The Features of Tragedy, Expressions of Sympathy, and Debates over Policy: A Time Series Analysis of Mass Shootings and Social Media Discourses

Abstract
Social media responses to mass shootings in the United States provide important opportunities to consider the social and political nature of public mourning and debate in response to tragedy. In this paper, we focus the outpouring of grief in response to mass violence and the subsequent contestation over gun policy on Twitter, tracing these discourses to features of the tragic event. By measuring Twitter discourses with two distinct approaches that yielded highly consistent results and applying time-series modeling, we find that the characteristics of mass shooting victims affect the levels of collective grieving and gun policy discussions, highlighting the unfortunate fact that not all lives are equally valued and grievable by society. Additionally, the dynamics of responses to mass violence differ, with expressions of sympathy and discussions on gun policy more ephemeral and the second amendment gun rights discourse much more sustained.

Social media responses to mass shootings in the United States provide important opportunities to consider the social and political nature of public mourning and debate in response to tragedy. In this paper, we focus on the outpouring of grief in response to mass violence and the subsequent contestation over gun policy on Twitter, tracing these discourses to features of the tragic event. Examining citizen expression on social media extends work on citizen communication in a democratic society that emphasizes the views of social theorists like Dewey (1927/1984) and Habermas (1989) as well as sociologists like Tarde (1898/1969) and Young (1996). Habermas' (1989) work emphasizes how individuals gather to deliberate on issues of public interest and form a discursive public sphere, which mediates between the state and the private realm (Dahlberg, 2001). For Tarde, it is through conversation with others that people form and crystallize their own opinions, encouraging political action (Shah, Culver, Hanna, Yang, 2015). Young (1996) focuses upon public discussion as a political process in a diverse society. Through shared social knowledge and appeals to social justice, different social perspectives are brought in as "a necessary resource for making… decisions" (Young, 1996, p. 399). Regardless of whether this form of citizen expression is understood as part of the public sphere, a crystallizing agent for action, or a perspectival process in pluralist societies, social posting about mass violence merits attention.

The proliferation of social networking sites creates ample opportunities for members of society to communicate with each other about issues affecting democratic societies. It is through these communication platforms that people can express their thoughts about contemporary happenings, propose policy options, defend cherished values, and organize themselves to pursue collective goals and causes (e.g., Benkler, 2006; Bennett & Segerberg, 2012; Freelon, Mcllwain, & Clark, 2016). As such, these sites also provide a window into contemporary political

discourse, offering insights into the social values, forces and dynamics at play around

controversial issues and consequential events. People's collective responses to controversies and

events on social media platforms offer a window into contested political meaning, debates over

policy options, and formations of public opinion. In this paper, we examine the social media

response to mass shootings in the United States, as reflected on Twitter. We consider the

changes over time in three discourses in response to the 59 mass shootings that occurred between

2012 and 2014: "Thoughts and Prayers," "Gun Policy," and "Second Amendment."

First, we examine the interrelationship between these three discourses and how sustained

they are in response to mass shooting events. Next, we analyze the variance in these discourses

over time in relation to event features, exploring whether the features of mass shootings — i.e.,

the number of victims, the age, gender, and race of those killed, and nature of the relationship

between shooter and victims — shape the patterns of the social media response. In theorizing the

response to mass violence and interpreting our results, we rely on work concerning: (a) the

nature of mourning and grieving in response to tragedy, (b) communication research on public

responses to tragic events and crises, and (c) contestation over policy in a pluralist society where

different perspectives are brought onto the social stage. To do this, we employ computational

methods — utilizing machine learning and hashtag grouping — to generate our social media

response data and then employ time-series modeling to understand the relationship to the

features of the mass shooting events.

Grieving Public Tragedies

Mass shooting events have haunted American society. Defined by the FBI as events that

involve four or more deaths, these spasms of gun violence have risen dramatically since the

1970's, rising from 1.1 per year to a staggering 4.1 per year through 2010 (Krouse & Richardson,

2015). The average number of days between any given mass shooting event has shrunk from 282 in 1970 to just 74 from 2010 to 2013. Not only have mass shootings become more prevalent, they have also become increasingly deadly, with the average number of total victims rising by nearly 3 percent between the 1970's and 2010 (Krouse & Richardson, 2015). In the years since 2010, these numbers have continued to rise, driven by the increasing frequency of high casualty events like Aurora Theater, Sandy Hook School, Pulse Night Club, and Las Vegas shootings.

Many of these events rise to the level of public tragedy, "disruptive, catastrophic events that cause physical or psychological trauma for individuals, communities, organizations, and social support networks regardless of whether they are directly or indirectly impacted by the circumstances" (Hayes, Waddell, & Smudde, 2017, p. 257). It is because of this status that mass shootings draw a disproportionate amount of public attention and media coverage, despite being less than one percent of all homicides in the United States. Indeed, while mass shootings are a worldwide phenomenon, the United States is a tragically exceptional outlier, with over six times as many mass shootings as would be expected based on population size (Lankford, 2016).

Not surprisingly, social media has become a site for expressions of grief, mourning, and vulnerability in the aftermath of these events. Judith Butler (2003) has directed particular attention toward public discourses surrounding violence done to marginalized individuals and groups. Across a long line of work, she bemoans the limits on certain forms of public grieving, especially in relation to at those living precarious lives (Butler, 2003, 2014, 2016). She argues that, "certain names of the dead are not utterable, certain losses are not avowed as losses, and violence is derealized and diffused." These limits on responses to tragedy "suppress any internal dissent that would expose the concrete, human effects of its violence." (Butler, 2003, p. 26).

We are, of course, all vulnerable. As Mackenzie, Rogers and Dodds (2014) note, human

life is fundamentally characterized by vulnerability. We may be injured, become sick, or die. We are at risk of neglect, misery, and mental harms. Humans, across the globe, are vulnerable to rights abuses, subjugation and authoritarian control. And, as Butler notes, this vulnerability […] becomes "highly exacerbated under certain social and political conditions, especially those in which violence is a way of life and the means to secure self-defense are limited" (Butler, 2003, pp. 28-29). Within this framework, certain lives will be prioritized and threats to their well-being mobilize action. Other lives will not find such support and will not even qualify as "grievable." (McIvor, 2012). This begs the question: What is it that makes for a grievable life?

Interestingly, for Butler, grief holds potential when it works as a political tool that spurs "responsiveness." She argues:"Many people think that grief is privatizing, that it returns us to a solitary situation and is, in that sense, depoliticizing. But I think it furnishes a sense of political community of a complex order, and it does this first of all by bringing to the fore the relational ties that have implications for theorizing fundamental dependency and ethical responsibility"(Butler, 2003, p. 12). In this way, grief may be socially and personally productive, part of a process by which one identifies with suffering itself. Such suffering might revise the frames around which grief is organized, cultivating ethical dispositions like humility and generosity (Butler, 2016).

Mass Shootings and Expression

The news media and the public share certain recurrent themes that shape the discourses surrounding tragic events. The dynamics of tragedy and opinion have been studied in a number of communicative contexts, including public health (Paul & Drezde, 2011; Chung & Lee, 2016), terrorism (Huddy, Khatib, & Capelos, 2002; Noelle-Neumann, 2002), natural disasters (Vieweg, Hughes, Starbird, & Palen, 2010; Hjorth & Kim, 2011; Liu, Fraustino, & Jin, 2015), and even

assassinations (Boomgaarden & de Vreese, 2007). Mass shootings, while unique among these, also captivate media audiences in inescapable ways, becoming focusing events in public consciousness, and sites of collective psychological trauma. As suggested above, all tragic events provide opportunities to examine public grieving (Butler, 2004) and civil repair (Alexander, 2006).

In this capacity, social media may be not only an important technological vector for the transmission of information and expressions of sympathy, it is also a potential site political debate and contestation, a space for generating solidarity, and a location for symbolically repairing a body politic. Similar to the response to the 9/11 terrorist attacks (Collins, 2004), mass shootings have the potential to function as solidarity-generating events, motivating involvement in collective rituals that rebuild communities following mass violence (Hawdon & Ryan, 2011). As such, digital information ecologies do not simply transmit information about tragic events like mass shootings, they also actively participate in the symbolic constitution of grievable subjects and even the construction of worthy human life itself (Butler, 2016). Certain lives are symbolically marked within, or erased from, public consciousness. Doka (2003) posits that society usually copes with public tragedy by rituals and memorialization. People show solidarity with victims, rehabilitate community, and solidify social cohesion that is threatened by a tragic event (Doka, 2003). Memorializing tragic events often occur in virtual space (Doka, 2003; Hayes et al., 2017). Sympathetic responses — expressions of sympathy and thoughts and prayers — on social media show solidarity with victims (Salmela, 2014; Smith, 2010).

Twitter is one of the social media spaces people use as memorials for devastating events such as mass shooting incidents. By collectively expressing "thoughts and prayers" on Twitter, this discourse may open up other forms of responding to the tragedy. Mass shootings can often

become inflection points that create opportunities for social and political change as increased attention is translated into awareness of policy dissatisfaction in addition to increased public pressure for change (Baumgartner & Jones, 1993). At the same time, Birkland and Lawrence (2009) note that politicians and media figures construct boundaries around subsequent mass shooting events that "limit and redirect those events' imaginative impact." (p. 1422). After Columbine, they argue, the media focus on school shootings waned even as smaller-scale events provided ample opportunity to resurrect the issue in public discourse. There are structural incentives between Congress and media organizations that can influence the "interinstitutional positive feedback in the problem-defining process." (Lawrence & Birkland, 2004, p. 1193).

The "Ideal Victim"

So who constitutes the victim that evokes the greatest level of sympathy? Christie (1986) defines the concept of ideal victim as "a person or a category of individuals who most readily are given the complete and legitimate status of being a victim" (p. 18). Usually, ideal victims in tragic incidents have common characteristics; they are innocent people who are believed to have no skills to defend themselves against crimes (Lindgren & Ristanović, 2011). News media set a hierarchy of victims for citizens when tragic incidents occur, considering characteristics such as the age, gender, and race of crime victims influences the presumed newsworthiness. This reveals that not only stereotypical images of offenders, but also stereotypical images of victims shape attention and emotional arousals toward public tragedy (Madriz, 1997).

Children are considered the most innocent when confronted with violence. Children are more likely to be seen as ideal victims compared to adults and draw particularly sympathetic responses. Along these lines, Sorenson, Manz and Berk (1998) found out that young age victims were overrepresented in homicide news coverage. Female victims generated a larger and more

sympathetic responses (Madriz, 1997). Implicitly controlling for age, Greer (2017) found that news stories about crimes toward young girls outpaced news stories about crimes toward young boys. *As this suggests, children and women are particularly sympathetic victims, and will generate considerable amounts of public grieving and spur policy debate.*

In contrast to these idealized victims, Greer (2017) found out that news media marginalized victims who were racial minorities in crime coverage. Sorenson et al. (1998) also present evidence that white victims are considered more "worthy" victims in news articles than victims from other races. The prejudicial view that white victims are more likely to be innocent than non-white victims seems to shape news media reporting on tragic events. African American victims, in particular, get less attention from news. Sorenson et al. (1998) found that even though there were more black homicide victims than white homicide victims in Los Angeles from 1990 to 1994, black victims were poorly represented in news coverage compared with white victims. *So in contrast with women and children, we expect that African American victims will be generate less public grieving and be less likely to spur policy debates.*

Perpetrators inflicting harm on unknown victims has been one defining feature of mass shooting events like the Aurora theater shooting and the Sandy Hook School shootings. In those cases, the innocence of victims is determined by the public and often random nature of the crime. However, some mass shootings were attributable to the conflicts between private citizens, or within families. Although no less extreme, the distinction between violence in the private sphere of the home and the public sphere of work, school, or commons likely generates a different level of sympathy. *Therefore, we predict that public shootings will trigger a sympathetic response and initiate policy debates, whereas family type mass shootings will be less likely to do so.*

Debating Gun Rights and Regulation

Mass shootings are also periods of contestation over gun rights and regulations. Cook and Goss (2014) show that public opinion toward gun control rises right after mass shooting events, but evaporates quickly. According to Cook and Goss (2014), the public expressed strong support for the gun control right after the Columbine High School shooting in April 1999, but this support decreased to the level of gun support before the shooting by December of that year.

Pew Research Center (2012) also found out that mass shooting events do not change overall public opinion about gun control. It seems that mass shooting events trigger public expressions of sympathy and discourse about gun control, but this discourse does not last long enough to change public opinion about gun regulations. Of course, this discourse about gun control is countered by those who believe their beliefs, their standing, their preferred practices are under threat. As Melzer (2009, p. 74), asserts, echoing Edelman's work on symbolic politics, "words or phrases such as 'gun control' can become symbolically linked to broader threats, leading to reactionary mobilization that far exceeds the actual threat." (Melzer, 2009, p. 74).

As this suggests, the discourse of gun rights is extraordinarily resilient and powerful in the US. Indeed, gun culture is part of the myth of American identity, even if historical evidence suggests guns were much less prevalent in colonial American than pictured in fictional accounts or our popular imagination (Bellesiles, 2000). The organization most responsible for advancing this myth and defending 2nd Amendment Rights is the National Rifle Association. While the NRA has 5 million members, they claim to speak for the 70-80 million American adults who own over 300 million guns. Yet, while many gun owners favor outlawing specific categories of firearms, high capacity accessories, instituting waiting periods, and requiring background checks, defenders of the 2nd Amendment are unwilling to yield any ground. Mass shootings, which elicit sympathy and policy discussion, also spark a powerful counter narrative reflecting a

constitutional defense of the right to bear arms (Sugarmann, 1992; Ingraham, 2015). *We predict that such 2nd Amendment discourse, however, would be much sustained and persistent.*

Methods

Measuring Social Media Content

With the digitalization of contemporary life, social media has emerged as a site of research and analysis given that it contains deep troves of digital trace data on individuals and societies, providing insights into their thoughts, emotions, and behaviors (Kosinski, Stillwell, & Graepel, 2013). Not only rich in content and volume, social media data are also naturally occurring, both networked and longitudinal in scope, and provide the potential to paint a dynamic picture of human interactions over time. As such, social media offer a vantage point for examining the content, structure, and change of human expression, capturing multiple facets of individual and collective behaviors (Lazer et al., 2009; Shah, Cappella, & Neuman, 2015).

Generally speaking, to analyze social media data, researchers have leveraged its structural component such as social networks (e.g., Adamic & Glance, 2005; Golbeck & Hansen, 2014), the behavior component such as the "likes" people click (e.g., Kosinski et al. 2013), and the language used by people detected by sentiment markers (e.g., Young & Soroka, 2012). Language analysis of social media provides another means for gauging the public reaction to a particular object or event. Semantic analysis, unsupervised machine learning like topic modeling, and supervised machine learning using classification algorithms like SVM, Naive Bayes and neural networks are among the methods commonly applied to measuring large quantities of social media discourse. For example, supervised machine learning techniques were used to build classification models predicting the categories of political campaign messages on social media; the models achieved a relatively high performance with around 75% accuracy (Zhang et al.,

2017).

Some other researchers have relied on markers of language, such as hashtags in a post or tweet, to measure expressions on social media. A hashtag is "a word or phrase marked with # to identify an idea or topic and facilitate a search for it," an affordance provided by social media platforms for people to "create discursive clusters around a shared interest" (Bode, Hanna, Yang, Shah, 2015, pp.149-150). Studies have relied on hashtag usage to predict the candidate a Twitter user supports (Hanna et al., 2013), to map political networks (Bode et al., 2015), to identify a certain discourse (Papacharissi & de Fatima Oliveira, 2012), to group different frames of discourse (Shah et al., 2015), and to study the coordination of messaging in online collective actions (Freelon et al., 2016).

With previous studies demonstrating the viability of using hashtags to map discourse, we elect to take a hashtag-grouping approach to measure social media responses, along with the supervised machine learning technique. By taking two methods to measure social media response, we can validate the results obtained from one method against the results from the other, boosting the internal validity of our study. Additionally, we can compare the two methods and derive methodological insights for future work on social media expression measurement.

Data

Two sets of data were used in this study: 1) data on the features of mass shooting events between 2012 and 2014 and 2) Twitter discourse data on mass shooting during this period.

Event data. This study uses a definition of the phrase "mass shooting" that is in line with the FBI definition of a "mass murder," counting any shooting event that resulted in four or more deaths, excluding the assailant(s). Event data was collected from three databases: the Stanford Mass Shootings in America (MSA) project, the Gun Violence Archive (GVA), and the USA

Today Behind the Bloodshed Project (USA Today). The MSA is collected based on online news media sources, the GVA database is based on a combination of online news sources, police media outlets, and police blotters, and the USA Today database is based on the Supplementary Homicide Reports (SHR) from the FBI. While no individual event dataset claims to be exhaustive, they represent three diverse levels of source selection (news media, local police reports, and data reported to the FBI) and each have their own form of source validation.

After compiling the event data and removing events that did not fit our timeframe or definition of mass shooting, 59 mass shooting events were identified from the beginning of 2012 to the end of 2014. In the few instances where multiple mass shootings occurred on the same day, the features of the more violent event on that day was included for analysis. Three trained coders gathered data in each event through online news sources, which also referenced police reports and judicial proceedings, to collect a range of event features, both manifest and latent. We used five mass shooting event features in our analyses: total number of victims, women killed, children killed, proportion African Americans killed, family shooting or public shooting.

Total number of victims. This variable is a total count of the number of people who were killed or wounded during the event. Since deaths and injuries were highly correlated, the categories were collapsed for inclusion in our time-series models.

Women killed. This variable is a total count of the number of women who were killed by the shooter. Coders were trained to balance a series of factors in rendering this determination. The primary criterion was whether or not a police report or news organization identified the sex of the victims. Phenotypical attributes were only used in combination with other kinds of contextual information as a means of classification.

Children killed. This variable is a total count of the number of people under the age of 18

who were killed by the shooter. Again, coders balanced a range of factors when rendering a coding decision. The primary criterion was whether or not a police report or news organization identified the age of the victims. Phenotypical attributes were only used in combination with other kinds of contextual information as a means of classification.

Proportion African American killed. Every victim of each mass shooting event was coded to one of six categorical variables ($\alpha = .86$): White, African-American, Asian, Native American, Hispanic, or unknown. Coders first reviewed event source data for a police report or news organization that explicitly identified the race of the victim. Phenotypical attributes were only used in combination this kind of contextual information. If there is any ambiguity whatsoever, coders deferred to marking their race unknown. The proportion of victims in each race/ethnicity category was calculated for each event for use in the models. For our analyses, the proportion of African American victims was calculated by dividing the number of African Americans killed by the total number of victims killed during the mass shooting event.

Shooting type. This variable ($\alpha = .72$) classified each mass shooting event into one of four types of shootings: family killings, public killings, robbery/burglary, or other. Family killings are defined as a shooting where the majority of victims were either related to or deeply familiar with the assailant, whereas a public killing is when the majority of victims had little to no personal connection to the assailant. Notably, while this variable correlated highly with the physical location of each shooting, they are distinctly coded. The shooting type variable is more about the relationship between the shooter and the victims than the physical location of the shooting. While there are cases where family killings happen in public and strangers are killed in residential homes, these categories do closely track the location of the shooting.

Social media data: We retrieved social media data from an archive of Twitter data

collected through streaming API access. Our archive consists of a random sample (10%) of Twitter's global stream of tweets between 2012 and mid 2015. Two steps were taken to optimally retrieve relevant data about mass shootings from the archive. First, general search strings—"gun," "shooter," "shooting," "firearm," "second amendment," "2nd amendment", "nra"—were used to capture relevant content comprehensively. The search strings yielded 13,169,470 tweets. The second step involved reducing noise in the harvested dataset. Two coders were assigned to produce an exclusion list (Appendix I) containing words and phrases that marked irrelevant tweets based on topic modeling results. Notably, we applied Latent Dirichlet Allocation (LDA), a form of topic modeling, to classify tweets into 100 topics. Two graduate student coders each went through 50 topics, evaluating documents and terms with the goal to further reduce irrelevant tweets by adding words/phrases to the exclusion list. Then all tweets containing one of the exclusion words or phrases were deleted. Foreign language tweets were also removed through using the exclusion list. Eventually, 4,971,996 tweets were retained for analysis.

We applied two different approaches to measuring the three discourses on Twitter in the context of mass shootings - "Thoughts and Prayers," "Gun Policy," and "2nd Amendment.".*Supervised Machine Learning Technique.* We first used supervised machine learning (ML) to classify tweets into the three categories (discourses). Specifically, we used Python's scikit-learn package implementation of Linear Support Vector Classification (LinearSVC). Human coders labeled 2,195 tweets as falling into one or more of the three of the mentioned categories. The tweets that did not fall in any category were labeled as irrelevant and removed in the subsequent analysis. Coders labeled the tweets based on rules mentioned in Appendix II, and met multiple times to resolve any discrepancies. Subsequently, these human

labeled tweets were randomly split into a "training set" of 1,741 tweets and a "test set" of 454 tweets. The training set was fed to the ML classifier along with the corresponding human coded labels, and a model to predict the labels was constructed. Next, the test set was used to assess the performance of these classifiers - the tweets in this set were labeled using the ML classifier, and compared with the human coded labels. The performance of the three ML classifiers are described in Table 1.

<Table 1 about here>

As it can be seen from Table 1, the classifier performance varies depending on the category. Different sensitivity and precision for each category, and specially the row values of sensitivity, means that one should not compare the total volume of tweets in one category versus the other, but rather the relative changes in volume over time. This is because sensitivity determines how many tweets were retrieved by the ML classifier out of the total relevant tweets. Getting a fraction of relevant tweets still gives the underlying trends. For our purposes, precision is the more important metric since precision determines if the tweets are being labeled correctly.

After training and testing, these ML classifiers were used to categorize a larger sample of 143,000 tweets. This sample was a random subsample of the full dataset (see first three columns of Appendix III). We chose to work with this subsample rather than the full dataset because of computational limitations. The process of running these ML classifiers is memory intensive and only about 200,000 tweets could be handled at a time. At the end of this process, we were able to construct three variables corresponding to each discourse, reflecting over time volume of tweets.

Hashtag based approach. We also applied a hashtag based approach to measuring the three discourses. The rationale behind this approach was that particular hashtags are able to represent the substantive content of the tweets where they are embedded. Each hashtag within

each tweet were extracted and labeled the date when the tweet was created. The daily counts of

each hashtag within the three-year span were tabulated and the top 1000 hashtags in terms of

total volume were selected. Four graduate students coded for the relevance of hashtags by

skimming through the actual tweets, and reached inter-coder reliability of 0.78.

Among the 717 relevant hashtags, we selected hashtags indicative of thoughts and

prayers discourse (e.g., "#pray," "#prayer," and "#prayfornewtown"), gun policy discourse (e.g.,

"#backgroundcheck," "#guncontrolnow" and "#gunlaws"), and second amendment discourse

(e.g., "#2ndamendment," "#constitution," and "#selfdefense") (See Appendix IV for the

complete lists). We then aggregated the daily counts of hashtags of the same discourse to

construct the three variables, just like machine learning approach.

As Table 2 shows, the supervised machine learning technique and the hashtag technique

produce highly similar results. The correlation between the "Second Amendment" tweets based

on the ML classifier and the hashtags is 0.80; the correlation between the "Thoughts and

Prayers" tweets based on the ML classifier and the hashtags is 0.87; and the correlation between

the "Gun Policy" tweets based on the ML classifier and the hashtags is the highest at 0.91. The

high correlations between the outcome variables measured by two very different techniques

speaks of the robustness of our methods and provides triangulation for our analysis.

<Table 2 about here>

Time-series modeling

As shown in the times series plots in Figure 1 and Figure 2, the three dependent

variables—thoughts and prayers discourse, gun policy discourse and second amendment

discourse—measured by both tweets and hashtags fluctuated greatly throughout the time frame,

had sustained presence, and contain significant variation. They are times series data that are no

doubt highly dependent over time. As shown by the dotted lines in each figure, the level of each series is also clearly correlated with external mass shooting events.

<Figures 1 and 2 about here>

And while we are mainly interested in what external factors, including the nature of the shooting events themselves, it is important that we take account of the highly autoregressive nature of the social media data. To do so, we fit Autoregressive Integrated Moving Average (p, d, q) models to our data. In ARIMA (p, d, q), p, d, q refer to the Auto-Regressive order, the degree of differencing (integration), and the Moving Average order respectively. ARIMA models apply some combination of these three filters to the time series (the dependent variable) until the observations resemble a white noise time series, which is amenable to analyzing with exogenous variables. We want to understand how much of the series is explaining itself through autoregressive, integrated (random walk), or moving average processes. Once the self-sustaining portions of the series are removed, the remainder can be explained by other variables.

For each time series, we followed a similar set of procedures in diagnosing the underlying data-generating process. First, each series was checked for the possibility of non-stationarity (also known as a unit root or random walk). In no case, was any evidence found that was suggestive of an integrated process. Second, we generated autocorrelation and partial autocorrelation graphs to assess whether the underlying process appeared to be a autoregressive versus moving average process. Figure 3, shown in the next section, always was indicative of an autoregressive process. Notably, nearly every series also contained significant amounts of seasonality – cyclical patterns suggestive that a spike in the value of the series would re-surface every seven days. The most appropriate model was selected based on model fit and information criteria. Once the appropriate model was fit, residuals were saved for later analysis.

One final note on the ARIMA modeling. We had some concerns that the raw data contained some irregularities due to issues with the Twitter database. These usually surfaced in the form of lower than average numbers of tweets captured in 2012. To address the potential risk posed by this imbalance of data volume, we included a control variable in the ARIMA models that was an indicator (dummy) variables coded as "1" for that time period of concern. Introducing this variable to the ARIMA model allowed for the equilibrium data-generating process to vary during those periods. If the coefficient estimate of that dummy variable was statistically significant, it remained in the model and was used to generate the residual series. If it was not statistically significant (suggesting no underlying differences in the data during the irregular periods), it was removed from the ARIMA model before residuals were generated.

For the purposes of our regression analyses, we use the six "whitened" time series that resulted from the ARIMA modeling process. This does not mean that the ARIMA models themselves are also not informative in important ways. Indeed, before turning to our multivariate analyses, we discuss our diagnostic ARIMA results on our six time-series.

Results

What are the dynamics of the social media response variables?

Figures 3 and 4 display the Auto-Correlation Function (ACF) and Partial Auto-Correlation Function patterns for the social media response variables obtained from the machine learning technique and the hashtag technique respectively. For the former, the three categories display distinct patterns of auto-correlation. For the thoughts and prayers tweets, $\varphi_1 = 0.35$, $\varphi_2 = 0.1$ and $\varphi_3 = 0.08$ for the first 40 lags, whereas φ_4 is not statistically significant at 95% confidence bands. This points out to the ephemeral nature of the thoughts and prayers discourse—one day's observation can be correlated with at most the previous 3 days and the correlations are very low.

This is different from the gun policy tweets, where $\varphi_1 = 0.75$ for the first 40 lags and day one is still, although weakly, $\varphi_{37} = 0.20$, correlated with day 37's observation. This suggests that gun policy discourse is much more sustained than the thoughts and prayers discourse. However, its duration is eclipsed by the second amendment tweets, whose pattern stands in stark contrast to the thoughts and prayers pattern. For the first 40 lags, a particular day's observation in the second amendment discourse is as high as almost 0.80 correlated with its previous day and the observation 40 days ago can still positively predict the observation on that day. The pattern is clear: second amendment tweets tend to stay in the system and do not disappear quickly. As a practical matter, this means that a large increase in tweets about second amendment on one day will only shrink by a small amount the next day. By contrast an outpouring of thoughts and prayers will mostly disappear after only one day. Discussions of second amendment and gun control tend to be more "self-sustaining," though the latter less so than the former, whereas thoughts and prayers are not.

<Figures 3 and 4 about here>

Moreover, these observations seem to follow a weekly pattern, suggesting the regularity of second amendment and gun policy discourse. These patterns could be driven by "anniversary effects" – on weekly and monthly anniversaries of major events, social media becomes active again on these issues. Interestingly, this same is not true for thoughts and prayers: policy debates engendered by tragedies appear to have a cyclical nature, but sympathies do not.

The patterns repeat themselves in the three types of hashtags. Thoughts and prayers hashtags are short-lived, with $\varphi_1 = 0.50$ and $\varphi_2 = 0.1$ and φ_3 dropping to a statistically non-significant value, meaning observations are correlated at most two days apart for the first 40 lags. Gun policy hashtags are much more durable, with two consecutive observations correlated at

0.60 and observations correlated at most 34 days apart for the first 40 lags. Second amendment

hashtags sustain without signs of abating for the first 40 lags, correlation between observations

one day apart as high as 0.90. It is also worth noting that the same weekly pattern (a seven day

cycle) can be observed in the second amendment and gun policy hashtags as in the ML classified

tweets.

Event Features and Social Media Discourse

Using the pre-whitened time series of social media activity, we estimated regression

models using mass shooting event features. Given how instantaneous social media responses can

be to external events, we specified contemporaneous effects. Table 3 summarizes the six

regression models.

<Table 3 about here>

Two multiple linear regressions were performed to test the relationship between event

features and talk surrounding thoughts and prayers. Total R^2 for the "Thoughts and Prayers"

models was 0.720 for the ML classified tweets and 0.732 for the hashtags, suggesting that event

variables explained a great amount of variance in thoughts and prayers discourse. Specifically,

the number of victims was a positive predictor of both ML classified tweets ($\beta = 0.0004$, $p <$

0.001) and hashtags ($\beta = 38.260$, $p < 0.001$). The number of female death also positively linked

to the "Thoughts and Prayers" ML classified tweets ($\beta = 0.0023$, $p < 0.01$) and hashtags ($\beta =$

316.103, $p < 0.01$), as was the number of child victims ($\beta = 0.0025$, $p < 0.01$ for tweets; $\beta =$

379.901, $p < 0.01$ for hashtags). However, the proportion of African American victims was

negatively associated with "Thoughts and Prayers" discourse, in terms of both ML classified

tweets ($\beta = -.0057$, $p < .01$) and hashtags ($\beta = -750.815$, $p < 0.01$). Family shooting was a

negative predictor, indicating that the events where a shooter and victims had previous

relationships as family or friends yielded fewer "Thoughts and Prayers" discourse ($\beta = -.0121$, p < 0.001 for tweets; $\beta = -1706.568$, $p < 0.001$ for hashtags). Public shooting was associated with more hashtags of "Thoughts and Prayers", $\beta = -625.351$, $p < .01$, but not ML classified tweets.

The regression equation testing "Gun Policy" ML classified tweets also explained a fair amount of gun policy discussion, $R^2 = 0.57$. The multiple regression predicting gun policy hashtags was also robust, with $R^2 = 0.53$. More specifically, the number of females positively killed ($\beta = 0.001$, $p < 0.01$ for ML classified tweets; $\beta = 160.160$, $p < .01$ for hashtags) and the number of children killed ($\beta = 0.001$, $p < 0.001$ for ML classified tweets; $\beta = 168.153$, $p < 0.001$ for hashtags) positively predicted increased "Gun Policy" discussions on Twitter. A higher proportion of African American victims ($\beta = -0.001$, $p < 0.05$ for ML classified tweets; $\beta = -272.646$, $p < 0.05$ for hashtags) and family shootings ($\beta = -0.004$, $p < 0.000$ for ML classified tweets; $\beta = -754.963$, $p < 0.001$ for hashtags), however, predicted fewer gun policy discussions. Public shootings were somewhat surprisingly, a significant negative predictor for "Gun Policy" ML classified tweets ($\beta = -0.001$, $p < 0.05$), but not for hashtags (-166.176, n.s.).

However, the Second Amendment discourse exhibited a completely different dynamic. Only family shooting predicted less "Second Amendment" posting ($\beta = -4.623$, $p < 0.001$ for ML classified tweets; $\beta = -48.652$, $p < 0.01$ for hashtags). Additionally, R^2s of the two models are small (.014 for ML classified tweets and .015 for hashtags) suggesting that features of mass shooting events are not largely responsible for explaining variance in second amendment discourse.

Discussion

Traditional mass media have long been one primary agent in society, as a gatekeeper, to reflect and maintain social order and social norm (Gans, 1979; Shoemaker & Vos, 1996). Our

results show that social media, as a collective social space, also rise to be a venue where collective mourning and healing take place upon the heels of mass shooting tragedies. The outpouring of sympathy, as evidenced in enormous amounts of thoughts and prayers tweets and hashtags on social media, shows how society comes together to grieve and recover—to cope with tragedies on an emotional level. In the meantime, those overwhelming tragedies triggered social responsiveness in the form of discussions about gun policy, a collective reflection on how society should address these tragedies on a rational level. However, these two kinds of responses are as intense as they are fleeting, dissipating quickly following major mass shooting events. This might be attributed to the unpleasant nature of tragedies as well as the short attention span that society has in an overloaded information environment. In contrast, the counter discourse, probably emerging out of the fear of infringement upon the right to bear arms on the part of second amendment proponents, has resisted the notion of public attention deficit. Though a small group of American public, second amendment proponents have kept their voice and demand not only loud but also strong and persistent, as shown in the fact that gun rights discourse has it own cycle and is barely affected by mass shooting event features. In this sense, social media are also the field of idea contestation, where arguments and counter-arguments coexist. From our case, second amendment discourse obviously had an upper hand.

This observation might add to our understanding of why there is so little legislative success with gun control measures. Admittedly, organized interest groups have played a heavy role—gun rights groups such as National Rifle Association and Second Amendment Foundation have been working aggressively to lobby legislators to preserve the status quo, which stands in sharp contrast to the weak organizational power of gun control groups such as Moms Demand Action for Gun Sense and Brady Campaign. Our study adds subtle nuances. As second

amendment discourse on social media persisted while gun policy discourse and sympathy discourse only had an ephemeral life, the signal sent to both journalists and politicians might be that the appeal to gun rights merits much more attention and seriousness than the appeal to gun control.

Our study ultimately demonstrates the selectivity in social responses to mass shootings, showing an unfortunate dynamic that not all lives are equally cherished. The killing of innocent women and children received significantly more expressions of sympathy and generated more gun control discussions, while African-American victims received systematically less such treatment. This result is a social media corollary to the finding that when traditional media covers homicides, women and children receive more focus whereas minorities and more intimate homicides receive less attention (Sorenson et al., 1998).

Our finding is also striking given that both public shootings and family shootings have null or negative effects on social media responses. This suggests that it is not the nature of the relationship between the perpetrators and their victims, but rather the victims themselves, that affect social media responses.

All these observations directly speak to the discussion of precarious life. Certain mass shooting events are clearly sites for digital mourning and grieving, but the fact that this solidarity is so stratified between social groups leads one to believe that some lives are more grievable than others. In this case, the prospects for the equal construction of worthy life (Butler, 2004) and civil repair (Alexander, 2006) on social media platforms appear truncated at best.

Methodologically, we have attempted to explore the aforementioned phenomena using two very different methodologies, namely the machine learning approach and the hashtag based approach. The agreement between the results from the two methods are significant for two

reasons. Firstly, it cross validates our results. Secondly, by providing a comparison between the two methods we add to the existing literature on computational methodologies dealing with text classification problem on Twitter data. It should be noted that using machine learning to classify tweets is a much more time consuming and effortful process in comparison to simply extracting the hashtags from a tweet. The machine learning text classification problem is made even more difficult by the short length of tweets (140 characters). The high level of agreement between the results from our ML classifier and hashtag methods seem to suggest that a hashtag based approach might be a computationally inexpensive and less time consuming replacement of the machine learning approach, thus more fruitful to pursue for problems like this one that have clearly defined hashtags. These need to be explored in other contexts.

We see our study as the first installment toward a research program on mass shootings and media. While it demonstrates the dynamics of attention on social media toward mass shootings and the selectivity of social media responses to mass shootings with different characteristics, future studies can tease out the relationship between traditional media coverage and social media responses, the discursive structure and major actors on social media, and investigate how both social media and traditional media relate to real life indices such as gun legislation and gun purchase.

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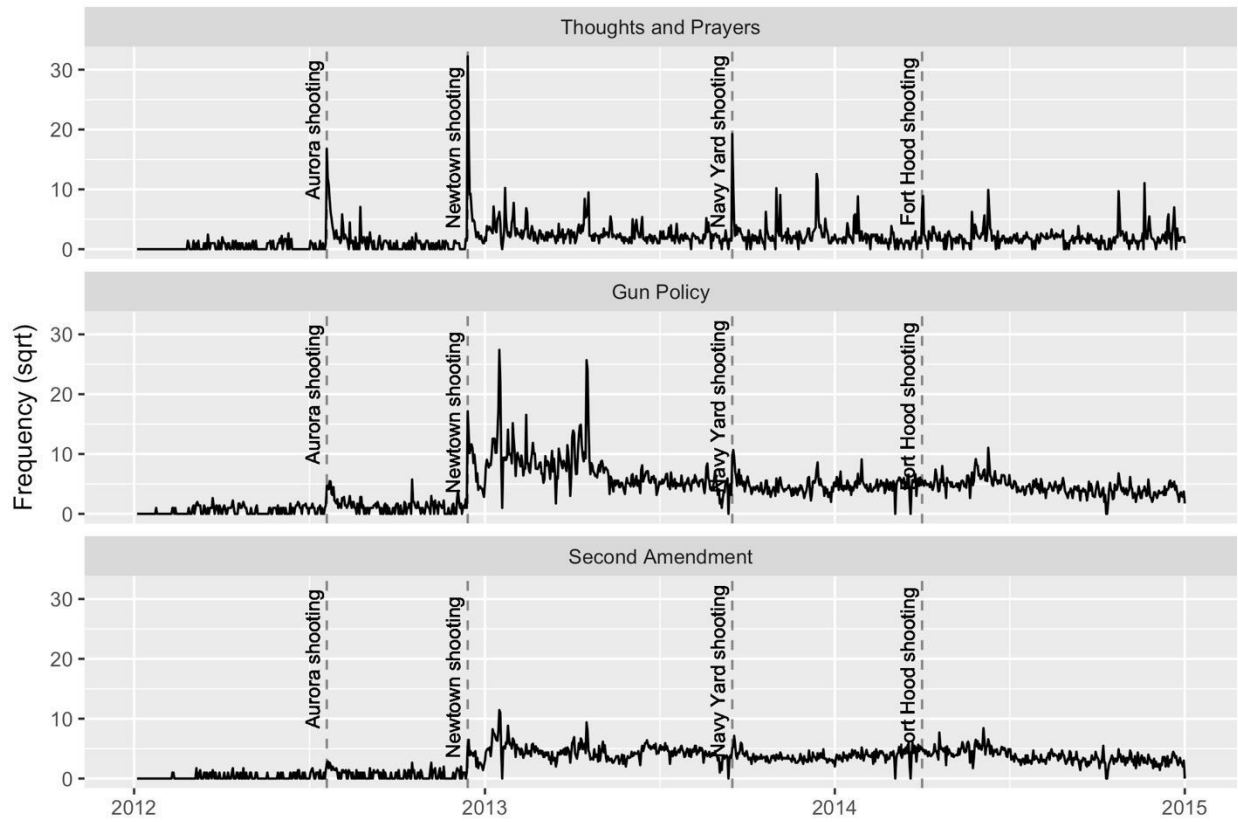
Figure 1. Tweets as DVs identified through the supervised machine learning technique
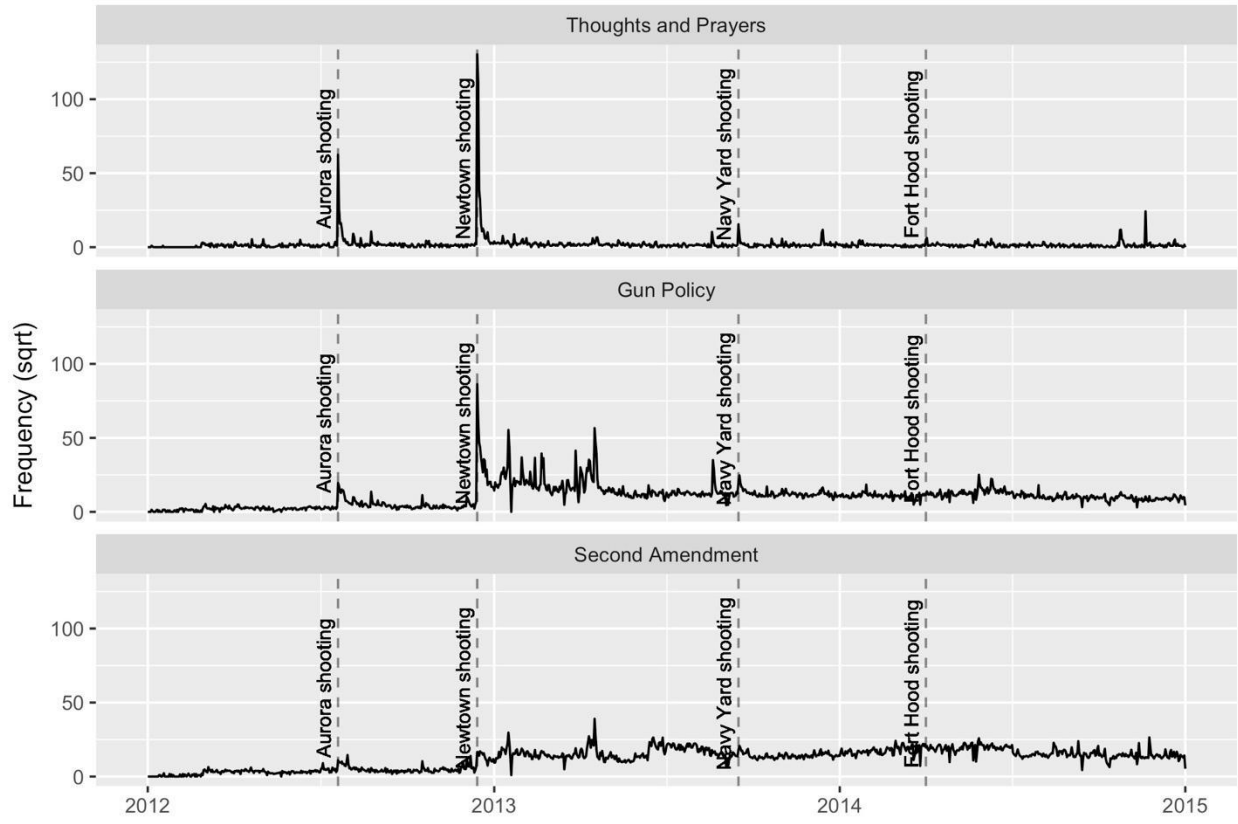
Figure 2. *Hashtags as DVs identified through the hashtag-based approach*

Figure 3. *Auto-Correlation Function (ACF) and Partial Auto-Correlation Function for "Thoughts and Prayers"/ "Gun Policy"/ "Second Amendment" Tweets based on ML Classifier.*
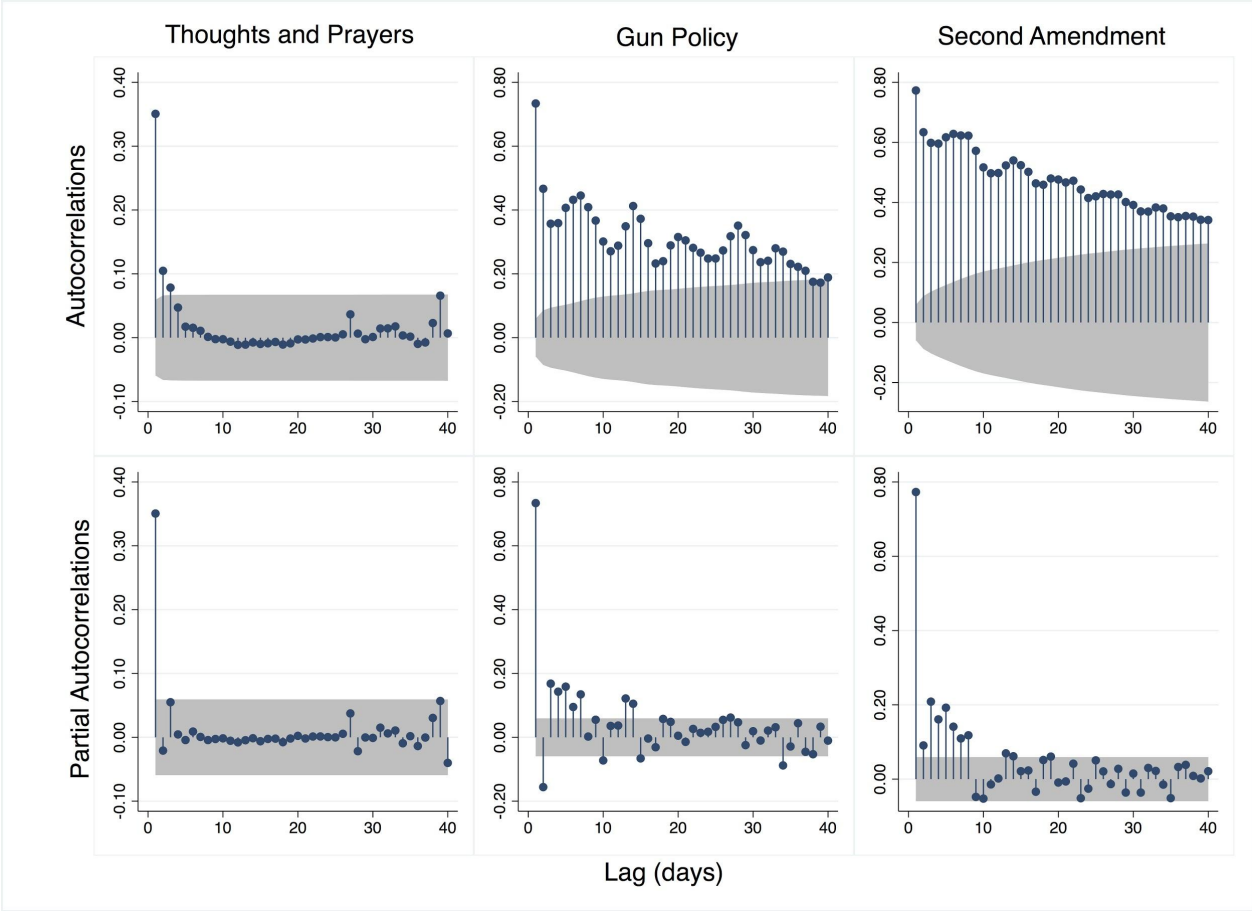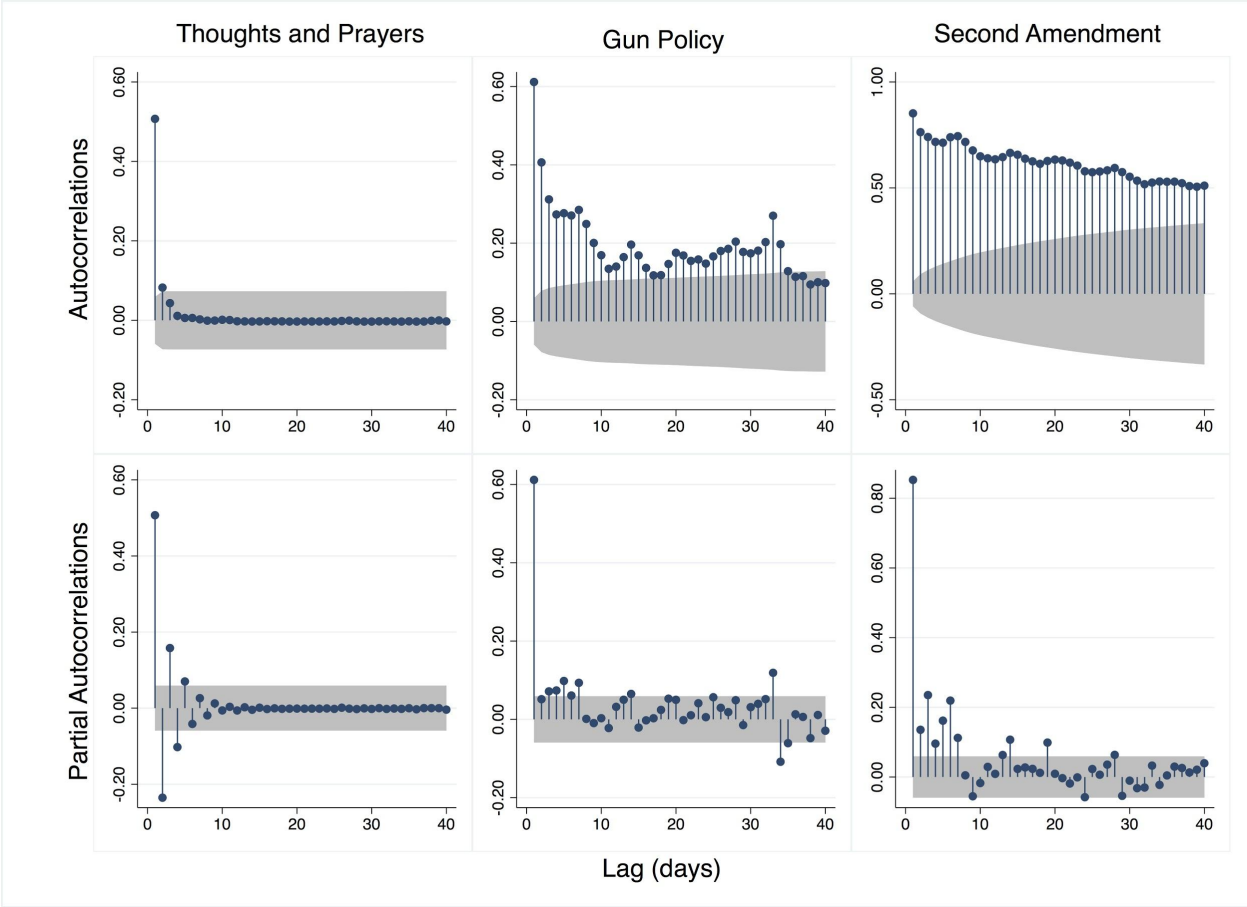
Figure 4. *Auto-Correlation Function (ACF) and Partial Auto-Correlation Function for "Thoughts and Prayers"/ "Gun Policy"/ "Second Amendment" Tweets based on Hashtag approach.*

Table 1. Performance of Machine Learning Classifiers

	Sensitivity (0-1, worst-best)	Precision (0-1, worst-best)	ROC (0-1, worst-best)
	Measures how many tweets were retrieved by the ML classifier out of the total relevant tweets for that category.	Measures how many retrieved tweets were labeled by the ML classifier correctly, where correctness is established by comparing with the human coded label.	Measures sensitivity as well as instances of ML classifier raising a false alarm (labeling an irrelevant tweet as relevant).
Thoughts and prayers	0.51	0.90	0.93
Second amendment	0.40	0.80	0.92
Gun policy	0.45	0.86	0.92

Table 2. Correlation Matrix: Supervised Machine Learning Approach and Hashtag Approach

	Thoughts and Prayers (hashtags)	Second Amendment (hashtags)	Gun Policy (hashtags)
Thoughts and Prayers (tweets)	**0.8699**	0.0982	0.7078
Second Amendment (tweets)	0.0758	**0.7996**	0.5142
Gun Policy (tweets)	0.6955	0.2537	**0.9118**

Table 3. *Time Series Regression Models Predicting Types of Tweets and Hashtags*

	Supervised Machine Learning Technique			Hashtag Technique		
	Thoughts and Prayers	Gun Policy	Second Amendment	Thoughts and Prayers	Gun Policy	Second Amendment
# of victims	.0004*** (.0001)	-.0000136 (.0000243)	.028 (.043)	38.260*** (9.839)	-4.794 (3.847)	.859 (.632)
# of female deaths	.0023** (.0009)	.0010** (.0003)	.141 (.615)	316.103** (114.214)	160.160** (50.595)	-1.780 (6.342)
# of child victims	.0025** (.0010)	.0011** (.0003)	.946 (.483)	379.901** (109.504)	168.153*** (47.823)	8.366 (4.921)
% of African American victims	-.0057** (.0021)	-.0015* (.0007)	-2.035 (1.607)	-750.815** (268.905)	-.272.646* (115.074)	-38.863 (28.924)
Family shooting	-.0121*** (.0022)	-.0049*** (.0009)	-4.623*** (1.446)	-1706.568*** (189.114)	-754.963*** (146.836)	-48.652** (18.387)
Public shooting	-.0025 (.0025)	-.0012* (.0006)	.727 (2.304)	-625.351** (189.114)	-166.176 (95.409)	21.687 (18.971)
Constant	-.0003*** (.0001)	-.00007* (.00003)	.014 (.235)	-30.640*** (7.250)	-10.357 (5.525)	.721 (2.389)
R-squared	.720	.567	.014	.732	.527	.015

Note. Standard errors are in parentheses.
* *p* < .05, ** *p* < .01, ***p < .001

Appendix I:
Exclusion List: words/phrase used to exclude Twitter data noise

bangun, gunna, bingung, guna, video, que, lagunya, camera, film, photo, movie, smoking, smokes, algun, song , gundy, gunzo, begun, topgun, top gun, laguna, flu shot, moscow, canada, rcmp, moncton, indonesia, toronto, vancouver, britain, lancaster, manchester, london, australia, france, paris, french, pakistan, karachi, afghanistan, iraq, baghdad, yemen, syria, isis , egypt, bahrain, qatar, saudi, turkey, turkish, malala, taliban, charliehebdo, charlihebdo, ukrain, kenya, nairobi, sudan, africa , nigeria, borno , bomb, bird , tiger , india , delhi, idf , gaza , israel, palestin, director, tony scott, arsenal, nuclear, germany, berlin, dutch, venezuela, uae, walking dead, talking dead, walkingdead, talkingdead, russian, nemtsov, tulsa, robbery, zombie, walkers, wii , kiev, montolivo, missile, meyiwa, segund, segunod, palestinian, anzhi, copenhagen, charlie, hebdo, music, singer, latore, alguns, chikungunya, screenshot, walker, haram , boko , ninguno, kabul, pregunta, abeokuta, malaysian, dungun, gratata, benghazi, laden, drone, ebola, gunter, shottar, russia, khalifa, soviet, wwii, birth control, horse, kashmir, gundam, xbox, tayo, malaysia, riot, jordan, rubber, lagos, canadian, homie, check twitter, bright, sydney, ankara, beckham, free kick, shot me, istanbul, sex , mug shot, mugshot, police shooting, ferguson, cop shooting, deadass, coffee, stoppoliceviolence, gungtang, already killed me, tamerlan, tsarnaev, rideau, vote rigging, pull my trigger, knife, freeze, chris brown, chrisbrown, mike brown, mikebrown, ontario, shmurda, trayvon, zimmerman, gunpoint, jim crow laws, tamir rice, anggun, gung, take a shot, brazil, brasil, german, jihad, tunisia, tunis, libya, segun, korea, peshawar, milan, gunung, somali, islamist, libyan, melbourne, deadline, pergunta, zedi, feruzi, abuja, jamaica, japan, denmark, mali, benue, singapore, afghan, columbia, switzerland, marseille, tripoli, rio, burundi, ottawa, sweden, china, macedonia, belfast, swiss, swedish, iran, abuja, gunplay, just killed a man, waking up beside you , ambulance i think my friend is dead, his estranged wife and another woman are dead, mexico mayor-elect, shotgun, lol, military, battle, police brutality, nigga, nerf, buckingham palace, deadshot, kansas city chiefs, columbian drug barons, screenshot , screenshooting, ebonyi, nigga, nerf, buckingham palace, deadshot, columbian drug barons, gaza, call of duty, long-shot, longshot, head shot, sharpshooter, monyashooter, goodshooter, shootout, ladiesshooting, troubleshooting, sharpshooter, teamshooter

Appendix II:
Coding rules for tweets

Category	Coding guidelines	Example tweet
Second amendment – Tweets related to Second Amendment language	(1) Rights, Constitution, 2nd Amendment language (2) Use of #2A hashtag (3) Independence, freedom liberty, civil liberties language	"RETWEET if you support the NRA and your Second Amendment right to keep and bear arms! #maga #2A"
Gun policy – Tweets related to support or opposition for gun policy (the user's position is irrelevant)	(1) References to bans, legislation, and policies (2) Both positive and negative reactions to gun policy (3) Ambiguous references to bans and legislation	"Let's pass a gun ban!" "Because GA does not require background checks on private gun sales and audience could include armed criminals? Welcome to being a civilian." "Guns don't kill people, people kill people" "Pro-gun activist"
Thoughts and prayers – Expressions of sadness	All expressions of sadness, grief, or praying. This is often related to one or more specific mass shootings	"prayers for the victims of yet another shooting, this one in wisconsin."

Appendix III: Tweet volume

Year	Full dataset	Sample for Machine Learning	Second Amendment	Gun Policy	Thoughts and Prayers
2012	994,277*	13,923	460	1,990	2,823
2013	4,940,764	77,362	7,105	19,295	3,753
2014	3,395,747	51,476	5,561	8,331	2,161
Total	**9,330,788**	**142,761**	**13,126**	**29,616**	**8,737**

* The low volume of tweets is due differences in the retrieval process from the Twitter archive, but this sample is nonetheless representative of the total volume and overtime change.

Appendix IV:

Three types of hashtags

thoughts and prayers hashtags	gun policy hashtags	second amendment hashtags
pray	backgroundcheck	2a
prayer	backgroundchecks	2nd
prayerfornewtown	fixdvgunlaws	2nda
prayers	gunc	2ndamend
prayersforconnecticut	gunco	2ndamendment
prayersfornewton	guncon	billofrights
prayersfornewtown	guncont	constitution
prayf	guncontrol	donttreadonme
prayfo	guncontrolnow	gunright
prayforaurora	gunlaw	gunrights
prayforcolorado	gunlaws	iamforgunrights
prayforct	gunlawsareajoke	right2defend
prayforfsu	gunreform	rights
prayforne	gunregistry	righttobeararms
prayforneworleans	control	protect2a
prayfornewto	demandaction	secondamendment
prayfornewton	demandaplan	cc
prayfornewtown	momsde	ccw
prayforpilchuck	momsdemand	concealedcarry
prayfortheparents	momsdemandaction	freedom
praying	nowisthetime	liberty
rip	Universal…checks	nogunregistry
	wedemandavote	opencarry
	whatwillittake	selfdefense
		shallnotbeinfringed