What Was the Problem in Parkland? Using Social Media to Measure the Effectiveness of Issue Frames

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Abstract

Agenda setting and issue framing research broadly investigates how problem framing impacts public attention, policy decisions, and political outcomes. Social media sites, such as Twitter, provide unique opportunities to study such dynamics in an increasingly important area of political discourse. We present a method for identifying frames in tweets and measuring their effectiveness using tweet interaction data. We use topic modeling combined with manual validation to identify recurrent problem frames and topics in thousands of tweets by gun rights and gun control groups following the Marjory Stoneman Douglas High School shooting. We find that each side used Twitter to advance competing policy narratives about the problem in Parkland. Gun rights groups' narratives implied that more gun restrictions were not the solution. Their most effective frame focused on officials' failures to enforce existing laws (implying that new gun regulations were unnecessary). In contrast, gun control groups most effectively portrayed easy access to guns as the problem (not mental illness), and emphasized the importance of mobilizing politically to force change. Computational methods, such as topic modeling with careful validation, offer new research opportunities for policy scholars in the increasingly important yet challenging domain of social media.

Keywords— Framing; Social Media; Mass Shootings; Parkland, Florida; Marjory Stoneman Douglas

1 Introduction

Public policy scholars have long been interested in how public perceptions of issues and policies are formed and how those perceptions influence policy action and outcomes. The literature is extensive and includes studies of issue framing, agenda setting, social construction, problem definition, policy narratives, and more. New media, such as social media, offer new framing venues and opportunities for many more actors to participate in framing contests compared to traditional media. For researchers, this expansion of opportunities poses new methodological challenges in how we can study so much activity. We use computational methods to study how a large number of groups sought to frame a problem on Twitter. Prior studies of social media framing start with a set of assumed frames. In contrast, we use topic modeling combined with manual validation to discover recurrent problem frames and topics across thousands of tweets. We then show how the effectiveness of different framing efforts can be assessed using social media metrics such as retweets and changes in followers. Although our substantive focus is on a particular problem-framing contest in one social media domain, the methodology has broad application.

The framing contest of interest is how gun control and gun rights groups explained a tragic mass shooting. On February 14, 2018, a 19-year-old gunman killed 17 people and wounded 17 more at Marjory Stoneman Douglas (MSD) High School in Parkland, Florida. Sadly, mass shootings are a regular occurrence in the United States.[1] One might suppose that the extreme drama of mass shootings, along with the media coverage they receive, would be sufficient to bring about change. After all, a majority of American favor stricter gun regulations. But this is not the general pattern. More commonly, there is a relatively brief flurry of media coverage, calls for reform, and little if any action.

Where gun control is concerned, the minority of Americans who oppose stricter gun laws are very well organized and easily mobilized.[2] Mobilizing other Americans to act on behalf of stronger gun laws has proven more difficult. Gun rights groups also have well-developed strategies for responding to mass shootings that reflect an understanding of media (and public) dynamics. If they avoid

[1]The Washington Post maintains a database of mass shooting events here: `https://www.washingtonpost.com/graphics/2018/national/mass-shootings-in-america/?noredirect=on&utm_term=.efb250749954`

[2]For Gallup opinion poll results about guns over time, see here: `https://news.gallup.com/poll/1645/guns.aspx`

fanning the flames, the media and public will eventually be distracted by other events (Downs 1972).[3]

Policy scholars have shown that it is generally easier to prevent policy change than to cause it (Schattschneider 1960). Change requires that the current losers elevate the issue to the top of multiple, crowded public and government agendas. To do this, they need to gain the attention of currently inattentive publics, usually through favorable media coverage, and persuade policymakers to take action. The current winners,[4] in contrast, only need to prevent policymakers from acting, which can be accomplished in any number of ways (Cobb and Ross 1997).[5]

Gun-related tragedies do occasionally threaten to “expand the conflict” in ways that may lead to policy change (Schattschneider 1960). The Parkland shooting was not the largest mass shooting in the U.S. - far from it - but it did receive more sustained media coverage than similar recent events. One reason for the sustained attention was the activism and social media skills of Marjory Stoneman Douglas students: "With their consistent tweeting of stories, memes, jokes and video clips, the students have managed to keep the tragedy that their school experienced — and their plan to stop such shootings from happening elsewhere — in the news for weeks, long after past mass shootings have faded from the headlines" (Bromwich 2018).

One impact of this sustained attention was to raise concern among pro-gun activists and politicians that the “passion gap” that has long given gun rights groups the upper hand (21 percent of gun owners have contacted a public official to express an opinion on gun policy compared to 12 percent of non–gun owners) was narrowing (Zornick 2018). Social media data also suggest that the Parkland shooting touched a nerve in ways not seen in other recent shootings. Figure 1 compares the total change in followers on Twitter for nine gun control groups during the month after after the mass shootings in Las Vegas (October 1, 2017, 58 dead, 851 wounded), Sutherland Springs, Texas (November 5, 2017, 26 killed, 20 wounded), and Parkland (February 14, 2018, 17 killed and 17 wounded).[6] Even though there were fewer casualties, many more people were inspired to follow

[3] Following this standard strategy, after the Parkland shooting the National Rifle Association (NRA), the largest and most prominent gun rights group in the U.S., did not tweet for six days.

[4] For clarity we define winners as “social organizations focused on maintaining the status quo” and losers as “social organizations focused on policy change.”

[5] Strategies include denying a problem actually exists, refusing to recognize the groups raising the issue, attacking the group initiating the new policy position, symbolic placation, and more.

[6] Twitter accounts indicate the number of people subscribing to (following) the account on a given day.

gun control group organizations after the Parkland shooting.[7]

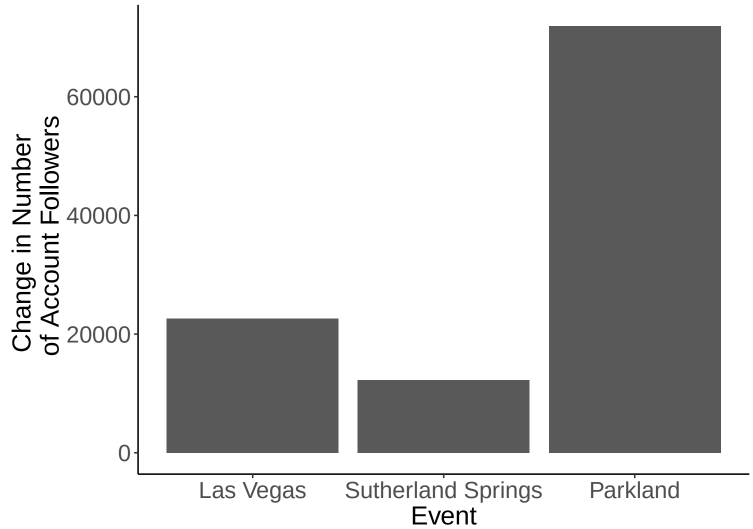


Figure 1: Change in Gun Control Twitter Followers around Mass Shooting Events

Figure 2 compares the average number of followers for both gun control and gun rights groups immediately around the Parkland shooting (the dashed line is the shooting date). Perhaps surprisingly, gun rights groups also experienced substantial increases in followers after the shooting. However, these increases were delayed by about a week compared to the increases for gun control groups. If the increase in gun control group support offers evidence that Parkland narrowed the "passion gap," how do we explain the later increase in gun rights group support?

[7]These results do not appear to be "bot" driven. In July 2018 Twitter announced that it has removed millions of fake, suspicious or dormant accounts (bots). These removals had no detectable impact on gun group follower numbers (for more, see Confessore and Dance 2018).

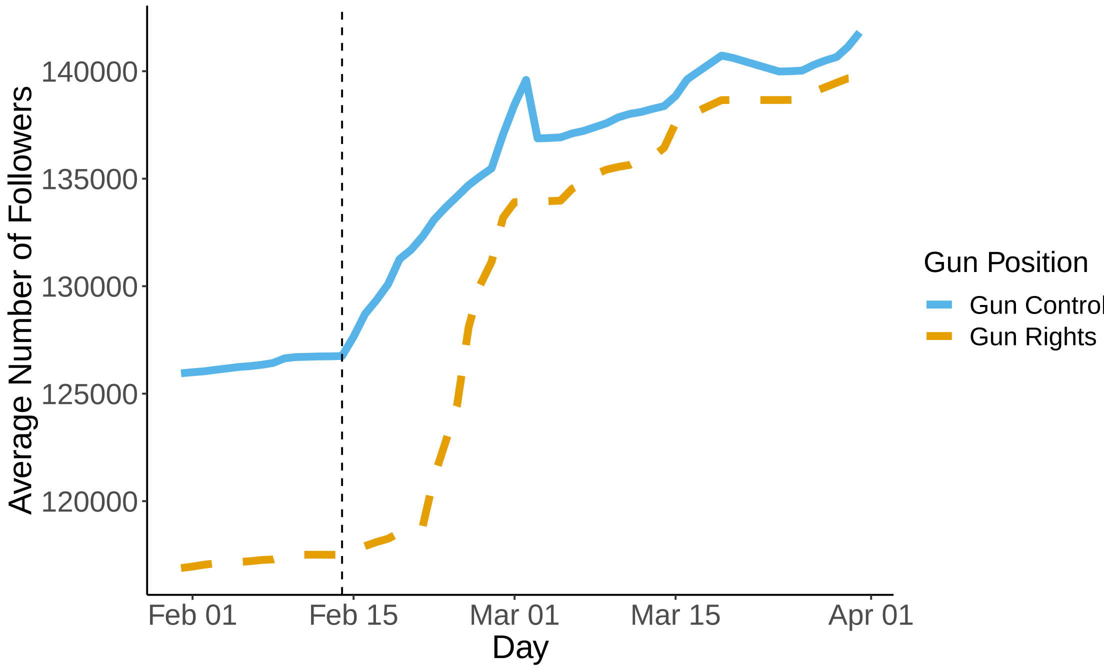


Figure 2: Twitter Followers around Parkland by Gun Group Type

Can we find the explanations in group social media communications? How did gun control and gun rights groups frame the Parkland shooting on Twitter? Which frames were most effective? To be sure, this is not the first study of social media framing (e.g. Gupta, Ripberger, and Wehde 2018; M. Merry 2016a; M. Merry 2020). However, we believe that we make several unique contributions. First, we investigate a framing "contest" – how did different groups define the same salient event for the public? Second, we employ a unsupervised computational approach (with manual validation) that allows for the discovery of frames a researcher may not anticipate. Compared to manual labeling alone, this computational approach facilitates more ambitious, big data studies. Finally, we draw on social media metrics to compare frame effectiveness. Previous studies have used retweets (Gupta, Ripberger, and Wehde 2018) and Facebook "likes" (M. Merry 2020) in this way. We move beyond these short term visibility effects to also assess longer-term downstream mobilizing effects in the form of attracting new account subscribers (followers)[8].

Our attention to followers is consistent with prior research arguing that, on issues where preferences are well established (such as the gun debate), framing is more effective as a tool of mobilization

[8]Retweets increase attention in the short-term, but an increase in followers increases attention in the long-term. Increased followers increases the number of users that are likely to view future messages from the group on their newsfeed.

than of persuasion (Chapman and Gerber 2019; Baumgartner, De Boef, and Boydstun 2008; Chong and James N. Druckman 2010). We ultimately argue that gun rights groups' success in attracting new followers after Parkland was indicative of a successful effort to re-energize their base at a time when many may have found it difficult to continue to support gun rights. This resurgence helped to discourage further action at the state and federal levels. The research question of interest is: How were they able to re-energize their base? We argue that issue framing provides part of the explanation.

The remainder of this paper is organized as follows. We first discuss prior issue framing research, including studies examining social media. Although we do not make predictions about specific frames, we do expect general differences in framing strategies. We then describe our computational method for discovering issue frames across thousand of tweets including how we address the validity concerns inherent in conventional unsupervised topic modeling. Using this method, we identify 12 common problem frames and topics related to Parkland. Many of the differences between gun control and gun rights group framing are predictable. Gun rights groups were more likely to frame the problem in Parkland in such a way that implied that additional gun restrictions were not the solution (Stone 1989). This included blaming the tragedy on the actions of individuals. Gun control groups were more likely to blame easy access to guns and unresponsive politicians, underscoring the importance of mobilizing gun control supporters (Schattschneider 1960). We also find each side devoted a lion's share of their communications to contesting frames advanced by the other side.

We then use indicators of reader responsiveness - retweets and changes in Twitter followers - to assess the effectiveness of these different frames. The most effective frame for gun control groups attributed the central problem in Parkland to easy access to guns, not mental illness. The most effective frame for gun rights groups blamed the shooting on individual failures to enforce existing laws. This frame absolved gun rights supporters of responsibility for the tragedy while implying that new gun regulations were unnecessary.

2 Issue Framing and the Rise of Social Media

Public policy and communications scholars have long been interested in the formation of public perceptions of issues and how those perceptions shape policy choices and outcomes. This extensive literature includes issue framing, agenda setting, social construction, problem definition, causal stories, policy narratives and more.[9] Perhaps the biggest conceptual difference is between agenda setting research that is primarily concerned with the issue or policy selection process, and research that is primarily concerned with policy discourse.[10] We take the liberty of grouping the latter under a single umbrella term – framing. As Entman (1993) famously puts it, the goal of framing is "to select some aspects of a perceived reality and make them more salient in a communicating text, in such a way as to promote a particular problem definition, causal interpretation, moral evaluation and/or treatment recommendation for the item described" (52). Frames often take the form of "stories with a beginning, middle, and an end, involving some change or transformation. They have heroes and villains and innocent victims, and they pit forces of evil against forces of good" (Stone 2002, 138; see also M. Jones and McBeth 2010; M. Merry 2016b).

Frames have implications for policy choices and action. Whether government intervention is appropriate is often a point of contention in liberal democracies, and the answer can depend on how a problem is defined. Are individuals or broader societal forces to blame for problems (Stone 1989; Edelman 2001)? Is the affected population deserving or undeserving of our concern and resources (Schneider and Ingram 1993; M. Jones and McBeth 2010; M. K. Merry 2017)?

Framing research also highlights general differences in framing goals and strategies during policy debates. Schattschneider (1960), for example, argues that current losers can only succeed by expanding the scope of conflict to include new publics. To do this they must make those publics aware of the costs of the status quo policy, often by linking the specific problem to broader concerns. Other studies focus on the conditions under which such mobilizations are possible (Riker 1986; Kingdon 1989; Baumgartner and B. Jones 1993; Thomas A Birkland 1998; Walgrave et al. 2017; Chong and James N Druckman 2007; Hilgartner and Bosk 1998).

Social media has transformed the politics of framing in important ways. It is no longer the case that a small number of actors (newspapers, television, elected officials) control the narrative (Thomas A. Birkland and Lawrence 2009). Groups and individuals now have many more opportunities to independently promote their messages (Barberá et al. 2015). Indeed, social media has now become an

[9] An excellent review of these literatures can be found in Cobb and Ross 1997, Chapter 1.

[10] Of course, agenda setting scholars will be quick to note that they too are interested in discourse to the extent that it can explain issue or policy agendas. "Issue definition" plays a key role in explaining policy change for example (Baumgartner and B. Jones 1993).

important conduit of stories for the mainstream media (Stoycheff et al. 2018). Equally important, new media allows for two-way communications that provide immediate feedback, enabling users to monitor others responding and adjust their messages accordingly (**bimber_collective_2012**; Bennett and Segerberg 2013; Neuman et al. 2014; Karpf 2012).

These media developments create new opportunities and challenges for researchers interested in framing. In terms of opportunities, the proliferation of voices offers new insights into political movements and strategies, not only in terms of who participates but also in terms of how they communicate their messages (text, images, video etc.). The fact that others are able to respond to those communications (in traceable ways) creates unprecedented opportunities to study framing dynamics and effectiveness. The challenges stem from those same opportunities. With so many sources and voices, new methodological approaches are required to take advantage of this richness.

2.1 Studies of Gun Control Framing on Social Media

Gun control politics has been an important subject of framing and agenda setting studies (**Goss2006**; Vizzard 2000; Lawrence and Thomas A. Birkland 2004; Thomas A. Birkland and Lawrence 2009; Hurka and Nebel 2013; Smith-Walter et al. 2016; Joslyn and Haider-Markel 2018) including studies of social media framing (**WasikeB.2017Pi1c**; Auger 2013; M. Merry 2016a; M. Merry 2016c; Huff et al. 2017; Stoycheff et al. 2018). This research has explored a number of questions about the social media strategies of gun groups and their impact. However, prior studies tend to focus on the general framing behavior of groups in isolation. As discussed, we focus on framing dynamics around a particular event involving a large number of groups. We also do not pre-define the frames examined in the analysis. Finally, we leverage the two-way characteristics of social media to investigate the effectiveness of groups' varied efforts to frame a contested problem.[11]

2.2 The Problem in Parkland

We are specifically interested in how gun control and gun rights groups explained the shooting at Marjory Stoneman Douglas High School in Parkland, Florida. The shooting occurred on a school

[11] Whether social organizations adjust their strategies in response to this feedback is an interesting question not addressed in this paper. Similarly, do social organizations share successful frames with other organizations supporting the same cause?

day (February 14), when a former student opened fire with a semi-automatic rifle. 17 individuals were killed and 17 were injured. The assailant, who previously exhibited signs of mental illness, walked out of the school with other students but was later arrested. The Broward County Sheriff's office received intense media and public scrutiny after the shooting. Critics alleged that the office did not appropriately respond to earlier information about threats made by the assailant. In addition, surveillance footage revealed that an armed sheriff's deputy was present but did not enter the building to confront the shooter.

This paper does not attempt to explain all of the social media activity generated by the Parkland shooting or its effects. In addition to the groups and accounts we tracked, MSD students and families of the victims also employed social media to advocate for change for months (well beyond the scope of this study, which is limited to one month after the shooting). A number of prominent events also inspired substantial social media attention during our period of analysis, including powerful speeches by students, a CNN Town Hall on February 21st where MSD students questioned gun rights spokesperson Dana Loesch, and an MSD student march on March 10th. The on-line activities of gun control and gun rights groups were undoubtedly shaped by these prominent events. In this respect, our analysis may suffer from potential endogeneity effects – public interest in a group's tweets may be driven by interest in the event (e.g.) the group is tweeting about. However, as we will show, most of the frames we discovered and tested for effectiveness were not directly related to off-line advocacy events. They were attempts to define the problem that needed to be addressed in order to prevent future school shootings.

How did gun rights and gun control groups frame the problem in Parkland? The complicated reality is that there were many potential causes: the perpetrator's possible mental illness, isolation and family circumstances; lax social services oversight; access to an exceptionally deadly weapon; insecure schools; government failure in preventing the weapons sale; the delayed response of law enforcement officials; and much more.

Yet, portraying a complex issue as complicated may not be the most effective framing strategy. The purpose of strategic framing is to focus public attention on the cause or causes that most effectively advance a group's agenda. Our starting point is to assume that the central objective of gun rights groups is to oppose additional restrictions on the sale and use of guns. In this vernacular, guns don't kill people, people kill people. And if people are the problem, then more gun restrictions do not imply greater safety. In the words of National Rifle Association President Wayne LaPierre: "To stop a bad guy with a gun, it takes a good guy with a gun."[12]

Of course, gun control groups do not claim that guns kill people. Their general position is that easy access to guns makes it more likely that people will kill people - strangers, students, spouses and even themselves. For example, the group Mom's Demand Action did not blame guns for the Parkland shooting. It did tweet that gun access was an important contributing factor: "It is a mental health issue, it is a gun safety issue" (Webb 2018).

Although we do not begin our analysis with a pre-determined set of frames, the framing literature and the subject itself lead us to propose some expectations. First, we expect gun rights groups to frame the problem in Parkland in ways that imply that further gun restrictions are not the solution. They should also highlight the costs of additional gun restrictions. Related to this, Stone (1989) suggests that gun rights groups will be more likely to blame the shooting on the actions of individuals because such an explanation reduces the urgency of a systemic response.

Gun control groups, in contrast, should be centrally concerned with mobilizing the public to take action, given their need to "expand the scope of conflict" and given that most Americans favor additional gun restrictions (Schattschneider 1960). Gun control groups should also be more likely to employ frames that imply that gun access was the problem in Parkland and should highlight the costs of the nation's lax gun laws – implying that a systemic response is needed.

Because gun control and gun rights groups were engaged in a framing contest, we also expect some overlap in frame usage. For example, if gun control groups frame the problem as easy access to assault weapons, then gun rights groups might want to refute that frame directly rather than offering a different explanation. Indeed, the most effective frames for a group may be the ones where we observe the greatest disparities – indicating that one side did not feel that it had an effective response.

Finally, we ask whether a problem frame is effective. We are interested in immediate public responsiveness to a problem frame (as measured by number of retweets) as well as longer term impacts on group attention (as measured by changes in followers). We expect that increasing the salience of a frame in the immediate term (as measured by retweets) will produce downstream effects in the form of more group followers (and more attention to future tweets by the group). The three

[12] See Beatty (2018)

expectations we test in the rest of the paper are listed below:

2.2.1 Expectations

1. To defend existing policy, gun rights groups will emphasize frames that imply that further gun restrictions are not the solution, or that the costs of further restrictions are too high.

2. Gun control groups will emphasize frames that imply that easy gun access is the problem, that there are high costs of doing nothing, and that it is important to become involved politically (Stone 1989).

3. Retweets are positively associated with changes in followers – accounts that receive more retweets will also receive more followers.

3 Data and Findings

To identify gun control and gun rights groups for this analysis, we first searched the names and descriptions of "public affairs" organizations in the Encyclopedia of Associations (EoA) for the terms "gun", "rifle", or "firearm" (*Encyclopedia of Associations: National Organizations of the US* 2016). We soon discovered that this approach omitted the National Rifle Association (which was classified by the EoA as a "sporting" association). We next turned to the internet and used our EoA list of gun-related groups to search their websites for additional partner groups. This process yielded 24 gun control and 16 gun rights organizations in the U.S. (see Table 4 of the Appendix). Our subsequent Twitter analysis also revealed three prominent and active individuals: Shannon Watts, Michael Bloomberg, and Dana Loesch. Dana Loesch is a spokesperson for the NRA, Shannon Watts is the founder for Mom's Demand Action, and Mike Bloomberg is the founder of Everytown for Gun Safety. Given their leadership positions, we added their accounts to the Twitter data collection list. Several of the original groups did not tweet during the period of study and were subsequently excluded from the analysis. As a result, our final list includes 24 gun control and 13 gun rights Twitter accounts.

Our original collection included all of the original tweets from these groups for the period from two weeks before the Parkland shooting to one month after (14,012 tweets in all).[13] The analysis reported here is restricted to 7,106 Parkland-related tweets from the day of the shooting until a month afterward (February 14 - March 15). We chose this time period to ask two main questions: (1) How do social organizations frame arguments directly after mass shooting events? (2) What explains the increase in followers following Parkland?[14] For each tweet we collected the text, information about attached media (images, videos, links, etc.), the number of times it was retweeted, and other metadata such as the current number of people following the Twitter account.

4 A Topic Modeling Approach to Discovering and Validating Issue Frames in Tweets

The next step was to discover discourse patterns across thousands of tweets by the 37 accounts. If we were starting with a pre-defined set of issue frames, we could create a dictionary of terms for each frame (see e.g. M. Merry 2020) or we could manually label a large sample of tweet texts in order to train a supervised machine learning model (Theocharis, Barberá, et al. 2016). Because we did not know what to expect, we turned to an exploratory method – unsupervised topic modeling.

In an unsupervised topic model, a topic is a set of words that co-occur among the documents (tweets). As such, topics do not come with labels and must be interpreted by the researchers. There is also no objective way to select "the" correct model or number of topics. There are metrics for comparing the fit of alternative models to the data, but it is ultimately up to the researcher to select the best fitting model based on the goals of the project. This is typically accomplished by examining the most frequently co-occurring words of the topics for models that vary by number of topics, k (e.g. a 10, 30, or 50 topic model). As one would expect, models with smaller ks have (possibly too) general topics, whereas the topic of models with larger ks have topics that are (possibly too) narrow. It is also often the case that some topics of the chosen model are not relevant to the project's goals and are therefore excluded from the analysis. This is because words can co-occur for reasons that

[13] Automated scripts ran nightly using the Twitter Search API to check for new tweets from the tracked accounts.

[14] Follower increases for gun control and gun rights groups slowed substantially after the first month (see Figure 2).

have nothing to do with the substance of the study.

There are also single and mixed membership topic models. In a single membership model, each document is restricted to one (and only one) topic. The advantage of a mixed membership model is that a document (or in the case of this study: a tweet) can address more than one topic (**Blei2003**; Roberts, Stewart, and Tingley 2018). But, if desired, the topic weights of a mixed membership model can also be used to assign each documents to a single ("primary") topic.

We used the diagnostic tools of the Structural Topic Model (stm) package to compare a large number of models before deciding that a 32 topic mixed membership model best captured our subject of interest (Roberts, Stewart, Tingley, and Airoldi 2013). The stm framework builds from a Latent Dirichlet Allocation (LDA) model. The framework allows for the specification of metadata variables in the model, meaning that topics are estimated as a function of document metadata (e.g. the source of a tweet) as well as the texts of the documents. We include two metadata covariates in our model: the tweet source account and the policy position of the organization (gun rights or gun control). With the addition of the covariates, Sparse Additive Generative (SAGE) topics are enabled automatically in stm.[15]

We next examined each of the 32 topics (using top terms and the texts of tweets with 0.1 probability or higher of being about the topic) to determine whether they were about the Parkland shooting.[16] This process, summarized in Figure 3, produced 12 Parkland-related topics containing 7,106 tweets.

We then used the most common topic terms and some of the tweets that were most strongly associated with a topic to give the topic a label and decide whether the topic highlighted a problem that implied a particular solution (i.e. whether the topic qualified as a problem frame). Table 5 in the Appendix presents the top words for our identified frames. For example, a topic that we ultimately labeled "school security" included tweets by gun rights group advocating for arming school employees as the solution to mass shootings and tweets by gun control groups critical of the same proposal. This is a frame (thorough definitions of frames and topics can be found in the next section). Another topic included tweets (mostly by gun control groups) about the individual victims. This is a topic, not a frame, because there is no attempt to define the problem. In all, eight of the

[15]Readers may see the associated replication materials for additional stm coding details.

[16]For example, groups also tweeted about upcoming gun shows and domestic violence.

twelve topics were deemed frames, while the four remaining were topics. Table 6 in the Appendix contains examples of tweets using each of the eight frames.

Typically, the next step in a mixed membership topic model analysis is to assign tweets to their highest probability topic before examining the patterns. We add another step to address potential concerns about validity - manual validation. We first choose a relatively low probability threshold (0.1) to identify tweets that are potentially about each of the frames/topics. We then manually inspect them, excluding those not judged to be relevant.

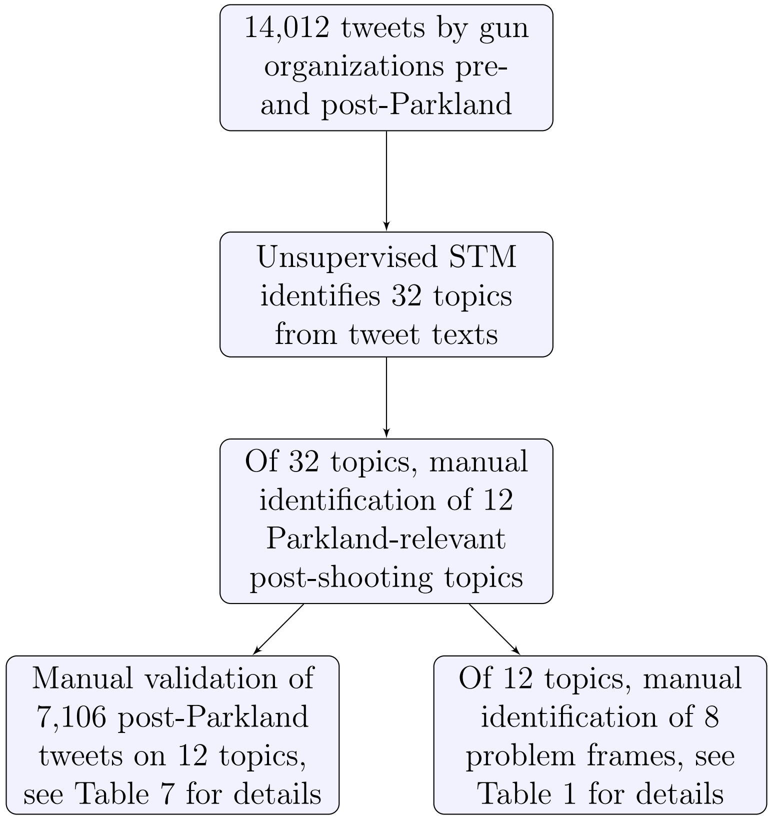
More specifically, the authors began by labeling a sample of 100 to 200 tweets per frame or topic for relevance (expressed as a binary yes or no for relevant or not).[17] We then used this "gold standard" dataset to train six undergraduate coders. When they achieved acceptable reliability (comparing our labels to theirs), we asked them to label all of the other tweets above the 0.1 threshold in each frame and topic. We also continued to monitor their reliability by having two coders label 10 percent of the tweets.[18] Table 8 in the Appendix provides additional details about inter-rater reliability (IRR). For the 10 percent of tweets labeled by two coders, there was 90 percent agreement in ten of the eleven frames/topics, and 85 percent agreement for one other.

This additional manual validation effort made a substantial difference in determining which tweets truly fit into the 12 topics and frames of interest. Of the initial 7,106 tweets with a greater than 0.10 predicted assignment to the 12 relevant topics and frames, 2,317 were manually validated as belonging to those topics and frames of interest. It is crucial to validate the results of machine learning models to ensure they correspond to human interpretations. Although surprising given their short length (maximum length: 280 characters), we found that 349 tweets addressed more than one frame/topic (examples of tweets addressing multiple frames/topics are in Table 9 in the Appendix). Table 7 of the Appendix provides summary statistics for each frame and topic.

[17]The exception was the "gun free zones" frame, which included only 57 tweets.

[18]In the cases of disagreement, we had a third coder break the tie before adding the result to our final dataset.

Figure 3: Procedure for Identifying Issue Frames



5 Findings: Framing the Parkland School Shooting

Table 1 summarizes the substance of the 12 Parkland-related frames and topics.[19] All of the frames are topics, but not all of the topics are frames. To be considered a frame (specifically, a problem frame), the topic must have a clear story about the problem that led to the Parkland shooting. "N/A" in Table 1 indicates the topics that are not problem frames. For example, a typical "political action" frame tweet defines the problem as inaction by incumbent politicians and calls on supporters to get involved politically. A representative tweet from this frame is the following from Moms Demand Action leader Shannon Watts: "... show your lawmakers - state and federal - that they will win or lose based on their allegiance to the @NRA. You do that by sitting in gun bill hearings, going to in-district meetings, standing up at town halls..." (see Table 6 in the Appendix for the full tweet). The "enforcement failure" frame defines the problem as the failure of law enforcement

[19]Table 5 of the Appendix lists the top 10 most frequent words for each frame (after stemming and removing stopwords) while Table 6 provides two example tweet texts for each frame.

to act properly, implying that the solution is better individuals in law enforcement, not a change in gun policy. A representative tweet from this frame is the following from NRA spokesperson Dana Loesch: "...people are obsessing because it distracts from the real issue of massive failure by Broward Sheriff" (see Table 6 in the Appendix for the full tweet).

In contrast, the "school shootings" topic (a non-frame topic) includes tweets that either provide information about the fact that a shooting is occurring or remind their audience that this is not the first school shooting. For example, the Alliance for Gun Responsibility account wrote: "We are monitoring the situation developing at a high school in Parkland, Florida, and thinking of the students and families impacted." In topics, there is no effort to define the problem.

According to Stone (1989), a systemic frame defines a policy problem as having a broader cause that implies that government action is warranted. For example, income inequality can be explained as a symptom of an unfair economic system or as a result of differences in individual work ethic. Only the former implies a need for government intervention.

As noted above, we generally expect gun control groups to emphasize systemic explanations for the shooting and the high costs of doing nothing. In contrast, gun rights groups should be more likely to emphasize individual explanations and the high costs of additional gun restrictions. We had little difficulty assigning frames and topics to these categories (Table 2). The one exception was the mental health frame. Here, the example tweets we examined suggested a stark difference between gun rights groups' emphasis on the shooter's mental illness (individual) and gun control groups' emphasis on the broader (systemic) problem of mental health and gun access.

Table 1: Topic/Frame Descriptions

Topic	Defined Problem (Indicator that the Topic is a Frame)
School security	The problem is teachers need to be armed and schools made more secure
Political action	The problem is elected officials
Mental health	The problem is mental illness
Gun-free zones	The problem is only criminals have guns
Gun control	The problem is easy access to guns
Enforcement failure	The problem is officials did not enforce the laws on the books
Background checks	The problem is bad people can buy guns
Assault weapons	The problem is access to especially deadly guns (inc. bump stocks)
School shootings	N/A (e.g. tweets mentioning school shootings)
Remembrances	N/A (e.g. tweets listing the names of victims)
Gun violence	N/A (e.g. tweets about recent acts of gun violence)
Gun rights	N/A (e.g. tweets supporting the 2nd amendment)

Table 2: Topic/Frame Annotations

Topic	Gun Rights Group Frame/Topic	Gun Control Group Frame/Topic
School security	Systemic Frame	Systemic Frame
Political action	Systemic Frame	Systemic Frame
Mental health	Individual Frame	Systemic Frame
Gun-free zones	Individual Frame	Individual Frame
Gun control	Systemic Frame	Systemic Frame
Enforcement failure	Individual Frame	Individual Frame
Background checks	Systemic Frame	Systemic Frame
Assault weapons	Systemic Frame	Systemic Frame
School shootings	Highlights costs to status quo	Highlights costs to status quo
Remembrances	Highlights costs to status quo	Highlights costs to status quo
Gun violence	Highlights costs to status quo	Highlights costs to status quo
Gun rights	Highlights costs to reform	Highlights costs to reform

5.1 Contesting the Problem in Parkland

Figure 4a compares frame emphasis by the two types of groups using raw tweet frequencies. The fact that there are nearly twice as many gun control groups (24 versus 13) helps to explain why there are so many more gun control tweets in Figure 4a. The conventional strategy of gun rights groups to avoid fanning the flames until the media and public are distracted is also part of the explanation (as noted the NRA didn't tweet at all for the first 6 days after the shooting).

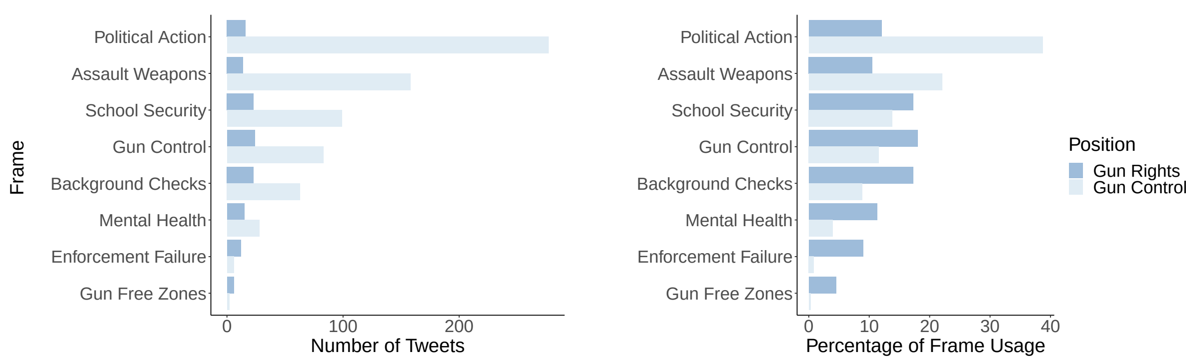
Figure 4b compares proportions of total tweets to provide a better sense of relative frame emphasis. The vast majority of tweets by gun control organizations focused on two systemic frames, "political action" (calling for action among their supporters) and "assault weapons." Tweets by gun rights groups, in contrast, were distributed more evenly across a larger number of systemic and individual frames. Thus, whereas gun control groups did focus overwhelmingly on systemic problem frames, gun rights group did not focus exclusively on individual problem frames.

The most used frame of gun rights groups is "gun control." This indicates that these groups spent much of their energy arguing against the need for (or futility of) new gun laws. School security and background checks are other popular frames used by gun rights groups that contradict our expectation that gun rights groups would emphasize individual problem framing but for a different reason. In the first case, gun rights groups blamed lax school security and advocated arming school employees as the solution (while gun control groups opposed this suggestion in response). The second frame, background checks, includes gun rights group tweets opposing additional background checks (the same can be said for the assault weapons frame) and criticizing human failures associated with current background check systems.

The other interesting point of comparison is the relative usage of a frame by the two types of groups. If similar attention indicates that a frame is being vigorously contested, disparate attention may indicate a framing advantage. The "political action" frame received disparate attention from the two groups ("owned" by gun control groups), probably because, as defenders of the status quo, gun rights groups were primarily interested in preventing political action rather than inciting it. Another example of this disparate attention is the "enforcement failure" frame. Gun control groups did not strongly contest the rights groups' assertion that the tragedy would have been avoided if officials had just done their jobs.

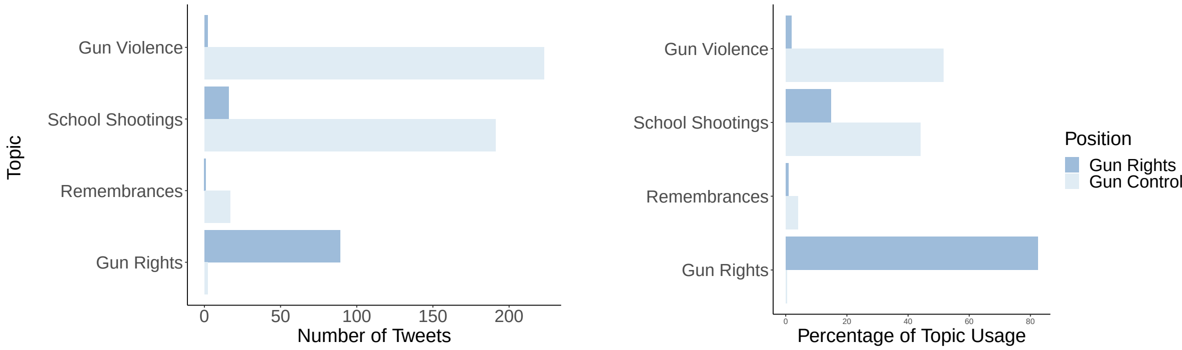
The four non-frame topics (Tables 5a and 5b) also demonstrate clearer issue ownership. Not surprisingly, the "gun rights" topic is owned by gun rights groups (reminding people of the second amendment rights at stake). The other three, reminding people of the enduring costs of the nation's lax gun laws, are owned by gun control groups.

Figure 4: Frame Usage By Gun Group



(a) Frequency of Frame Usage By Group **(b)** Percentage Of Frame Usage By Group

Figure 5: Topic Usage By Gun Group



(a) Frequency of Topic Usage By Group **(b)** Percentage Of Topic Usage By Group

5.2 Frame Effectiveness: Spreading the Message through Retweets

The two-way characteristics of social media makes it possible for groups and researchers to study which communications are working as intended. In this case, we assume that groups wanted to see their messages spread to as broad an audience as possible. We measure the diffusion of the message by examining retweets - decisions by group followers to share a tweet with their own followers (Theocharis, Lowe, et al. 2015; Barberá et al. 2015; Casas and Williams 2019).[20] The specific question of interest is whether tweets about certain frames or topics result in disproportionate number of retweets. The left panels of Figures 6 and 7 compare percentages of total group tweets (from the previous figures) to percentages of total retweets for each frame and topic.[21] The right panels of Figures 6 and 7 highlight these differences. Bars to the right of the midline indicate that the percentage of total retweets for a frame/topic is greater than the percentage of total tweets by the group. Tweets using the mental health frame appear to have elicited the greatest response from the followers of gun control groups. For gun rights groups, tweets using the law enforcement failure frame appears to have been most effective.

[20]The actual impact of a retweet may go well beyond what we measure in that a retweet may inspire retweets of the retweet.

[21]The raw numbers of tweets and average retweets can be found in the Appendix (Table 7).

Figure 6: Percent of Gun Control Tweets and Retweets on Topics and Frames Around Parkland

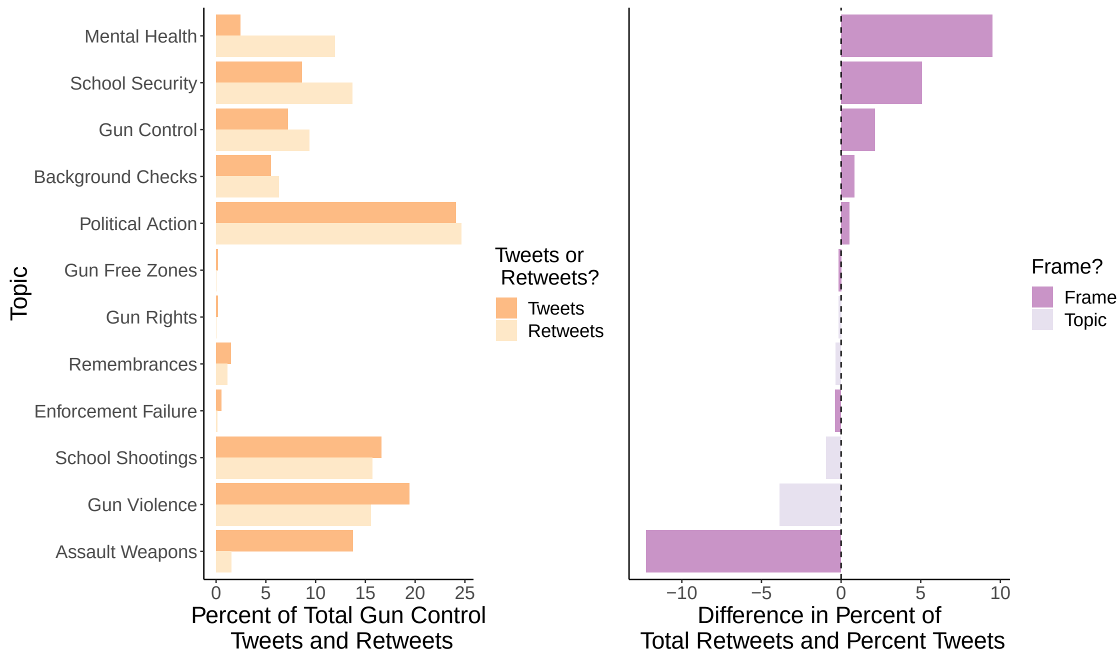
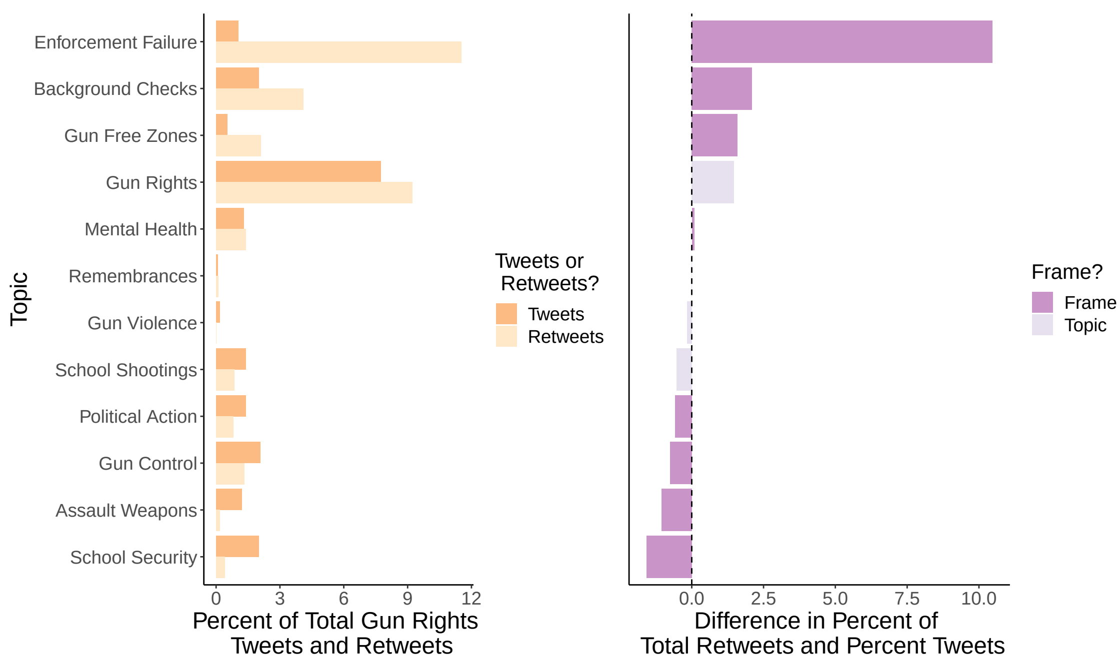


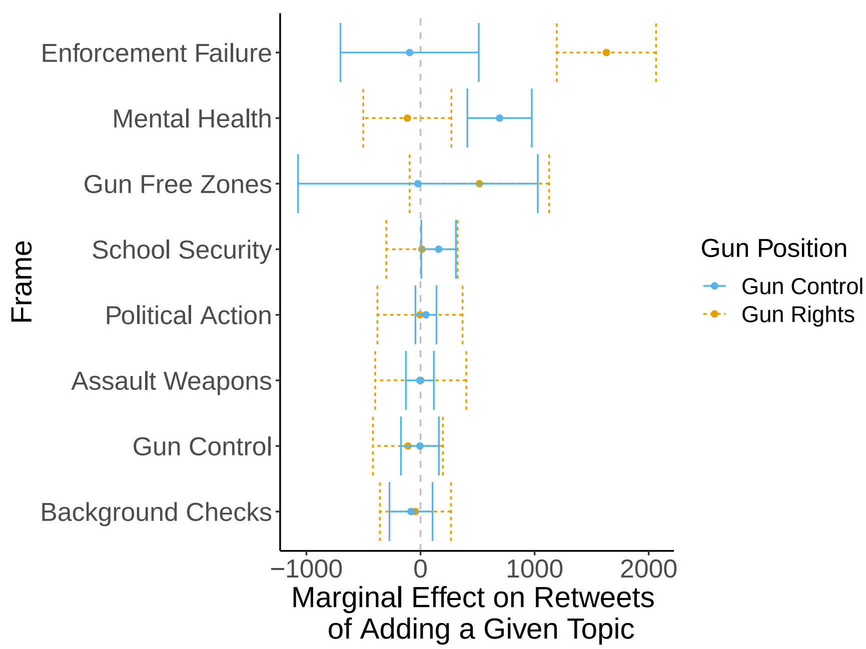
Figure 7: Percent of Gun Rights Tweets and Retweets on Select Topics Around Parkland



The above figures do not control for other covariates that may impact retweet frequencies. For example, retweets should be more common for groups with more followers. To better control for such confounders, we estimate an OLS regression model predicting the number of retweets of a tweet. Our primary independent variables are the different tweet frames/topics interacted with the type of group (gun rights or gun control). We then control for the number of account followers, whether the tweet contains an image (on the assumption that images may also inspire retweets), general twitter activity on that day (number of tweets on that day), and group fixed effects (to allow for differences in behavior among the followers of different groups).

Figure 8 presents the estimated marginal effect of using a specific frame on retweets for each type of group after controlling for other factors.[22] The frames have been rearranged so that those with the largest effects on retweets are at the top. As we saw earlier, for gun rights groups (in dashed orange) the law enforcement failure frame inspired significantly more retweets than other frames or topics. For gun control groups (in solid blue), tweets using the mental health frame (contesting the gun rights claim that the shooter's mental health was to blame) were also significantly more effective.

Figure 8: Which frames were more likely to be shared?



[22]The baseline average number of retweets is 146. The full regression results are reported in the Appendix (Table 10).

5.3 Frame Effectiveness: Attracting New Followers

The previous analysis demonstrates that some frames inspired significantly more retweets by existing group followers. These retweets helped to get out the immediate message, but could they also benefit the group's longer term messaging and policy efforts? We conclude our analysis by testing our third expectation and ask whether retweets have additional downstream effects in the form of attracting new followers to a group. Here we test an OLS model predicting the change in a group's followers at time t.[23] The primary independent variables are the number of retweets received by the group's tweets at time t and time $t-1$. We control for the total number of tweets sent by the organization in time t and time $t-1$, one particular event "shock," a widely watched February 21 CNN Town Hall event (that included Marjory Stoneman Douglas students and parents, Senator Marco Rubio, and NRA spokesperson Dana Loesch among others), additional organization-level characteristics (number of followers and friends and the age of the group), and organization fixed effects.

Table 3 confirms that retweets do predict changes in followers, with both statistical and substantive significance. A standard deviation increase in retweets on a given day (roughly 4,892 retweets) is associated with an increase of around 580 followers, on average and all else equal.[24] For context, the average daily increase in followers for these accounts over the 13 days prior to Parkland was only 82. A boost of 580 followers represents, on average, a 7% increase in account followers, based on the number of followers accounts had on the day prior to Parkland. On the next day, that same increase in retweets is associated with an additional increase of around 340 followers. That is, other things equal, for every 8 retweets the messages from the organization receive today, the organization gets a new follower that same day. For every 14 retweets received today, the organization gets an additional follower tomorrow. This indicates that choosing frames that garner more retweets may hold positive downstream effects. We do not measure how long these downstream effects persist (how long followers stay following these accounts), but we know from previous research that unfollowing is a rare behavior on Twitter. Myers and Leskovec (2014) showed that over a whole month only 2.3 % of all following relationships on Twitter were ended. From this work we can assume that these downstream benefits wane over time but are unlikely to immediately disappear. At the very least

[23] The first difference of the daily number of followers.

[24] The 580 estimate comes from applying the dot product between the coefficient for *Total daily retweets* in Table 3 and the standard deviation of that variable in our dataset: $0.12 * 4,892 = 587.04$. The same applies for the estimate of next-day follower increase: $0.07 * 4,892 = 342.44$.

they should persist past the short-term benefits of retweets.

Table 3: OLS Regression using retweets to predict change in followers of gun rights and gun control organizations.

	Coefficient (Std. Error)
(Intercept)	297.51 (365.85)
Post CNN Debate	-322.57 (157.78)*
Total daily tweets	-24.84 (8.05)*
Total daily tweets (lag)	6.38 (7.75)
Total daily retweets	0.12 (0.02)*
Total daily retweets (lag)	0.07 (0.02)*
Organization Fixed Effects	✓

N = 1,485
$R^2 = 0.14$
F Statistic = 7.559*
*$p<0.05$

6 Discussion and Conclusion

Social media is an increasingly important domain of political discourse and offers many promising research opportunities for policy scholars. In addition to being an important source of information for traditional media coverage, groups and organizations use social media to communicate directly with the public. These groups receive almost immediate feedback on whether their messages are working, and are able monitor and respond directly to the messaging efforts of other groups. Thus, policy researchers can study not only framing efforts and their effectiveness, but also how groups interact as they learn from these interactions.

The challenge for researchers is that there are so many more actors and so much more content on social media. In this paper we have demonstrated a new computational approach for efficiently studying problem framing across thousands of social media posts. The central advantage of unsupervised topic modeling is that it enables the discovery of common themes within large volumes of text. We did not begin with a pre-defined set of problem frames, but instead used topic modeling to reveal the frames and topics that were actually being used by gun rights and gun control groups on Twitter. We then manually validated the individual tweets assigned to each frame and topic with high probability to ensure that the tweets assigned to each frames and topics were actually relevant. We then compared frame usage and tested frame effectiveness using retweets (an indicator of message resonance) and increases in followers (an indicator of more sustained attention to a group's messaging efforts).

The 24 gun control and 13 gun rights groups employed eight common problem frames and addressed four other common topics as they sought to control the narrative following the Parkland shooting. Gun control groups emphasized systemic problem frames that implied that government action was needed. Gun rights groups also employed systemic frames supporting particular kinds of government action (such as arming school employees) but were more likely to emphasize individual problem frames that implied that additional regulations were unnecessary. We also found frequent overlap in frame attention as one side contested a frame advanced by the other side. As gun rights groups argued for greater school security, gun control groups tweeted outrage at the suggestion that teachers should be armed.

We also found that the most effective frame for gun control groups questioned the gun rights group assertion that mental health was the primary cause rather than easy access to guns. This systemic frame implied that new gun regulations were the solution. For gun rights groups, the most effective frame blamed the tragedy on officials' failure to enforce existing laws. This individual frame implied that new gun regulations were not needed.

As political dialogue continues to migrate to the internet, computational methods will become a more important part of empirical policy studies. Unsupervised topic modeling is just one of many methods that hold promise for studying issue framing (broadly defined) quantitatively (Wilkerson and Casas 2017). M. Merry (2020) uses a dictionary-based method to apply a pre-existing set of frames in a study of gun group social media activities. Card et al. (2015) examine media frames in the *New York Times* by first having human label a sample of cases, training a supervised machine learning algorithm on that sample, and then using the trained algorithm to label other cases. Another important area of research, natural language processing (NLP), seems particularly well suited to applications of the Narrative Policy Framework (M. Jones and Song 2014). Using NLP methods, a researcher can automatically parse texts by grammatical structure, systematically revealing (for example) "who is doing what to whom" across thousands of entries.[25]

[25]Event data, where Reuters newsfeeds are automatically monitored to measure international conflict, is an important application of NLP in Political Science (e.g. Schrodt 2011)

The main benefits of computational methods are the ability to study subjects at scale with near perfect reliability (for some methods). To be sure, these methods are not always as perceptive as human-centered qualitative approaches. But we have also shown how validity concerns can be addressed by incorporating human input into a research design. Rather than simply using the results generated by the topic model, we took the additional step of training human annotators to verify that each tweet included in each frame or topic of our analysis was in fact relevant. This additional step produced a high quality dataset that also leverages the exploratory benefits of unsupervised topic modeling.

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8 Appendix

Table 4: Accounts/Groups with Known Gun Position

Name	Twitter Handle	Gun Position
Alliance for Gun Responsibility	wagunresponsib	Gun Control
Americans for Responsible Solutions	giffordscourage	Gun Control
Brady Campaign to Prevent Gun Violence (HCI)	bradybuzz	Gun Control
Coalition to Stop Gun Violence (CSGV)	csgv	Gun Control
Educational Fund to Stop Gun Violence (EFSGV)	efsgv	Gun Control
Everytown for gun safety	everytown	Gun Control
Gabby Giffords	gabbygiffords	Gun Control
Guitars Not Guns (GNG)	guitarsnotguns	Gun Control
I Vote #GunSafety	votegunsafety	Gun Control
Keep Guns Off Campus	keepgunsoffcamp	Gun Control
Michael Bloomberg	mikebloomberg	Gun Control
Million Mom March New York	mmmnewyork	Gun Control
Moms demand action for gun sense in America	momsdemand	Gun Control
National Gun Victims Action Council (NGAC)	gunvictimsact	Gun Control
National Law Enforcement Partnership to Prevent Gun Violence	lepartnership	Gun Control
Newtown Action Alliance	newtownaction	Gun Control
Pride fund to end gun violence	pride_fund	Gun Control
Protest Easy Guns	protesteasyguns	Gun Control
Sand Hook Center	sandyhookcenter	Gun Control
Sandy Hook Promise	sandyhook	Gun Control
Shannon Watts	shannonrwatts	Gun Control
States United to Prevent Gun Violence	supgvnetwork	Gun Control
Student Pledge Against Gun Violence	studentpledge	Gun Control
Women Against Gun Violence (WAGV)	wagv	Gun Control
American Rifleman	nra_rifleman	Gun Rights
Ammo Land	ammoland	Gun Rights
Armed Females of America (AFA)	armedfemales	Gun Rights
CA Rifle and Pistol	crpanews	Gun Rights
Calguns Foundation	calgunsfdn	Gun Rights
California Association of Federal Firearms Licensees (CAL-FFL)	calffl	Gun Rights
California NRA	calnra	Gun Rights
Dana Loesch	dloesch	Gun Rights
Firearms Policy Coalition	gunpolicy	Gun Rights
Gun owners of America	gunowners	Gun Rights
Gun Owners of CA	gunownersca	Gun Rights
Jews for the Preservation of Firearms Ownership (JPFO)	real_jpfo	Gun Rights
National Association for Gun Rights (NAGR)	natlgunrights	Gun Rights
National Rifle Association (NRA)	nra	Gun Rights
Students for Concealed Carry (SCC)	concealedcampus	Gun Rights
The Truth About Guns	guntruth	Gun Rights

Table 5: Frames with Top 10 Most-Frequent Words

Frame	Top 10 Words
School Security	teacher, arm, school, gun, educ, offic, shoot, secur, train, neveragain
Political Action	gun, march, marchforourl, student, join, violenc, enough, will, action, make
Mental Health	mental, ill, gun, health, like, crime, violenc, nra, peopl, violent
Gun Free Zones	gun-fre, school, zone, gun, shoot, time, secur, –blame, cpac, definit
Gun Control	gun, bill, carri, law, pass, state, conceal, safeti, danger, public
Enforcement Failure	law, gun, enforc, erpo, risk, state, order, extrem, danger, pass
Background Checks	gun, check, background, support, sale, system, law, buy, nra, bill
Assault Weapons	weapon, assault, ban, gun, support, parkland, neveragain, weaponsofwar, enough, militari

Table 6: Examples of Tweets Using Each Frame

School Security
Alliance for Gun Responsibility (Gun Rights): Want to Prevent the Next School Shooting? Arm Educators With More Resources to Do Their Jobs https://t.co/0ieGPwJK84.
Americans for Responsible Solutions (Gun Control): #Parkland teacher @chefkurth, who sheltered 65 students in her classroom asks: "Am I supposed to have a kevlar vest?" #CNNTownHall #ParklandStudentsSpeak.
Political Action
Shannon Watts (Gun Control): 2) And you have to show your lawmakers - state and federal - that they will win or lose based on their allegiance to the @NRA. You do that by sitting in gun bill hearings, going to in-district meetings, standing up at town halls. And by making this a priority issue you vote on.
Gun owners of America (Gun Rights): With the ATF comment period over, President Trump is the last line of defense against a bump stock ban that could lead to magazine and semi-auto bans. Take action! Tell Trump to rein in the ATF and to not ban bump stocks: https://t.co/b0NEdjI8k0 https://t.co/hQ8PtW04Pf'
Mental Health
Coalition to Stop Gun Violence (CSGV) (Gun Control): Nice applause line but 1) not backed up by research & 2) demonizes an entire population. 2 things liberals hate when Trump or Fox does them. Data shows those w/ mental illness are NOT more prone to violence. We can stop #GUNviolence w/o reinforcing neg stereotypes #EndTheStigma https://t.co/903B9c4kNx.
Ammo Land (Gun Rights): Mental Health & Gun Violence: What Do We Know https://t.co/ev8pFArctA https://t.co/xORa8aYtWE.
Gun-free Zones
Gun owners of America (Gun Rights): Why do we protect our lawmakers with guns, but our children with a gun free zone sign? GOA's @erichmpratt says it's time to end gun-free schools. https://t.co/gdpcXojfA4.
Americans for Responsible Solutions (Gun Control): Wayne LaPierre speaking at #CPAC18 –blames FBI, mental illness, school security, & gun-free zones for school shootings but definitely NOT guns. #gunlobbylies.
Gun Control
Americans for Responsible Solutions (Gun Control): The House already passed this bill that would allow dangerous, untrained people to carry loaded, hidden guns in every state. The Senate is voting next. You can help make sure it doesn't become law. Join our fight for safer communities: https://t.co/0DIWoZVySM https://t.co/URrkzqtJjV.
Moms demand action for gun sense in America (Gun Control): If the NRA gets its way and "Concealed Carry Reciprocity" becomes law, people with dangerous histories and no training will be allowed to carry hidden, loaded guns across the country. #StopCCR https://t.co/sH9mYwAIZX.
Enforcement Failure
Firearms Policy Coalition (Gun Rights): According to #guncontrol advocates, we're all supposed to be disarmed and helpless while we wait for law enforcement to arrive. But what about when *they* hide? https://t.co/hXjybTca9X.
Dana Loesch (Gun Rights):@MoElleithee Also all I'm saying. There is a distinction. And what they spend is a drop in the bucket compared to others. But people are obsessing because it distracts from the real issue of massive failure by Broward Sheriff.
Background Checks
Women Against Gun Violence (WAGV) (Gun Control): White House slashing funds for background checks on guns! It's already a weak system we've been fighting to strengthen. This is clearly a payback to the NRA, who paid 30 million to get Trump elected. https://t.co/LCmIGrKZuI.
Firearms Policy Coalition (Gun Rights): If waiting periods and ID/background check requirements are "reasonable" to impose on law-abiding gun purchasers, why are they unreasonable to be imposed upon the exercise other (even unenumerated) rights?
Assault Weapons
Keep Guns Off Campus (Gun Control): Ban Military-Style Assault Weapons and Large Capacity Magazines Now Sign the petition https://t.co/N9Vudk5dSB @moveon #enough #parklandshooting.
Ammo Land (Gun Rights): New Assault Weapons Ban for Pistols And Shotguns https://t.co/rDJc4PVlUJ https://t.co/YIyG3kvijt.

Table 7: Parkland Tweets per Topic

Topic	Number of Tweets with > 0.1 Prob	Number Validated	Average Retweets	Max Retweets
Political Action	1512	502	159	8336
Gun Violence	1097	392	131	3558
School Shootings	977	358	145	5448
Assault Weapons	473	284	55	6878
School Security	381	189	167	9489
Gun Control	336	171	231	5076
Background Checks	377	141	310	11211
Gun Rights	657	132	67	4638
Mental Health	228	67	315	10076
Remembrances	285	40	327	14658
Enforcement Failure	719	29	263	15340
Gun Free Zones	54	10	392	6103

Table 8: Inter-Rater Reliability Statistics By Topic

Topic	Agreement	Cohen Kappa Score	Coder 1	Coder 2	Tweets Coded By Both
School Shootings	0.85	0.69	05	06	82
Gun Violence	0.95	0.87	03	012	96
Political Action	0.90	0.78	02	06	136
Assault Weapons	0.90	0.78	03	04	29
School Security	0.95	0.90	03	02	21
Background Checks	0.94	0.87	05	06	32
Gun Control	0.9	0.8	03	012	20
Enforcement Failure	1.0	1.0	10	11	567
Remembrances	1.0	1.0	05	06	12
Gun Rights	1.0	1.0	02	012	23
Mental Health	0.96	0.83	02	02	25
Gun Free Zones	NA	NA	NA	NA	NA

Note: There are only a few true positives within the Enforcement Failures frame, so we needed both annotators to code all the tweets.
Note: Only 54 tweets were identified as within the Gun Free Zones frame by the topic model. Therefore, all these tweets were coded when the training sets were created. Therefore no coders were used to individually validate these tweets, although the coders did validate the training set that was created.

Table 9: Tweets Validated Under Multiple Topics/Frames

1. Assault Weapons, School Shootings
Fueled by the NeverAgain student movement after the #Parkland school shooting, 70% of Floridians want stricter gun laws, including an outright ban on assault weapons. ://t.co/jy5rJiKWYF #GunControlNow #BanAssaultWeapons #MarchForOurLives #EndGunViolence
2. Political Action, Assault Weapons
Have you called your Senators yet!? It's time to BanAssaultWeapons – Text WeCallBS to 877-877 and you'll be connected w/ your Senators. Noweaponsofwar https://t.co/VNcpEC9wtm
3. Background Checks, Mental Health
We call BS!!! His school safety plan is opposed by nearly everyone and would result in more gun deaths. He could strengthen the background system by requiring them on all gun sales. He uses mental health as a scapegoat and stigmatizes that community
4. Gun Violence, Political Action
There are two funerals today for high school freshmen in Parkland, Florida. I'll be reflecting on how you and Congress haven't done anything to prevent America's gun violence crisis despite horrific shootings in the past year in Plano; Las Vegas; Sutherland Springs; Alexandria... https://t.co/hOxCSZBFsM
5. School Shootings, Background Checks
In the wake of Florida's school massacre, South Carolina efforts to strengthen background checks before gun purchases could be gaining steam.

Table 10: OLS Regression Results: Retweets as a Function of Topics

	Dependent variable:			
	Retweets			
	(1)	(2)	(3)	(4)
Number of Followers	0.0005*** (0.00003)	0.001* (0.0003)	0.0004*** (0.00003)	0.001* (0.0003)
Gun Control	17.259 (17.447)	12.081 (147.116)	−21.411 (22.744)	5.987 (147.174)
Contains Image	−37.100** (15.051)	33.576** (16.980)	−100.664*** (29.607)	43.951 (52.894)
Assault Weapons Frame	−77.262 (52.252)	−7.017 (51.585)	−60.444 (197.506)	2.285 (191.825)
Background Checks Frame	55.287 (73.254)	−46.238 (71.173)	27.476 (154.506)	−44.453 (150.062)
Gun Free Zones Frame	312.064 (233.296)	302.279 (227.147)	569.939* (300.788)	515.862* (293.965)
Gun Rights Frame	79.312 (78.734)	31.626 (78.765)	53.842 (79.103)	24.845 (78.757)
Mental Health Frame	423.903*** (109.029)	405.397*** (106.076)	−175.723 (191.191)	−115.472 (185.708)
Gun Control Frame	55.340 (65.427)	−23.220 (63.913)	7.715 (151.170)	−110.537 (147.494)
Gun Violence Frame	16.394 (48.431)	13.796 (47.124)	−108.039 (520.860)	5.566 (510.720)
Enforcement Failure Frame	819.016*** (157.567)	831.587*** (153.412)	1,609.718*** (213.935)	1,629.255*** (209.157)
Political Action Frame	32.945 (36.997)	32.067 (36.324)	29.225 (184.751)	−4.389 (179.529)
Remembrances Frame	3.330 (174.843)	−43.966 (170.807)	−214.446 (736.170)	−172.188 (713.641)
School Security Frame	104.339* (62.835)	114.667* (61.286)	−61.238 (154.537)	13.392 (150.321)
School Shooting Frame	30.570 (48.792)	31.928 (47.514)	32.429 (48.768)	32.552 (47.508)
Gun Control:Contains Image			86.780** (34.555)	−12.631 (55.847)
Gun Control:Assault Weapons			−24.467 (204.752)	−11.362 (199.166)
Gun Control:Background Checks			31.719 (175.425)	−9.667 (170.403)
Gun Control:Gun Free Zones			−644.416 (475.358)	−539.693 (462.605)
Gun Control:Mental Health			866.038*** (232.620)	749.231*** (226.001)
Gun Control:Gun Control			63.079 (167.647)	107.829 (163.602)
Gun Control:Gun Violence			122.999 (523.109)	7.121 (512.905)
Gun Control:Enforcement Failure			−1,687.093*** (316.273)	−1,686.053*** (307.803)
Gun Control:Political Action			3.648 (188.559)	38.709 (183.315)
Gun Control:Remembrances			223.894 (757.785)	136.079 (734.619)
Gun Control:School Security			198.731 (169.021)	120.360 (164.548)
Constant	70.652*** (17.840)	−27.059 (121.288)	104.831*** (21.931)	−21.069 (121.383)
Org fixed effects?	N	Y	N	Y
Observations	12,227	12,227	12,227	12,227
R^2	0.034	0.097	0.038	0.100
Adjusted R^2	0.033	0.093	0.036	0.096
Residual Std. Error	737.166 (df = 12211)	713.727 (df = 12174)	735.963 (df = 12200)	712.813 (df = 12163)
F Statistic	28.611*** (df = 15; 12211)	25.192*** (df = 52; 12174)	18.519*** (df = 26; 12200)	21.517*** (df = 63; 12163)
Note:				*p<0.1; **p<0.05; ***p<0.01