Supplemental Information for Weaving it in: How Partisan Media React to Events

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Contents

1 Radio recordings and transcripts

Recording of radio stations was an automated process, starting with scraping the publicly available audio streaming URLs of US terrestrial radio stations from the website Radio-Locator.com. The audio from these URLs was ingested and saved in 5-10 minute chunks on Amazon S3. Next, the audio was automatically transcribed using a custom speech-to-text model, based on an model entered in the IARPA ASpIRE challenge by Peddinti et al. (2015). The speech transcription algorithm was gradually improved in the course of data collection, with the error rate going from 27% in April 2018 to 13% in November 2018, and staying stable since. This error rate was measured using existing transcripts from NPR and Rush Limbaugh.

Beeferman et al. (2019) describe the features of (a subset of) this data set in more detail. This data subset is available for download at `https://github.com/social-machines/RadioTalk`, and the data collection team can be contacted for further technical documentation and code sharing requests at `https://socialmachines.org/`.

Recording started in May 2018, with 72 stations. The number of stations followed increased from there, reaching 175 in August 2018. The number dropped to 155 in March 2019 and remained there until the end of the period analyzed (October 2019). Figure 1 illustrates the number of stations in the data set over time. Of the initial stations, 50 were chosen randomly from the population of US talk radio stations, and more stations were added and dropped from the data set in the course of the next few months according to the interests of the team at the Laboratory for Social Machines. The total number of US terrestrial talk stations (with registered formats Business News, News/Talk, Public Radio, News, College, Talk) in the covered period was 1897, according Radio-Locator.com.

Figure 2 shows where in the United States the transcribed stations are located. Table 1 describes the distributions of these stations in terms of content and station subtype, compared to the population of all talk radio stations. Underrepresented station types include stations from the Midwest, college stations (which unlike the two college stations included in this data set typically air more music than talk content), and public radio stations. Underrepresentation

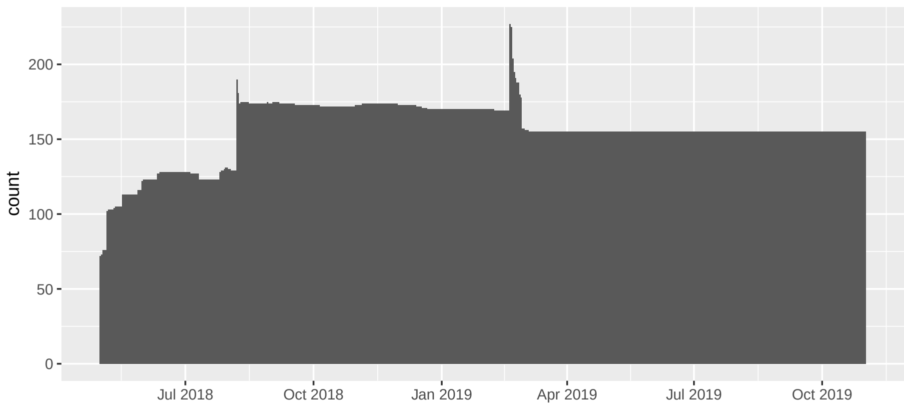

Figure 1: Number of talk radio stations in data set over time.

of public stations is not likely to be consequential for the final sample of shows. This is because many public radio stations broadcast the same set of shows, produced for nation-wide broadcasting by public radio networks such as NPR.

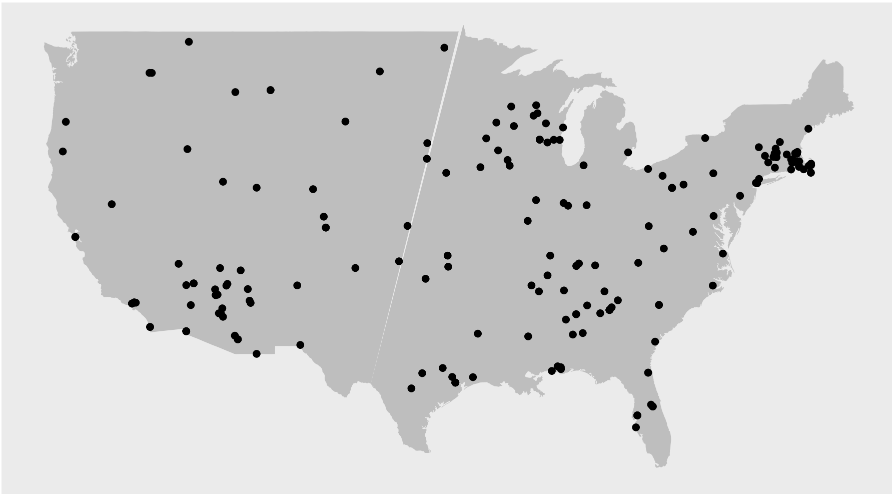

Figure 2: Locations of the continental radio stations in the data set. Two more stations are in Alaska, and one is on Hawaii.

	Sample %	Population %	t-test p-value
region: Midwest	16	28	0.00
region: Northeast	22	16	0.04
region: South	33	30	0.35
region: West	29	27	0.46
format: Business News	0	1	0.09
format: College	2	13	0.00
format: News	2	2	0.91
format: News/Talk	49	27	0.00
format: Public Radio	32	45	0.00
format: Talk	15	12	0.18

Table 1: Balance table comparing region and format for radio stations in the sample to the population of US talk radio stations.

The number of distinct radio shows broadcast by these stations added up to 675 by June 2018, and over 1000 by August. Figure 3 shows the total number of shows captured in each week of the observed period.

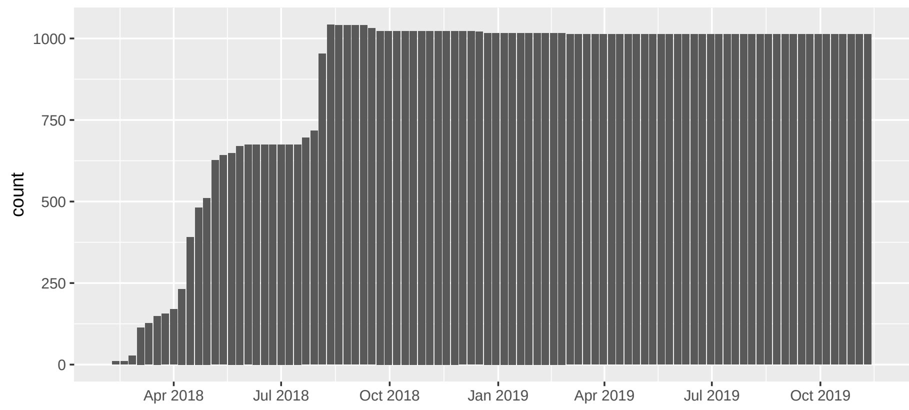

Figure 3: Total number of shows recorded, by week.

2 Ascribing mentions to shows

In principle, ascribing a topic mention to a show should be easy. A topic term counts as being part of a show if it was mentioned on a radio station, during a time slot when we know that show is being broadcast on that station. There are two issues with that approach, however. First, the speech-to-text algorithm creating the transcriptions is not perfect. Some topic term mentions are missed, whereas others are false positives. Second, radio schedule data (which show is on when) was pooled from a range of sources, some more reliable than others. An hour of audio coming from a particular station could have the wrong show label if there is no correct, up-to-date schedule for the station.

Both problems can be remedied when there is more than one airing of a show episode—that is, when the show is broadcast on more than one of the stations that were recorded that day. I followed the procedure below to decide which topic mentions should be ascribed to each show.

1. For each topic mention, create a "slice" of content that includes up to ten words coming before and after the topic term. For example: "years from now, fifty years, there isn't any evidence of climate change" (aired on KBTK, April 25th 2018).

2. In the entire set of transcripts coming from a particular day, search for clusters of similar mentions (low string distance).

3. For each cluster, do the following:

   (a) Take all mentions in the cluster, and check which show labels they have, based on station scheduling data. For example, the first mention above comes from audio labeled as The Glenn Beck Program, but it is in a cluster together with five (very similar) mentions that are all labeled as being part of the Rush Limbaugh Show.

   (b) For each of the shows that occur at least once as show labels in the cluster, calculate confidence that it is the correct show label for this cluster of mentions. Calculations take into account how many mentions in the cluster have this show label, and also how many times each show was aired on different stations that day, *without* containing a similar mention.

(c) Compare the show label likelihoods, and choose the one with the highest confidence. For example, the mention cluster above was ascribed to The Rush Limbaugh Show with a confidence of .6. This relatively low confidence mostly comes from the fact that there are many airings, labeled in the scheduling data as broadcasts of The Rush Limbaugh Show on April 25th 2018, that did not include any mentions with a content slice similar to this one.

4. Treat each cluster, with its most likely show label, as a single unique mention that happened on that show—but only if its show label confidence is greater than .5. Otherwise, discard the cluster.

3 Mechanical Turk coding task

Each time one of the political topics was mentioned, its ideological frame was coded by workers on Amazon's crowdsourcing platform, Mechanical Turk. Workers were allowed to code as many mentions as they wanted, for a payment of $0.14 per mention.

Coders listened to short audio fragments surrounding each mention, so that the ratings are based on vocal as well are verbal cues. We know from previous work that tone of voice confers unique information (Dietrich et al., 2019). Audio fragments started 10 seconds before the topic keyword (e.g. "global warming") was said, and ended 20 seconds after. Next, the coder was asked to choose between two frames (e.g., "skeptical" or "convinced" about climate change), or neither frame.

In the case of climate change, for 71% of mentions, the first two coders agreed on the classification. In another 25% of the cases, a third coder broke the tie, and I used the majority opinion as the code for that mention. In the final 4%, all three coders disagreed, and I labeled the fragment "neither". In the case of gun policy, the distribution was: 61% two-coder agreement; 32% two-out-of three majority; 6% no agreement. Immigration fragments were the most difficult to code: the percentages were 54%, 37%, and 9%.

For all three topics, it was rare for two coders to assign opposite frames to the same fragment. In the case of climate change, only 7% of mentions were assigned one frame (skeptical or concerned), even though one of the coders suggested the opposite frame. In the cases of gun control and immigration, this was 9% and 8%. In other words, coding disagreements are unlikely to have resulted in mentions being assigned the wrong slant. They would, however, have caused some neutral topic mentions to be incorrectly coded as employing a frame, and vice versa.

Right next to the audio player, coders always saw the following brief instructions on their screen:

Climate:

- Skeptical: climate change evidence is false or unclear, climate change is not an important problem, it is too costly to fight against climate change.

- Concerned: climate change evidence is solid, climate change caused by humans, it is a threat and we need action.
- Neutral: no clear opinion about climate change, and no mention of evidence for or against climate change.

Gun policy:

- Pro-gun: right to own guns, looser gun control laws, guns protect people, second amendment
- Anti-gun: stricter gun control laws, guns cause violence/mass shootings
- Neither: no opinion about gun rights/ gun control, no hints whether the speaker is pro- or anti-gun.

Immigration:

- Supporting immigration: we don't need a wall or more deportations, families should stay together, immigration is good for our country
- Tough on immigration: border needs protection, illegal immigration should be stopped, immigration is bad for our country
- Neither: just news, no opinion about immigration, no hints whether the speaker is supportive or tough.

Finally, coders were encouraged to click through to the longer instructions ("code book") if they were doing the task for the first time, or had not done the task in the past day. The sections below contain the descriptions of each issue frame from those instructions. Instructions received minor changes during the coding process, in order to account for common mistakes.

Climate, Skeptical - The evidence for climate change is false or not certain; predictions did not come true. Scientists are hiding evidence against global warming. The climate is always changing. Humans did not cause global warming. Problems we see today (e.g. wildfires) are not caused by climate change. Even if global warming exists, the effects are not so bad, or they are positive. Climate change is not important compared to other problems. It is too expensive or risky to take action, it would cost too many jobs, it is too soon to take action, it is not our responsibility.

Climate, Concerned - The evidence for climate change is clear. Humans and their greenhouse gas (CO_2) emissions cause global warming. Climate change will have negative effects (e.g. sea levels rising, plants or animals dying) now or later. Problems we see today (e.g. storms, droughts) are due to global warming. We need to act on it (e.g. by using less energy or clean energy). People who are looking for solutions or who are passing climate laws are doing the right thing.

Gun policy, Pro-gun - People have the right to own guns, protected by the second amendment. The government should not take our guns away. There should be fewer laws and rules about owning or buying guns and ammo (e.g. bullets). Gun control does not prevent crimes. People who own guns prevent crimes from happening, because they can defend themselves, their family, and others. People need guns to protect themselves if the government turns against the citizens. Mass shootings are a mental health problem. The US does not have more gun violence because it has more guns.

Gun policy, Anti-gun - There should be stricter rules about who can own and buy guns. People who want to buy a gun should have to pass a background check or get a license. Some types of guns, like assault rifles, should be banned. We need stronger measures to prevent teenagers, or people with mental health problems from having guns. The United States has more gun violence than other countries because it has more guns. Mass shootings would happen less often if it was harder to get a gun.

Immigration, supportive - There should not be a wall on the border with Mexico, and we should deport fewer people. Unauthorized immigrants are often running from violence in their home country. They should be treated well and families should stay together. The rules for legal immigration should not be made stricter. People who were brought into the country as children should be allowed to stay. Immigrants are hard-working, and they contribute to our society. America is a nation of immigrants.

Immigration, tough - We should invest more money and manpower into protecting the border and deporting unauthorized immigrants. If immigrants come or stay here illegally, they broke the law. Immigrants raise crime rates, they do not pay taxes and should not get government help. We also need stricter policies on legal immigration. Many immigrants don't speak English well, don't adopt American culture, or take jobs from Americans. American-born citizens should come first.

In the code books, coders were encouraged to classify mentions as "neither" if there was not enough context to classify them, if they did not fall into any of the other categories, or if the audio fragment was not about the topic. For example, a piece of news (with no negative or positive tone) about a climate law that was passed, or a commercial about climate-proofing your windows. However, the code books also explained that topic mentions can support ideological frames even if the speaker is not giving their own opinion. For example, a news item about new evidence for (or against) climate change would still count as concerned (or skeptical) and not neutral, because its effect could be to make a listener more concerned (or skeptical).

4 Google trends and topic mentions

To define "pre-event" and "post-event" weeks, I use Google Trends data. This data comes in the form of a day-by-day index of the number of Internet searches for a search term describing the event (e.g., "hurricane Florence" or "hurricane Michael"). On each day, I compare search activity to the peak-activity day for that event. By my definition, pre-event weeks end on the last day where search activity was less than 5% compared to the peak. Post-event weeks start on the

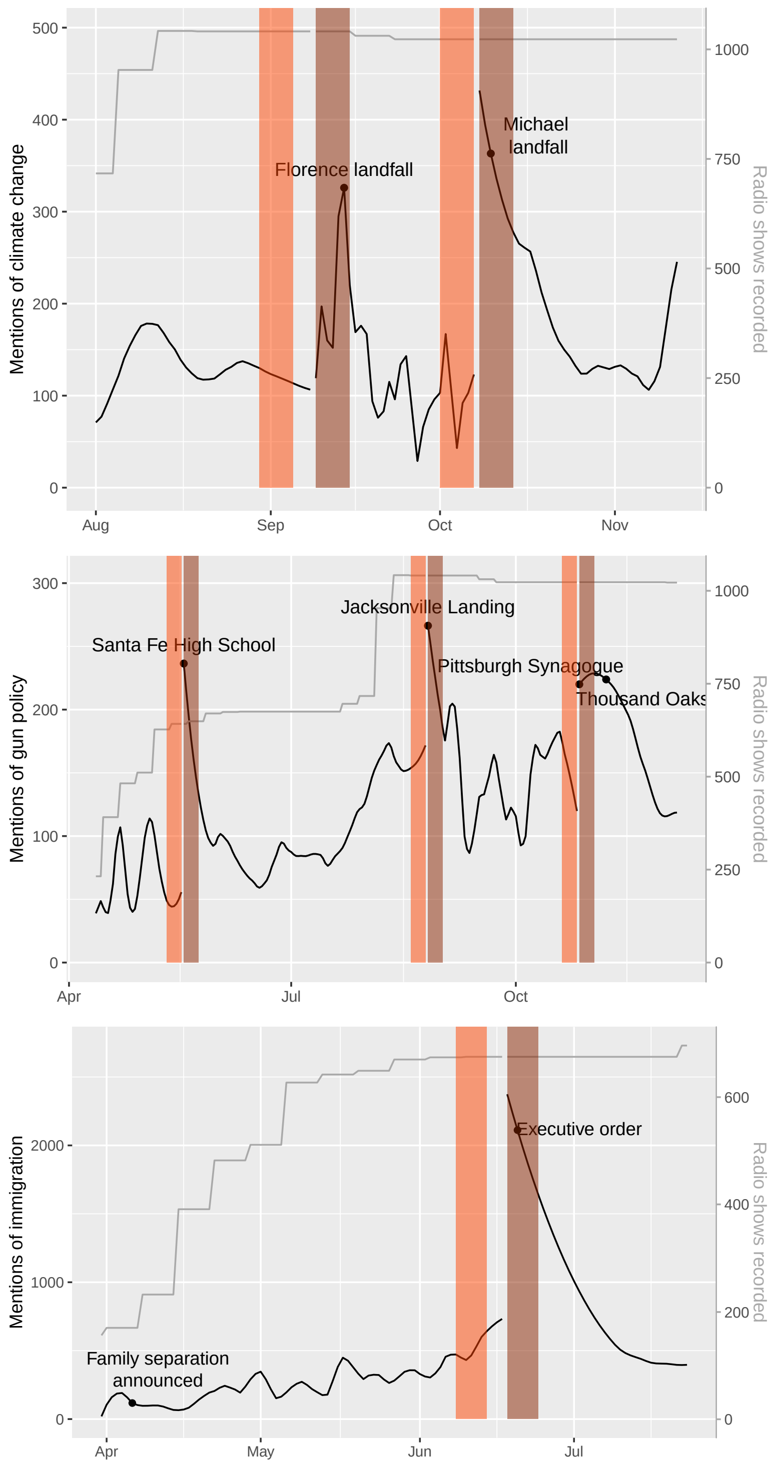

Figure 4: Daily number of talk radio mentions of climate, gun policy and immigration, with significant events. Bands show the pre- (orange) and post- (brown) event weeks as defined by Google Trends. Mention trends smoothed using Loess regression, allowing for discontinuities at the beginning of each post-event week. Light gray lines show the number of talk radio shows recorded on each date.

first day where search activity was at least 20% compared to the peak.

Figure 4 shows these periods, along with the number of topic mentions per day on all talk radio shows.[1] While these decision rules do not always line up perfectly with the "before" and "after" of talk radio attention, they do a reasonable job of capturing the baseline and the peak. The "pre-event" weeks also appear to be acceptable baselines, even though no week is ever completely free of (at least local) events that are relevant to these political topics.

5 Classifying radio shows

Table 2 contains all non-political shows that I used to train the political/non-political classifier. Table 3 lists all political shows, with two or more sources backing its ideological label. A source is considered to confirm an ideological label if it names the program, its host, or another closely associated entity as either "conservative" or "right-wing"; or as "liberal", "left-wing" or "progressive".

Requiring more than one source hedges against the possible ideological bias in ideological bias judgments themselves. For example, the Center for American Progress is itself classified as left-wing by the Media Bias/Fact Check group. However, I never came across two sources that contradicted each other in their judgments of any given show's bias; when two sources existed, they always agreed.

Two NPR programs (All Things Considered and Morning Edition) were left out of the ideology model's training set for the main analyses, despite the fact that several sources labeled NPR as liberal. Section 10.1 below provides a robustness check that includes these NPR shows in the training set.

In total, the labeled shows had almost 8500 episodes, of which almost 5800 were political. Before training the model on these shows, I held out 10% of each show's episodes, to be used for model testing. To transform the show transcripts into data, I counted and normalized the number of occurrences of 5000 tokenized word pairs in each transcript. In other words, the features fed to the model are term frequency–inverse document frequency (TF-IDF) vectors for 5000 tokenized bigrams. I left out any features whose TF-IDF score was correlated too strongly with any particular show label—for example, hosts' verbal tics, their names or show sponsors.

Existing literature on categorical ideology classification at the phrase (Iyyer et al., 2014) or document (Yan et al., 2017) level suggests that regularized logistic regression (LR) works well with this amount of data. I tried both LR (with L2 regularization) and Support-Vector Machines (SVMs). I decided between these two models, and tuned both the show-specific feature correlation threshold and the shrinkage parameter c, via blocked k-fold cross-validation. That is, I left out all episodes from the same show at once, and then tried to predict their label with a model trained on the other shows. LR slightly outperformed SVM for the political/non-political classifier, and SVM slightly outperformed LR for the ideology classifier.

Once tuned, I tested the final models' performance by using them to label the hold-out episodes of each show, which were all completely new to the model.

[1] These are unique mentions, not double-counting mentions on radio shows that are broadcast on more than one station. See section 2 for more on this.

Show	Topic
Food Friday Vox Pop	food
WMT Cooking Show	food
Better Lawns and Gardens	gardening
Classic Gardens and Landscape	gardening
GardenLine w/ Randy Lemmon	gardening
Dr. Bob Martin	health
Purity Products	health
Your Health with Dr. Joe Galati	health
At Home with Gary Sullivan	home
House Talk with Ray Trimble	home
Sturdy Home Improvement	home
Texas Home Improvement	home
Handel on the Law	legal
The Legal Exchange	legal
Your Legal Rights	legal
Financial Advisors with Aubrey Morrow	money advice
Money Matters with Ken Moraif	money advice
The Dave Ramsey Show	money advice
The Financial Exchange	money advice
Afropop Worldwide	music
Afternoon Jazz	music
Classic Jazz with Michele Robins	music
Classical 24 with Andrea Blain	music
Classical 24 with Bob Christiansen	music
Homegrown Music	music
Jesus Christ Show (PRN)	religious
Lutheran Hour	religious
St. John's Lutheran Church	religious
Ben Maller	sports
Buckey Sportsman with Dan Armitage	sports
FOX Sports Radio	sports
Fox Sports Weekends	sports
The Big Sports Show	sports

Table 2: Non-political shows in training set, with their hand-coded topic.

For each show, when trying to classify its hold-out episodes, I trained a model on all *other* shows. This way, I avoided rewarding the model for making predictions based on show-specific features. The political/non-political LR correctly classified all 50 shows based on their hold-out episodes. The conservative/liberal SVM successfully classified 14 out of 15 political shows. After tuning and testing, I trained the classifiers on the full labeled data sets (training and hold-out). Finally, I applied the political/non-political classifier to all 1005 recorded shows, and the ideology classifier to the 429 shows that were labeled as political.

There are a few reasons to treat show ideology as binary, rather than continuous. First, existing evidence suggests that radio shows are ideologically sorted, suggesting that it is reasonable to divide shows into a liberal and a conservative group. Second, having two ideology categories is a common choice in studies of

Conservative

Show	Sources
Ben Shapiro	Media bias/fact check (as The Daily Wire), Politifact, Wikipedia
Glenn Beck	CAP, Pew, Wikipedia
Hugh Hewitt	CAP, Media bias/fact check (as Salem Radio Network News), Wikipedia
Joe Pags	CAP, Wikipedia
Laura Ingraham	CAP, Politifact, Wikipedia
Mark Levin	CAP, Media bias/fact check (as Conservative Review)
Mike Gallagher	CAP, Wikipedia
Rush Limbaugh	CAP, Pew, Politifact, Wikipedia
Sean Hannity	CAP, Pew, Politifact, Wikipedia
The Savage Nation	CAP, Politifact, Wikipedia

Liberal

Show	Sources
Democracy Now!	Media bias/fact check, Wikipedia
Mike Malloy	CAP, Wikipedia, Liberal Talk Radio Wiki
Ring of Fire Radio	Media bias/fact check, Wikipedia
Stephanie Miller	Media bias/fact check (as Fstv), Politifact, Wikipedia, Liberal Talk Radio Wiki
Thom Hartmann	CAP, Media bias/fact check (as Fstv), Politifact, Wikipedia, Liberal Talk Radio Wiki

NPR

Show	Sources
All Things Considered	Media bias/fact check (as NPR), Pew (as NPR)
Morning Edition	Media bias/fact check (as NPR), Pew (as NPR)

Table 3: Political shows in training set, with their ideology label and sources. Sources: CAP (Center for American Progress and Free Press, The Structural Imbalance of Talk Radio, 2007, ampr.gs/2UegLbP); Liberal Talk Radio Wiki (ltradio.fandom.com/wiki/List_of_personalities); Media bias/fact check (mediabiasfactcheck.com); Pew Research Center (journalism.org/interactives/media-polarization); Politifact (politifact.com/personalities/); Wikipedia (wikipedia.com). The entity labeled by the source is in parentheses, if it is something other than the show or its host.

talk radio (cf. Yanovitzky and Cappella 2001; Sobieraj and Berry 2011; Center for American Progress and Free Press 2007; Jamieson and Cappella 2008, p. 86). The classification results support this—most political shows can be classified with fairly high confidence as either liberal or conservative, suggesting it is not as important for a model to cover the ideological "middle ground". Finally, the training data can be reliably classified into two ideological bins. Sources that designate radio shows as right- or left-leaning usually give categorical labels. Ratings on a spectrum would be more debatable. In a study on

TV news, Martin and Yurukoglu (2017) solved this by training a classifier on Congressional speech, with continuous DW-NOMINATE scores as the ideology outcome variable. I found that a domain-adapted binary classifier trained on speeches in the 114th Congress misclassified 3 out of 17 political training shows. Switching to a Congress-based model could thus lead to a significant drop in prediction quality.

6 Modeling mention proportions and counts

For each week on each radio show, there are two relevant outcomes: the number of mentions of a topic; and the proportion of mentions that feature a particular framing of the topic.

The number of mentions of each topic across shows-weeks has a very skewed, overdispersed distribution. As a result, a linear model of mention counts would have large uncertainty around its coefficients. Moreover, conclusions would be heavily dominated by a handful of shows that have far more mentions than the others. Instead, I use a negative binomial model.

The full model, which tells us about the differential effect of events on shows with different ideologies, is:

$$\mathbb{E}[Y_i^{count}] = exp(\beta_0 + \beta_1 post_i + \beta_2 liberal_i + \beta_3 post_i \times liberal_i + \beta_4 minutes_i)$$

where Y_i^{count} is the number of topic mentions in show-week i. It has a negative binomial distribution. $post_i$ indicates whether the show-week happened pre-event (0) or post-event (1). $liberal_i$ indicates whether the show was classified as conservative (0) or liberal (1). $minutes_i$ is the show's airtime in minutes per week. I control for total airtime because shows with more content naturally have more opportunities to mention a topic.

To model frame proportions, I use a so-called fractional logit model (Papke and Wooldridge, 1996).[2] The full model is:

$$\mathbb{E}[Y_i^{prop}] = logit^{-1}(\beta_0 + \beta_1 post_i + \beta_2 liberal_i + \beta_3 post_i \times liberal_i)$$

where Y_i^{prop} is the fraction of topic mentions on in show-week i that use a particular frame (e.g. climate skepticism). This is the proportion among mentions with an ideological frame, leaving out mentions coded as "neither". It has a quasi-binomial distribution. In both models, standard errors are clustered at the show level.

The key quantities of interest, which are reported in the main text, are predicted mention counts and predicted frame proportions before and after an event. The p-values accompanying these predictions in the main text refer to the relevant (combinations of) model coefficients. For instance, $\hat{\beta}_1$ represents the estimated change in topic mentions (or frames) from pre- to post-event for a conservative show. $\hat{\beta}_1 + \hat{\beta}_3$ represents the change for a liberal show. $\hat{\beta}_2$ is the

[2]This is a generalized linear model with a logit link function and a quasi-binomial probability mass function for the outcome. Using a quasi-binomial distribution instead of a binomial one does not change the estimates but gives us more robust standard errors (Papke, ND).

estimated difference between liberal and conservative shows before an event, and $\hat{\beta}_3$ captures how the event differentially affects liberal and conservative shows.

In order to calculate confidence intervals for the predicted quantities (as seen in main text Figures 2 and 3), I use a non-parametric block bootstrap technique (Cameron et al., 2008) with percentile confidence intervals. In each iteration of the bootstrap, I sample shows with replacement, extracting the same number of shows as there are in the original data set. For each sampled show, I include all of its observations (show-weeks) in a new simulated data set. I then run the models above on the simulated data and calculate the predicted quantities of interest. Iterating 1000 times results in 1000 predictions. The 2.5th and 97.5th quantiles of these predictions are the bounds of the confidence intervals.

7 Regression tables

Tables 4 and 5 below show regression results for the number of mentions (negative binomial model) and proportion of mention frames (fractional logit model) for all three topics. All significance tests are two-tailed.

For the negative binomial models, the coefficient on `post` ($\hat{\beta}_1$) amounts to the estimated increase in log topic mentions on a conservative show after an event. The coefficient on `liberal` ($\hat{\beta}_2$) represents the effect on log topic mentions of moving from a conservative to a liberal show, pre-event. The coefficient on `post x liberal` ($\hat{\beta}_3$) is the change from pre-event to post-event topic mentions among liberal shows, compared to the change among conservative shows.

For the fractional logit models, the coefficients represent analogous changes in the (logit-transformed) proportions of climate-concerned, anti-gun, and tough-on-immigration frames. These models have fewer observations, because show-weeks with no topic mentions have no information on frame proportions.

Table 4: Regression table for number of mentions of climate change, gun policy and immigration. Model is negative binomial regression with standard errors clsutered at the show level.

	climate	gun	immig.
	(1)	(2)	(3)
Constant	-0.484^{***}	0.483	1.188^{***}
	(0.122)	(0.313)	(0.149)
	p = 0.0001	p = 0.124	p = 0.000
post	0.968^{***}	0.577^{***}	1.782^{***}
	(0.116)	(0.124)	(0.094)
	p = 0.000	p = 0.00001	p = 0.000
liberal	1.018^{***}	-1.013^{***}	0.541
	(0.195)	(0.338)	(0.405)
	p = 0.00000	p = 0.003	p = 0.182
post x liberal	-0.329	-0.222	-1.100^{***}
	(0.240)	(0.221)	(0.400)
	p = 0.171	p = 0.317	p = 0.007
minutes	0.001^{***}	0.001^{***}	0.001^{***}
	(0.0001)	(0.0002)	(0.0001)
	p = 0.000	p = 0.0002	p = 0.000
Observations	1,412	1,896	524
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 5: Regression table for proportion of mentions that are concerned about climate, anti-gun, or tough on immigration. Model is fractional logit regression with standard errors clsutered at the show level.

	climate	gun	immig.
	(1)	(2)	(3)
Constant	-0.505^{***}	-1.326^{***}	0.850^{***}
	(0.178)	(0.152)	(0.188)
	p = 0.005	p = 0.000	p = 0.00001
post	0.175	0.422^{**}	-0.153
	(0.179)	(0.165)	(0.190)
	p = 0.331	p = 0.011	p = 0.421
liberal	2.959^{***}	2.232^{***}	-1.651^{***}
	(0.422)	(0.296)	(0.289)
	p = 0.000	p = 0.000	p = 0.000
post x liberal	0.339	-0.122	-0.060
	(0.398)	(0.376)	(0.320)
	p = 0.395	p = 0.745	p = 0.851
Observations	529	653	320

Note: *p<0.1; **p<0.05; ***p<0.01

8 Counting non-neutral mentions of immigration

One obvious concern about the finding of increased immigration mentions might be that it would be difficult to report on the event (family separation) without mentioning the topic terms. For that reason, I re-do the analyses leaving out any mentions that the coders labeled "neither". These are mentions that support no stance on immigration, largely because they are simply pieces of news on the topic. On both ideological sides, the proportional increase in the "non-neither" mentions is roughly the same size as the overall increases above (conservative: from 1.9 to 9.4; liberal: from 4.0 to 6.4). In other words, the change in attention to immigration is not only due to outlets reporting on the events themselves—it is as much due to an increase in opinionated commentary on the topic of immigration.

9 Long-term effects: agenda half-lives

Studies of the agenda-setting power of major events in mainstream media often find effects that last for months (Lawrence, 2000; Birkland, 2004; Zhang et al., 2017). Here, I describe how trends in topic mentions tend to evolve once they have peaked after an event. In other words, I analyze how quickly attention to a topic dissipates on talk radio. Here, I fit a model to the post-event trends.

For each topic, I look at total topic mention counts in the month after each event, day by day. Because I am interested in the downward trend, the start of this month is not the start of the post-event week (which I defined earlier as the first day on which the event reaches some level of social significance). Instead, it is the peak of talk radio attention to the topic: the day with the most mentions.

To avoid catching the beginning of attention to the *next* event, I leave out any days that fall in the next post-event week. This results in six dropped observations for climate change, and six for mass shootings. Finally, for the Pittsburgh Synagogue shooting, I only include the first nine days. This is because ten days after the shooting, there was another mass shooting in Thousand Oaks, California.

After pooling the data across events within topics, I estimate the following simple model:

$$\mathbb{E}[Y_{d,e}^{pct}] = 2^{-\beta d}$$

$Y_{d,e}^{pct}$ is the total number of mentions of the topic on day d after the peak for event e. It is measured as a percentage of peak attention–i.e., attention on day $d = 0$. I did not include an intercept, as $Y_{d=0,e}^{pct} = 1$ by definition. Using base 2 for the exponential decay conveniently allows us to interpret the inverse of β as the half-life of attention; the number of days it takes for mention counts to halve. I estimate the model using non-linear least squares.

This model is not perfect—for instance, attention likely returns to some baseline level in the long run, rather than eventually going to zero. However, it fits the time trend in topic mentions reasonably well.

Figure 5 shows the predicted post-peak attention trend for each topic, alongside the data. The estimated beta coefficients are 0.14 for hurricanes and climate

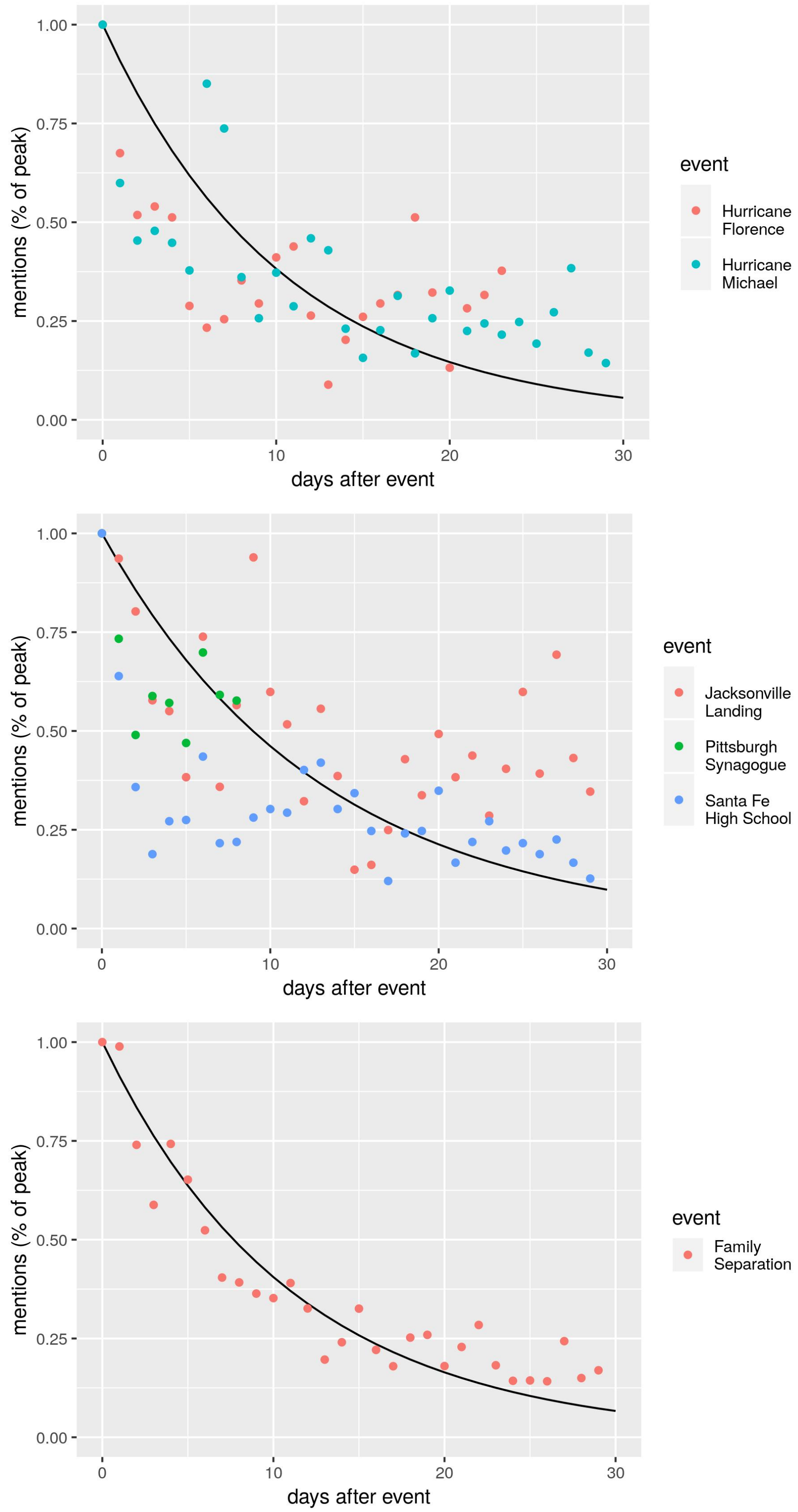

Figure 5: Decline in attention (number of topic mentions) after the peak for each event. Line graphs show the estimated exponential decay of attention. Points show observed attention by event.

change, 0.11 for mass shootings and gun policy, and 0.13 for family separation and immigration. This means that the half-life of attention to topics after these events is 7–9 days.

10 Robustness checks

10.1 News and public radio shows

Most of the existing literature has treated news and public radio shows as separate from political talk radio. I find that by a number of quantitative measures, these shows are not necessarily more "neutral" than the other programs in our data set. In this section, I show that the results are not affected by whether or not news and public radio shows are included.

Among shows classified as political, 25 shows have the word "news" in their name (e.g. "Alabama Morning News"), and 14 shows are produced and distributed by National Public Radio (NPR). First, I look at whether these shows, when they mention a political topic, tend to use neither of the two established frames. Mentions coded as "neither" are usually presentations of facts or straightforward pieces of news about a topic. Bundling all of the observed weeks, just 16% of climate mentions on the average news show use neither a supportive nor a skeptical frame. The same is true for NPR shows. With respect to gun policy, 33% of mentions on the average news show are neutral in this way. On NPR shows it is 34%. Immigration is the topic that invites the most neutral discussion, with 42% of news mentions and 55% of NPR mentions.

A second possibility is that these shows are neutral in the sense that they present both sides of the story equally, for instance by inviting guests with opposite points of view. Among the topic mentions that use an ideological frame, however, I do not find this type of balance. In the case of climate change, the average news show dedicates more than 89% of its non-neutral mentions to one side of the issue (be it skeptical or convinced). For the NPR shows, it is 95%. On gun policy, these shows spend 73% of their non-neutral mentions arguing for the same side. For the average NPR show, that is 84%. On the topic of immigration, the average news show has 72% of its non-neutral mentions supporting the same side. For NPR shows, it is 69%. Not surprisingly, all NPR shows tend to take the same side (in particular, they overwhelmingly feature "climate-convinced" content). The shows in the news category are more mixed in the direction of their slant. Crucially, none of the numbers above look much different in the sample of non-news, non-NPR shows.

To check the robustness of these findings, I experiment with alternative definitions of news and public radio shows, based on what stations broadcast them. All US radio stations have a self-selected format that broadly describes their programming, mostly for the purposes of marketing and statistics. An alternative criterion for news shows would be those shows that are broadcast at least one station with the"All News" format. An alternative criterion for public radio shows would be those shows that are broadcast on at least one station with the "Public Radio" format. These definitions lead to the same conclusion: on news and public radio shows, the discussion of political topics looks no more neutral or balanced than it does on any other political show.

Given these findings, we might view news and public radio shows as simply

		without news, public				with news, public			
		counts		frames		counts		frames	
topic	ideology	pre	post	pre	post	pre	post	pre	post
climate	conservative	0.8	2.1	38	42	0.8	2.2	38	41
climate	liberal	2.2	4.1	92	95	2.0	4.1	93	95
gun policy	conservative	1.9	3.3	21	29	2.0	3.3	22	30
gun policy	liberal	0.7	1.0	71	77	0.7	1.1	68	79
immigration	conservative	4.3	25.3	70	67	5.1	27.4	70	66
immigration	liberal	7.3	14.5	31	27	8.2	17.7	30	28

Table 6: Predicted mention counts and frames (percentage "convinced", "anti-gun" and "tough on immigration" frames), pre- and post-event, for each political topic, without and with NPR shows or news shows.

another type of talk radio with political content. For that reason, I repeat the analyses, including shows with "news" in the name and shows produced by NPR. I also add two NPR programs to the liberal show training set for the ideology classifier. This improves performance: testing the model on unseen episodes, the classifier now correctly guesses the ideology of *all* shows. Table 6 shows the results, alongside the original ones without NPR and news shows. We can see that the basic thrust is the same.

10.2 Show classification thresholds

In the analyses above, shows are classified based on 50% thresholds: they are labeled political, and conservative, if classifiers assign them a 50%-or-higher probably of being so. However, the training set for each model is a simply set of shows that can reliably be labeled as non-political, liberal or conservative. This set probably does not reflect the actual balance of show ideologies in the full sample. It is likely, then, that the models' intercept estimates are biased. Moreover, perhaps not all political shows are slanted: it is possible there are moderate shows in the sample, which I am unjustly labeling as ideological.

Figure 6 shows the results of the show classification effort. It looks like the choice of 'politicalness' threshold could be important, because some shows are in fact difficult to classify. Only 70% of shows can be labeled as political with at least 70% certainty. In terms of ideology, the picture looks somewhat more robust. 80% of political shows get an ideological label with over 70% certainty. Nonetheless, we may be interested in how results change if we exclude shows whose ideological class is unclear.

Here, I repeat the key analyses, varying my decisions about show classes in two ways. First, I move the political decision threshold above or below 50%, biasing the model towards labeling fewer or more shows as political. Second, I create bands around the ideology threshold, excluding shows that the model is uncertain about. For example, I might only include shows for which the classifier is at least 60% certain that they are either liberal or conservative. Table 7 shows the results of the former analysis. Table 8 shows the latter. Neither decision changes the results in any significant way, except that stricter 'politicalness' thresholds lead to somewhat more topic mentions at baseline. This makes sense, since I am excluding shows that spend less time covering political topics.

		climate				gun policy				immigration			
		counts		frames		counts		frames		counts		frames	
threshold	ideology	pre	post	pre	post	pre	post	pre	post	pre	post	pre	post
0.4	conservative	0.7	1.9	38	45	1.6	2.9	22	29	3.8	23.3	66	63
0.4	liberal	1.9	3.7	92	95	0.6	0.8	69	78	6.4	12.5	28	25
0.5	conservative	0.8	2.1	38	42	1.9	3.3	21	29	4.3	25.3	70	67
0.5	liberal	2.2	4.1	92	95	0.7	1.0	71	77	7.3	14.5	31	27
0.6	conservative	0.8	2.3	37	41	2.0	3.5	20	29	4.3	25.8	70	68
0.6	liberal	2.4	4.6	91	95	0.7	1.2	72	78	5.2	16.6	28	30

Table 7: Predicted mention counts and frames (percentage “convinced”, “anti-gun” and “tough on immigration” frames), pre- and post-event, for each political topic. Threshold indicates level of certainty we need in order to call a show “political” and include it in the data set.

		climate				gun policy				immigration			
		counts		frames		counts		frames		counts		frames	
threshold	ideology	pre	post	pre	post	pre	post	pre	post	pre	post	pre	post
0.5	conservative	0.8	2.1	38	42	1.9	3.3	21	29	4.3	25.3	70	67
0.5	liberal	2.2	4.1	92	95	0.7	1.0	71	77	7.3	14.5	31	27
0.6	conservative	0.8	2.1	37	41	1.9	3.4	21	29	4.4	25.8	70	67
0.6	liberal	2.4	4.4	93	96	0.7	1.0	75	75	8.0	14.8	31	27
0.7	conservative	0.8	2.1	35	40	2.0	3.5	20	29	4.2	25.2	71	69
0.7	liberal	2.5	5.9	96	97	0.9	1.2	78	81	5.5	17.0	31	26

Table 8: Predicted mention counts and frames (percentage “convinced”, “anti-gun” and “tough on immigration” frames), before and after events, for each political topic. Threshold indicates level of certainty we need in order to call a show “conservative” or “liberal”, and to include it in the data set.

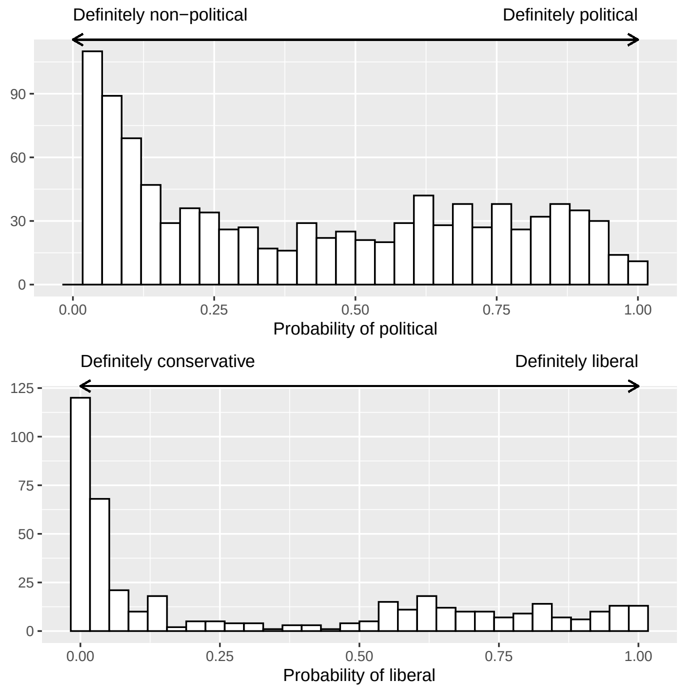

Figure 6: Distribution of prediction probabilities for shows, resulting from politicalness and ideology classifiers.

References

Doug Beeferman, William Brannon, and Deb Roy. Radiotalk: A large-scale corpus of talk radio transcripts. Technical report, Lab for Social Machines, MIT Media Lab, 2019.

Thomas A Birkland. "The world changed today": Agenda-setting and policy change in the wake of the September 11 terrorist attacks. *Review of Policy Research*, 21(2):179–200, 2004.

A Colin Cameron, Jonah B Gelbach, and Douglas L Miller. Bootstrap-based improvements for inference with clustered errors. *The Review of Economics and Statistics*, 90(3):414–427, 2008.

Center for American Progress and Free Press. The structural imbalance of political talk radio, 2007. URL `https://cdn.americanprogress.org/wp-content/uploads/issues/2007/06/pdf/talk_radio.pdf`. Accessed April 2022.

Bryce J Dietrich, Matthew Hayes, and Diana Z O'Brien. Pitch perfect: Vocal pitch and the emotional intensity of congressional speech. *American Political Science Review*, pages 1–22.

Bryce J Dietrich, Ryan D Enos, and Maya Sen. Emotional arousal predicts voting on the us supreme court. *Political Analysis*, 27(2):237–243, 2019.

Mohit Iyyer, Peter Enns, Jordan Boyd-Graber, and Philip Resnik. Political ideology detection using recursive neural networks. In *Proceedings of the 52nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1113–1122, 2014.

Kathleen Hall Jamieson and Joseph N Cappella. *Echo chamber: Rush Limbaugh and the conservative media establishment*. Oxford University Press, 2008.

Regina G Lawrence. *The politics of force: Media and the construction of police brutality*. University of California Press, 2000.

Gregory J Martin and Ali Yurukoglu. Bias in cable news: Persuasion and polarization. *American Economic Review*, 107(9):2565–99, 2017.

Leslie E Papke. Papke and Wooldridge (1996) flogit instructions. ND.

Leslie E Papke and Jeffrey M Wooldridge. Econometric methods for fractional response variables with an application to 401 (k) plan participation rates. *Journal of applied econometrics*, 11(6):619–632, 1996.

Vijayaditya Peddinti, Guoguo Chen, Vimal Manohar, Tom Ko, Daniel Povey, and Sanjeev Khudanpur. Jhu aspire system: Robust lvcsr with tdnns, ivector adaptation and rnn-lms. In *2015 IEEE Workshop on Automatic Speech Recognition and Understanding (ASRU)*, pages 539–546. IEEE, 2015.

Sarah Sobieraj and Jeffrey M Berry. From incivility to outrage: Political discourse in blogs, talk radio, and cable news. *Political Communication*, 28(1): 19–41, 2011.

Hao Yan, Allen Lavoie, and Sanmay Das. The perils of classifying political orientation from text. *Linked Democracy: Artificial Intelligence for Democratic Innovation*, 858:8, 2017.

Itzhak Yanovitzky and Joseph N Cappella. Effect of call-in political talk radio shows on their audiences: Evidence from a multi-wave panel analysis. *International Journal of Public Opinion Research*, 13(4):377–397, 2001.

Yini Zhang, Yidong Wang, Jordan Foley, Jiyoun Suk, and Devin Conathan. Tweeting mass shootings: The dynamics of issue attention on social media. In *Proceedings of the 8th International Conference on Social Media & Society*, page 59. ACM, 2017.