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Whose Lives Matter? Mass Shootings and Social Media Discourses of Sympathy and Policy, 2012–2014

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This study focuses on the outpouring of sympathy in response to mass shootings and the contestation over gun policy on Twitter from 2012 to 2014 and relates these discourses to features of mass shooting events. We use two approaches to Twitter text analysis—hashtag grouping and supervised machine learning (ML)—to triangulate an understanding of intensity and duration of "thoughts and prayers," gun control, and gun rights discourses. We conduct parallel time series analyses to predict their temporal patterns in response to features of mass shootings. Our analyses reveal that while the total number of victims and child deaths consistently predicted public grieving and calls for gun control, public shootings consistently predicted the defense of gun rights. Further, the race of victims and perpetrators affected the levels of public mourning and policy debates, with the loss of black lives and the violence inflicted by white shooters generating less sympathy and policy discourses.

Keywords: Attention Dynamics, Automated Text Analysis, Citizen Expression, Hashtag Activism, Online Activism, Machine Learning (ML), Time Series Analysis.

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Social media response to mass shootings in the United States provides an important window into the nature of public mourning and policy debates in the wake of these tragedies. This study focuses on the outpouring of sympathy in response to mass violence and the contestation over gun policy on Twitter, tracing these discourses to features of mass shooting events. This article begins with the assumption that external events can affect social media response, and that social media reflect underlying social dynamics and values. With the digitalization of contemporary life, social media provide a treasure

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trove of digital trace data on individuals and societies, yielding insights into the thoughts, emotions, and behaviors of those who choose online expression (Kosinski, Stillwell, & Graepel, 2013; Lazer & Radford, 2017). Aside from being rich in content and volume, social media also offer a space for "real-time" actions that allow insights into the content, structure, and drivers of human expression, both individual and collective (Shah, Cappella, & Neuman, 2015). By treating social media response as a central object of study and tying it to offline events, we trace the deepening entanglement between everyday life and communication technologies (Couldry & Hepp, 2018).

As such, this work extends research regarding citizen expression on social media. Online public expression research builds upon scholarship about citizen communication in democratic societies, informed by social theorists like Habermas, Tarde and Young. Habermas (1989) describes 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. For Tarde (1969), it is through conversation with others that people form and crystallize their own opinions, encouraging political action. Public discussion is also understood as a political process in a diverse society, where different social perspectives are brought in as "a necessary resource for making (…) decisions" (Young, 1996, p. 399). With the proliferation of social media come ample opportunities for members of a society to communicate with each other about pressing issues. People can express their thoughts, propose policy options, defend cherished values, and organize themselves to pursue collective goals (Freelon, Mcllwain, & Clark, 2016; Mercea & Bastos, 2016). In this regard, online citizen expression reflects personal values and social forces at play around consequential events and controversial issues.

Building on these ideas, we examine the social media response to 59 mass shootings occurring between 2012 and 2014 in the United States, as reflected on Twitter. Specifically, we employ two approaches to Twitter text analysis—hashtag grouping and supervised machine learning (ML)—to triangulate the temporal patterns of intensity and duration of three dominant discursive topics in the wake of mass shootings: expressions of sympathy in the form of "thoughts and prayers," and calls to support gun control or defend gun rights. We then connect variation in these online discourses to specific features of mass shooting events using time series analyses, including characteristics of the victims and the shooter(s), and types of the mass shooting. To understand these patterns, we rely on work concerning: (a) the nature of public mourning and grieving in response to tragedy; (b) public attention dynamics, particularly public response to mass shootings; (c) the social construction of innocent, precarious, and criminal lives; and (d) the modeling of relationships using time series analysis. In doing so, this work contributes to research on computer-mediated communication in three ways: (1) building theory on social media as a dynamic reflection of events and a site of citizen expression; (2) advancing methods for validating computational text analysis in social media research; and (3) providing techniques for guarding against the presence of bots when testing relationships using Twitter data.

Mass shootings, public grieving, and political contestation

Mass shooting events haunt American society. While mass shootings are a worldwide phenomenon, the United States is an exceptional outlier, with over six times as many mass shootings as would be expected based on its population size (Lankford, 2016). Defined by the FBI as events involving four or more deaths, these spasms of gun violence have risen dramatically from 1.1 per year in the 1970s to 4.1 in 2010 (Krouse & Richardson, 2015). Victim counts also continue to rise, driven in part by the increasing frequency of events like Aurora, Sandy Hook, Pulse Night Club, Las Vegas, and Parkland shootings. We approach mass shootings as public tragedies: "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). These tragedies draw a disproportionate amount of public attention, becoming focal events in public consciousness and sites of collective trauma.

Doka (2003) posits that society usually copes with public tragedy by rituals and memorialization: people show solidarity with victims, rebuild communities, and tighten social linkages threatened by a tragic event. Similar to the response to the 9/11 terrorist attacks (Collins, 2004), mass shootings have the potential to function as solidarity-building events, motivating involvement in collective rituals that reconstitute communities following mass violence (Hawdon & Ryan, 2011). Memorializing tragic events often occur, now, in virtual space (Hayes et al., 2017), as evidenced in sympathetic response—expressions of commiseration, condolences, and "thoughts and prayers"—on social media to show support for victims. In this way, social media do not simply transmit information about tragic events; they also participate in the symbolic construction of grievable subjects, and as Butler (2016) writes, even the recognition and constitution of a worthy human life.

Expressions of grief, especially in public settings, may be socially productive as a political tool that spurs public responsiveness (Butler, 2003). As such, collective expressions of "thoughts and prayers" on social media may open up other ways of responding to a tragedy. Mass shootings can become inflection points that create opportunities for social and political change, as increased attention translates into awareness of policy dissatisfaction and intensifies public pressure for change (Baumgartner & Jones, 1993). Therefore, social media are also a potential site of political debate and contestation, where citizens publicly share their viewpoints and agitate for a course of action (Dutta-Bergman, 2006; Freelon et al., 2016).

To examine the use of social media as sites of collective grieving and policy contestation, we focus on three prominent Twitter discourses following mass shootings—expressions of sympathy in the form of "thoughts and prayers," calls for more gun control, and defense of gun rights. These discourses stand out among other forms of social media response such as news updates on the events, discussion of underlying causes, and expression of anger and frustration. "Thoughts and prayers" discourse represents an immediate and ephemeral reaction to tragic events. Although some have come to see this expression as merely perfunctory, public statements of sadness and sympathy might trigger or coexist with other sentiments (Doré, Ort, Braverman, & Ochsner, 2015; Lin & Margolin, 2014). Therefore, we expect expressions of sympathy to be coupled with broader calls for gun control, and these calls may meet counter-arguments in favor of gun rights. Research on attention dynamics and public response to tragedy suggest temporal patterns and event features drive these discourses.

Attention dynamics in response to mass violence

Public attention tends to have a short life span. Issue attention cycle research suggests that an event might trigger an immediate and intense response that quickly fades in public consciousness (Downs, 1972). The public may become fatigued after intensive exposure to an issue (Kinnick, Krugman, & Cameron, 1996). Also, public attention has become "a scarce resource" that is difficult to obtain and sustain in a competitive environment (Wu, 2017). This is evidenced by public opinion toward gun control following mass shooting events. Cook and Goss (2014) show that public support of gun control surged immediately following the Columbine School shooting but evaporated quickly. The Pew Research Center (2012) also finds that mass shooting events do not change overall public opinion about gun control, suggesting that gun control-supportive discourses may be countered by an opposing narrative after mass shootings.

Following a mass shooting, supporters of gun ownership are likely to circulate gun rights discourse by claiming that their beliefs, constitutional protections, and traditional practices are under threat (Sugarmann, 1992). As Melzer (2009, p. 74) asserts "words or phrases such as 'gun control' can become symbolically linked to broader threats, leading to reactionary mobilization that far exceeds the actual threat." This may have its roots in the longstanding existence of a social and symbolic "gun culture" in the United States, centered around firearm ownership for hunting, recreation, and defense (Kalesan, Villarreal, Keyes, & Galea, 2016). Among gun rights supporters, leaders mobilize members by framing calls for gun control as threats to an American way of life, appealing to constituents' anxieties (Lio, Melzer, & Reese, 2008).

Empirical evidence from Twitter also supports the ephemerality of event-driven discourse. Siegel et al. (2018) examine online hate speech from June 2015 to June 2017 and find that events only resulted in short spikes of hateful language. Similarly, Lin, Margolin, and Wen (2017) note that emotional response to a terrorist attack on Twitter was short-lived, returning to normal levels within two weeks. However, it is unclear whether "thoughts and prayers," gun control, and gun rights discourses will follow this ephemeral pattern and how they compare to each other despite potentially short attention cycles. Our first research question addresses this gap by asking how ephemeral "thoughts and prayers," gun control, and gun rights discourses were as observed on Twitter between 2012 and 2014 (**RQ1**).

Precarious lives, mass casualties, and innocent victims

Discourses of sympathy and contestation over policy do not necessarily arise equally for all events involving mass causalities, or for all victims. As Butler (2003) notes, while some forms of mass violence spur limited public grieving, especially for those already living precarious lives such as racial minorities: "certain names of the dead are not utterable, certain losses are not avowed as losses" (p. 26). In contrast, other lives, such as those of children and other valued groups, are deeply mourned, becoming objects of public grieving (McIvor, 2012). Within this framework, certain lives are prioritized and threats to their well-being mobilize action; other lives will not qualify as "grievable" and will trigger little action (Butler, 2016).

Who are the victims that evoke the greatest level of sympathy? How is *victimhood* socially constructed? Christie (1986) defines the 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 are innocent people who are believed to have no skills to defend themselves against crimes (Lindgren & Ristanović, 2011). When crimes occur, news media rely upon a hierarchy of victimhood and their presumed newsworthiness, considering characteristics such as the age, gender, and race of victims (Madriz, 1997). Children are seen as most innocent when confronted with violence (especially relative to adults), drawing particularly sympathetic response. Along these lines, studies have found that young victims are overrepresented in homicide news coverage (Sorenson, Manz, & Berk, 1998).

Accordingly, we hypothesize that expressions of sympathy in the form of "thoughts and prayers" will rise with the number of victims (H1a), especially when children are killed (H1b), as both characteristics signal the innocence of the victims. Large-scale violence suggests the targets did not do anything to bring the tragic fate upon themselves, especially when those victims are minors. These same factors should drive gun control discourse. As the grieving of innocent lives changes into calls for actions, we should see calls for stricter gun control measures to prevent such tragedies from repeating themselves. Accordingly, we hypothesize that a rising number of victims (H2a) and children killed

(H2b) will lead to more intense calls for gun control. However, it is unlikely that Second Amendment advocates will raise their voices when faced with "ideal victims," leading us to omit hypotheses about gun rights discourse.

Race and media constructions of crime

In contrast to the portrayal of innocent victims by media, a long line of research finds that racial minorities are disproportionately associated with criminality as opposed to victimhood. For example, when covering Virginia Tech School shooting, news articles tended to emphasize the perpetrator's racial minority status (Park, Holody, & Zhang, 2012). Romer, Jamieson, and De Coteau (1998) encapsulate such news coverage in the term "ethnic blame": people of color are overrepresented as perpetrators of crime, whereas white people are presented as either victims suffering from it or responders reacting to it.

Victims who were racial minorities are marginalized and considered less "worthy" in news media coverage. African-American victims, in particular, get less attention from news—even though there were more black homicide victims than white homicide victims in the context of specific studies (Dixon, 2017; Dixon, Azocar, & Casas, 2003; Greer, 2017; Sorenson et al., 1998). The prejudicial and deeply problematic view that black victims deserve less attention and sympathy might also be prevalent in public response to tragic events.

The race of perpetrators may also affect public response. As blacks are more likely than whites to be portrayed as lawbreakers on news (Dixon et al., 2003), their association with crimes such as mass shootings is normalized. Also, whites are overrepresented as police officers and thus a force for justice (Dixon et al., 2003; Dixon, 2017). Thus, white perpetrators are perceived as more of an anomaly and less abhorrent (Gilliam, Iyengar, Simon, & Wright, 1996). As Metzl and MacLeish (2015) posit, "historical tensions suffuse discourses linking guns and mental illness in ways that subtly connect 'insane' gun crimes with oft-unspoken assumptions about 'white' individualism or 'black' communal aggression" (p. 241).

As black lives are seen as less grievable than white lives, we hypothesize that black victims will spur less public grieving and fewer expressions of sympathy in the form of "thoughts and prayers," than white victims (H3a). White shooters do not fit the narrative of criminality so often seen in the news, leading us to hypothesize that white shooters will spur less "thoughts and prayers" discourse (H3b), as they do not reinforce the construction of minority criminality. Indeed, discussions of mental illness that emerge after mass shootings are typically linked to white shooters, reflecting larger cultural stereotypes about how violence intersects with race and ethnicity. Along these same lines, we hypothesize that there will be fewer calls for gun control in the wake of shootings that claim a higher number of African-American lives (H4a) or are perpetrated by a white shooter (H4b), and less gun rights discourse when shootings have these characteristics (H5a, more African-American deaths, and H5b, white shooters).

Public versus private violence

Another factor that may affect social media response to a mass shooting event is its publicness. Public shootings, where perpetrators inflict harm on unknown victims, should intensify the perceived innocence of the victims, as opposed to mass shootings that are attributable to conflicts between private citizens (e.g., burglary/robbery) or within families. The distinction between violence in the private sphere of home and the public sphere of work, school, or common spaces is likely to generate different levels of sympathy.

We thus hypothesize that public shootings (H6a) and school shootings (H6b) will lead to a stronger sympathetic response, because both trigger perceptions of innocent victims. These characteristics should also encourage advocates of stricter background checks and restrictions to be more outspoken, driving increases in gun control discourse. Yet, gun rights supporters may use these types of shootings to justify their rhetoric of self-defense (i.e., "the only thing that stops a bad guy with a gun is a good guy with a gun") and policies like concealed carry and arming teachers. Thus, we hypothesize that gun control and gun rights discourses will increase after public shootings (H7a and H8a respectively) and school shootings (H7b and H8b respectively).

Measuring social media content

To analyze social media data, researchers leverage the data's structural components, such as social networks (e.g., Golbeck & Hansen, 2014); behavior components, such as the "likes" a post accrues (e.g., Kosinski et al., 2013); and the semantic features of those posts (e.g., Feldman, 2013). Sentiment analysis, unsupervised ML like topic modeling, and supervised ML using classification algorithms like Support Vector Machine and Naive Bayes are commonly applied to measuring large amounts of social media text. Supervised ML uses a training set, a sample of a larger corpus with labels according to the characteristic under investigation, to generate a mathematical representation for mapping that larger corpus.

Other researchers have relied on language markers, such as hashtags, to measure social media expressions. A hashtag is "a word or phrase marked with # to identify an idea or topic and facilitate a search for it," an affordance 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 use to map political networks (Bode et al., 2015), identify discourse streams (Papacharissi & de Fatima Oliveira, 2012), and study coordination of collective action messages (Freelon et al., 2016). Furthermore, hashtags have been found to be more predictive of political alignment than complete tweets (Conover, Gonçalves, Ratkiewicz, Flammini, & Menczer, 2011).

With previous studies demonstrating the viability of using both ML and hashtags to map discourses, we take both approaches to measuring social media response to mass shootings. By doing so, we can cross-validate the results and boost the validity of automated text analysis (Grimmer & Stewart, 2013). Additionally, we can compare the two methods and derive methodological insights for future work on measurement of social media expression.

Methods

Two sets of data were generated for this study: (a) key features of mass shooting events between January 1, 2012 and December 31, 2014; and (b) time series of different Twitter discourses concerning mass shootings during this same period.

Event data

This study defines "mass shooting" 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*). After compiling event data for all applicable events while excluding those outside of our timeframe, 59 mass shootings were identified. Three trained coders achieved intercoder reliability using a random subset of one-third of shooting events prior to coding all 59 events. Each mass shooting was coded using online news sources, referenced police reports, and judicial proceedings to capture six discrete event features for each incident.

First, shooting victims were split into three variables: (a) total number of victims, which includes injuries; (b) total number of children killed under the age of 18; and (c) total number of African-Americans killed. The race of the shooter was initially coded using six categories but was collapsed for this analysis into a binary white/non-white dummy variable (Krippendorf's alpha = .85) with 24 white shooters (40.6%), 24 non-white shooters (40.6%), and 11 unknowns (18.8%). The race of the victims was coded similarly but was operationalized as the total number of African Americans killed (Krippendorf's alpha = .86) during each event. Of the 400 total victims across the 59 events, 62 African-American (15.5%) lives were lost. Public shootings (Krippendorf's alpha = .72) were coded as a binary indicator indicating that the majority of victims had little to no personal connection to the assailant. While shooting type correlates highly with the physical location of shootings, this variable focuses on the relationship between shooter and victim. The only geographic indicator in our analyses is a dummy variable indicating whether the shooting occurred at a school. See descriptions of the event data in Appendix I.

Social media data

We retrieved social media data on mass shootings and firearms between 2012 and 2014 from an archive that contains a random 10% of Twitter stream, collected through Twitter REST API. After applying search strings ("gun," "shooter," "shooting," "firearm," "second amendment," "2nd amendment", and "nra") and removing irrelevant tweets through exclusion words, 13,156,564 tweets were retained (see Appendix II for details).

Supervised machine learning

We first used supervised ML to classify tweets into the three discourse categories. Since the 13 million filtered tweets still contained a significant amount of noise, we went through two steps of the ML procedure. First, we built a relevance classifier to determine whether a tweet is related to mass shootings; next, we built three discourse classifiers, each of which was used to classify a tweet as indicating "thoughts and prayers," gun policy, or gun rights.

To build the relevance classifier, we first constructed a human-coded set of tweets. Five trained coders labeled the same 200 tweets (Krippendorf's alpha = .80), randomly drawn from the 13 million tweets. We defined relevant tweets as those about domestic/U.S. shootings (so long as it is not about terrorist attack), general gun-related violence, gun rights, gun policy, and the National Rifle Association (Appendix III). After achieving sufficient inter-coder agreement, the five coders labeled another 3500 randomly selected tweets as either relevant or irrelevant, which were used to train and test the relevance classifier. The steps include: (a) using Glove Word Embedding to convert each word to a numerical vector; (b) building a tweet vector matrix in which each tweet was converted to a numerical vector; and (c) applying Logistic Regression in the Python scikit-learn package to train a classifier with 10-fold cross-validation to test the performance. Two common metrics are used to assess the performance of a ML classifier: precision and recall; these are often combined in a summative statistic called the "F1 score" (Gilbert, 2014). The precision, recall and F1 score of this relevance classifier are .89, .88 and .88 respectively. After achieving good performance of the relevance classifier and using it to classify the 13 million tweets, we retained 1,620,872 (12.32%) relevant tweets.

We applied the same process to constructing the three discourse classifiers. Each tweet was coded for its "topic," which fell exclusively into one of three categories: "thoughts and prayers," gun control, or gun rights. Tweets expressing condolences and sadness toward a mass shooting were categorized as "thoughts and prayers." Tweets were treated as gun control if they called for stricter gun legislation or restricted access to guns, including news and opinions on particular gun control policy. Tweets defending Second Amendment rights, the U.S. Constitution, freedom, and liberty in the context of firearms were labeled gun rights (Appendix IV). The same five coders achieved intercoder reliability on a random sample of 200 relevant tweets (Krippendorf's alpha = .74) and labeled 4000 tweets for the three topics. For the "thoughts and prayers" discourse classifier, precision, recall and F1 scores were .89, .87 and .88 respectively; for the gun control discourse classifier, they were .60, .31 and .41; for the gun rights discourse classifier, they reached .69, .52 and .59.[1] We classified 146,337 "thoughts and prayers" tweets, 172,837 gun control tweets, and 94,612 gun rights tweets.

Hashtag-based approach

We also applied a hashtag-based approach to measuring the three discourses. The rationale behind this approach is that particular hashtags represent the substantive content of the tweets where they are embedded. Each hashtag within each tweet was extracted and labeled for the date of the tweet. We then identified the top 115 relevant hashtags, which appeared at least 200 times within the three-year span in our data.[2] Next we selected hashtags indicative of "thoughts and prayers" discourse (e.g., "#pray" and "#prayfornewtown"), gun control discourse (e.g., "#backgroundcheck" and "#demandaction"), and gun rights discourse (e.g., "#2ndamendment" and "#selfdefense"; see Appendix V for the complete lists of hashtags). We aggregated the daily counts of hashtags in the same discourse to construct the three variables, making it comparable to the ML strategy. In total, we had 54,410 "thoughts and prayers" hashtags, 258,595 gun control hashtags, and 346,517 gun rights hashtags.

Although the tweet counts generated by the ML approach and the hashtag counts produced by the hashtag-based approach differ, the correlations between the time series of daily tweets and daily hashtags within each discourse are high ("thoughts and prayers": .94; gun control: .86; gun rights: .89), whereas the correlations between variables from different discourses are lower (Appendix VI). Through additional analyses, we further ascertained that the high correlations were not a result of the ML classifiers using hashtags to infer the tweet content (Appendix VII). The high consistency of the outcome variables measured by two different techniques speaks to the robustness of our methods.

Time series modeling

Time series analysis has a long, if underutilized, history in communication research (Barnett, Chang, Fink, & Richards, 1991; Davis & Lee, 1980; Watt & Van Den Berg, 1978). Our time series modeling approach builds on this work and extends past research that uses this technique to explore social media response to social movements (Bastos, Mercea, & Charpentier, 2015; Chan & Fu, 2017) and presidential debates (Shah et al., 2016). Our analysis uses data aggregated at the daily level. As shown in the time series plots in Figure 1, the three dependent variables—"thoughts and prayers," gun control, and gun rights discourses—measured by both tweets and hashtags, fluctuated greatly in the three-year time span. As indicated by the vertical dotted lines, major spikes in the time series coincided with high-profile mass shooting events.

To account for the highly autoregressive nature of social media data, we fit several Autoregressive Integrated Moving Average (ARIMA) models to our data. In ARIMA (p, d, q) models, the letters p, d, and q refer to the autoregressive (AR) order, the degree of differencing (integration, I), and the moving-average (MA) order, respectively. ARIMA models apply some combination of these three filters to time series data until the observations resemble a "white noise" time series, removing the

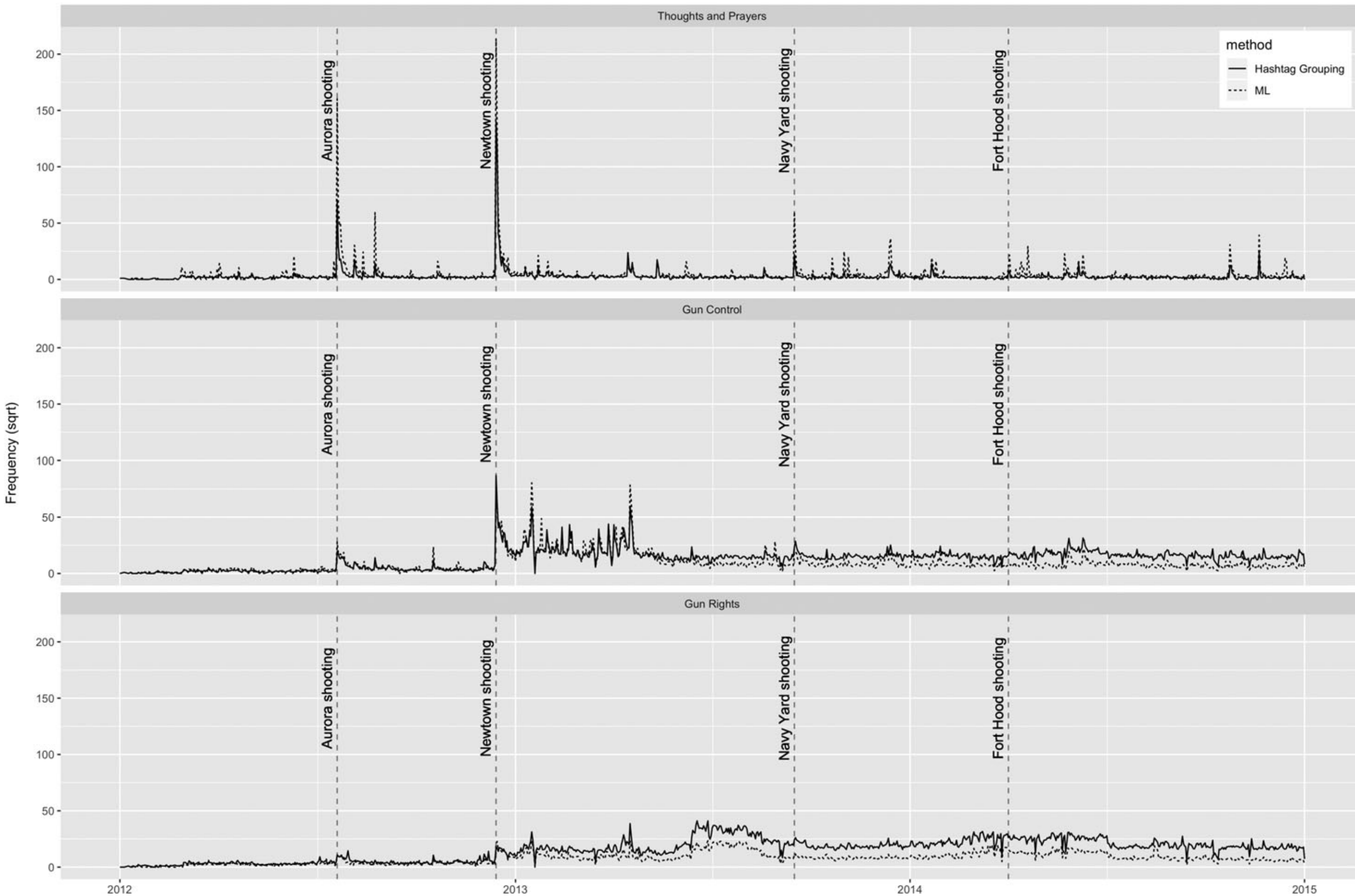

Figure 1 Daily counts of tweets and hashtags over time.

variation within the series that is simply explaining itself through autoregressive, integrated, 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 to diagnose 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). Interestingly, the two series measuring *gun rights* (both the hashtag-grouping and ML approaches) show evidence of non-stationarity, as determined by Dickey Fuller and KPSS tests. Substantively, non-stationarity implies that shocks to the data-generating process create permanent shifts in the series. Statistically, this requires first-differencing the two non-stationary series.

Second, we generated autocorrelation and partial autocorrelation graphs to assess whether the underlying process contained autoregressive or moving average processes. Figures 2 (ACF) and 3 (PACF) indicate an autoregressive process. Nearly every series also contained notable amounts of seasonality—cyclical patterns suggestive that a spike in the value of the series returns 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 subsequent analyses.[3]

For the purposes of our regression analyses, we took the residuals from the ARIMA modeling process, treating them as six "pre-whitened" time series. This does not mean that the ARIMA models themselves were not informative but analyzing the residuals in relation to other data (e.g., event data) can yield other important information. Indeed, before turning to our multivariate analyses, we discuss our diagnostic ARIMA results on our six time series.

Results

Temporal dynamics of the three discourses

RQ1 asks how ephemeral "thoughts and prayers," gun control, and gun rights discourses were. In Figures 2 and 3, X-axis represents the lagged number of days from a starting day and y-axis the correlation (φ) between the starting and the lagged days. The three categories display distinct patterns of auto-correlation. For "thoughts and prayers" tweets, φ_1= .33 and φ_2= .08, whereas φ_3 is not statistically significant at the 95% level. This points to the ephemeral nature of "thoughts and prayers" discourse: one day's observation is modestly correlated with the previous two days, but no more. This is different from the gun control tweets, where φ_1= .67 and day one is still, although weakly, correlated up to 37 days away, φ_{37}= .17. This suggests that gun control discourse is much more sustained than "thoughts and prayers" discourse.

However, this tenacity is eclipsed by gun rights discourse, whose pattern stands in stark contrast to "thoughts and prayers." A particular day's observation in the gun rights tweets is nearly correlated at .90 (φ_1= .88) with its previous day, and the observation 38 days ago can still positively predict the observation on that day. The pattern is clear: gun rights tweets stay in the system and do not disappear quickly—an idea reinforced by our finding that the series is non-stationary. This means that a large increase in tweets defending Second Amendment rights on one day will only shrink by a very small amount the next day and the impact lasts for 38 days. By contrast, an outpouring of "thoughts and prayers" tweets mostly disappears after only two days. Gun control and gun rights discourses tend to be more "self-sustaining," though the former less so than the latter, answering our first research question.

Moreover, gun control and gun rights tweets seem to follow a weekly pattern. This regularity may be driven by the general weekly tweeting pattern, where more tweets are posted on weekdays than on

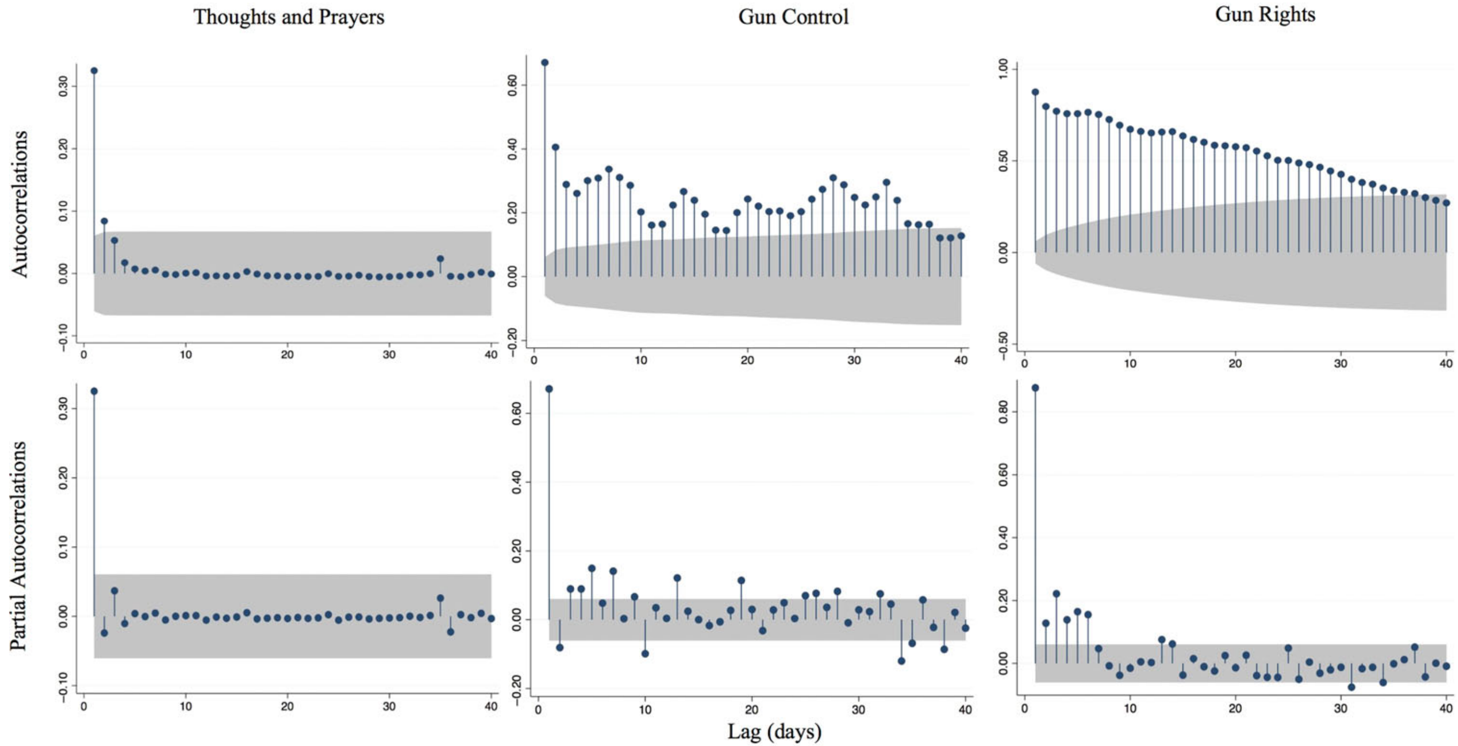

Figure 2 Auto-correlation function (ACF) and partial auto-correlation function for "thoughts and prayers"/gun control/gun rights tweets based on machine learning classifiers.

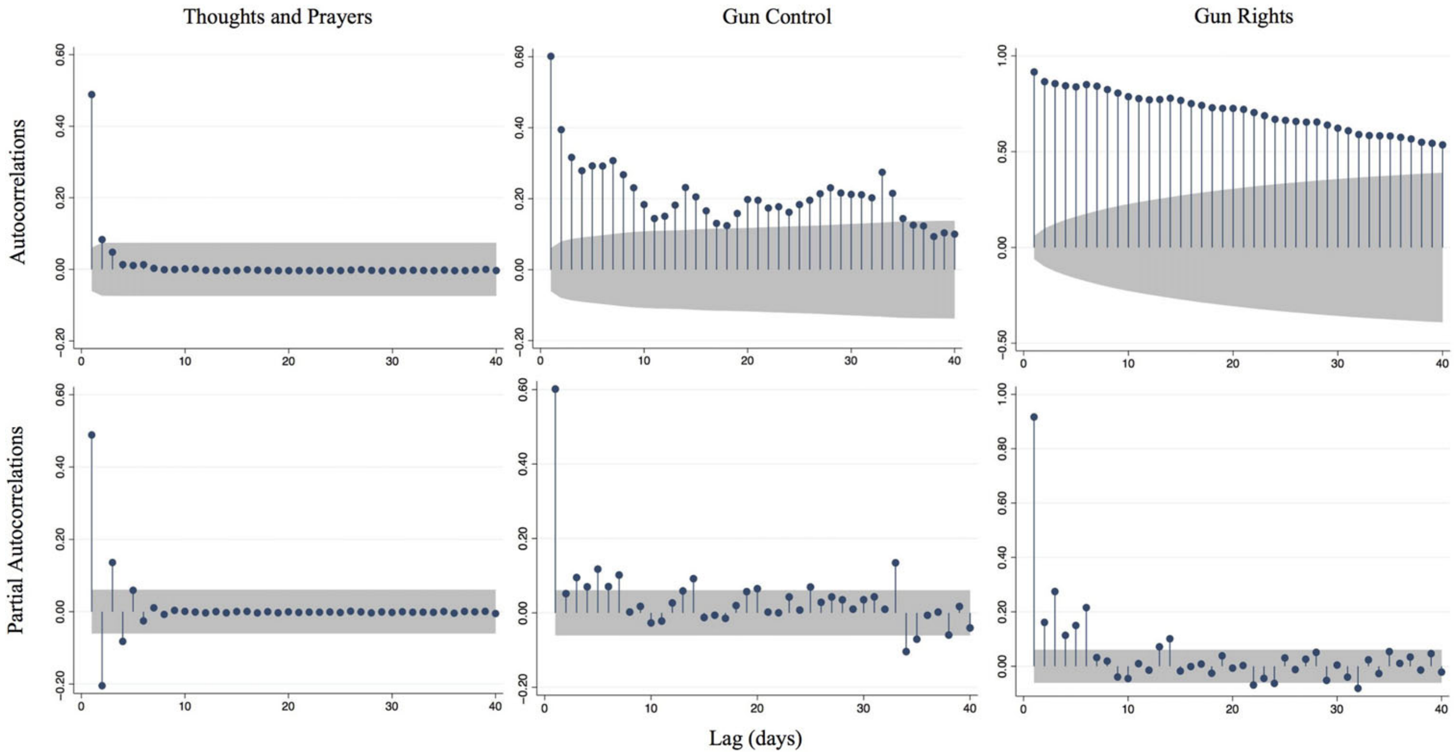

Figure 3 Auto-correlation function (ACF) and partial auto-correlation function for “thoughts and prayers”/gun control/gun rights hashtags based on hashtag grouping.

weekends, or by "anniversary effects" marking the weekly and monthly occurrence of the events. Interestingly, the same is not true for "thoughts and prayers." Thus, policy debates triggered by tragedies appear to have a cyclical pattern, but sympathies do not.

These same patterns for the three categories of tweets repeat themselves in the same groups of hashtags. "Thoughts and prayers" hashtags are short-lived, with φ_1= .49 and φ_2= .08 and φ_3 dropping to a statistically non-significant value, meaning observations are correlated at most two days apart. Gun control hashtags are again more durable, with observations correlated at most 35 days apart. Gun rights hashtags sustain without signs of abating for at least the first 40 lags, and correlation between observations one day apart exceed .90. The same seven-day cycle can also be observed in the gun control and gun rights hashtags.

Event features and Twitter discourses

Using the pre-whitened time series of social media activity, we estimated regression models using mass shooting event features (see Appendix VIII for the correlation matrix of all independent variables). Given how immediate social media response can be to external events, we specified contemporaneous effects. We performed time series regressions for "thoughts and prayers," gun control and gun rights discourses, as measured by both approaches.

H1 hypothesizes that "thoughts and prayers" discourse will rise with: (a) the total number of victims; and (b) the number of children killed. Our results, seen in Table 1, reveal that the total number of victims and the number of children killed were positively associated with "thoughts and prayers" discourse, measured by both tweets and hashtags. That is, mass shootings events involving both more total victims and more children killed generated more expressions of sympathy, supporting H1a and H1b. We further hypothesize that these two factors will intensify gun control discourse. However, the total number of victims only positively drove gun control tweets, but not gun control hashtags, partially supporting H2a. The number of children killed was positively associated with the volume of gun control discourse, measured by both tweets and hashtags, which supports H2b. These factors had little relation to gun rights discourse.

We hypothesize that mass shooting events with a greater number of African Americans killed will generate fewer "thoughts and prayers" tweets (H3a), as will white shooters (H3b). Our results support H3a and H3b. While the seeming innocence of victims consistently drove "thoughts and prayers" discourse, the number of African-American deaths and the shooter's race were negatively associated with it, indicating that mass shootings with a high number of African-American deaths or a white perpetrator generated less sympathetic response on Twitter. The pattern was consistent across tweets and hashtags. We also hypothesize a decrease in intensity of gun control and gun rights discourses with events involving more deaths of African Americans (H4a and H5a, respectively) and a white perpetrator (H4b and H5b, respectively). As illustrated in Table 1, both the ML and hashtag-based approaches reveal that events involving a higher number of African-American deaths or perpetrated by whites were related to fewer calls to actions and defense of gun rights, supporting H4a, H4b, H5a and H5b.

For the relationship between event settings and social media response, we predict that: (a) public shootings; and (b) school shootings will spur a higher volume of all three discourses: "thoughts and prayers" (H6), gun control (H7), and gun rights (H8). Our results show that public shootings predicted a higher amount of "thoughts and prayers" hashtags, but not tweets. School shootings were not significantly associated with "thoughts and prayers" discourse, either in the form of tweets or hashtags, which may be due to the powerful predictive power of the children killed measure. Therefore, H6a is partially supported while H6b rejected. A similar pattern holds for gun control discourse, with public shootings (but not school shootings) positively related to gun control hashtags only, partially supporting H7a and rejecting H7b. However, the results are different for gun rights discourse. Public

Table 1 Time Series Regression Models Predicting the Volume of Tweets and Hashtags

	Supervised machine learning approach (tweets)			Hashtag-based approach (hashtags)		
	Thoughts and prayers	Gun control	Gun rights	Thoughts and prayers	Gun control	Gun rights
Number of victims	344.144***	8.252*	1.133	63.960***	.683	.631
	(13.346)	(4.155)	(.784)	(6.888)	(3.391)	(1.992)
Number of children killed	1096.920***	130.812***	13.909***	459.557***	201.244***	9.954
	(45.392)	(14.133)	(2.664)	(23.428)	(11.535)	(6.768)
Number of African Americans killed	−789.124***	−47.241*	−7.404*	−238.900***	−71.680***	−19.574*
	(58.499)	(18.195)	(3.447)	(30.182)	(14.851)	(8.759)
Shooter race (1 = white)	−2983.470***	−220.784**	−32.121*	−929.467***	−309.236***	−67.698*
	(221.087)	(68.783)	(13.016)	(114.077)	(56.140)	(33.070)
Public shooting	364.543	60.867	34.344*	350.329*	250.083**	112.011**
	(287.541)	(89.563)	(16.846)	(148.427)	(73.097)	(42.805)
School shooting	−190.933	132.145	−5.894	103.716	133.985	−47.747
	(523.793)	(163.080)	(30.739)	(270.339)	(133.099)	(78.108)
Constant	17.952	150.360***	−.932	14.927	224.762***	.405
	(45.269)	(31.569)	(1.312)	(27.265)	(23.560)	(3.334)
Adjusted R^2	.695	.132	.048	.462	.324	.008

Notes: Standard errors are in parentheses.
$^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$ (two-tailed).

shootings predicted a higher volume of gun rights discourse with a consistent pattern for both tweets and hashtags, lending strong support to H8a. School shootings were not associated with the volume of gun rights discourse by either measure, leading to the rejection of H8b (See Appendix IX for additional models using data imputation and forecasting).

Supplemental bot analysis

One concern regarding political expression and activism on Twitter, especially hashtag activism, centers on the role of bots, and whether they are responsible for observed patterns. Bots are automated accounts controlled by computer algorithms or programs, which mimic and interact with real users (Ferrara, Varol, Davis, Menczer, & Flammini, 2016). There is a track record of bots attempting to manipulate political communication processes and outcomes (e.g., Howard & Kollanyi, 2016; Metaxas & Mustafaraj, 2012; Ratkiewicz et al., 2011). Mass shooting discourse, especially that focused on the policy debate, may be subject to such manipulation. In this section, we examine the presence of bots and see whether they provide an alternative explanation for our findings.

Bot detection has been challenging. Metadata such as account name and creation date, friendship network, linguistic cues and temporal activity are the major features for bot detection. A public facing and free service, Botometer (formerly BotOrNot) relies on those features (Davis, Varol, Ferrara, Flammini, & Menczer, 2016), which we use to examine the presence of bots.

To do so, we randomly sampled 10% of the tweets classified into each of the three discourse categories based on the ML and hashtag-based approaches. We then identified that unique user IDs for each tweet. For the hashtag datasets, we obtained 5,036 IDs from "thoughts and prayers" tweets, 13,227 from gun control tweets, and 7,382 from gun rights tweets. For the ML data sets, those numbers are 14,557, 14,748, and 3,705 respectively. Then we ran those IDs through Botometer. Botometer returns two kinds of results: bot probabilities (numeric scores) and reports (either "not authorized" for blocked accounts or "pages doesn't exist" for deactivated accounts). Probabilities are calculated in many ways; we chose "cap_universal," which uses a comprehensive set of network, content, and interaction factors to estimate the likelihood that an account is a bot. We treated those with a bot probability higher than .25 as "bot likely" users and otherwise "bot unlikely" users (Appendix X). For all discourse categories and in both datasets, the proportions of bot likely users are uniformly low, all under 10% of sample total users. Gun control tweets classified by the ML approach has the highest proportion of bot likely users (9%). Moreover, the proportion of tweets in each discourse traced to bot likely accounts range from a high of 14% in gun rights tweets to a low of 5% in "thoughts and prayers" tweets, both classified by the ML approach (Appendix XI). These results point to the relatively small proportion of bots in our data.

To further investigate whether we need to remove bots from our analysis, we compared the time series of sample tweets produced by bot unlikely users (excluding bot likely, not authorized, and nonexistent accounts) with the time series used in our modeling. The correlations within the same discourse are high, ranging from .89 to .99 (Appendix XII). As the time series produced by tweets from "genuine Twitter users" is highly correlated with the time series used in our analysis, we are confident the observed results cannot be attributed to bots.

Discussion

Traditional mass media have long been a gatekeeper reflecting and reproducing the extant social order and their attendant norms (Gans, 1979; Shoemaker & Vos, 1996). This article shows that social media now offer a collective social space for public mourning and contestation, and a window into what triggers these responses. The temporal dynamics and selectivity of social media response provide evidence, beyond polarization, incivility and manipulation (e.g., Conover et al., 2011; Dahlberg, 2001), for the limits of social media serving as a public sphere.

While the outpouring of sympathy, as evidenced by "thoughts and prayers" tweets and hashtags on Twitter, shows how society comes together to grieve and to react to tragedies emotionally, sympathetic expression on Twitter was both intense and fleeting, dissipating quickly after mass shootings. This might be attributed to the unpleasant nature of tragedies or the short attention span of citizens in a crowded information environment (Kinnick et al., 1996).

In contrast, the discourses over policy, emerging out of calls to restrict or further regulate the possession, sale, and purchase of firearms and out of concerns about infringements on the right to bear arms, resist the notion of public attention deficit. In particular, Second Amendment proponents sustain their perspective, maintaining a strong and persistent discourse of opposition to any change in gun laws. It is notable that these advocates "bit their tongues" when mass casualties or child victims were involved but rode on the "wave" of public shootings to argue for self-defense provided by firearms. In this light, in addition to a site of grieving, social media was also a field of policy contestation, where arguments and counter-arguments coexisted. And gun rights discourse was more sustained than the gun control discourse it opposed.

This observation might add to our understanding of why there is so little legislative success with gun control policies. Admittedly, organized interest groups have played a heavy role—gun rights groups such as the National Rifle Association and Second Amendment Foundation have been lobbying legislators to preserve the status quo, which stands in sharp contrast to the weaker organizational power of gun control groups such as Moms Demand Action for Gun Sense and the Brady Campaign. Our study adds subtle nuances. As gun rights discourse on social media persisted more than gun control discourse, and sympathy discourse had an ephemeral life, the signal sent to both journalists and politicians may be that the passion of gun rights supporters merits more attention and action than short-lived appeals for gun control.

More importantly, our study also demonstrates the selectivity in social response to mass shootings, confirming a disturbing dynamic that not all lives are equally cherished. The killing of innocent children received significantly more expressions of sympathy and generated more calls for gun control, while the loss of African-American lives systematically received fewer expressions. 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. These observations speak directly to the discussion of precarity. Certain mass shooting events are clearly sites for digital mourning and grieving, but the fact that this solidarity is stratified between social groups suggests that some lives are seen as more worthy than others, that some lives matter more. In this case, the prospects for the equal construction of grievable life (Butler, 2003) on social media platforms appear limited at best.

Moreover, the finding that shootings committed by non-white attackers and public shootings generated more calls for gun ownership and access suggests a darker undercurrent to the rhetoric of gun rights, tinged by a combination of race and fear. White shooters also generated fewer expressions of sympathy or calls for gun control, again suggesting a racial element to social media discourse about mass shootings and firearms, and further calling into question the value of social media as a public sphere for discussing controversial issues.

Methodologically, we have attempted to explore the aforementioned phenomena using two different approaches, namely a supervised ML approach and a hashtag-based approach. The two methods produce highly consistent results, with some small differences likely caused by the ML approach's sensitivity to the subtlety of language and the hashtag approach picking up more content, including "hashjacking" of key hashtags by contrasting groups with the hope of invading the discourse stream of opponents. The high agreement between the results from the two methods are significant because: (a) it cross-validates our results and increases internal validity, a concept emphasized by computational text analysis scholars; and (b) it provides a comparison between the two methods, adding to the existing literature on computational methodologies dealing with the classification of social media text. It should be noted that using ML to classify tweets is a much more time-consuming and effortful process than extracting and aggregating hashtags. The ML classification problem is made even more difficult by the short length of tweets. The high level of agreement between the tweets and hashtags seems to suggest that a hashtag-based approach might be a computationally efficient alternative to the ML approach, especially in cases where tweets have clearly-defined hashtags. But this needs to be explored in other contexts.

Additionally, our analysis takes steps to guard against the presence of bots as a factor driving our findings. As bots have become an increasing concern for social media research, researchers must develop their own bot detection approaches or harness existing techniques. Although our conclusions remain the same after accounting for bots, it does not mean that bots do not pose a threat to the validity of similar research in other contexts.

We see our study as the first installment toward a research program on mass shootings, media, and social outcomes. Our examination of the temporal dynamics of social media discourses around mass shootings and event features that shape them ignores the role of local, partisan and mainstream news media in this process. Future studies must examine the association between news coverage and social media response; consider the role of elite accounts such as advocacy organizations, politicians, candidates, and journalists in shaping citizens' reactions; and investigate how both social media response and traditional media coverage relate to market outcomes like gun sales and stock values. This is less a limitation of the current study than directions of research spurred by this effort to examine social media responses to mass shootings.

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Appendix I—XII

Additional supporting information may be found in the online appendices at https://dshah.journalism.wisc.edu/files/JCMC19-MassShootings.pdf

Footnotes

1 Although the gun control classifier performed less well, we note the difficulty in identifying tweets with expressions of support for more stringent gun control policies, even for human coders, because this idea was expressed in variant forms in our data. However, even with the comparatively weaker performance, the machine learning classification yielded results consistent with the hashtag-based approach.

2 Since our data is a 10% sample of Twitter stream, selected hashtags appeared more than 2000 times in the global tweet stream. The distribution of the frequency of hashtags is highly skewed, with the most frequent hashtags like "#2a" and "#guncontrol" appearing 196,310 and 108,159 times in our sample. Although 200 was an arbitrary threshold, we observed that hashtags appearing few than 200 times became much less relevant.

3 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. Since the coefficient estimate of that dummy variable was not statistically significant (suggesting no underlying differences in the data across the three years), it was removed from the ARIMA model before residuals were generated.

References

Barnett, G. A., Chang, H. S., Fink, E. L., & Richards, Jr, W. D. (1991). Seasonality in television viewing: A mathematical model of cultural processes. *Communication Research*, 18, 755–772. doi:10.1177/009365091018006003

Bastos, M. T., Mercea, D., & Charpentier, A. (2015). Tents, tweets, and events: The interplay between ongoing protests and social media. *Journal of Communication*, 65(2), 320–350. doi:10.1111/jcom.12145

Baumgartner, F. R., & Jones, B. D. (1993). *Agendas and instability in American politics*. Chicago, IL: University of Chicago Press.

Bode, L., Hanna, A., Yang, J., & Shah, D. V. (2015). Candidate networks, citizen clusters, and political expression: Strategic hashtag use in the 2010 midterms. *The Annals of the American Academy of Political and Social Science*, 659(1), 149–165. doi:10.1177/0002716214563923

Butler, J. (2003). Violence, mourning, politics. *Studies in Gender and Sexuality*, 4, 9–37. doi:10.1080/15240650409349213

Butler, J. (2016). *Frames of war: When is life grievable?* London, England and New York: Verso.

Chan, C. H., & Fu, K. W. (2017). The relationship between cyberbalkanization and opinion polarization: Time-series analysis on Facebook pages and opinion polls during the Hong Kong Occupy Movement and the associated debate on political reform. *Journal of Computer-Mediated Communication*, 22(5), 266–283. doi:10.1111/jcc4.12192

Christie, N. (1986). The ideal victim. In E. A. Fattah (Ed.), *From crime policy to victim policy* (pp. 17–30). London, England: Macmillan.

Collins, R. (2004). Rituals of solidarity and security in the wake of terrorist attack. *Sociological Theory*, 22(1), 53–87. doi:10.1111/j.1467-9558.2004.00204.x

Conover, M. D., Gonçalves, B., Ratkiewicz, J., Flammini, A., & Menczer, F. (2011, October). Predicting the political alignment of twitter users. In *2011 IEEE Third International Conference on Social Computing* (pp. 192–199). doi:10.1109/PASSAT/SocialCom.2011.34

Conover, M. D., Ratkiewicz, J., Francisco, M., Gonçalves, B., Menczer, F., & Flammini, A. (2011, July). Political polarization on twitter. In *Fifth international AAAI conference on weblogs and social media*.

Cook, P. J., & Goss, K. A. (2014). *The gun debate: What everyone needs to know*. New York: Oxford University Press.

Couldry, N., & Hepp, A. (2018). *The mediated construction of reality*. New York: John Wiley & Sons.

Dahlberg, L. (2001). Computer-mediated communication and the public sphere: A critical analysis. *Journal of Computer-mediated communication*, 7(1), JCMC714. doi:10.1111/j.1083-6101.2001.tb00137.x

Davis, D. K., & Lee, J. (1980). Time series analysis models for communication research. In P. R. Monge & J. N. Cappella (Eds.), *Multivariate techniques in human communication research* (pp. 429–454). New York: Academic.

Davis, C. A., Varol, O., Ferrara, E., Flammini, A., & Menczer, F. (2016, April). Botornot: A system to evaluate social bots. In *Proceedings of the 25th International Conference Companion on World Wide Web* (pp. 273–274). International World Wide Web Conferences Steering Committee. doi:10.1145/2872518.2889302

Dixon, T. L. (2017). Good guys are still always in white? Positive change and continued misrepresentation of race and crime on local television news. *Communication Research*, 44(6), 775–792. doi:10.1177/0093650215579223

Dixon, T. L., Azocar, C. L., & Casas, M. (2003). The portrayal of race and crime on television network news. *Journal of Broadcasting & Electronic Media*, 47(4), 498–523. doi:10.1207/s15506878jobem4704_2

Doka, K. (2003). Memorialization, ritual, and public tragedy. In M. Lattanzi-Light & K. Doka (Eds.), *Living with grief: Coping with public tragedy* (pp. 179–189). New York: Routledge.

Doré, B., Ort, L., Braverman, O., & Ochsner, K. N. (2015). Sadness shifts to anxiety over time and distance from the national tragedy in Newtown, Connecticut. *Psychological Science*, 26(4), 363–373. doi:10.1177/0956797614562218

Downs, A. (1972). Up and down with ecology: The issue-attention cycle. In D. Protess & J. McCombs (Eds.), *Agenda Setting: Readings on media, public opinion, and policymaking* (pp. 27–34). New York: Routledge.

Dutta-Bergman, M. J. (2006). Community participation and Internet use after September 11: Complementarity in channel consumption. *Journal of Computer-Mediated Communication*, 11(2), 469–484. doi:10.1111/j.1083-6101.2006.00022.x

Feldman, R. (2013). Techniques and applications for sentiment analysis. *Communications of the ACM*, 56(4), 82–89. doi:10.1145/2436256.2436274

Ferrara, E., Varol, O., Davis, C., Menczer, F., & Flammini, A. (2016). The rise of social bots. *Communications of the ACM*, 59(7), 96–104. doi:10.1145/2818717

Freelon, D., Mcllwain, C., & Clark, M. (2016). Beyond the hashtags: #Ferguson, #blacklives-matter, and the online struggle for offline justice. *American University Center for Media & Social Impact*.

Gans, H. J. (1979). *Deciding what's news*. New York: Pantheon Books.

Gilbert, C. H. E. (2014). Vader: A parsimonious rule-based model for sentiment analysis of social media text. In *Eighth International Conference on Weblogs and Social Media (ICWSM-14).*

Gilliam, F., Iyengar, S., Simon, A., & Wright, O. (1996). Crime in black and white: The violent, scary world of local news. *Harvard International Journal of Press/Politics*, 1, 6–23. doi:10.1177/1081180x96001003003

Golbeck, J., & Hansen, D. (2014). A method for computing political preference among Twitter followers. *Social Networks*, 36, 177–184. doi:10.1016/j.socnet.2013.07.004

Greer, C. (2017). News media, victims and crime. In P. Davies, C. Francis, & C. Greer (Eds.), *Victims, crime, and society* (2nd ed., pp. 48–65). London, England: Sage.

Grimmer, J., & Stewart, B. M. (2013). Text as data: The promise and pitfalls of automatic content analysis methods for political texts. *Political analysis*, 21(3), 267–297. doi:10.1093/pan/mps028

Habermas, J. (1989). *The structural transformation of the public sphere: An inquiry into a category of bourgeois society*. Cambridge, MA: MIT press.

Hawdon, J., & Ryan, J. (2011). Social relations that generate and sustain solidarity after a mass tragedy. *Social Forces*, 89(4), 1363–1384. doi:10.1093/sf/89.4.1363

Hayes, R., Waddell, J., & Smudde, P. (2017). Our thoughts and prayers are with the victims: Explicating the public tragedy as a public relations challenge. *Public Relations Inquiry*, 6(3), 253–274. doi:10.1177/2046147x16682987

Howard, P. N., & Kollanyi, B. (2016). Bots, #StrongerIn, and #Brexit: Computational Propaganda during the UK–EU Referendum. doi:10.2139/ssrn.2798311

Kalesan, B., Villarreal, M. D., Keyes, K. M., & Galea, S. (2016). Gun ownership and social gun culture. *Injury Prevention*, 22(3), 216–220. doi:10.1136/injuryprev-2015-041586

Kinnick, K., Krugman, D. M., & Cameron, G. T. (1996). Compassion fatigue: Communication and burnout toward social problems. *Journalism & Mass Communication Quarterly*, 73(3), 687–707. doi:10.1177/107769909607300314

Kosinski, M., Stillwell, D., & Graepel, T. (2013). Private traits and attributes are predictable from digital records of human behavior. *Proceedings of the National Academy of Sciences*, 110(15), 5802–5805. doi:10.1073/pnas.1218772110

Krouse, W. J. & Richardson, D. J. (2015). *Mass murder with firearms: Incidents and victims, 1999–2013* (CRS report: 7-5700). Congressional Research Service, Library of Congress.

Lankford, A. (2016). Public mass shooters and firearms: A cross-national study of 171 Countries. *Violence and Victims*, 31(2), 187–199. doi:10.1891/0886-6708.VV-D-15-00093

Lazer, D., & Radford, J. (2017). Data ex machina: introduction to big data. *Annual Review of Sociology*, 43, 19–39. doi:10.1146/annurev-soc-060116-053457

Lin, Y. R., & Margolin, D. (2014). The ripple of fear, sympathy and solidarity during the Boston bombings. *EPJ Data Science*, 3(1), 31. doi:10.1140/epjds/s13688-014-0031-z

Lin, Y. R., Margolin, D., & Wen, X. (2017). Tracking and analyzing individual distress following terrorist attacks using social media streams. *Risk Analysis*, 37(8), 1580–1605. doi:10.1111/risa.12829

Lindgren, M., & Ristanović, N. (2011). *Crime victims: International and Serbian perspective*. Organization for security and cooperation in Europe, Law Enforcement Department.

Lio, S., Melzer, S., & Reese, E. (2008). Constructing threat and appropriating "civil rights": Rhetorical strategies of gun rights and English only leaders. *Symbolic Interaction*, 3, 5–31. doi:10.1525/si.2008.31.1.5

Madriz, E. I. (1997). Images of criminals and victims: A study on women's fear and social control. *Gender and Society*, 11(3). 342–356. doi:10.1177/089124397011003005

McIvor, D. W. (2012). Bringing ourselves to grief: Judith Butler and the politics of mourning. *Political Theory*, 40(4), 409–436. doi:10.1177/0090591712444841

Melzer, S. (2009). *Gun crusaders: The NRA's culture war*. New York: NYU Press.

Mercea, D., & Bastos, M. T. (2016). Being a serial transnational activist. *Journal of Computer-Mediated Communication*, 21(2), 140–155. doi:10.1111/jcc4.12150

Metaxas, P. T., & Mustafaraj, E. (2012). Science and society. Social media and the elections. *Science (New York, N.Y.)*, 338(6106), 472–473. doi:10.1126/science.1230456

Metzl, J. M., & MacLeish, K. T. (2015). Mental illness, mass shootings, and the politics of American firearms. *American Journal of Public Health*, 105(2), 240–249. doi:10.2105/AJPH.2014.302242

Papacharissi, Z., & de Fatima Oliveira, M.(2012). Affective news and networked publics: The rhythms of news storytelling on #Egypt. *Journal of Communication*, 62(2), 266–282. doi:10.1111/j.1460-2466.2012.01630.x

Park, S. Y., Holody, K. J., & Zhang, X. (2012). Race in media coverage of school shootings: A parallel application of framing theory and attribute agenda setting. *Journalism & Mass Communication Quarterly*, 89(3), 475–494. doi:10.1177/1077699012448873

Pew Research Center (2012). *Views on gun laws unchanged after Aurora shooting*. Retrieved from http://goo.gl/nzaGxg

Ratkiewicz, J., Conover, M. D., Meiss, M., Gonçalves, B., Flammini, A., & Menczer, F. (2011). Detecting and tracking political abuse in social media. Retrieved from https://www.aaai.org/ocs/index.php/ICWSM/ICWSM11/paper/viewFile/2850/3274

Romer, D., Jamieson, K. H., & De Coteau, N. J. (1998). The treatment of persons of color in local television news: Ethnic blame discourse or realistic group conflict? *Communication Research*, 25(3), 286–305. doi:10.1177/009365098025003002

Shah, D., Cappella, J., & Neuman, W. (2015). Big data, digital media, and computational social science. *ANNALS of the American Academy of Political and Social Science*, 659, 6–13. doi:10.1177/0002716215572084

Shah, D., Hanna, A., Bucy, E., Lassen, D., Van Thomme, J., Bialik, K., ... Pevehouse, J. (2016). Dual screening during presidential debates: Political nonverbals and the volume and valence of online expression. *American Behavioral Scientist*, 60(14), 1816–1843.

Shoemaker, P., & Vos, T. (1996). Media gatekeeping. In D. Stacks & M. Salwen (Eds.), *An integrated approach to communication theory and research* (pp. 75–89). New York: Routledge.

Siegel, A. A., Nikitin, E., Barberá, P., Sterling, J., Pullen, B., Bonneau, R., Nagler, J., & Tucker, J. A. (2018). Measuring the prevalence of online hate speech, with an application to the 2016 US election. Retrieved from https://smappnyu.org/wp-content/uploads/2018/11/Hate_Speech_2016_US_Election_Text.pdf

Sorenson, S. B., Manz, J. G., & Berk, R. A. (1998). News media coverage and the epidemiology of homicide. *American Journal of Public Health*, 88(10), 1510–1514. doi:10.2105/AJPH.88.10.1510

Sugarmann, J. (1992). *National Rifle Association: money, firepower & fear*. Washington, DC: National Press Books.

Tarde, G. (1969). *Gabriel Tarde on communication and social influence: Selected papers* (Vol. 334). Chicago, IL: University of Chicago Press. (Original work published 1898)

Watt Jr, J. H., & Van Den Berg, S. A. (1978). Time series analysis of alternative media effects theories. *Annals of the International Communication Association*, 2(1), 215–224. doi:10.1080/23808985.1978/11923727

Wu, T. (2017). *The attention merchants: The epic scramble to get inside our heads*. New York City: Vintage.

Young, I. M. (1996). Communication and the other: Beyond deliberative democracy. In S. Benhabib (Ed.), *Democracy and difference: Contesting the boundaries of the political* (pp. 120–136). Princeton, NJ: Princeton University Press.