# Words and Weapons: Analyzing Reactions to Gun Violence with a Social Media Panel

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**Abstract**

One of the most popular theories of public opinion formation, the Receive-Accept-Sample (RAS) model (Zaller, 1992), posits a specific procedure for how partisan citizens process elite messages concerning policy issues. However, many of the empirical studies using the RAS model rely on cross-sectional survey data without detailed information on a citizen's specific elite message streams. To better test the RAS model at a time when social media allows information to be exchanged instantly between identifiable individuals, this paper applies the RAS model to a panel of Twitter users, analyzing the impact of elite messages concerning gun control on citizen engagement with gun policy issues in the wake of high-profile mass shootings. By building a Twitter panel, I am able to better determine which elite messages each user receives and whether the recipients of the messages chooses to engage with the issue topic. I find that elite messages increase the likelihood a user will engage with gun policy issues in a way consistent with the RAS model, but further determine that the notion of *elite* must be broadened to include users that would only be considered influential on the Twitter platform.

## 1 Introduction

How do citizens form and express opinions on important policy matters? This fundamental question is at the core of understanding voter behavior in representative democracy. Perhaps the most influential modern theory of mass opinion formation is John Zaller's Receive-Accept-Sample (RAS) model described in *The Nature and Origins of Mass Opinion* (1992). The RAS model posits citizen opinion formation is based on the intersection of political elite messaging and a citizen's own ideological leaning. In the two decades since the book's release, scholars have further expanded and tested the RAS model by questioning Zaller's definition of political elites (Friedman 2012), broadening a citizen's ability to question the source of elite messaging (Kam 2012), and allowing for direct interactions between individuals (Malarz, Gronek & Kulakowski 2009).

While these are all important developments to the RAS model, it is also necessary to address the fact that, with the rise of social media, the medium of political communication has changed dramatically since the publication of Zaller's book. Social media websites are the modern Political Forum, a place where, for better or worse, over two-thirds of Americans receive and discuss news and current events as stories unfold (Shearer & Gottfied 2017). With social media, politicians can directly communicate with citizens, and users can fine-tune their incoming message streams. I explore the extent to which models of public opinion formation and issue engagement apply in the world of social media by using data from the Twitter platform, finding strong evidence that these models are still able to explain important patterns in how elite messaging influences citizen behavior. I further highlight a few important ways these theories differ in a social media setting, finding that non-conventionally defined elites often wield just as much influence over public opinion as conventional elites.

I analyze the implications of the RAS model by investigating a substantively important issue area: discussions of gun control policies in the wake of mass shootings. I focus on this issue-area for several reasons. First, mass shootings have a predictable pattern of elite messaging, with an inevitable increase in messages concerning gun policy by politicians and journalists following deadly shootings. Second, gun control is an "easy issue" in American politics (Carmines & Stimson 1980), making it simple for citizens to discern an elite's position towards gun legislation based on partisan leaning. Third, few previous studies track individual-levels of engagement towards gun control in the wake of mass shootings, making it useful to further analyze the dynamics of conversations towards gun policy as America undergoes a distressing increase in the number of shootings each year.

Beyond simply testing theories of public opinion in a new environment, utilizing social media data allows for methodological innovations that can better evaluate key components of the RAS model, providing a richer and more robust understanding of American public opinion. While the RAS model describes a process where individual citizens receive and process different streams of elite messaging, many tests of this theory rely on aggregate cross-sectional survey data instead of large panel datasets. With cross sectional data, even if collecting a large sample at several points in time, it is extremely difficult to isolate whether an individual's exposure to a specific elite-message stream induces opinion change. Determining the particular set of elite messages an individual is exposed to is nearly impossible with survey methodologies, often requiring researchers to assume all individuals are subject to similar media streams. This was perhaps an innocuous assumption when Americans had relatively few choices over media channels, but in a world where social media allows individuals to fine-tune the exact source of their information, these assumptions can potentially result in a misleading understanding of public opinion and representative democracy.

Instead of using survey data, I create a large panel dataset of social media users on Twitter, tracking a selection of partisan individuals' tweet history over time. This allows me to solve many of the problems of cross-sectional survey research in analyzing issue engagement. By looking at a user's full Twitter history, I am able to pinpoint exactly when certain users become engaged with a policy topic. Additionally, by observing each user's 'friend list,' an enumeration of all accounts they follow, I am able to measure which elite message streams each user is exposed to. With a direct estimate of each user's incoming message stream and the ability to observe precisely when a particular user engages with an issue topic, social media data allows me to make better inferences with the RAS model than traditional cross sectional survey methodologies.

In using social media text data to study conversations about gun policy, my paper follows an emerging literature at the crossroads of computer and political science. However, most previous studies using Twitter data to track public opinion and issue engagement collect text data with a researcher-specified filter, obtaining only those messages containing specific words, phrases, or hashtags. This introduces a sample-selection problem, as this data-collection methodology necessarily excludes the subpopulation who are active participants in the gun debate but who do not discuss the topic with the researcher-selected keywords. By examining the Twitter histories of a partisan panel, my work not only includes everyone discussing gun policies following a high-profile mass shooting, regardless of keywords, but further includes detailed information on users choosing *not* to discuss gun polices at all. This allows my analysis to not only highlight vocal citizens, but also those who choose to remain silent when gun violence occurs.

The remainder of the paper proceeds as follows. In Section Two, I describe how my current work fits in with theories of mass opinion formation and previous work on public opinion towards gun policies. In Section Three, I explain my data collection scheme and methodology. In Section Four, I test the key predictions of the RAS model before expanding the definition of political elites in Section Five. Finally, I conclude in Section Six.

## 2 Theories of Mass Opinion Formation and Activation

Central to many of the important questions in political science is understanding how and why citizens form and express opinions on crucial policy matters. One of the most influential books on public opinion is Zaller's *The Nature and Origins of Mass Opinion* (1992), which develops a precise and parsimonious model of mass opinion formation. In this work, Zaller outlines a "Receive-Accept-Sample" (RAS) framework. This model involves three steps: first an individual *receives* messages from partisan elites, who consist of politicians, journalists, and other policy experts (pg. 6). Second, citizens are more likely to *accept* those messages from elite sources consistent with their own ideological leaning, filtering out most messages from the opposing party elites. Finally, when forced to evaluate their opinion towards a policy issue, they *sample* from their recently accepted messages. By mostly processing like-minded messages, partisan citizens will begin to reflect the policy attitudes of the partisan elite. In this way, elites act as an "information shortcut," allowing partisan citizens to hold ideologically consistent beliefs over a wide variety of policy areas (Lupia 1992, Lupia 1994, Popkin 1991).

Zaller continues by arguing that changes in public opinion can be explained by changes in elite messaging. This process is described in the context of a "two-sided information flow" model, where the intensity of Republican and Democrat messaging changes over time (1992, pgs. 185-215). This "two-sided information flow" model is especially useful in explaining how people form opposing opinions about controversial policy issues. In these debates, partisan elites compete fiercely over how they market their own party's solution, framing issues in a way that better supports their side of a policy debate (Baumgartner & Jones 1993, Chong & Druckman 2007). These elite messages are often filtered through the news media, which plays a critical role in disseminating partisan messages to the public (Sheufele 1999, Scheufele & Tewksbury 2007). One of the main problems in work looking at the "two-sided information flow" model is the difficulty identifying which citizens are exposed to which information flows, and researchers have traditionally been forced to make unrealistic assumptions that all citizens receive a similar set of messages in a given unit of time.[1]

In some issue areas, topics are so strongly tied to ideology that opinion change is highly unlikely (Dunlap, McCright & Yarosh 2016). In spite of this, increased partisan messaging may still serve to reinforce pre-existing beliefs (Bennett & Iyengar 2008), and mass media messaging can influence public perception of an issue's *salience* (McLeod, Becker & Byrnes 1974, Mutz & Soss 1974). The "agenda-setting" power of elite messaging is especially pronounced in the wake of major events, which force the public to confront, update, or

[1] There is an emerging literature exploring novel ways to measure "exposure" to media content. See Vreese and Neijens (2016) for an overview of developing methodologies.

reconsider their existing beliefs (Page & Shapiro 1992, Atkeson & Maestas 2012, Rogowski & Tucker Forthcoming). Most of the time, only a narrow subset of the population – so called "issue publics" – will engage with a particular issue (Converse 1964, Krosnick 1990, Hutchings 2003). However, in moments of crisis the population as a whole may find itself evaluating policy issues they might normally ignore (Downs 1972, Peters & Hogwood 1985). With the advent of social media, this news cycle can move extremely quickly, with specific stories having the power to rise and decay with extreme alacrity (Asur, Huberman, Szabo & Wang 2011). This makes it increasingly difficult to accurately collect snapshots of public opinion after major events with traditional survey methods.

## 2.1 Mass Response to Gun Violence?

Theories of mass opinion formation and issue engagement are useful in considering how the public responds to gun violence. While there is normally a large participation gap in the gun policy debate, with a small number of extremely active gun owners representing a single-issue voting block capable of wielding an out-sized influence on gun laws (Spitzer 2007), mass shootings represent exogenous events that force American citizens to consider and reevaluate their opinions toward gun policy. These events consistently attract a large amount of media coverage, increasing the salience of gun control as an issue topic and prompting normally silent citizens to engage in discussions concerning gun regulation.

The gun policy debate can easily be described with Zaller's "two-sided message" model, with Republican and Democratic elites taking radically different stands on guns and crime in recent decades (Gimpel 1998, Haider-Markel & Joslyn 2003). There is, however, sparse evidence that in the wake of a mass shooting elite messaging induces opinion change. While there is empirical evidence that, in the aggregate, support for gun control legislation increases shortly after a major shootings (McGinty, Webster, Vernick & Barry 2013), only a few studies investigate individual-level changes in opinion. Newman and Hartman (Forthcoming) use CCES data and find that *proximity* to a mass shooting has an impact on individual opinions towards gun control, but opinions are unlikely to change from prior attitudes. Rogowski and Tucker (Forthcoming) use a panel survey to measure whether the 2012 Sandy Hook shooting changed opinions on gun policy, concluding that the "shooting had little effect on public support for gun control" (pg. 9-10).

## 2.2 Current Study and Hypotheses

Based on existing empirical evidence that partisan citizens are unlikely to alter their opinions towards gun control in the short-term following a mass shooting, the present study is not concerned with identifying opinion change. Rather, I strive to locate partisan actors who become "activated" – citizens who discuss gun control as an important policy in the wake of mass shootings.

I choose to investigate citizen engagement in the space of time following major shootings for two reasons. First, mass shootings represent exogenous events that inevitably increase the intensity of elite messaging on the gun control issue, allowing me to better test how elite messages impact an individual's likelihood of engaging with gun policy as an issue topic. Second, mass shootings focus national attention on gun policy, increasing the likelihood individuals will discuss gun legislation. I found it was important to focus my analysis on the days after a mass shooting given the normally large participation gap in the gun policy debate – a small number of pro gun-rights voters constantly engage with gun policy while citizens in support of gun regulation usually remain silent.

I proceed by examining whether citizen behavior on Twitter is consistent with the RAS model. Specifically, I test the following pair of hypotheses:

1. **Hypothesis One (H1):** After a mass shooting, users receiving more messages about gun control from elites are more likely to themselves tweet about gun control.

2. **Hypothesis Two (H2):** After a mass shooting, a partisan who receives more messages from *elites of the same party* is more likely to tweet about gun control. Messages

from *elites of the opposing party* are less likely to be accepted, and will not be associated with the partisan sending more messages about gun control.

In *The Nature and Origins of Mass Opinion*, Zaller outlines a relatively narrow definition of elites. However, later empirical work points to the importance of other actors in shaping public opinion (e.g. Friedman, 2012). On Twitter, 'influencer' status is determined largely by a user's ability to disseminate their messages to a large number of followers. While many of these users have the 'verified' status, there are also a large number non-verified users that manage to attract a large following. While not traditionally defined 'elites,' these users may still be able to influence public opinion on Twitter. Thus, I test a third hypothesis:

1. **Hypothesis Three (H3):** *Influencers* that are not considered *traditionally defined elites* will affect users in a way similar to *traditionally defined elites.*

I test these hypotheses with a unique set of Twitter data. I describe these data and my identification strategy in the following section.

# 3 Data and Methods

The main weaknesses present in empirical work using the RAS model are 1) the difficulty in measuring elite information flows, 2) estimating which citizens receive these messages, and 3) uncertainty as to when certain issues will become important in the public discourse. Compounding these issues is the high difficulty and costs in running large panel surveys, with most empirical work instead relying on cross-sectional samples.

By using a Twitter panel, my data and methodology are uniquely suited to overcoming these limitations, and can offer direct empirical tests of the predictions offered by the RAS model. This section briefly describes the source of my social media data and how I processed the data for analysis.

## 3.1 Advantages of a Twitter Panel

Twitter has become an increasingly useful source of text data in political science, used for such various purposes as tracking elections (Larsson & Moe 2012, Tumasjan, Sprenger, Sandner & Welpe 2013), gauging levels of political participation (Boulianne 2015), and measuring public opinion (O'Connor & Routledge 2010, Beauchamp 2017). The most popular method to obtain Twitter data is via the Streaming Application Program Interface (API), which allows researchers to obtain tweets matching certain criteria as they are sent in near real-time.[2]

To utilize the Streaming API, researchers must specify criteria for the tweets they wish to track. When monitoring issues, this is often done by specifying a series of **track words**, terms and phrases tied to a specific issue or event, using the Streaming API to obtain tweets mentioning one or more of these **track words**. However, in many circumstances it is difficult to predict which words will capture conversations about a specific event, and not until an event is unfolding will people gravitate towards specific words and phrases to describe the incident.[3] Though cutting-edge data collection schemes have begun utilizing dynamic keyword algorithms to predict new keywords as events unfolds, the fact that the Streaming API prevents access to historical data means one cannot obtain old tweets with new 'learned' keywords, preventing these schemes from collecting initial conversations about unexpected, breaking events.

A more fundamental problem with using the streaming API to analyze issue engagement is that one *only* obtains tweets featuring the **track words**, necessarily *selecting on the dependent variable*. That is, data obtained from the Streaming API by construction only includes users choosing to discuss a specific issue topic in a certain way, and will never include information about users choosing not to tweet about the particular issue. Unless it

[2]It is important to note that data obtained the Twitter Streaming API does not grant researchers access to the full universe of messages, with rate limits preventing researchers from obtaining *all* messages containing a researchers track words.(Morstatter, Pfeffer, Liu & Carley 2013)

[3]On Twitter, this is most apparent by noting that, during a breaking event, only one or two hashtags will become 'trending,' with future tweeters encouraged to use those particular hashtags to discuss.

is random which populations choose to discuss or not discuss the issues under analysis, this sampling bias can lead to misleading results.

## 3.2 Collecting the Twitter Panel

To overcome this limitation, I create a panel of Twitter users, none of whom were selected on the basis of discussing gun control policy. This allows me to avoid selecting on the outcome of interest.

In build this panel by first locating a group of users who discuss general political issues and have clear partisan leanings. I make this sampling decision because, although I do not want to select a panel based on a user's proclivity to discuss gun policy issues, I do want to ensure a panel with politically engaged users. To this end, I used the Streaming API to locate users discussing either of the two political parties during the 2016 election and explicatively mention affiliation with a political party or ideology in their Twitter profile.[4] In total, 55,674 users fit these criteria: 24,219 Democrats and 31,455 Republicans.[5]

After locating a large group of politically active partisans, I pulled each user's Twitter history from the Search API. Unlike the Streaming API, the Search API allows a researcher to obtain a user's full history of Twitter messages, not simply those messages matching certain specified keywords.[6] I also use the Search API to pull additional information about each user, such as their number of followers and their entire friend list. The friend lists index the full set of accounts a particular user follows. This information is critical in analyzing issue engagement with the RAS model, as it allows me to track each users source of incoming information.

[4] The population of interest is strong partisans, and thus my inferences are made in particular regard to this subpopulation. In the RAS model, it is necessary to be certain of a user's partisan leaning, and this sampling procedure represents the best way I can ensure each user's partisan leaning is correctly identified.

[5] Users clearly not residing in the United States (based on time-zone and location information) were filtered out of the final panel.

[6] The Search API limits a pull of a specific user's history to their last 3200 tweets. One issue using the Search API is the large time-cost: the Search API is subject to strict rate-limits, making it difficult to collect information on a large number of users. This limited the number of users I could feasibly include in my panel. I pulled each user's history twice, once in January 2018 and again in April 2018.

## 3.3 Elite Messages About Gun Policy

To supplement the panel data, I also collect tweets from the Streaming API, obtaining messages from users beyond my panel that contain keywords about gun policy and gun control.[7] This monitor allowed me to capture many of the conversations concerning gun policies in the wake of major shootings, which I then merged with each panel user's friend list to estimate the number and source of gun policy messages each user was exposed to after a shooting. The monitor ran from September 2017 to May 2018, and captured tweets about gun control following the Las Vegas mass shooting on October 1, 2017 and the Parkland High School shooting on February 14, 2018.

One problem with relying on the Streaming API to collect data about gun rights during major shootings is the issue rate limiting. Rate limits are triggered when a monitor makes too many calls to the API, resulting in a 15-minute penalty.[8] While on most days, there was not enough traffic to make rate limiting an issue, on the days immediately following a major shooting, the Twitter population sent a large enough volume of tweets containing my selected keywords to trigger rate limiting. This means I cannot guarantee the full range of elite messages on the first few days following a shooting. However, given I measure fewer elite messages precisely at the moments users in my panel are most likely to send their own messages about gun violence, this data censuring biases *against* my hypotheses, allowing any evidence that elite messages about gun control increase the probability a user themselves tweets about gun policies to be interpreted as a conservative estimate.

In order to utilize the RAS model, I need two additional pieces of information about each received message: whether the tweet originates from a member of the political elite and the ideological leaning of the message sender. In order to label a user as being a member of

[7]These trackwords were: 'gun control' , 'gun violence' , 'firearm control' , 'firearm regulation' , 'second amendment' , '2nd amendment' , 'concealed carry' , 'conceal carry' , 'conceal and carry' , 'concealed weapon' , 'shooting' , 'gun rights' , 'gun ownership' , 'gun safety' , 'gun regulation' , 'handgun' , 'arms control' , 'gun regulation' , 'access to guns' , 'gun policy' , 'gun policies' , 'gun law' , 'right to bear arms' , 'right to keep and bear arms' , 'NRA' , 'national rifles association' , '#2a'

[8]See https://developer.twitter.com/en/docs/basics/rate-limiting.html for details.

the political elite, I use the Twitter "verified" status. Verified users are individuals Twitter determines are people "of public interest," most often users in "music, acting, fashion, government, politics, religion, journalism, media, sports, business, and other key interest areas."[9] While this notion of elite is broader than Zaller's original conception of the political elite, it encompasses this group, as nearly every elected official in Congress and all major news organizations and interest groups have verified accounts.[10]

To categorize the ideology of the message sender, I use labels estimated with Pablo Barberá's methodology described in "Birds of the Same Feather Tweet Together" (2015).[11] To briefly summarize, Barberá's method takes advantage of each user's follower network to predict the likelihood a user is a Republican or Democrat. Intuitively, the more Republicans one follows, the more likely that user is labeled a Republican, and vice versa for Democrats.

In total, 994,857 friends of the users in my panel tweeted about gun control in the 28 days following the Las Vegas and Parkland shooting.[12] 120,681 of these friends were 'verified' users, and I was able to merge 38,508 of these 'verified' users with Barberá's ideological labels: 25,939 democrats and 12,569 republicans. This group represents the potential incoming message stream each panel user was exposed to after each shooting.

In addition to serving as an estimate of how many messages each user receives about gun policy after major shootings, the Streaming API data serves a second equally important purpose: allowing me to observe the phrases and keywords elites use to discuss gun policy. By performing a variety of unsupervised keyword extraction algorithms, I was able to locate a set of words and phrases across each shooting event that indicated conversation about gun policy. These keywords allowed me to filter through the large variety of issues each panel user tweeted about, extracting only those messages concerning gun control and legislation.[13]

[9]From https://support.twitter.com/articles/119135.

[10]See https://twitter.com/verified/lists/ for a selection of verified users on Twitter.

[11]I thank Barberá for granting me access to his dataset.

[12]I only analyzed friends that appear in at least ten different panel user's friends list.

[13]I used the package UDPIPE (Straka & Straková 2017) to run these keyword extraction algorithms. This procedure involved breaking the text into individual tokens and using a part-of-speech tagger to extract all nouns. I then located the most commonly occurring unigrams and bigrams in the tweets sent in the wake of Las Vegas and Sutherland Shootings, removing any keywords that were specific to a particular shooting.

Combining the information I collect from the Search and Rest API allows me to observe detailed information about each user's tweet history and incoming elite message stream on a particular day. I aggregate all data to the day level, and each row of my panel dataset includes both the number of messages a user sends and receives from partisan elites concerning gun control.

# 4 Testing The RAS Model

In order to estimate whether elite messages concerning gun control increase the likelihood an individual will tweet about gun policy themselves, I use a binary probit regression estimator with time-level fixed-effects. I divide my panel of 55,674 users over the 28 days following the Las Vegas and Parkland mass shooting. My outcome of interest is if, over the course of a day, a user sends at least one tweet about gun policy. For my primary analysis, I convert this to a binary indicator taking on the values zero or one.

The independent variable of interest is the number of tweets concerning gun policy each user receives from elites, and I additionally add several time-invariant control variables. The equation I estimate is as follows:

$$Prob(y_{it} = 1) =$$
$$\Phi\Big(\beta_0 + \beta_1 message_{it} + \beta_2 friends_i + \beta_3 followers_i + \beta_3 GOP_i + \beta_4 ActivePrePeriod_i + \beta_5 day_t + \epsilon\Big)$$

where $i$ indexes users and $t$ indexes time. $y_{it}$ is the main outcome of interest: a binary indicator measuring whether or not individual $i$ tweeted about gun control on day $t$. In testing the RAS model, $\beta_1$ is the primary coefficient of interest, as this estimates the impact of receiving elite messages concerning gun policy on the probability an individual tweets themselves about gun control.

I also control for a number of time-invariant control variables. Most importantly, I control for the number of elite accounts each user follows. This is an important variable to include in my model specification, as it is entirely possible that what is ultimately driving a user's predilection to tweet about gun control is the initial decision to follow elites, *not* the number of messages they receive from elites. By controlling for the number of elite users followed, I am able to identify the impact of receiving elite messages across individuals following similar numbers of elite accounts.

Additionally, I control for the user's party identification, their number of followers, and whether or not they were *active in the pre-period*, which I define as having tweeted about gun policy in the two months prior to the mass shooting. The distribution of each user's number of followers, number of elite friends, and number elite messages received each follow a power distribution, so all these variables are transformed with a $log(x+1)$ transformation. Finally, I include time-level fixed effects, to control for the fact that the Twitter community sent more messages about gun control in the early days following a mass shooting.

## 4.1 Elite Influence on Discussions of Gun Policy

My methodology allows me to test the two core predictions of the RAS model using Twitter data: 1) users *receiving* messages from elites are more likely to tweet themselves about an issue topic and 2) users are more likely to *accept* messages from elites of the same party.

I begin by considering the first process in isolation: is the number of elite messages a user receives about gun policy, regardless of the partisanship of the sender, positively correlated with the probability the user sends their own message about gun policy? I present the results of this analysis in Table 1, which includes four model specifications. Models one and two model gun policy conversations in the 28 days following the shooting Las Vegas shooting on October 1, 2017 at Mandalay Bay Resort while models three and four look at the 28 days following the Parkland, Florida school shooting on February 14, 2018 at Marjory Stoneman Douglas High School. Analyzing two separate but similar incidents helps confirm that the results are not due to the specific circumstances of a single event, but rather a general trend. In models one and three, the dependent variable represents *any* user tweet concerning gun policy, including retweets, while models two and four restrict the outcome

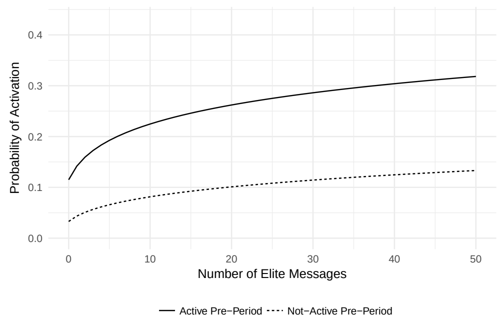
Table 1: The Effect of Elite Messaging On Tweeting About Gun Control

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Tweet About Gun Control | | | |
| | Vegas Shooting | | Parkland Shooting | |
| | All | No Retweets | All | No Retweets |
| | (1) | (2) | (3) | (4) |
| Intercept | −1.28 | −2.08 | −1.57 | −2.27 |
| | (0.02) | (0.03) | (0.01) | (0.03) |
| Elite Messages | 0.19 | 0.15 | 0.21 | 0.16 |
| | (0.00) | (0.01) | (0.00) | (0.01) |
| Active Pre-Period | 0.64 | 0.87 | 0.72 | 0.84 |
| | (0.01) | (0.03) | (0.00) | (0.01) |
| GOP | −0.02 | −0.05 | 0.02 | −0.03 |
| | (0.01) | (0.01) | (0.00) | (0.01) |
| Elite Friends | Yes | Yes | Yes | Yes |
| Followers | Yes | Yes | Yes | Yes |
| Log Likelihood | -108486.90 | -27042.34 | -300592.96 | -62879.10 |
| N | 55,674 | 55,674 | 55,674 | 55,674 |
| T | 28 | 28 | 28 | 28 |

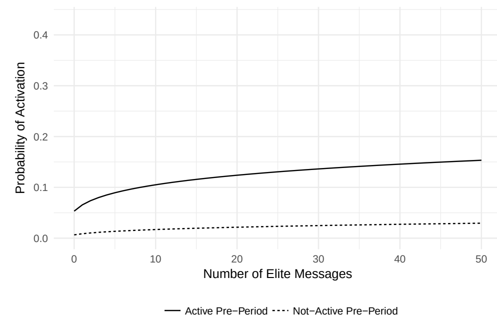
to original tweets, excluding retweets. As writing an original message about gun control is a more costly action, examining the elite influence on this behavior is in some ways a stricter test of the RAS model.

In Table 1, I find positive and statistically significant **elite messages** coefficients across each model specification. This shows that the number of elite messages concerning gun policy a user receives is positively correlated with the probability the user sends their own message about gun policy. This result holds when I restrict attention away from retweets, indicating that elite messages increase the probability a user will write their own, original message concerning gun policy. In the case of the Las Vegas shooting, going from receiving no elite tweets about gun control to ten elite tweets (the median) raises the probability a user sending their own tweet about gun control on a given day by 4.85% (1.05% excluding retweets), and in the case of Parkland, raises the probability by 6.96% (1.63% excluding retweets). Figure 1 visualizes how an increased number of elite tweets increases the probability a user sends their

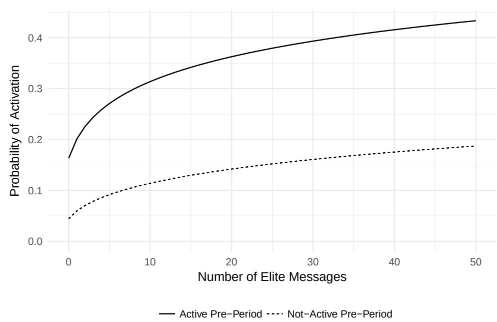
Figure 1: The Impact of Elite Messages on the Probability of Tweeting About Gun Control



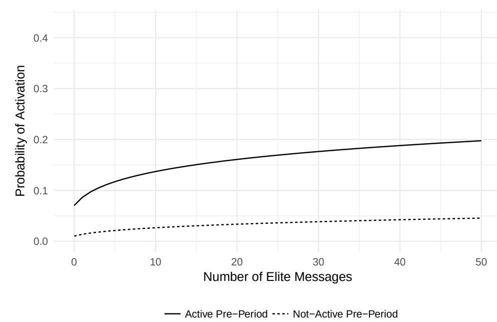

(a) Vegas: All Tweets




(b) Vegas: No Retweets




(c) Parkland: All Tweets




(d) Parkland: No Retweets

own tweet about gun control in each model specification.[14]

It is important to note that all these effects all represent conservative estimates given rate limiting prevented me from collecting the full universe of incoming elite messages on precisely the days with the most Twitter traffic. As these days also represent the moments panel users were *most likely* to send a tweet about gun policy, this biases *against* finding a positive impact between the number elite messages received and a user's probability of tweeting about gun control.

Turning to the other variables in Table 1, I find a large negative intercept across each model specification. This indicates that, overall, each user has a low-likelihood of sending a message about gun control on a given day. This is to be expected given my data collection scheme – users in my panel were *not* selected on the basis of their predilection to tweet about

[14] To calculate these probabilities, I consider a democrat user tweeting on the second day after a shooting who did not tweet in the pre-period and has the mean number of elite friends and followers as the users in the panel.

gun policy related issues. Indeed, the large, positive, and highly significant **Active Pre-Period** coefficient demonstrates that users who previously tweeted about gun control in the two months prior to a shooting had a much higher chance of tweeting about gun control in the aftermath of both shootings. It is important to note if I collected data from the Streaming API in the fashion of most studies utilizing Twitter data to track issue engagement, these would be the *only* users that I could analyze. As Figure 1 demonstrates, restricting attention to this subpopulation overestimates the probability a given user will tweet about gun policy.

Overall, the results in Table 1 are consistent with the RAS model – users receiving more messages from *elite* accounts concerning gun control were more likely to themselves tweet about gun control. These effects are attenuated given the missing elite message data, providing even stronger evidence in favor of my first Hypothesis (H1).

## 4.2 Impact of Partisan Messaging

The second core process described in Zaller's RAS model is the tendency of partisans to *accept* mostly their own party's elite messages and *resist* the opposing party's elite messages. To test this behavior in my current study, I ran the binary probit regression outlined above, but differentiated between the partisan source of the elite message. For a Democrat user, I define **Own Party Elite Messages** as a message from a Democrat elite and **Opposing Party Elite Messages** as messages from a Republican elite, and vice versa for Republican users. Once again, I control for the number of elite accounts followed, specifying the partisanship of each elite account.

I run a total of four models. Models one and two look at conversations following the Las Vegas shooting, differentiating between the subpopulation of Democrat and Republican users respectively. Models three and four provide the same analyses following the Parkland shooting.

Table 2 presents the results of this analysis. Each model specification in Table 2 serves to confirm the second core process of Zaller's model – partisan messages have a differential

Table 2: Accepting and Rejecting Elite Partisan Messages

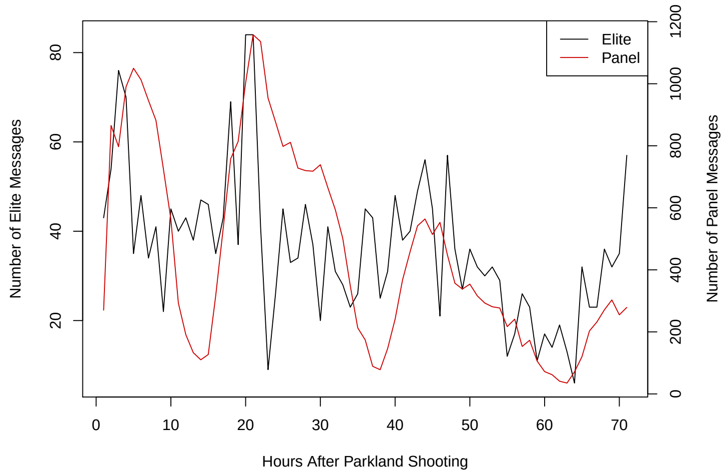
| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | Tweet About Gun Control | | | |
| | Vegas Shooting | | Parkland Shooting | |
| | Dem | Rep | Dem | Rep |
| | (1) | (2) | (3) | (4) |
| Intercept | −1.11 | −1.59 | −1.41 | −1.89 |
| | (0.02) | (0.02) | (0.02) | (0.02) |
| Own Party Elite Messages | 0.15 | 0.15 | 0.16 | 0.19 |
| | (0.01) | (0.01) | (0.00) | (0.00) |
| Opposing Party Elite Messages | 0.05 | 0.02 | 0.04 | 0.02 |
| | (0.01) | (0.01) | (0.00) | (0.00) |
| Active Pre-Period | 0.59 | 0.67 | 0.68 | 0.77 |
| | (0.02) | (0.01) | (0.01) | (0.01) |
| Own Elite Friends | Yes | Yes | Yes | Yes |
| Opposing Elite Friends | Yes | Yes | Yes | Yes |
| Followers | Yes | Yes | Yes | Yes |
| Log Likelihood | -46299.24 | -61773.45 | -132062.89 | -167377.31 |
| N | 24,219 | 31,455 | 24,219 | 31,455 |
| T | 28 | 28 | 28 | 28 |

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

impact on a user's propensity to tweet, with gun policy messages from partisan elites of a user's own party associated with higher probabilities of tweeting about gun control. While receiving opposing party elite messages is also positively correlated with the propensity to tweet, the effect is much smaller. Taken together, this provides evidence that users filter elite messages based on their partisan content, with users more likely to engage with an issue if the message comes from an elite of the same party, supporting my second hypothesis (H2).

Table 2 also reveals some interesting differences between how Democrats and Republicans respond to partisan elites. For Republicans, receiving elite messages from Democrats has a much smaller impact on their propensity to tweet than Republican elites. Zaller's filtering process thus seems to describe Republican behavior better than Democrats in the current analysis.

Figure 2: 72 Hours Post Parkland Shooting




## 4.3 Determining the Timing of Elite Tweets

The results of Table 1 and Table 2 offer strong support in favor of my first two hypotheses: people respond to elite messaging by engaging more with the issue topic themselves, and this effect is strongest when receiving messages from their own party elites. However, one potential issue with these analyses is determining the timing of when tweets were sent and received. That is, while Table 1 and Table 2 indicate receiving more elite messages on a given day is correlated with a user sending their own message on that day, it is difficult to tell if elite messages are received *before* the user sends their own tweet about gun violence. If messages are sent after receiving elite messages, the evidence of a causal link is much stronger.

While challenging to disentangle the timing of messages at the individual level, it is possible to look at the aggregate time trends to determine whether an increase in elite messages is correlated with an increase in messages from the users in my panels. To examine these time trends, I aggregate the number of messages about gun control sent from elites and panel users at the hour level, looking at the trends 72 hours after the Parkland shooting.[15]

These trends are visualized in Figure 2. It is important to note the different scales: there

[15]For this analysis, I restrict attention to original tweets, excluding retweets.

are far fewer elite messages sent on an hourly basis than panelist messages. However, the number of messages sent is somewhat misleading, given elites tend to have much higher follower counts than the users in my panel (elites have a median of 24,473 followers while my panel users have a median of 226 followers). Therefore, each elite message has a much wider potential reach, with a single elite message capable of reaching a larger number of users on the Twitter network.

Figure 2 also reveals how rate limiting impacted elite message collection from the Streaming API. Roughly 24 hours after the shooting, the point in time with the highest number of tweets sent by panel users, there is a large, sudden drop in the number of elite messages collected due to rate limiting. This confirms that I obtain fewer elite messages precisely in the moments the panel users are most likely to tweet about gun legislation, biasing against my hypotheses. This attenuation bias allows me to interpret my results as conservative, lower-bound estimates.

In spite of rate limiting impacting the number of elite messages recorded, Figure 2 does to indicate that an increase in the number of elite messages about gun control tends to be followed by an increase in the number of messages from users in my panel. This provides evidence that elite messaging about gun control tends to proceed panel user's messages, a necessary assumption of the RAS model.

Beyond a visual inspection, one way to formally test if the fluctuations in one time trend are correlated with similar fluctuations in another time trend is to look at Granger causality. Tests of Granger causality consider the null hypothesis that lagged x-values fail to explain variations in the y-values. I test for Granger causality by considering whether the number of elite messages sent in hour t help predict the number of panel user messages sent in hour t+1.

The results of these tests are found in Table 3.[16] Looking at the impact of all elite messages on all panel messages in column one (the trends I visualize in Figure 2), I find the

[16] Once again, all these results should be interpreted as conservative estimates; due to rate limiting I collect fewer elite messages precisely at moments there are large increases in panel messages.

Table 3: Granger Causality - P Values

| | | Own Partisan Elite | | Against Partisan Elite | |
|---|---|---|---|---|---|
| Lag | Elite → Panel (1) | Dem. Elite → Dem. Panel (2) | Rep. Elite → Rep. Panel (3) | Rep. Elite → Dem. Panel (4) | Dem. Elite → Rep. Panel (5) |
| 1 Hour | **0.002** | **0.001** | 0.323 | 0.102 | **0.003** |
| 2 Hours | **0.041** | **0.001** | **0.049** | 0.133 | 0.119 |
| 3 Hours | 0.530 | **0.022** | 0.335 | 0.342 | 0.45 |

fluctuations in elite messages have a statistically significant impact on the fluctuations in panel messages. This is true for one and two hour lags, but I fail to reject the null at the three hour lag.

When I alter the message streams by the partisan-leaning of the elites and panelists, I see that most of these results are driven by Democrat users in my panel. Democrats seem highly responsive to elite messages from fellow Democrats, as evidenced by the highly significant p-values in column 2. Column 4 demonstrates that Democrats are *not* as responsive to elite messages from Republicans, providing further evidence that Democrats are more likely to accept messages from their own party's elite.

The results are less clear when looking at the Republican users in my panel. I do not find evidence that the trends in messages from Republican elites are correlated with the trends of the Republican users in my panel, as shown by the largely null results in column 3. Moreover, I find evidence that, at the one-hour lag, Democrat elite messages explain trends in the Republican message stream, which is not what I would expect in the RAS model. This may indicate that the filtering process in the RAS model does not fully explain Republican behavior online – Republicans may choose to engage in the gun policy debate after a large, overall increase in the number of messages sent by Democrat elites.[17]

[17]It is possible that this issue engagement comes in the form of countering claims made by Democrats, with Republican users arguing in favor of gun rights precisely when Democrats bring up gun control. This would require a more detailed look at the content of tweets, which is beyond the scope of the current paper.

# 5 Expanding the Notion of Elite

The previous analysis demonstrates that conventionally defined elite messaging impacts behavior in a way consistent with the RAS model. However, Zaller's original definition of *elite political actors* described in *The Nature and Origins of Mass Opinion* has since been expanded by later scholarship (e.g. Friedman 2012, Zaller 2012). Given the somewhat egalitarian nature of Twitter as a platform, where any user can amass any number of followers, it is a natural extension of my present work to consider the impact of other kinds of actors on tweeting behavior.

I conceptualize a *non-conventional elite actor* as a user who is able to reach a large number of other users on Twitter, but would *not* be considered an *elite* outside of the Twitter platform. To define these actors, I look at users with a high follower count, and thus have high out-degree centrality on the Twitter network, but do not possess the 'verified' tag. These users might be considered 'Twitter famous' given they manage to amass a large following without being "of public interest."[18]

In order to specify which users are *non-conventional elite actors*, I need to choose a threshold value for 'a large number of followers.' I define this threshold value as 24,473 followers, the median number of followers of the elite actors defined in the previous section. While choosing this threshold value guarantees I choose *non-conventional elite actors* with similar reach on the Twitter network, I also in some ways bias against the verified elites, half of whom will have fewer followers. Thus, I may be underestimating verified elite actors impact in driving conversations in the following analysis.

To test the impact of 'Twitter famous' actors on conversations about gun policy, I reran the models from Table 1, additionally including the number of messages each panel user receives from non-conventional elites. The result of these test are found in Table 4.

Table 4 demonstrates that **non-verified elite messages** have a large, positive, statis-

[18]See https://support.twitter.com/articles/119135 for more information on how Twitter determines which accounts receive a verified tag.

Table 4: Expanding the Definition of Poltical Elites

| | *Dependent variable:* Tweet About Gun Control | | | |
|---|---|---|---|---|
| | Vegas Shooting | | Parkland Shooting | |
| | All | No Retweets | All | No Retweets |
| | (1) | (2) | (3) | (4) |
| Intercept | −1.12 | −2.04 | −1.47 | −2.29 |
| | (0.02) | (0.03) | (0.01) | (0.03) |
| Elite Messages | 0.09 | 0.10 | 0.07 | 0.09 |
| | (0.00) | (0.01) | (0.00) | (0.01) |
| Non-Verified Elite Messages | 0.10 | 0.05 | 0.13 | 0.07 |
| | (0.00) | (0.01) | (0.00) | (0.00) |
| Active Pre-Period | 0.61 | 0.50 | 0.68 | 0.44 |
| | (0.01) | (0.02) | (0.00) | (0.01) |
| GOP | −0.11 | −0.10 | −0.10 | −0.08 |
| | (0.01) | (0.01) | (0.00) | (0.01) |
| Elite Friends | Yes | Yes | Yes | Yes |
| Non-Verified Elite Friends | Yes | Yes | Yes | Yes |
| Followers | Yes | Yes | Yes | Yes |
| Log Likelihood | -107618.79 | -27032.65 | -297235.56 | -62947.85 |
| N | 55,674 | 55,674 | 55,674 | 55,674 |
| T | 28 | 28 | 28 | 28 |

tically significant effect on the probability a user will tweet about gun control. This effect is similar in magnitude to receiving messages from **verified elite** actors, which suggests it is necessary to expand Zaller's original notion elite actors when using the RAS model to explain issue engagement online.

One interesting finding revealed in Table 4 is that receiving non-verified elite messages has a heterogeneous impact depending on the outcome of interest. When considering *any* tweet as the dependent variable, **non-verified elite** messages have a larger impact on the probability a user will tweet than **verified elite** messages. However, this is reversed when we consider *original* tweets as the outcome of interest, excluding all retweets. Given writing an original message on twitter is in many ways a more costly behavior, this may indicate conventional elites are still more important in driving people to engage with an issue topic. However, the overall results of Table 4 indicate the necessity in including **non-verified elites** in any model of opinion formation and activation on Twitter.

# 6 Conclusion

As major events unfold, citizens are forced to update their opinions and choose whether or not to participate in policy debates. In my work, I find that citizens are more likely to engage with an issue topic when they receive elite messages concerning that issue. Partisans react more strongly to incoming messages from elites within their same party, in a way consistent with the RAS model. I further find that people react in a similar way to messages received from non-conventionally defined elites, pointing to the importance of these agents in influencing political conversations online.

This paper also resolves a number of methodological issues that affect the study of issue engagement online. While a large number of studies track issue topics on Twitter, by selecting on the dependent variable all of this work has a sampling problem that could potentially bias results. I avoid this sampling problem by building a large panel of partisan Twitter users and obtaining their full Twitter histories, regardless of whether or not they discuss the policy issue in question. By supplementing these Twitter histories with a full list of the accounts each user follows, I am able to directly estimate each user's incoming message stream.

There are a number of ways this current work can be extended. First, I only look at a single issue area – discussions of gun policies in the wake of mass shootings. While I make this decision given the predictable nature of the elite message streams after a major shooting, future work should extend my analysis to other issue domains to find whether these results are consistent. Second, I only look at issue activation instead of issue change. In the domain of gun control, where partisan opinion is highly polarized and unlikely to change, this represents a necessary approach. In fact, finding that elite messaging can increase the likelihood of issue engagement even in this highly polarized issue domain provides stronger evidence that online behavior is consistent with the RAS model. Still, extending these analyses to other political topics in other issue areas where opinion change is more likely will allow for further confirmation that the RAS model applies in the realm of social media.

Overall, my current work finds that the RAS model still has the power to explain citizen behavior and how individual's form and express their opinions online. The unique attributes of social media data allow me to directly estimate each user's unique incoming message stream, granting me the ability to directly test how elite messaging impacts an issue topic's salience. These positive findings suggest that future scholarship using social media data to study and measure changing political opinions online can and should utilize the RAS model in organizing and interpreting empirical findings.

These findings have broad implications. In considering the gun control debate, these findings suggest elite messaging increases the likelihood citizens will themselves discuss gun control. The fact that citizens filter messages based on the partisan source of the elite sender helps explain why the issue remains so polarized – while Democrat elites can increase the likelihood Democrats will engage with the gun control debate, so too can Republican elites energize Republicans. Highlighting the importance of non-traditionally defined elite actors further demonstrates the power of citizens themselves to influence public opinion; despite being outside the ‘public eye,’ amassing a large network of followers can give any individual the power to influence public engagement with issues. Analyzing how individuals respond to elite messages and cues online can help explain voter behavior as social media continues to play an important role in fostering political communication.

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