floor to finish work.
		- Example: “This attack will not stop Congress from continuing the business of certifying the electoral college votes, come hell or high water.”
* Miscellaneous
	+ *Off-Topic* – Tweets not obviously related to the 2020 election or the Capitol attack.
		- Example: “If you or someone you know needs help, send a text to a crisis counselor by messaging the Crisis Text Line at 741741.”
	+ *External Links* – Links to statements and media appearances on other platforms
		- Example: “Catch me on @realtalk995 now discussing today’s events.”
	+ *Unclear* – All remaining tweets, primarily from conversations out of context.
		- Example: “@JosephFinn I honestly have no idea.”

**Table S3** provides the full breakdown of the classified “neither” tweets by topic, subtopic, and party. In addition to expected partisan divisions on the subtopics of the Floor Proceedings topics, we observe that Democrats were more likely to provide status updates during the day, while Republicans were more likely to express generic disapproval of events. However, none of the identified topics or subtopics are as prevalent in the data as our attack on democracy and lawless protest frames.

**Model Specification**

 **Tables S4-S6** present the full model specification and estimated coefficients for the modes presented in the paper. **Table S4** provides the coefficients of a negative binomial model estimated in R using the glm.nb function from the MASS package (Venables & Ripley, 2003), corresponding with the coefficient plot in **Figure 5**. The unit of analysis is the member of Congress, and the dependent variable is the number of tweets a member posted across all their Twitter accounts between 1 p.m. and 9 p.m. on January 6th. We use the negative binomial model because the dependent variable is a right-skewed count variable with overdispersion ($μ=3.51, σ^{2}=11.99$). A likelihood-ratio test shows that the negative binomial model provides a significantly improved fit over a Poisson model, at $p<0.001$.

**Table S5** provides the results of a multinomial logistic regression model estimated in R using the mlogit function from the mlogit package (Croissant, 2020). The unit of analysis is the individual tweet, and the dependent variable is whether the tweet invoked the attack on democracy frame, the lawless protest frame, or neither frame. Neither is the excluded reference category, and the coefficients are the log odds that a tweet uses either the attack on democracy or lawless protest frame relative to using neither frame. We test the model assumption of no multicollinearity with a variance inflation factor (VIF) test and find no variables with a VIF greater than 3.16. We test the independence of irrelevant alternatives (IIA) assumption with Hausman-McFadden tests and find that the model results hold when either the attack on democracy or lawless protest frames are removed. We used the model coefficients in **Table S5** to generate the predicted probability of frame utilization by party displayed in **Figure 6A**.

**Table S6** replicates the analysis in **Table S5** with the sample split based on the party of the member who posted the tweet. Again, we estimate the model in R using the mlogit function from the mlogit package (Croissant, 2020). The first model is estimated using the 1,243 tweets posted by Democratic members and corresponds to the coefficient plot in **Figure 6C**. The second model is estimated using the 618 tweets posted by Republican members and corresponds to the coefficient plot in **Figure 6D**. Again, the unit of analysis is the individual tweet, and the dependent variable is whether the tweet invoked the attack on democracy frame, the lawless protest frame, or neither frame, with neither as the excluded reference category. VIF tests on both models confirm that multicollinearity is not a threat to model validity and Hausman-McFadden tests confirm that the IIA assumption is not violated. We used the model coefficients from the Republican tweets model to generate the predicted probability of frame utilization as a function of district-level Trump support displayed in **Figure 6B.**

**Outcomes**

 **Tables S7-S8** provide descriptive information about future electoral outcomes and voting decisions for members based on how they framed the January 6th attack. In **Table S7**, we divide the members of each party into our four categories of frame usage: attack on democracy only, lawless protest only, both frames, and neither frame (excluding Senators who were not up for reelection in 2022.) Within each of these categories, we show how the members fared across eight different measures of electoral considerations in the 2022 election.

* *Primary challenge*: percentage of members with a challenger(s) from the same party who won at least 10% of their party’s vote.
* *Primary loss*: percentage of members who lost their primary election.
* *Primary vote %:* average percentage of their party’s vote that members received in the primary election.
* *# of primary cands*: average number of primary candidates who appeared on the ballot from the same party (including the member).
* *Retired*: percentage of members who did not run for reelection or another elected office.
* *Ran for other office*: percentage of members who ran for another elected office.
* *Lost general*: percentage of members who lost their general election.
* *Reelected*: percentage of members who were reelected in 2022.

Looking only at House Republicans, **Table S8** uses the same division of members into four categories of frame choice and examines the relationship between frame choice and vote choice on four key votes related to January 6th identified by Bartels & Carnes (2023) We calculate the percentage of members in each category who cast votes that reflected the pro-Trump position.

* *Reject AZ Electors*: vote in favor of agreeing to the objection to the electoral count from Arizona. (Vote failed 121-303, R split 121-83, January 6, 2021, 11:08 p.m.)
* *Reject PA Electors*: vote in favor of agreeing to the objection to the electoral count from Pennsylvania. (Vote failed 138-282, R split 138-64, January 7, 2021, 3:08 a.m.)
* *Oppose Impeachment*: vote against article of impeachment against Trump for “incitement of insurrection.” (Vote passed 232-197, R split 10-197, January 13, 2021)
* *Oppose Jan 6 Commission*: vote against H.R. 3233 establishing a national commission to investigate the January 6th attack. (Vote passed 252-175, R split 35-175, May 19, 2021)
* *All Four*: percentage of members who cast pro-Trump votes on all four of the above.

**Figure S1. Most used words as a proportion of partisan vocabulary**



**Table S1.** Attack on democracy dictionary and frequencies

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| american\_democracy | 12 | fascism | 7 | seditionists | 2 |
| assault\_democracy | 14 | fascist | 6 | seditious | 17 |
| attack\_democracy | 26 | impeach | 16 | subversion | 1 |
| attempt\_coup | 33 | impeachable  | 1 | subversive | 1 |
| attempt\_overthrow | 6 | impeachment  | 14 | subvert | 6 |
| attempt\_overturn | 6 | impeachtrumpnow | 1 | terror | 5 |
| authoritarian | 2 | impeach\_remove | 9 | terrorism | 6 |
| authoritarianism | 3 | insurrection | 30 | terrorist | 16 |
| banana\_republic | 2 | insurrectionist | 1 | terroristas | 1 |
| coup | 15 | insurrectionists | 10 | terrorist\_attack | 6 |
| coup\_attempt | 24 | invoke\_twentyfifth\_amendment | 13 | terrorist\_storm | 6 |
| danger\_democracy | 5 | must\_impeach | 9 | terrorize | 1 |
| defend\_democracy | 13 | no\_place\_democracy | 5 | threat\_democracy | 5 |
| democracia | 9 | overthrow | 7 | today\_insurrection | 9 |
| democracy | 220 | overturn | 13 | traitor | 6 |
| democracys | 1 | overturn\_election | 17 | traitorous | 3 |
| democracy\_need | 6 | overturn\_result | 5 | transfer\_power | 5 |
| democracy\_prevail | 23 | overturn\_will\_of | 6 | transition\_power | 2 |
| democracy\_win | 10 | peaceful\_transfer\_power | 21 | treason | 4 |
| dictator | 6 | peaceful\_transition\_power | 17 | treasonous | 3 |
| dictatorship | 2 | protect\_democracy | 13 | twentyfifthamendment | 1 |
| domestic\_terrorism | 19 | remove\_from\_office | 19 | twentyfifthamendmentnow | 1 |
| domestic\_terrorist | 35 | remove\_president | 5 | twentyfifth\_amendment | 19 |
| effort\_overturn | 11 | sedition | 17 | undermine\_democracy | 11 |
|  |  | seditionendstoday | 1 | violent\_insurrection | 5 |

**Table S2.** Lawless protest dictionary and frequencies

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| *against\_law\_enforcement* | 3 | law\_order  | 36 | protester\_breach | 8 |
| american\_right\_to | 11 | lawless | 15 | protester\_storm | 5 |
| attack\_law\_enforcement  | 6 | lawlessly | 1 | remain\_peaceful | 7 |
| attack\_police | 7 | lawlessness | 20 | respect\_law\_enforcement | 5 |
| constitutional\_right\_to  | 5 | lawlessness\_violence | 6 | restore\_order | 11 |
| criminal | 26 | nation\_law | 10 | right\_to\_peacefully\_protest  | 14 |
| criminally | 1 | order\_restore | 6 | right\_to\_protest  | 10 |
| demonstration | 7 | peaceful | 21 | riot | 36 |
| destruction | 14 | peaceful\_assembly | 5 | rioter | 33 |
| destructive | 8 | peaceful\_protest | 32 | riotous | 1 |
| disagree | 15 | peaceful\_protester | 2 | rule\_law | 29 |
| disagreeable | 1 | peacefully | 24 | rule\_law\_order | 1 |
| disagreement | 4 | peacefully\_protest  | 2 | support\_peaceful\_protest  | 6 |
| first\_amendment | 13 | prosecute\_full\_extent | 17 | unlawful | 5 |
| full\_extent\_law | 19 | protest | 46 | violence\_destruction | 9 |
| illegal | 5 | protest\_peaceful | 5 | violence\_lawlessness | 6 |
| illegally | 2 | protest\_peacefully | 6 | violent\_protest | 5 |
|  |  | protester | 58 |  |  |

Figure S2: Example Tweets

**Table S3.** Topics identified in tweets using neither the attack on democracy nor lawless protest frames

|  |  |  |  |
| --- | --- | --- | --- |
| **Topic** | **# of Tweets** | **% Dem Tweets** | **% Rep Tweets** |
| All “Neither” Tweets | 924 | 65.7% | 34.3% |
|  |  |  |  |
| Status Updates | 275 | 75.6% | 24.4% |
|  *I’m Safe* | *176* | *79%* | *21%* |
|  *Other Updates* | *99* | *69.7%* | *30.3%* |
|  |  |  |  |
| General Condemnations | 245 | 58.5% | 41.5% |
|  *Generic Disapproval* | *161* | *44.1%* | *55.9%* |
|  *Blame Trump* | *84* | *86.9%* | *13.1%* |
|  |  |  |  |
| Floor Proceedings | 230 | 61.7% | 38.3% |
|  *Pro-Certification* | *72* | *83.3%* | *16.7%* |
|  *Anti-Certification* | *47* | *0%* | *100%* |
|  *Generic Certification* | *27* | *48.1%* | *51.9%* |
|  *Return to Business* | *84* | *82.1%* | *17.9%* |
|  |  |  |  |
| Miscellaneous | 174 | 50.6% | 49.4% |
|  *Off-Topic* | *53* | *73.6%* | *26.4%* |
|  *External Links* | *33* | *42.4%* | *57.6%* |
|  *Unclear* | *88* | *68.2%* | *31.8%* |

**Table S4.** Results ofnegative binomialmodel predicting number of tweets posted

|  |  |
| --- | --- |
| Variables | Number of tweets on January 6 |
| Tweets per Year (logged) | 0.437\*\*\*(0.056) |
| Trump Margin | -0.061\*\*(0.019) |
| Senator | -0.344\*\*\*(0.099) |
| Democrat | 0.211(0.115) |
| Seniority | 0.002(0.009) |
| Leadership | -0.169(0.127) |
| Electoral Safety | 0.009(0.018) |
| Constant | -1.864\*\*\*(0.395) |
| N | 525 |
| $χ^{2}$  | 225.5\*\*\* |

\*\*\* p<0.001, \*\*p<0.01, \*p<0.05

**Table S5.** Results of multinomial logistic regression predicting frame usage for all tweets

|  |  |  |
| --- | --- | --- |
| Variables | Attack on Democracy Frame | Lawless Protest Frame |
| Democrat | 1.217\*\*\*(0.222) | -1.345\*\*\*(0.254) |
| Trump Margin | -0.051(0.037) | 0.015(0.041) |
| Seniority | 0.022(0.014) | 0.020(0.018) |
| Leadership | -0.167(0.202) | -0.267(0.307) |
| Primary Election | 0.085(0.142) | 0.420\*(0.174) |
| Electoral Safety | -0.074\*(0.036) | -0.023(0.035) |
| Quote Tweet | -0.477\*\*(0.176) | -0.633\*(0.265) |
| Reply Tweet | -3.203\*\*\*(0.601) | -3.035\*\*(1.018) |
| Tweet Thread | -0.103(0.155) | -0.032(0.192) |
| Time Trend (2-3pm) | 0.294(0.216) | 1.852\*\*\*(0.334) |
| Time Trend (3-4pm) | 0.281(0.210) | 1.880\*\*\*(0.323) |
| Time Trend (4-5pm) | 0.746\*\*\*(0.206) | 1.583\*\*\*(0.338) |
| Time Trend (5-6pm) | 0.724\*\*(0.233) | 1.383\*\*\*(0.376) |
| Time Trend (6-7pm) | 0.882\*\*\*(0.242) | 1.780\*\*\*(0.380) |
| Time Trend (7-8pm) | 1.134\*\*\*(0.233) | 1.082\*(0.425) |
| Time Trend (8-9pm) | 0.779\*\*\*(0.222) | 0.622(0.441) |
| Constant | -1.793\*\*\*(0.251) | -1.831(0.336) |
| N | 1861 |
| $χ^{2}$  | 553.67\*\*\* |

Neither is the reference category

\*\*\* p<0.001, \*\*p<0.01, \*p<0.05

**Table S6.** Results of multinomial logistic regression predicting frame usage for tweets by party

|  |  |  |
| --- | --- | --- |
| Variables | *Democratic Tweets* | *Republican Tweets* |
| Attack on Democracy | Lawless Protest | Attack on Democracy | Lawless Protest |
| Trump Margin | -0.079(0.056) | -0.139(0.103) | -0.348\*(0.139) | 0.080(0.096) |
| Seniority | 0.009(0.015) | 0.031(0.026) | 0.110\*\*(0.037) | 0.020(0.029) |
| Leadership | -0.187(0.212) | -0.677(0.488) | -0.035(0.680) | 0.035(0.446) |
| Primary Election | 0.036(0.155) | 0.211(0.269) | 0.470(0.386) | 0.523\*(0.256) |
| Electoral Safety | -0.105(0.057) | -0.165(0.107) | 0.122(0.091) | -0.043(0.071) |
| Quote Tweet | -0.387\*(0.188) | -0.158(0.345) | -1.311(0.761) | -1.209\*\*(0.409) |
| Reply Tweet | -3.602\*\*\*(0.731) | -2.422\*(1.029) | -1.313(1.078) | -17.58(1996.6) |
| Tweet Thread | -0.056(0.176) | 0.494(0.294) | -0.144(0.356) | -0.372(0.256) |
| Time Trend (2-3pm) | 0.134(0.234) | 1.327\*\*(0.441) | 2.354\*(1.093) | 2.538\*\*\*(0.517) |
| Time Trend (3-4pm) | -0.019(0.229) | 0.737(0.462) | 2.563\*(1.063) | 2.838\*\*\*(0.498) |
| Time Trend (4-5pm) | 0.454\*(0.225) | 0.594(0.485) | 3.163\*\*(1.060) | 2.545\*\*\*(0.517) |
| Time Trend (5-6pm) | 0.443(0.254) | 0.720(0.535) | 3.204\*\*(1.095) | 2.249\*\*\*(0.565) |
| Time Trend (6-7pm) | 0.802\*\*(0.267) | 1.560\*\*(0.483) | 2.999\*\*(1.126) | 1.995\*\*\*(0.591) |
| Time Trend (7-8pm) | 1.127\*\*\*(0.258) | 0.669(0.576) | 2.498\*(1.166) | 1.463\*(0.631) |
| Time Trend (8-9pm) | 0.627\*\*(0.239) | 0.445(0.549) | 2.933\*\*(1.113) | 0.842(0.719) |
| Constant | -0.320(0.206) | -2.732\*\*\*(0.444) | -4.296\*\*\*(1.063) | -2.547\*\*\*(0.504) |
| N | 1243 | 618 |
| $χ^{2}$  | 127.69\*\*\* | 149.91\*\*\* |

Neither is the reference category

\*\*\* p<0.001, \*\*p<0.01, \*p<0.05

**Table S7.** Electoral Outcomes for 2022 by Party and Frame Usage

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Outcome** | **Attack on Democracy****Frame** | **Lawless Protest****Frame** | **Both****Frames** | **Neither****Frame** | **P-Value** |
| **Democrats** |  |  |  |  |  |
| # of obs | 136 | 15 | 52 | 33 |  |
| Primary challenge | 24.4% | 33.3% | 53.5% | 33.3% | 0.007 |
| Primary loss | 2.9% | 0% | 1.9% | 3.0% | 0.899 |
| Primary vote % | 67.6% | 63.3% | 77.1% | 74.1% | 0.181 |
| # of primary cands | 1.60 | 1.44 | 1.93 | 1.59 | 0.493 |
| Retired | 10.3% | 20% | 11.5% | 12.1% | 0.735 |
| Ran for other office | 2.2% | 20% | 5.8% | 6.1% | 0.018 |
| Lost general | 1.5% | 6.7% | 3.9% | 3.0% | 0.562 |
| Reelected | 83.1% | 53.3% | 76.9% | 75.8% | 0.055 |
| **Republicans** |  |  |  |  |  |
| # of obs | 26 | 123 | 17 | 61 |  |
| Primary challenge | 78.3% | 51.8% | 53.8% | 56.6% | 0.139 |
| Primary loss | 11.5% | 1.6% | 0% | 3.3% | 0.054 |
| Primary vote % | 66.0% | 71.2% | 69.9% | 68.0% | 0.519 |
| # of primary cands | 2.83 | 2.05 | 2.46 | 2.47 | 0.097 |
| Retired | 11.5% | 4.9% | 11.8% | 9.8% | 0.430 |
| Ran for other office | 0% | 3.3% | 11.8% | 3.3% | 0.223 |
| Lost general | 0% | 0.8% | 0% | 1.6% | 0.852 |
| Reelected | 76.9% | 89.4% | 76.5% | 82% | 0.200 |
| P-values from $χ^{2}$ tests for binary variables and one-way ANOVA for continuous variables |

**Table S8.** Percentage of House Republicans Casting Pro-Trump Votes by Frame Usage

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Vote** | **Attack on Democracy****Frame** | **Lawless Protest****Frame** | **Both****Frames** | **Neither****Frame** | **P-Value** |
| Reject AZ Electors | 37.5% | 66.7% | 46.7% | 53.4% | 0.031 |
| Reject PA Electors | 37.5% | 74.8% | 60.0% | 63.8% | 0.005 |
| Oppose Impeachment | 79.2% | 97.3% | 93.3% | 91.4% | 0.012 |
| Oppose Jan 6 Commission | 58.3% | 85.8% | 100% | 84.2% | 0.003 |
| All Four | 33.3% | 62.8% | 43.8% | 44.1% | 0.014 |
| P-values from $χ^{2}$ tests |

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