## Methods Reporting

### Study 1 (Twitter)

We relied on a scraping process that relies on a large sampling of an individuals' following preference on Twitter. We began by building a sample of Twitter users. To do so, we used the "streamR" package in R (Barberá, 2015). To sample users that were at least somewhat engaged in politics, we included in our sample Twitter users that tweeted with one of several search parameters during one of four political events (see below).

Events that produced the sample in Study 1 on Twitter. Subjects were Twitter users that tweeted with any of the search parameters between the pertinent start time and end time (Central Standard Time).

| | Sample Identification | | | User Tweet Range | |
|---|---|---|---|---|---|
| Event | Start Time | End Time | Search Parameter | Oldest | Newest |
| Iowa Caucuses | 1 Feb 2016 9:05 pm | 2 Feb 2016 1:07 am | Trump, Cruz, Rubio, Carson, Kasich, Clinton, O'Malley, Sanders, "#IACaucus" | 18 Nov 2008 | 1 July 2016 |
| Fourth Democratic Party Presidential Debate | 17 Jan 2017 8:41pm | 17 Jan 2017 9:47 pm | Trump, Cruz, Rubio, Carson, Kasich, Paul, Clinton, O'Malley, Sanders, "#DemDebate", "#SCDebate" | 1 Apr 2009 | 1 July 2016 |
| Fourth Democratic Party Presidential Forum | 25 Jan 2017 8:50 pm | 26 Jan 2017 12:56 am | Trump, Cruz, Rubio, Carson, Kasich, Paul, Clinton, O'Malley, Sanders, "#DemForum", "#DemDebate", "#IADebate" | 25 Nov 2008 | 1 July 2016 |
| Eighth Republican Party Presidential Debate | 6 Feb 2017 8:42 pm | 7 Feb 2017 12:42 am | Trump, Cruz, Rubio, Carson, Kasich, Clinton, O'Malley, Sanders, "#GOPDebate", "#NHDebate" | 8 Aug 2007 | 1 July 2016 |

We chose these search parameters by examining hash tags that were considered "Trends" by Twitter's home screen and using the hash tags that are specific to the political event of interest. For example, one of the most used event-relevant hash tags on Twitter during the Iowa Caucuses was "#IACaucus", so that was included as a collection parameter along with the names of each presidential candidate running at that point. This produced tweets from 16,090 Twitter users. Following recently established procedures (Barberá, 2015), we excluded accounts that were likely fake (accounts that had fewer than 25 followers) and relatively inactive users (followed fewer than 100 accounts, or tweeted fewer than 100 times). Including these accounts produced similar results (see Table S3). The final sample included 14,480 Twitter users.

We collected the most recent tweets of each user in our sample using the "smappR" package in R (Barberá, Jost, Nagler, Tucker, & Bonneau, 2015). The Twitter Application Program Interface (API) produces the most recent tweets for a given user, with a maximum number of tweets for each user being 3,200. We excluded any retweets or reposts of another user's tweet, as these tweets do not represent the natural language use of our users. The final sample of tweets spanned approximately 8 years (2007-2016), however the vast majority (90%-95%) was from 2015-16. Within the final sample, we had an average of 233 tweets per user ($SD$ = 347), which summed to 2,803 words per user ($SD$ = 4,315). Collectively, the sample was comprised of 3,380,140 tweets, which amassed to 40,590,896 words.

**Political orientation.** We used Barberá et al.'s (2015) validated procedure to estimate the political orientation of each subject. The procedure is premised on the well-established confirmation bias (e.g., Nickerson, 1998): people tend to selectively consume ideologically congenial information. Liberals and conservatives are similarly prone to selective exposure (Frimer, Skitka, & Motyl, 2017).

The accounts that Twitter users followed determined their estimated political orientation. To summarize the procedure (see Barberá et al., 2015, for full details and validation), we matched the accounts that subjects followed to accounts on a pre-estimated list of conservative and liberal politicians, celebrities, and news outlets (using the political orientation estimates from Barberá et al., 2015). For example, Barack Obama and Rachel Maddow had political orientation scores of -1.50 and -1.93, respectively, which are on the liberal end of the spectrum. In contrast, Mitt Romney and Glenn Beck had political orientation scores of 1.07 and 1.62, respectively, which are on the conservative end of the spectrum. We then used correspondence analysis to situate Twitter users on this same ideological spectrum. Through this process, each user received a point estimate. Users that mainly followed liberal accounts like Barack Obama and Rachel Maddow would receive similarly negative scores, whereas users that primarily followed conservative accounts such as Mitt Romney and Glenn Beck would receive similarly positive scores.

Political orientation scores ranged from -2.45 to +2.45. For the sake of consistency across studies, we scaled these political orientation estimates to range from -1 to 1, where -1 is the most liberal user in our sample, 1 is the most conservative user in our sample, and 0 is ideologically moderate. Note that scaling did not alter 0 as a point of ideological moderation since the minimum and maximum values for this estimate are of the same magnitude in our sample.

**Extremism.** We calculated an extremism score as the absolute value of the political orientation score, meaning that extremism scores can range from 0 to 1 ($M = 0.49$, $SD = 0.25$).

**Text analysis.** Before performing text analyses, we removed non-traditional characters (i.e. embedded hyperlinks and special emoticons) and punctuation. Tweets are short, limited to 140 characters. To make the text files long enough to give reliable computer-scored results, we combined each user's tweets into a single text file, then split them into 34,809 1000-word text segments to allow Twitter users who produced more words to have more empirical clout.

The size of the Twitter database necessitates the use of computerized text analyses (rather than human coding). Following the conclusions of the validation analyses (see the Supplemental Materials), we operationalized emotional tone of language using the metric called *emotional tone* in Linguistic Inquiry and Word Count (LIWC; Pennebaker et al. 2015). Emotional tone is derived from analyses using the dictionaries called *positive emotion* and *negative emotion*. LIWC does not offer sub-dictionaries for positive emotion whereas sub-dictionaries called *anxiety*, *anger*, and *sadness* comprise the *negative emotion* dictionary. To flesh out the locus of effects that we find with our primary operationalization of emotional tone, we include auxiliary analyses with *positive emotion*, *negative emotion*, *anxiety*, *anger*, and *sadness* dictionaries.

## Study 2 (Organizations)

**List of organizations**. The first author and two research assistants used brainstorming and Internet searches to build a list of 100 organizations that had publicly available information, such as newsletters and magazines, and spanned the ideological spectrum. See Table S4 for the full list. The full ideological spectrum was represented in the sample, including extreme liberals like the *Black Panther Party* (political orientation = -0.79), moderate liberals like *Greenpeace* (-0.42), Centrists like the *Red Cross* (-0.11), moderate conservatives like the *Minnesota Tea Party Alliance* (0.51), and extremists conservatives like *ISIS* (0.94).

**Texts**. We searched each organization's webpage for publicly available materials, such as magazines and newsletters, and downloaded what we found. We then aggregated all materials for a single organization into a single text file. On average, each organization produced 35,700 words ($SD$ = 119,749; range: 1,253 to 883,988). The full corpus contained 3,569,992 words. We attempted to empirically capture the large variance in the amount of text that each organization produced by dividing each organization's texts into 1000-word segments (3,621 segments across all organization) before performing text analyses with LIWC.

**Political orientation/extremism of organizations**. We recruited two Internet samples to help us estimate the political orientation and extremism of the organizations. Both samples were Americans on http://crowdflower.com, a crowdsourcing website similar to Mechanical Turk. Sample 1 ($N$ = 189) was 40 years old on average ($SD$ = 13) and 64% male. Participants read:

> In this study, you will rate the political ideology of 30 organizations. If you are familiar with any of the organizations, please rate them based on that knowledge. Otherwise, give your best guess based on the description provided. Descriptions were gathered from the official websites of each organization. Where organizations lacked an official website, descriptions were taken from the organization's Wikipedia page.

Next, to avoid overtaxing participants, we presented to each participant 3 of 10 randomly selected blocks of organizations. Each block contained 10 organizations, all of which appeared on a single page. At the top of each page was a list of the organizations and a brief description of each (taken from the organization's webpage or Wikipedia.org; see Table S4).

The rating scale asked, "What is the ideology of each organization?" Participants responded on a 201-point slider scale anchored at -100 (*extremely liberal*), -50 (*somewhat liberal*), 0 (*moderate*), 50 (*somewhat conservative*), and 100 (*extremely conservative*). We averaged all the judgments for a particular organization to form a metric of political orientation. Participants later rated their own political orientation on social issues using the same scale.

Examining the sorted list of political orientation ratings, we noted anomalies, which caused us to doubt their validity. For example, the National Rifle Association (political orientation = 59) was rated as more politically extreme than ISIS (political orientation = 33). This anomaly seems to have been the result of conservative participants not wanting to identify with stigmatized right wing groups like ISIS, and thus calling ISIS a liberal organization (see Figure S2).

We circumvented this problem in two steps. First, we used the average political orientation rating to classify groups as either liberal (scores less than 0) or conservative (scores greater than 0). Second, using the same basic survey design, we asked a new sample (Sample 2) of 189 Americans on the same crowdsourcing website to rate *how extreme* each organization was on a 101-point scale anchored at 0 (*ideologically moderate*) and 100 (*ideologically extreme*). For each organization separately, we then regressed (OLS) extremism ratings on the political orientation of participants and took the intercept—the model implied extremism rating for politically moderate participants—as the extremism score for each organization. Extremism scores ranged from 33 to 85. So we scaled extremism scores to range from 0 to 1. We then multiplied liberal groups' extremism score by -1 and conservative groups' extremism scores by +1 to derive political orientation scores. Table S4 presents the political orientations of each organization.

## Study 3 (U.S. Congress)

The text corpus was the *U.S. Congressional Record*, the words spoken in U.S. Congress during floor debates between 1996-2014 inclusive ($104^{th}$ - $113^{th}$ sessions of Congress), which we downloaded from http://capitolwords.org. Each of the 5,416 documents contained the words that a single member of Congress uttered during a single 2-year session of Congress. The average document contained 48,588 words ($SD$ = 76,414) and the entire corpus contained 262,935,589 words. We divided each transcript into 1000-word segments (274,486 segments in total) before performing content analyses. Representatives were 56.8 years old on average ($SD$ = 10.3) and predominantly (85.4%) male.

**Political orientation**. We used a behavioral measure of political orientation called DW-Nominate, dimension 1 (Lewis & Poole, 2004) to operationalize political orientation and extremism. DW-Nominate is a metric that describes how liberal (negative values), moderate (values near zero), or conservative (positive values) each representative is, based on roll call votes. The metric is calculated using multidimensional scaling to estimate politicians' ideal points. These points represent their position on the issues and these points are comparable across years and politicians. Politicians that voted along party lines had DW-Nominate scores far from zero; politicians whose votes were generally unrelated to the party lines had DW-Nominate scores near zero. We were able to match the codes identifying transcripts (bioguides; e.g., K000336) to the codes identifying voting records (ICPSRs; e.g., 29748) in 4,979 of the 5,416 documents. Voting data were unavailable for an additional 21 representatives. Thus, we had full data on 4,958 transcripts.

The full spectrum of ideologies were represented in the sample, including extremely liberal politicians like Bernie Sanders (DW-Nominate = -0.72) and Elizabeth Warren (-0.70), moderates like Democrat Joe Manchin (-0.09) and Republican Susan Collins (0.04), and extremely conservative politicians like Ted Cruz (0.88) and Rand Paul (1.36).

DW-Nominate scores ranged from -0.75 to +1.36 in this sample. The distributions of the two political parties were effectively non-overlapping, with a DW-Nominate score of 0 meaningfully bifurcating the two parties. Nearly all (99.1% of) Democrats scored below zero and almost all (99.9% of) Republicans scored above zero. To form a measure of political orientation and to use a scale consistent across all of our studies, we scaled DW-Nominate scores by dividing them by 1.36. Political orientation scores ranged from -0.55 to +1.00, and 0 remained the centrist point.

**Extremism**. We calculated an extremism score as the absolute value of the political orientation scores. Republicans were more politically extreme ($M = 0.43$, $SD = 0.14$) than were Democrats ($M = 0.27$, $SD = 0.10$), $t(4939) = 45.03$, $p < .001$, $d = 1.29$.

## Study 4 (News Media)

The website http://allsides.com lists 59 featured news media sources, along with a "bias rating" for each (determined within the website by crowdsourcing). Bias ratings were *Left Wing* (which we coded as political orientation = -1.0), *Leans Left* (-0.5), *Center* (0.0), *Leans Right* (0.5), and *Right Wing* (1.0). For each media source, we searched the LexisNexis database. If LexisNexis offered the full texts from a source, we included the source in our sample. The result was 17 sources that spanned the political spectrum: *Left Wing* (New Republic), *Leans Left* (ABC, LA Times, New York Times, Newsweek, Slate, and Washington Post), *Center* (Associated Press, BBC, Bloomberg, Christian Science Monitor, NPR, Politico, and USA Today), and *Right Wing* (American Spectator, New York Post, and Weekly Standard). None of the *Leans Right* sources had full texts available on LexisNexus. Note that the sample including just 17 news outlets somewhat limits our ability to generalize from these results to the media in general. We took the absolute value of the political orientation score to form an extremism score.

We included articles that spanned Republican and Democratic presidencies and majorities in Congress to sample from a variety of political climates, which would boost the generalizability of the findings, and allow us to test whether political power moderates extremists' negative language. Using the search terms "politics or political", we searched LexisNexus for articles within 15 different sessions of Congress, from the 100$^{th}$ session (1987-88) to the 114$^{th}$ (2015-16). For each political orientation, we searched all of the sources at once, then downloaded the full text of the 500 most relevant results for each term of office, with "relevance" determined by the LexisNexus sorting algorithm. We used this political search term because the ideological bent of newspapers may be circumscribed to their coverage of social and political topics. We chose to download 500 articles because this is the maximum number of articles that LexisNexus will download at a time. The complete corpus contained 28,966,798 words.LexisNexus combines all results into a single text file. We divided text files into 1000-word segments (28,992 segments in total). Finally, we applied LIWC text analysis.

## References


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