What Counts as Terrorism?

An Examination of Terrorist Designations among U.S. Mass Shootings

Emily Kalah Gade [1]
Dallas Card[2]
Sarah K. Dreier[3]
Noah A. Smith[4]

[1]Acting Assistant Professor or Political Science and Moore/Sloan Innovations in Data Science Postdoctoral Fellow, *University of Washington*

[2]Ph.C., Machine Learning Department, *Carnegie Mellon University*

[3]Ph.C., Department of Political Science, *University of Washington*

[4]Professor, Computer Science and Engineering, *University of Washington*

Abstract

What factors delimit terrorist attacks from other violent incidents? We develop an original news corpus of U.S. mass shooting events to examine the factors most commonly associated with terrorist-designated incidents. We first conduct a statistical analysis to identify the factors that shape whether a mass shooter's attack is designated as terrorism. Next, we verify and contextualize this by qualitatively examining media coverage of the sixteen mass shootings designated as terrorism (Global Terrorism Database). Third, we use unsupervised learning to discover the archetypal portrayals media ascribe to mass-shooter perpetrators. This multi-method analysis demonstrates that perpetrators with certain racialized demographic characteristics (based on their race, religion, or immigrant status) are more likely than white offenders to be designated as terrorists. In addition, we find that media sources disproportionately frame white perpetrators sympathetically while ascribing racialized perpetrators more nefarious, villainous characteristics. We close with policy and social implications of these findings for marginalized communities and discuss avenues for future research.

Abstract word count: 161

Introduction

What factors delimit terrorist attacks from other violent incidents? To be considered "terrorism," violence must be motivated by some broad political objective or grievance. Conventional wisdom often presumes that terrorist events are objectively distinguishable from other forms of criminal violence for their severity and their perpetrators' political objectives. However, political motivations and terrorist tactics are often difficult to objectively define, identify, and categorize. Terrorism's lack of definitional clarity (Crenshaw, 2000; Horgan, 2003; Kearns et al., 2018; Kydd and Walter, 2006) introduces the potential for social biases in which events are designated as "terrorism." This confusion enables experts and journalists to rely (perhaps unknowingly) upon subjective, racialized heuristics to identify certain acts as terrorism.

A number of subjective characteristics—including a perpetrator's race and religion—shape the media's coverage of a violent incident. Media often cover violent attacks conducted by non-white perpetrators with greater volume or more threat-based frames (Kearns et al., 2018; Powell, 2011). Important recent studies have begun to document the biases that also shape the U.S. public's identifications of terrorism (Huff and Kertzer, 2018), especially in light of the post-September 11, 2001, racialization of Arab and Middle-Eastern Americans. However, these studies do not evaluate if, and to what extent, racialized biases shape which violent events become designated as acts of terrorism in the news.

We predict that perpetrators whose identities have been racialized will be more likely than their "white" counterparts to be treated as terrorists. Their crimes will be more likely elevated as national security threats and their identities and communities associated with nefarious violence. White perpetrators of exceptional acts of violence, on the other hand, will be more likely to be sympathetically framed, treated as mentally ill outliers among a non-threatening population. Because racialization in the United States is often subtle and implicit, we expect to see evidence of this racial treatment along indirect racial categories (e.g., immigrants or Muslims). To test these hypotheses, we examine the perpetrator factors that shape whether experts and media designate a given U.S. mass shooting as terrorism. U.S. mass shootings are relatively common and deadly,[5] can be part of a terrorism tactic, but are infrequently cognitively associated with terrorism. They therefore provide valuable insights about the racialized heuristics that drive designations of terrorism.

We generate an original corpus of major newspaper articles relevant to each of 335 U.S. mass shooting incidents that occurred between 1966 and mid-2016.[6] Using this news coprus and the Global Terrorism Database (GTD), we conduct three analyses about the relationships between perpetrator demographics and terrorist designations. First, we construct a statistical model to predict whether experts and media will treat an event as terrorism. Controlling for incident severity and media attention, we find that subtle racialized characteristics strongly predict terrorist designations, even among our relatively small sample of events. Second, we qualitatively analyze a subset of the sixteen mass shooting events designated by the GTD as terrorism to confirm and contextualize our statistical results. Third, we apply unsupervised, natural language processing learning techniques to identify archetypical "personas" the media attach to a specific violent perpetrator (an "entity"). This entity-centered unsupervised "persona" model allows us to make nuanced discoveries about the media's stereotypical descriptions of perpetrators, based on the immediate context of each news mention of the perpetrator. Applying this innovative approach, we demonstrate associations between a perpetrator's racial characterizations and the media's treatment of her/him as a villainous archetypal character.

[5] In 2015 alone, U.S. mass shootings killed 475 people and wounded 1,870.

[6] We get our comprehensive list of mass shootings from the Stanford Database of Mass Shootings in America.

We find that white perpetrators, on the other hand, are more likely to be associated with more morally ambiguous character types, like those suffering from mental illness.

To our knowledge, our is the first study to systematically evaluate these relationships between racialized heuristics, mental health frames, and designations of U.S.-based shooting incidents as terrorism. In doing so, we make three broad contributions. First, we identify the subjective biases that shape official designations of terrorism (including the widely used Global Terrorism Database) and therefore potentially contaminate academic understandings of terrorisms' causes and consequences. Second, we build on past work on unsupervised modeling of "personas" in text and develop approaches that are more appropriate for studying the diversity of framing of a specific type of individual (i.e. those who commit a mass shooting). Here, we experiment with two novel approaches to this problem – one borrowing from an approach to the unsupervised learning of word vectors Mikolov et al. (2013), and the other using a more general framework for document modeling with metadata Card et al. (2018). Third, we identify troubling policy implications of these racialized countours. Terrorist designations can justify policies that encourage national security profiling, punitive approaches to law enforcement, and racially discriminatory criminal justice policies, while undervaluing policies that could reduce U.S. gun violence and protect racially marginalized populations. With U.S. mass-shooting incidents on the rise and federal policies increasingly targeting immigrants and racial minorities as potential terrorists (Davis and Nixon, 2018; Valverde, 2018), understanding the biases in terrorist designations is a critical policy issue of our time.

This article proceeds as follows. We first discuss terrorism's definitional ambiguity and use surface-level text analysis to investigate how terrorism's social meaning has changed over time. Next, we apply research on racialized heuristics and biased media coverage to develop hypotheses about terrorism designations. We then discuss our case-study selection of U.S. mass shootings and detail the sources and structures of our variables of interest. After that, we present results from our statistical analysis, qualitative examination, and unsupervised learning approach. Finally, we discuss the implications of our analysis for racialized American citizens and residents. We close by presenting research limitations and outlining future research steps in this important research agenda.

1 Defining Terrorism

Terrorism is an amorphous concept that scholars consider impossible to define without applying subjective demographic stereotypes (Hodgson and Tadros, 2013; Lakoff, 2000). In the post-World War II era, "terrorism" has been used to describe both state violence against civilian populations and violence perpetrated by non-state actors. However, violence by non-state actors dominates current scholarship (Rich, 2013) and is the focus of our analysis. Even within this non-state subset, experts—including U.S. government agencies (e.g., the Central Intelligence Agency, the Federal Bureau of Investigation, and the Department of Homeland Security)—define terrorism inconsistently (Ruby, 2002; Schmid, 2004). Table 1 details inconsistent definitions of terrorism across U.S. government agencies.

Experts distinguish an incident of terrorism from other acts or threats of violence based on its subjective dimensions. They focus on a perpetrator's political motivations and the relevance of her/his identity in motivating that violence (Hodgson and Tadros, 2013). Terrorism tactics are often designed to create or exploit fear in order to advance those political objectives (Hoffman, 1986). Some definitions limit terrorism to "radical" or "extremist ideological" motivations. However, this notion is imprecise,[7] wide-ranging,[8] and potentially biased against those lacking power in other arenas.[9] We consider an incident "terrorism" if a perpetrator uses violence or the threat of violence against a non-combatant target[10] with a political goal that is broader than the target itself (Phillips, 2015).[11]

Unfortunately, identifying political motivation often proves challenging. When a given terrorist-designated group claims responsibility for a violent event, experts tend to automatically designate that event as terrorism. Political motivations are harder to identify when violent attacks are perpetrated by a single "lone wolf" (like almost all of the shootings we analyze here), when investigators are unable to clearly identify perpetrator motives (e.g., the 2017 shooting at the Route 91 Harvest Music festival in Las Vegas), or when a perpetrator claims affinity with a terrorist group for which they lack official membership (e.g., the 2016 shooting at Pulse Night Club in Orlando).

Furthermore, this focus on political objectives can leave considerable room for biases in application and ascriptions of blame. It can lead to racialized applications of terrorist designations and foster a presumption that terrorists are rational actors (rather than mentally unstable individuals) who present a challenge to the state or a national identity (rather than exerting random violence). Finally, terrorist designations often emerge as media and public officials with incomplete information break the news of exceptional violent incidents. The definition of terrorism thus changes over the lifespan of an incident's coverage and alongside longer-term public discourses.

[7] The use of violence for any objective, political or otherwise, can be considered extreme.

[8] Terrorist-motivated ideologies can include commitments to religion or to equality and human rights. For example, the IRA in Northern Ireland began as a civil rights movement.

[9] What might be considered radical to a person in power may be viewed by an oppressed group or an underprivileged perpetrator as the only available outlet to express a grievance.

[10] Non-combatant is more accurate than "civilian" in this case. See Gade (2010).

[11] This inclusion of "noncombatant" creates a conundrum - for example, according to this definition, the Fort Hood Shooting, which the FBI classified as terrorism, would not be considered a terrorist act because it targeted military personnel, not non-combatants.

Table 1: Definitions of Terrorism

Source	**Text**	**Themes**					
		Use of Violence	Threat of Violence	Political Motivation	Noncombatant Targets	Extreme Ideologies	Fear
Title 22 of the US Code	Premeditated, politically motivated violence perpetrated in a clandestine manner against noncombatants						
Central Intelligence Agency/ State Dept.	Title 22 of the US Code (no alterations)						
Federal Bureau of Investigation	Domestic terrorism: Perpetrated by individuals and/or groups inspired by or associated with primarily U.S.-based movements that espouse extremist ideologies of a political, religious, social, racial, or environmental nature.	*implied*					
Dept. of Homeland Security	The term "terrorism" means any activity that—(A)involves an act that-is dangerous to human life or potentially destructive of critical infrastructure or key resources; and (B)appears to be intended —to intimidate or coerce a civilian population; to influence the policy of a government by intimidation or coercion; or to affect the conduct of a government by mass destruction, assassination, or kidnapping.						
Global Terrorism Database	Threatened or actual use of illegal force and violence by a non-state actor to attain a political, economic, religious, or social goal through fear, coercion, or intimidation.	*illegal force*	*illegal force*				
RAND Incidents of Terrorism Database	Terrorism is defined by the nature of the act...: Violence or the threat of violence; Calculated to create fear and alarm; Intended to coerce certain actions; Motive must include a political objective; Generally directed against civilian targets; Can be a group or an individual.						

Terrorism's social meaning over time

Dictionary definitions notwithstanding, the meanings of words change over time, and can acquire new meanings as they appear in new contexts.[12] The terrorist attacks against the United States on September 11, 2001 (9/11), represent an exceptionally salient critical juncture which plausibly shifted terrorism's social meaning. Borrowing ideas from Kulkarni et al. (2015) and Hamilton et al. (2016), we explore whether there was a detectable change in the usage of the word "terrorism" following this event. To do so, we use the 1.8 million articles in the *New York Times* annotated corpus (Sandhaus, 2008) as a proxy for the the broader cultural discourse over the period 1987–2007.

Figure 1 demonstrates the *frequency* with which "terrorism" appears in the *Times* corpus. It illustrates the effect that the events of 9/11 had on the commonness of this word, though not necessarily its meaning. The usage of "terrorism" was approximately constant for more than a decade before the attacks. Unsurprisingly, 9/11 facilitated an exceptional spike of usage and a gradual decline to a new, higher baseline (relative to the pre-9/11 average). Terrorism is evidently a more prominent, important concept today than it was prior 9/11.

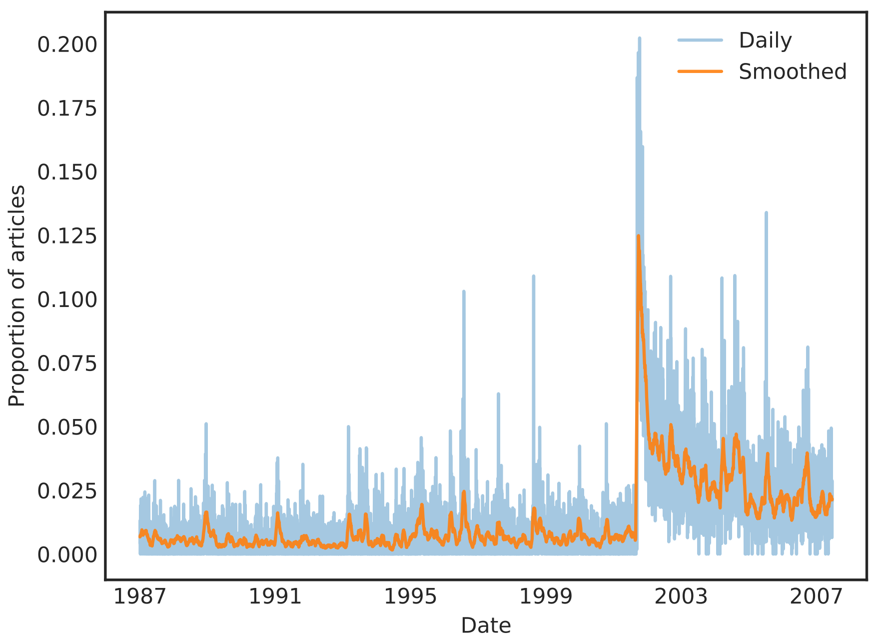

Figure 1: Terrorism Usage across time

Because a change in frequency does not necessarily imply a change in meaning, we also analyze the contexts in which the word "terrorism" occurs. We use *word vectors*, in which each unique word is associated with a multi-dimensional vector learned in an entirely unsupervised manner from a large corpus of text. Words which occur in similar contexts will be associated with similar vectors.[13] Using off-the-shelf tools, we learn word vectors for the words in

[12]The linguist J. R. Firth famously summarized this contextual dependence as "you shall know a word by the company it keeps" (Firth, 1957).

[13]As shown in Levy and Goldberg (2014), skip-gram with negative sampling (SGNS), a widely-used algorithm for learning word vectors, approximates a factorization of the shifted, positive point-wise mutual information (PMI) word-context matrix of the co-occurrence of words within a small context window (e.g. three words on either side of the term of interest; here, "terrorism"). Word vectors have recently become a standard component

the *Times* corpus, treating the mentions of "terrorism" pre- and post-9/11 as *different types*. Specifically, we replace all mentions of this word with one of two tokens (terrorism_pre911 and terrorism_post911) based on the date of the corresponding article, and then process the entire corpus using a standard package.[14] We then compare the nearest neighbors of the resulting vectors using cosine similarity. This analysis suggests considerable proximity between media's treatment of terrorism before and after 9/11. The vectors for the pre- and post-9/11 tokens are closer to one another than either is to any other word in the corpus. Comparing the lists of closest terms suggest that, although salient terrorist groups and methods have changed,[15] the term itself is used in very similar contexts before and after 9/11.[16] The terrorist attacks on September 11, 2001, do not appear to have shifted terrorism's implicit social meaning.

Third, to get a more fine-grained understanding of how the usage of terrorism may have shifted over this period, we examine the co-occurrence of "terrorism" with all other words in each article in the *Times* corpus. To do so, we compute the normalized point-wise mutual information (NPMI) between "terrorism" and each other word that appears in the corpus. Taking into account the term's overall frequency, this provides a surrogate for how likely a word is to appear in an article that mentions terrorism.[17] Figure 2 plots the yearly NPMI for each of the thirty terms with the highest overall NPMI to terrorism. Although the relative prominence of certain context-specific terms increase (e.g., al Qaeda, Bush) or decrease (e.g., Palestine, Israel), most words have approximately the same yearly-NPMI with terrorism over the entire twenty-year period. NPMI-stable words include "government," "military," "intelligence," and "counterterrorism." As above, we find the broader context in which media discusses terrorism has generally remained constant over time.

In sum, terrorism became a more prominent concept after September 11, 2001. Yet although terrorism itself is an amorphous concept, the general social meaning the U.S. media implicitly attaches to terrorism has remained largely stable.[18] This lexical analysis does not, however, provide insights about the subjective assessments that shape which acts of violence media outlets designate as terrorism in the first place. The following section theorizes that subjective heuristics lead the U.S. media to make biased assessments about which violent acts "count" as terrorism, based on the racialized identity of the perpetrator.

2 Theory of Racialized Heuristics and Terrorism

Humans commonly rely on heuristics to link their predispositions to an actual event or decision they face. These "short-cuts" can help people make expedited decisions that align with their preferences, even in the absence of complete information (Kahneman and Egan, 2011). However, heuristics also enable people to make biased, uninformed assumptions about others based on

of natural language processing systems.

[14] `https://bitbucket.org/omerlevy/hyperwords`

[15] For terrorism_pre911, the closest terms are terrorism_post911, terrorist, terrorists, violence, terror, libyan-sponsored, iraqi-sponsored, gulf-related, and subnational. For terrorism_post911, the closest vectors are terrorism_pre911, terrorist, terrorists, terror, qaeda, cyberterrorism, antiterrorism, cyberwarfare, extremism, and terrorist-related.

[16] To verify the reliability of this method, we replicate this approach for insecurity-related concepts not commonly associated with 9/11 (e.g., "murder" or "earthquake"). As we would expect, these tokens produce results comparable to the terrorism tokens, but exhibit even less change (greater cosine similarity) and more lexical stability before and after 9/11.

[17] The formulate for NPMI is given by $\left(\log \frac{p(x,y)}{p(x)p(y)}\right) / (-\log p(x,y))$. See Bouma (2009) for details.

[18] These findings are specific to the *New York Times*, but are considered to be an indicator of patterns in the larger U.S. news media.

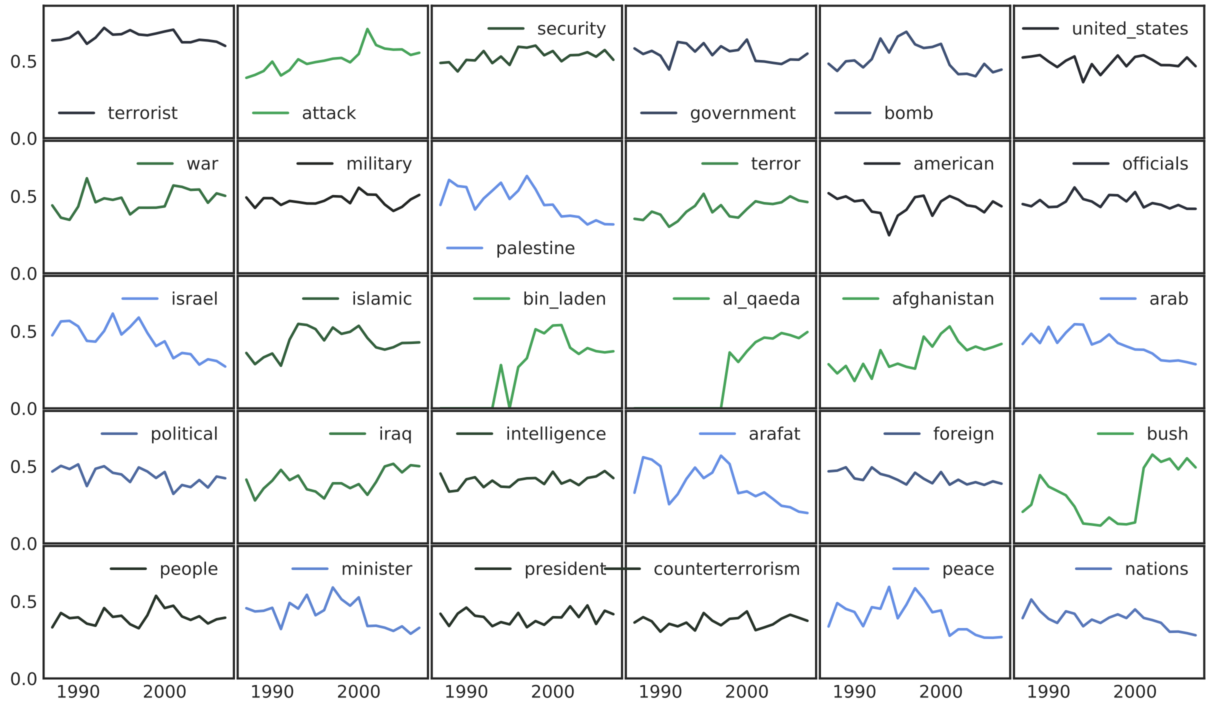

Figure 2: Normalized point-wise mutual information (NPMI) per year for the 30 terms with the highest overall NPMI with "terrorism" in the *New York Times* annotated corpus.

their racial identities or appearances (Lau and Redlawsk, 2001).[19] Racial distinctions and categories—including whiteness (Mingus and Zopf, 2010; Omni et al., 1994)—are subjective social constructions (Mingus and Zopf, 2010; Nagel, 1994; Omni et al., 1994) that shift over time (Barrett and Roediger, 2002)[20] Nevertheless, they have always been, and continue to be, used in the United States to justify violence, exclusion, exploitation, inequality, targeted incarceration, and white supremacy and privilege (Du Bois, 1920; Kobayashi and Peake, 2000).

Racially biased heuristics also pervade U.S. public attitudes. Surveys, experiments, and qualitative observation routinely demonstrate that Americans harbor strong, often damaging stereotypes against racial minorities, foreign-born residents, and other marginalized identities. Racial heuristics influence everything from criminal justice verdicts[21] to interpretations of an individual's personal accomplishments[22] and how different individuals are portrayed in the media. New sources continually over-portray whites as victims rather than perpetrator of crime and give white perpetrators more sympathetic treatment than their non-white counterparts (Dixon, 2017; Dixon and Linz, 2000a,b).

In the aftermath of 9/11, Arab Americans experienced a process of "racialization." Once

[19]When a candidate for public office does not conform to a set of stereotypes, heuristic short-cuts can also increase the chance that a voter will make an "incorrect" vote choice (Lau and Redlawsk, 2001).

[20]For example, Italian immigrants were historically understood as "non-white" in the United States, though this is not the case today (Barrett and Roediger, 2002).

[21]Racial priming has also been found to influence police and juvenile sentencing officers understanding of a perpetrator's culpability and crime (Graham and Lowery, 2004).

[22]Even in studies where subjects were asked to assess specific facts about a basketball player, for example, the player's race informed their perception of their skill (Stone et al., 1997) to the publics responses to new stories (Domke et al., 1999).

considered “white,”[23] they have become identified as a distinct, non-white racial category and heuristically linked to radical Islam and terrorism. They are now often “cast as a potentially threatening Other based on racial characteristics. Racialization...is the process by which American Muslims are identified and labeled through racial differentiation. ...While Muslims are not a ‘race,’ they are examined through a racial process that is demarcated by physical features” (Considine, 2017, 165).[24]

This heuristic association between Islam, Arab descent, and terrorism may affect what people interpret and designate as a terrorist act. Huff and Kertzer (2018) find that the public[25] are more likely to consider an event terrorism if it is conducted by a Muslim perpetrator. Similarly, the media determine a violent attack’s newsworthiness based on its severity, type, perpetrator identity, and attributable responsibility Chermak and Gruenewald (2006); Weimann and Brosius (1991). They are more likely to cover and sensationalize incidents with causalities, links to specific terrorist groups, and airline targets or hijacks (Chermak and Gruenewald, 2006). Attacks by Muslim or Arab perpetrators against “Christian America” generate disproportionately high levels of media attention Powell (2011). In fact, controlling for incident severity, target type, and other factors that should dictate if and how media cover an act of terrorism, (Kearns et al., 2018) find that U.S.-based terrorist incidents perpetrated by Muslims (between 2006-2015) received a dramatic 357-percent increase in news coverage, on average.[26]

This biased media coverage of violent events can buttress white privilege (Omni et al., 1994), construct non-whites (including Arab Americans) as “forever foreigners” (Mingus and Zopf, 2010) and reinforce social perceptions that link terrorism to certain identities (Domke, 2001; Domke et al., 1999).[27] It can do so explicitly (in its disproportionate coverage of Muslim-perpetrated terrorist events), and implicitly (in the facts it deems relevant to a particular case). See, for example, one media source’s coverage of a Bosnian immigrant’s mass-shooting murder of five people in Utah:

> “FBI agent Patrick Kiernan, in Salt Lake City, said the bureau had no reason to believe Sulejman Talovic, who was killed by police, was motivated by religious extremism or an act of terrorism.” (Foy, 2007)

Although explicitly denying a link to terrorism, the mention of the term implicitly associates religious extremism and non-Anglo names with acts of terrorism.

2.1 Hypotheses

We expect that experts will rely upon racialized heuristics to designate certain acts, and not others, as terrorism. The resulting designations will reflect and reinforce consequential social

[23] U.S. census categories still consider Arab Americans to be “white.”

[24] The United States has seen an increase in Islamophobic policies. To date, four “anti-*sharia*” policies have been signed into law in US states, and more than $42.6 million dollars was spent between 2001-2009 to support anti-Muslim rhetoric(Considine, 2017).

[25] MTurk survey respondents were more likely to consider an event terrorism if the incident was severe, motivated by socio-political agendas (defined as “hatred,” “policy change,” or “government overthrow”), and perpetrated by Muslims or political ideologues (“right wing” or “left wing”) (Huff and Kertzer, 2018).

[26] Of course, coverage also varies across news sources (Gerhards and Schäfer, 2014; Ruigrok and Van Atteveldt, 2007) and countries (Papacharissi and de Fatima Oliveira, 2008).

[27] In addition to shaping public opinion, scholars have evaluated (with mixed results) whether media attention to terrorist incidents generates “copy-cat” attacks (Braithwaite and Li, 2007; Chenoweth, 2015; Nacos, 2009; Nelson and Scott, 1992).

biases.[28] The particular racialization of Muslim and Arab identities in the United States has linked them directly with terrorist events, especially in the post-9/11 environment. However, the racialized contours of terrorism are not limited to these identities. Instead, they likely extend to other racialized groups whom white populations ostracize as "others," "foreigners," or atypical Americans that pose a threat to their racial hierarchies. This may be particularly the case when non-white populations seek redress for longstanding grievances or institutional inequalities. Therefore, our principal expectation is that media sources and experts will be more likely to designate violent attacks as "terrorism" if they are perpetrated by individuals considered "non-white."

> PRINCIPAL HYPOTHESIS: *Non-white perpetrators are more likely to be described as terrorists, relative to white perpetrators.*

However, it is exceptionally difficult to identify explicitly racialized treatment. U.S. leaders, institutions, and public attitudes generally responded to the country's racially violent, exploitative history by advancing commitments to "colorblindness." Although failing to alleviate or reduce racialized behavior or racist attitudes, politics of colorblindness have typically removed the most explicit mentions of racial distinctions from "acceptable" public vernacular. As a result, racialized cues and messages in contemporary American politics have almost always been implicit, subtle, indirect, and pervasive (Domke, 2001).[29] Racism shapes, and is reinforced by, public attitudes and discourses that elevate white, European, and Christian identities as quintessentially "American" (Lakoff, 2000). Those same attitudes racialize and sideline immigrants, Muslims, non-English speakers, foreign nationals, and other identities that deviate from these categories. Racialized attitudes are cued and expressed through discussions of these "deviant" categories.

We therefore expect that subtler racial categories will shape which violent perpetrators are treated as terrorists. Specifically, the post-9/11 American "War on Terror" enabled the increasing criminalization of immigration and legal conflation of immigrants and Muslims with criminals and terrorists (Kanstroom, 2003; Miller, 2005). We expect that media sources and experts will be more likely to designate violent attacks as "terrorist" threats if they are perpetrated by Muslims or foreign-born individuals:

> *H1: Perpetrators who are, or who are presumed to be, Muslim are more likely to be described as terrorists, relative to those who not Muslim.*

> *H2: Immigrant perpetrators are more likely to be described as terrorists, relative to U.S.-born perpetrators.*

Finally, acts of terrorism are often considered rational, intentional tactics designed to threaten U.S. institutions and identities (Pape, 2006). White American perpetrators of exceptional or high-casualty violence, by contrast, are more likely to be considered irrational individuals suffering from mental health ailments; their mental illness explains why they deviate from expected, nonviolent behavior. Indeed, social activists identify racialized disparities

[28] "The definition of terrorism triggers a range of controversial extensions of police and prosecutorial powers" (Hodgson and Tadros, 2013)

[29] Donald Trump's presidential campaign and Administration have routinely made less subtle, more explicit racialized public statements. It is possible that his Administration is shifting public discursive norms away from commitments to colorblindness to publicly accepted racism. Since the data we examine predated Trump's general-election campaign and presidency, we are unable to consider these potential shifts.

among media frames of violence. They frequently discuss non-terrorist mass shootings as indications of mental ill-health. Meanwhile, they attach "terrorist" incidents to calls for punitive, retributive, and immigration-control policies (Camacho, 2018; Harriot, 2018; McLaughlin, 2015; Ruiz-Grossman, 2017).[30] We therefore expect that media sources and experts will be less likely to consider mental ill-health as an explanation for violent attacks they have identified as terrorism:

> *H3a: Events described as terrorism will be less likely to contain a mental health frame (regardless of the perpetrators known mental-health history), relative to violent acts that are not described as terrorism.*

These mental-health distinctions "downgrade" the nefariousness of a violent act. If a perpetrator is deemed mentally unstable, the implication is that her/his own culpability is limited. Indeed, the U.S. legal system often exonerates or reduces criminal charges to perpetrators considered "insane." Framing a violent perpetrator as rational, on the other hand, elevates the depravity of her/his actions. In other U.S. contexts, frames of criminals' innocence or iniquity have cut along racial lines.[31] We therefore anticipate that white perpetrators are more likely to be afforded the assumption of mental illness, relative to non-white perpetrators:

> *H3b: Discussions of mental illness will be more likely for incidents with white perpetrators, relative to non-white perpetrators.*

In sum, we expect that racial heuristics will play an important role in determining which violence incidents media and experts designate as terrorism. Because racialized treatment is often subtle, indirect, and signaled through other identity categories, we expect this racialization to be expressed through discussions about Islam, immigration, and mental rationalism or illness. Evidence of interacting relationships between these categories (Islam, immigration, mental illness, and terrorism) will demonstrate that racial attitudes influence which violent actors become terrorists in the minds of the American people and policymakers.

3 Research Design

3.1 Case Selection: Mass Shootings

These hypotheses predict whether racial heuristics shape if an event is designated as terrorism. To test these hypotheses, we examine a specific type of violence: U.S. mass shootings. This subset of violent events is appropriate for our analysis specifically because there is often ambiguity about whether a mass shooting has been used as a terrorist tactic. For example, some

[30] Several experts challenge any frame that attributes gun violence to mental health issues. Only four percent of violence is associated with serious mental illness (Swanson et al., 2015) and only five percent of gun violence is linked to people diagnosed with a mental illness (Metzl and MacLeish, 2015). It is also important to note that the linking of mental illness and violence is recent. In the 1960s, elites considered black activists like Malcolm X and the Black Panthers "mentally ill" and urged gun control policies in order to protect against "the threat of civil disorder" they posed (Rotenberg and Sadoff, 1968). This frame has been reversed and now undermines the nefarious nature of a string of solo white male shooters (Metzl and MacLeish, 2015). Today, mental health frames "lead to calls to expand gun rights, focus on individual grants, or limit gunfights just for the severely mentally ill" (Metzl and MacLeish, 2015).

[31] For example, when crack cocaine and heroin were a problem in brown and black (urban) neighborhoods, drug use was understood as "deviance" and justification for a "war on drugs"; however, the rise of the prescription opioid epidemic in white neighborhoods has been re-framed as a mental and public health issue (Netherland and Hansen, 2017, 2016).

experts distinguish the 1999 massacre at Columbine High School in Aurora, CO, as a rampage (perpetrated by a person affiliated with the targeted community) rather than as a terrorist event (Muschert, 2007). Others, including the Global Terrorism Database, catalog Columbine as an act of terrorism. This ambiguity introduces the possibility that racial heuristics shape these designations, and therefore provides a unique opportunity to examine what incident- and perpetrator-demographic factors make a mass shooting more likely to be considered terrorism.

The Stanford Mass Shootings in America project provides a comprehensive database of U.S. mass shooting events (1966–2016). It defines a "mass shooting" as an incident in which the perpetrator(s) use firearm(s) to kill or injure three or more victims.[32] Mass shootings exclude organized crimes (e.g., gang or drug-related violence) but include terrorism. This clear definition and universal collection eliminates bias in our case-study parameters. We therefore adopt this database as the universe of cases we analyze. Figure 3 demonstrates a considerable increase in yearly mass-shootings since 1990.[33] The majority of these shootings involved ten deaths or fewer (Figure 4).

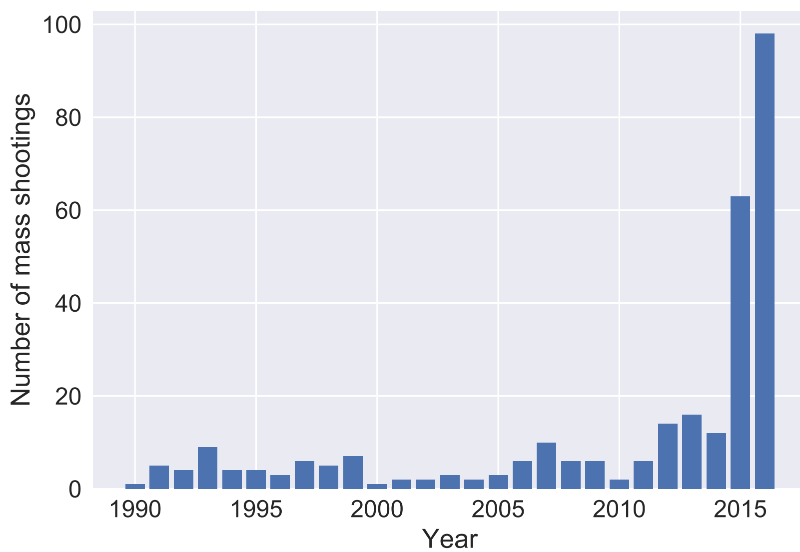

Figure 3: Number of events in the Stanford Mass Shootings database per year.

3.2 Outcome of Interest: Terrorism Designations

For each of the incidents included in the Stanford database (n=335), we examine if any perpetrator demographics—specifically ascribed race, religion, and immigration status—shape whether that incident is designated as an act of terrorism. We use three distinct measures for terrorism designation. The first is the Global Terrorism Database (GTD)'s official list of terrorist events worldwide. Among the Stanford databases' list of U.S. mass shooting events, the GTD designated sixteen as acts of terrorism (*positives*=16). These GTD designations are not necessarily

[32]`https://library.stanford.edu/projects/mass-shootings-america`. Another archive on mass shootings, Mass Shooting Tracker, which includes only the years 2013-present, has a significantly higher count of mass shootings than does the MSA for all overlapping years (2012-2016).

[33]It is possible this increase reflects increases in reporting and national awareness of mass shootings over time (i.e., reporting bias). However, in 2013, the FBI released a report stating that mass shootings in the United States have dramatically increased in recent years (Grow, 2014).

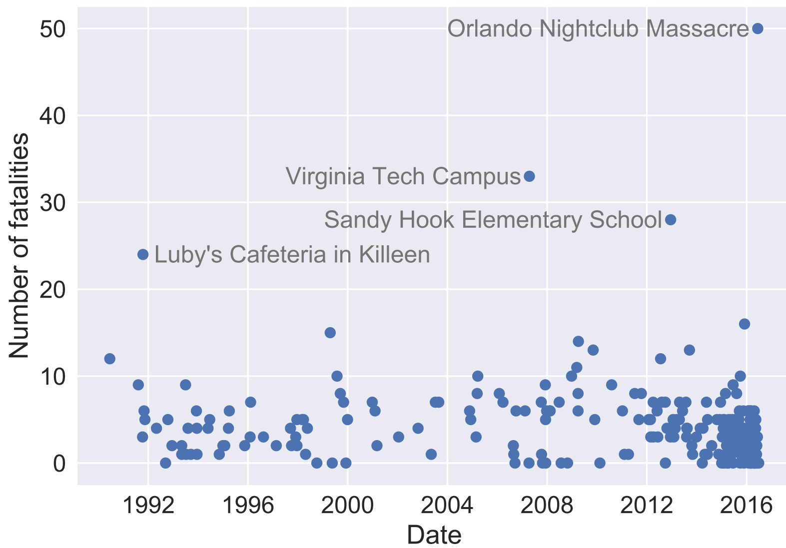

Figure 4: Number of fatalities for each incident.

unbiased or entirely consistent, however.[34] We employ two expert coders to validate and amend the GTD designations, using a rigorous coding ontology that distinguishes among various political motives.[35] This hand-coded measure identifies approximately twenty-two mass shooting incidentsas terrorism. Future analyses will incorporate these hand-coded terrorist designations.

We also examine whether national U.S. newspapers treated each mass shooting event as terrorism. Media treatment is informative for a number of reasons. First, and most importantly, datasets like the GTD are coded directly from news stories. Thus, biases in the news may yield biases in both official databases and the study terrorism more broadly. Second, news provides a more direct assessment of the social, subjective processes by which an event comes to be treated as terrorism. Media disseminate frames that can reinforce certain beliefs and discredit others. They are therefore likely more determinative of social attitudes about terrorism than official designations, which do not attract widespread consumption. Third, media coverage is part of a successful terrorist agenda. Terrorist groups seek to increase their media coverage, which helps them promote their cause and generate widespread fear (Kearns et al., 2018).[36] Fourth, terrorist and other mass shooting incidents attract significant media attention, particularly when they yield numerous, unexpected fatalities among innocent victims Maguire et al. (2002) like children (e.g., the 2012 massacre at Sandy Hook Elementary School massacre in Newtown, CT) (Schildkraut and Muschert, 2014).[37] This heightened media coverage provides a wealth of

[34] For example, Columbine is the only school mass shooting that the GTD categorizes as a terrorist incident. GTD designations are often based on media coverage, which is also subjective.

[35] These political motive categories include: left-leaning, right-leaning, explicitly anti-government, government target, and explicitly minority target. See Appendix XXX for full discussion and coding rules. This method allows for us to include or exclude hate crimes, for example, in the conception of "political motive" and conduct robustness checks among various subsets to evaluate whether the inclusion or exclusion of certain cases shift our findings.

[36] Media coverage of past events may also produce produce "clustering" and "copy cat" attacks (Chenoweth, 2015).

[37] Media mass-shooting frames anchor their coverage in "archetypal" mass shootings, which change over time.

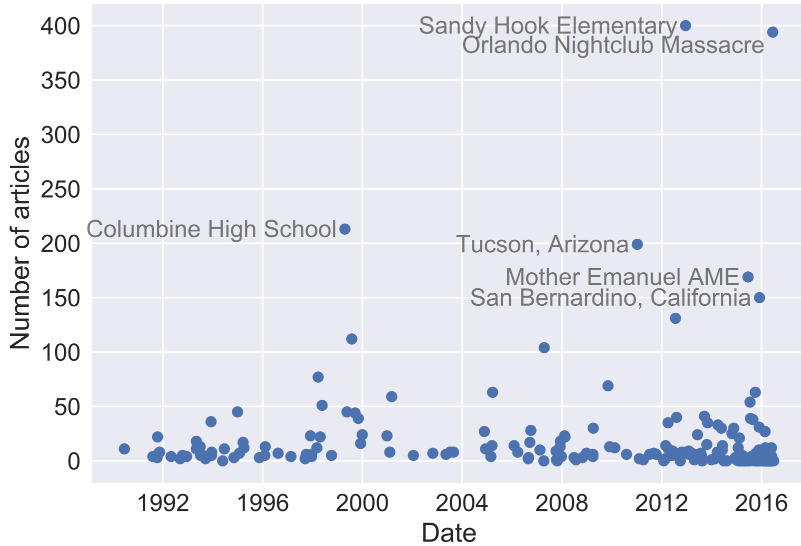

Figure 5: Number of articles about each event in the Stanford Mass Shootings database.

text data for our analysis.

To ascertain media coverage, we used the Lexis-Nexis Academic search interface to compile a set of news articles from eight mainstream U.S. newspapers relevant to each of the 335 U.S. mass shootings which occur after 1990.[38] We limit our analysis to articles that meet several criteria of relevancy. To be included in our analysis, an article must have been published within one week of the event's occurrence, been tagged with both the state in which it occurred and at least one of four Lexis-Nexis tags related to terrorism and shootings ("Mass shootings," "Shootings," "Terrorism," or "Terrorist attacks"), explicitly mentioned the city in which the event occurred, and mentioned either the name or age ("XX-year-old") of at least one suspected shooter.[39] Although likely omitting some relevant articles (false negatives) and including some unrelated coverage (false positives), we believe this filtering method provides a reliable corpus of news coverage.

The resulting news corpus contains 4,146 news articles, each linked to a specific U.S. mass-shooting event. News coverage is notably skewed toward a few high-profile events, each of which generated hundreds of articles while others received no national coverage (Figure 5).[40] Beyond these exceptional events, there is not a strictly determined, consistent relationship

Scholars generally identified Columbine as the archetype for school shootings. This framing has shifted after Sandy Hook, which may have become the new archetype (Chyi and McCombs, 2004; Schildkraut and Muschert, 2014).

[38]Newspaper data quality available on Lexis-Nexis deteriorates prior 1990.

[39]Because we examine the influence of perpetrator demographics on terrorist designations, we exclude twenty-four mass shootings events that had no identified perpetrator.

[40]Two events—the 2016 Pulse Nightclub shooting and the 2012 Sandy Hook shooting—were each covered in approximately 400 articles in the week following the event. In each case, this heightened coverage comports with research expectations. The Pulse shooting was the most deadly incident in our dataset (which excludes the 2017 shooting in Las Vegas that killed 58 people) and was perpetrated by a racialized minority who expressed an (unverified) affiliation with ISIS. The Sandy Hook perpetrator conducted an almost inconceivable attack on six and seven-year-old children, twenty of whom died, with no expressed motive.

Table 2: Key Variables

	Concept	Measurement	Data Source	Coding
DV	Designated as Terrorism	Officially designated (0-1)	GTD	As published
		Expert Coding (0-1)	News Corpus	Hand-coded
		Mention of terrorism (0-1)	News Corpus	Dictionary methods
		Treated as terrorism (%)	News Corpus	Dictionary methods
IV	Racialized Perpetrator	H(principal): Race	News Corpus	Hand-coded
		H1: Muslim (0-1); % mentions	News Corpus	Hand-coded; dictionary methods
		H2: Immigrant (0-1); % mentions	News Corpus	Hand-coded; dictionary methods
		H3: Mental Health Frame % mentions	News Corpus	Dictionary methods
		H3: Mental Health History (0,1)	MSA, News Corpus	Hand Coding; MSA

Appendix XXX provides a detailed coding ontology.

between severity (e.g., number of casualties) and news coverage (Figure 4).

Using this corpus, we calculate two additional measures of terrorist designations: whether the news media made reference (excluding negations) to a given incident as terrorism (0-1, where 1 indicates that at least five percent of articles mention the event this way), and the extent to which the news media linked the incident to terrorism (the percentage of incident-specific articles that mention terrorism). See Table 2 for detail. Figure 6 shows the proportion of articles in our corpus which associated a given mass shooting with terrorism.[41] All but one of the five incidents that were most strongly associated with terrorism involved Muslim perpetrators.[42] Likely confounding factors notwithstanding, the connection to religion (specifically Islam) is notable.

[41] It represents the number of articles in which the word "terrorism" or "terrorist" appears, but not in the same sentence as "not," "no evidence," "no solid evidence," etc.

[42] The exception is the Colorado Springs attack on a Planned Parenthood clinic.

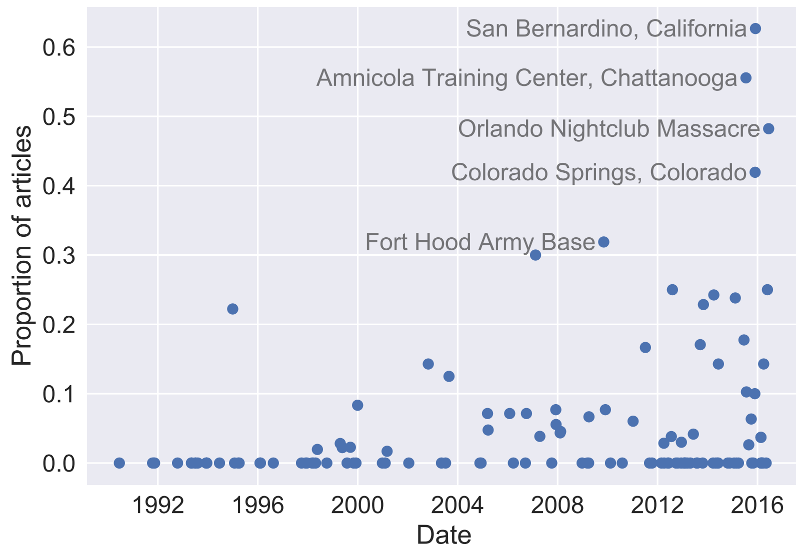

Figure 6: Proportion of articles about each event which mention "terrorism" or "terrorist".

4 Methodological Approach and Preliminary Results

We evaluate the relationships between the explanatory and outcome variables with three approaches: statistical analysis among the universe of mass shootings, qualitative examination among a subset of the sixteen mass shootings officially coded by the GTD as acts of terrorism, and using unsupervised methods to uncover relationships and narrative linkages. The later approach uses natural language processing methods to identify the archetypal character narratives (of victims or villains) journalists use to represent individual perpetrators (Bamman et al., 2013; Card et al., 2016; Schneider and Ingram, 1993; Van Gorp, 2010).

4.1 Predicting Mentions of Terrorism in the Media: Regression Analysis

We evaluate our hypothesis against likely alternative explanations found to be relevant in other studies (Huff and Kertzer, 2018; Kearns et al., 2018), including severity of the incident, link to an existing terrorist group, and religion of the perpetrator, in a conventional regression analysis using hand-coded data.

Because our dependent variable for evaluating news coverage is a proportion, we estimate our primary models with a beta regression.[43] This allows us to appropriately analyze the unique proportional structure of our outcome of interest (mentions of terrorism), in which most values fall close to the lower bound.[44] The formula for a beta regression is given as:

$$g(\mu i) = x_i^T \beta = \eta_i, \tag{1}$$

where $\beta = (\beta_1, ..., \beta_k)^T$ represents regression parameters (unknown), η_i houses a linear predictor, and g represents a link function (Cribari-Neto and Zeileis, 2009, 3). We use a logit model for

[43]We also use a negative binomial model (for a count of total mentions) and a logit model (for a binary dependent variable - whether an event has any news mention of terrorism). Both are discussed in Appendix XXX

[44]Because beta regressions do not allow true zero values, we increase any zero values to .0000001.

our binary dependent variable: coded as terrorism by GTD. Logit is a type of generalized linear model, which operates though the following link function:

$$\eta(p) = ln\left(\frac{p}{1-p}\right) \tag{2}$$

4.1.1 Preliminary Regression Results

Table 3 contains a first pass at regression analysis. Models one and two contain a count dependent variable: the number of articles which contain positive mentions of a given event as terrorism.[45] Model 3 evaluates the proportion: positive mentions of a given event as terrorism divided by the count of valid articles. We believe this model will the most appropriate formulation of the concepts we seek to measure going forward. Model 4 includes a binary assessment of whether any news source affirmatively mentioned this event at terrorism. Note that we have not finished hand-coding motives; thus, these results have significant potential for omitted variable bias and should be considered very preliminary.

That said, these preliminary results provide some suggestive evidence of our hypotheses. First, the proportion of articles that discuss an event as about "mental health" are statistically significant and negatively correlated with affirmative mentions of terrorism: most events do not appear to be described as terrorist and mental health issues simultaneously. Second, articles that mention Islam are also more likely to contain positive mentions of terrorism, according to three of our four preliminary models. We do not see a relationship in most models between a binary variable "white" and mention of terrorism, which we expected because of the way that discussions of race have been baked into less explicit language. Finally, and corresponding to previous studies, both the number of victims and the amount of news attention seems to be positively related to the news considering an event terrorism. Again, without accounting for "political motive", we are hesitant to draw any major conclusions from these results or engage in extensive robustness tests/alternative model formulations.

However, given our hypotheses expect subtle shifts in the language around certain events, we explore these data in two alternative specifications: qualitative analysis of key incidents, and unsupervised approaches over the text corpus we have collected.

4.2 Qualitative Examination

We plan to select key incidents of overlap (mass shootings which are also terrorism incidents) as well as difference (critical cases which are *not* considered terrorism) and conduct in-depth process tracing on the framing of these events as relates to our hypotheses presented above. This within-case qualitative approach of key cases provides several analytic benefits. First, it enables us to test and critically evaluate several competing or complimentary hypothesized mechanisms: for example, are frames of "immigrant status" and "Islam" co-occurring? Are "mental health" and "terrorism" frames competing or complementary? Second, it allows us to take a deeper, careful dive into these events than is possible with an unsupervised or statistical approach, and evaluate whether the patterns that we observe in those analysis hold under careful scrutiny. Finally, it provides the space to conduct a deductive hypothesis-testing analysis (Schimmelfennig, 2015) alongside inductive theory development, shaped by unanticipated mechanisms evidenced in our data (Pouliot, 2015). In all, we hope this analysis will help verify

[45] We include a negative binomial model here as the count DV is not normally distributed, and because the variance is different from the mean, making a negative binomial model more appropriate than a Poisson.

Table 3: Preliminary Regression Results

	Dependent variable:			
	Count		Proportion	Binary
	OLS	*Negative Binomial*	*Beta*	*Logistic*
	(1)	(2)	(3)	(4)
Number of Victims	0.422***	0.006	0.016**	0.009
	(0.072)	(0.020)	(0.007)	(0.038)
White	−2.960***	0.187	0.092	0.181
	(1.070)	(0.368)	(0.127)	(0.400)
Prop Mental	−11.100***	−0.660	−3.180***	−3.800**
	(3.500)	(1.170)	(0.405)	(1.490)
Prop Islam	5.530***	0.325	1.590***	1.900**
	(1.750)	(0.582)	(0.203)	(0.747)
N Valid Articles	0.161***	0.047***		0.085***
	(0.018)	(0.004)		(0.018)
Constant	−2.220**	−1.600***	−2.110***	−2.380***
	(0.953)	(0.305)	(0.148)	(0.397)
R^2	0.536		0.151	
Adjusted R^2	0.529			
Log Likelihood		−219.000	1,465.000	−81.000
θ		0.244*** (0.046)		
Akaike Inf. Crit.		451.000		174.000
Note:				*p<0.1; **p<0.05; ***p<0.01

CaseID	Title	Date	# articles	Prop. terrorism
3	New Orleans Police Shootings	12/31/1972	0	0.00
71	Columbine High School	4/20/1999	213	0.03
91	Party in Capitol Hill, Seattle	3/25/2006	8	0.00
116	Fort Hood Army Base	11/5/2009	69	0.39
133	Sikh Temple in Wisconsin	8/5/2012	40	0.27
141	Los Angeles Police Department	2/3/2013	6	0.00
155	Los Angeles International Airport (LAX)	11/1/2013	35	0.26
161	Seattle Pacific University	6/5/2014	10	0.00
162	Nellis Plaza	6/8/2014	14	0.14
168	Massachusetts Abortion Clinic	12/30/1994	45	0.24
181	Chapel Hill	2/10/2015	21	0.24
215	Mother Emanuel AME Church	6/17/2015	169	0.18
222	Amnicola Training Center, Chattanooga	7/16/2015	54	0.61
224	Grand 16 Theatre, Louisiana	7/23/2015	40	0.17
243	Minneapolis, Minnesota	11/23/2015	10	0.30
244	Colorado Springs, Colorado	11/27/2015	31	0.42
245	San Bernardino, California	12/2/2015	150	0.64
343	Orlando Nightclub Massacre	6/12/2016	394	0.52

Table 4: 16 Crossover Incidents between the GTD and the MSA. Note that GTD collection methodology changed in 1998 and also 1993 is missing from the GTD entirely.

the mechanism we propose above, as well as uncover additional texture about the way in which these dynamics are understood and described.

4.2.1 Proposed qualitative analysis of crossover incidents

Sixteen incidents appear in both the Mass Shootings Database and the Global Terrorism Database (see Table 4). Almost all of the events that involve a high proportion of terrorism mentions in the media are in the GTD, with the one major exception being the 2014 shooting at Fort Hood Army Base, which is not in the GTD, as distinct from the 2009 event at the same location, which is. Note, however, that many of the mentions of terrorism in the coverage of the 2014 incident are in reference to the earlier event. The perpetrator of the 2014 incident was white. The 2009 event, by contrast, is a case where the perpetrator was Muslim, and did make some statements about opposition to the government, but many felt it was unclear whether the shooter had a broader political goal in the shooting or whether the shooting was a result of depression. The FBI classified the event as terrorism, but the Department of Defense classifies it as “workplace violence.” We are considering doing an in-depth qualitative comparison of these two events.

By contrast, several events in the GTD involve zero or very few mentions of terrorism in the media, most notably Columbine. A few other well-covered events in the GTD involve relatively few mentions of terrorism, such as the shootings at Mother Emmanuel AME church and the Grand 16 Theater. We are considering doing an in-depth qualitative analysis of the coverage of the Dylann Roof case.

Finally, in an event that is not in the GTD, in 2007 a Bosnian immigrant opened fire on Trolly Square, in Salt Lake City, Utah. The event was not generally considered terrorism, and though the perpetrator was Muslim, he made no statements of a religious nature during the shooting. However, U.S. Representative from Utah Chris Cannon made a public statement that the shooter had yelled "Allahu Akbar" during the shooting, an assertion that he claimed to hear on Fox News (Speckman et al., 2007). This appears to have generated significant news coverage around the event. The FBI and local police subsequently stated that there was not evidence of any religious statements during the attack, nor should the event be considered terrorism (Speckman et al., 2007). We are considering doing an in-depth qualitative analysis of this and other non-terrorism cases with Muslim shooters or Middle Eastern shooters who are not Muslim.

While this deep-dive adds important value, we are also interested in broad-based, subtle characterizations of these perpetrators, and whether those correspond to our variables of interest. Thus, we make use of techniques from entity-centric natural language processing, which allows us to characterize the ways in which individuals are described in text with grater nuance.

4.3 Unsupervised Learning about Perpetrator Characters

We hypothesized that certain violent perpetrators will be racialized as terrorists, based on their demographic characteristics. In this third analysis, we use unsupervised methods to identify whether these characteristics also inspire media portrayals of perpetrators according to specific archetypal characters. We expect that media will characterize un-racialized (e.g., white) perpetrators primarily in a sympathetic frame, perhaps in terms of their mental or emotional state of ill-health. Meanwhile, media characterizations of racialized perpetrators will emphasize their ethnic, national, or religious affiliations and mirror villainous archetypes.

To conduct our analysis, we build on previous work on unsupervised discovery of "personas" in short film summaries (Bamman et al., 2013). Although they report on real-world events, we nevertheless expect news articles to make use of archetypal characterizations to describe the individuals (Van Gorp, 2010). By analogy with "characters" in films, we hope to discover common ways of framing perpetrators which may capture more subtle negative and positive associations than explicit mentions of terrorism. However, the model in Bamman et al. (2013) assumed one text per character, but our text corpus often includes multiple articles for each perpetrator "character," with coverage skewed toward a few high-profile events. Furthermore, this approach was developed to identify archetypes among fictional characters, which likely display a wider variety of easily distinguishable archetypes (e.g., dark hero, romantic lead, comedic sidekick, etc.) than will exist among our spectrum of violent perpetrators. The similarity among shooters (all are villains) may make it more difficult to find clearly differentiated personas.

Despite these challenges, we apply two unsupervised natural language processing (NLP) approaches in novel ways to discover media characterizations: entity vectors and personas.

4.3.1 Preprocessing

Past work in natural language processing has developed effective methods for on recognizing entities in text (e.g., people, organizations, etc.) Lee et al. (2017) and extracting relations between them Singh et al. (2013). As a first step for both of our approaches, we first use Stanford CoreNLP[46] to preprocess all articles and identify entity mentions of type PERSON, along with co-referring expressions. We then extract the mentions which refer to the perpetrator, identified either by name, or by age using the construction "XX-year-old", which is commonly used when the perpetrator is not identified by name. In addition, we consider all occurrences of the words "gunman" and "shooter" to be references to the perpetrator. In this way, we collect many mentions of each perpetrator, in context, in each article.

4.3.2 Entity vectors

As a first attempt, we again re-purpose unsupervised learning of word vectors (SGNS) to create a vector representation of each perpetrator. Similarly to our analysis of the word "terrorism" above, we treat each mention of each perpetrator as a token unique to that incident: as before we replace each mention with an event-specific token and then learn low-dimensional embeddings of all words, including these event-specific tokens. As before, the words which occur in a small window around each mention provide the relevant context for our analysis.[47] In order to have a sufficiently large corpus of text, we combine all articles in our corpus with the full set of articles in the *New York Times* annotated corpus. In this way, in addition to learning vectors for all words, we learn a unique vector for each perpetrator, based on the context windows in which they appear, *pooled across all news articles about each event*.

Preliminary Entity Vector Analysis

After removing events which had insufficient perpetrator mentions for this analysis, we end up with 78 events with a perpetrator-specific token. The resulting vectors show two interesting properties:

1. For most events, the vector for the perpetrator is closer to a vector for another perpetrator than to any other word in the vocabulary. This is not surprising, as we have created these tokens by combining names, pronouns, and particular words ("shooter" and "gunman") in such a way that the resulting token occurs in slightly different context than a name or pronoun normally would. In addition, these tokens will share many contextual words, simply because they all represent individuals who committed mass shootings.

2. Inspecting the closest vectors to the word "gunman" (which we do not replace in the articles from the *Times* corpus), 7 of the 20 closest terms (in terms of cosine similarity) are tokens representing shooters. This offers strong evidence that this method is indeed learning representations of entities that conserves their identity. (Other most-similar terms include "assailant", "attacker", "sniper", etc.).[48]

[46] `http://corenlp.run`

[47] The output of SGNS is two matrices, one of which represents each *content* word as a k-dimensional vector, and one which represents each *context* word as a k-dimensional vector. Typically the second of these two matrices is ignored, and the first is taken to be the k-dimensional representation of each word that we are interested in.

[48] Note that this does not hold for "shooter," as this term is overloaded by its use in the context of reporting on basketball.

Although it is difficult to arrive at any definitive grouping of events using unsupervised methods, a basic spectral clustering algorithm demonstrates clear patterns.[49] The most conspicuous cluster is one in which either the perpetrators or the victims were people of color (Chattanooga, Chapel Hill, Fort Hood (2009), Orlando, San Bernardino, and the Sikh Temple in Wisconsin). Other clusters seem to have similarly obvious characteristics, such as school shootings, or workplace shootings. Although further work is required to extract quantitative insights from this analysis, using a SGNS as a way to learn representations of individuals appears to be a promising technique for future scholars.

4.3.3 Framing of Individuals: Persona Model

Our second unsupervised approach is more targeted. In addition to the preprocessing described above, we also use dependency parsing to obtain a tree-structured grammatical parse of each sentence in each article, and restrict what we consider as context to *adjectives* which refer to the individual of interest.[50] This limits the evidence we will consider to descriptive terms that are directly about the perpetrator. We then make use of the Scholar framework (Card et al., 2018), to learn representations of each perpetrator in each article. Scholar provides an approach to unsupervised learning, similar to topic modeling, which allows for flexible incorporation of metadata and other side information. In particular, for each article, we will end up with a low-dimensional representation on a simplex. Each dimension of this representation corresponds to a vector of deviations, indicating which words are more or less common than their overall frequency for that particular dimension.

Specifically, the probability of a word occurring in the context of an entity is given by

$$p(w \mid \boldsymbol{\theta}_i) \propto \exp(\mathbf{b} + \boldsymbol{\theta}_i^T \mathbf{B}^{(topic)} + \mathbf{c}_i^T \mathbf{B}^{(covariate)}) \tag{3}$$

where $\boldsymbol{\theta}_i$ is a representation of the entity on the k-dimensional simplex, $\mathbf{b}$ is a V-dimensional background term (where V is the size of the vocabulary), $\mathbf{c}_i$ is a vector of entity covariates, and $\mathbf{B}^{(topic)}$ and $\mathbf{B}^{(covariate)}$ are weight matrices. In addition, we can also optionally include a text classification component as an additional term in the objective function, such that we learn topics that are useful for predicting labels. This classification component takes the form of a neural network operating on the latent representation and covariates

$$p(y_i \mid \boldsymbol{\theta}_i) = f_y(\boldsymbol{\theta}_i, c_i) \tag{4}$$

where y_i is the label for document i, and f_y represents a multi-layer perceptron, or other component appropriate to the data.

Note that equation (3) has a similar form to the objective of SAGE (Eisenstein et al., 2011) and the structural topic model (Roberts et al., 2014), but Scholar provides more scalable inference and allows for incorporating metadata in additional ways. In this case, we also make use of pretrained word vectors to obtain greater coherence in each dimension. As in topic models, the end result is a set of interpretable latent dimensions, each of which corresponds to a high and low probability words. Unlike standard topic models, however, these lists correspond to words which are *more or less likely* than the overall frequency for that word (i.e., positive or negative deviations from the background term $\mathbf{d}$.

The parameters in this model are learned using the variational autoencoder framework Kingma and Welling (2014), in which we construct an *encoder network* to convert each document into a posterior distribution over the latent variable of interest (in this case, $\boldsymbol{\theta}$). Other

[49] Results reported here are for the assumptions of 6 clusters, but similar patterns are found with other choices.
[50] Dependency parses are also obtained from Stanford CoreNLP.

variables are treated as parameters to be maximized, and the model is fit using a variation on stochastic gradient descent. For more details, please refer to Card et al. (2018).

In this case, each "document" is the set of context words extracted from one article. Unlike the word vector approach above, we treat each news article as an a separate document, allowing for the possibility that different sources or articles may represent certain perpetrators in different ways.

Because certain events receive vastly more news coverage than others, we use covariates to include information indicating when an article refers to one of the most common events. For any any event which has at least 35 articles about it (after preprocessing, and excluding articles which do not mention the shooter), we represent this information as a one-hot vector, included in the model as $\mathbf{c}_i$. Thus, in addition to the latent dimensions which represent common characterizations of shooters, we also end up with similar positive and negative deviations in $\mathbf{B}^{(covariate)}$, which represent the words which are more and less frequent than the background in articles about these most-covered events. These additional offset terms effectively account for the most common terms associated with those events that received lots of coverage, leaving the topical dimensions to account for deviations which are shared *across* events.

As with all unsupervised models, evaluation is difficult. Moreover, there are inevitably preprocessing errors that occur when using tools such as NER and coreference. As such, we will rely primarily on the face validity of the results of these analysis, and interpret their significance with caution.

Preliminary Findings: Scholar

The output of the entity modeling using the Scholar framework are somewhat different in character, as we attempt to learn a representation of each shooter in the context of each article. Moreover, by restricting ourselves to certain types of evidence (adjectives which refer to the shooter), we ignore much of the information that is used in the word vector approach above. The specific results are also somewhat dependent upon the randomness involved in the optimization and initialization. However, the advantage is that the patterns discovered are highly interpretable.

In order to force the model to learn dimensions which are shared across events, we include covariate terms for the most common events, as described above. There are 5 events that fall into this category, and Table 5 shows the most strongly positive deviations associated with these perpetrators (representing terms that are much more frequent in coverage of these events than overall).

Event	Terms
Fort Hood (2009)	major muslim devout military outspoken cleric stable
Movie Theater in Aurora	booby-trapped alleged due doctoral black-clad graduate
Orlando Nightclub Massacre	gay abusive terrorist cool religious elementary muslim
Sandy Hook Elementary School	nervous new smart awkward boisterous regular prone
Tucson, Arizona	violent jittery suspect mental able disturbed polite

Table 5: Adjectives found to be most strongly associated with the most well-covered events (in terms of mentions of the perpetrators) when the model includes explicit deviations for these events.

Several things stand out when examining Table 5. First, Fort Hood, Orlando and Tucson are all at least sometimes categorized as terrorism. However, Fort Hood and Orlando were perpetrated by non-white Muslim shooters, while Aurora, Sandy Hook and Tuscon were perpetrated by white shooters. While far from systematic, we do see some important differences between the key adjectives used to describe the Tuscon shooter and the adjectives used to describe the Fort Hood and Orlando shooters: in the first case, there is a clear mental health frame, while in the later two cases, the frames appear to focus on the shooters' religion and indeed describe the shooter as a terrorist. Second, the frame for all three white shooters seems to emphasize some sympathetic attributes - describing shooters varyingly as a doctoral or graduate student, as "smart," "nervous" or even "polite."

Table 6 displays the most probable words in the set of topics learned by one instantiation of the model, along with a subjective categorization. These topics appear to fall into three types. Some are *procedural*, in the sense that they refer to details of the events, such as whether the shooter was killed or captured, or whether the motive was clear or unclear; others have to do with the perpetrators *mental, behavioural, or emotional state*; the last has more to do with the perpetrators *identity*, especially in terms of ideas such as race, religion, and citizenship. Unsurprisingly, individual perpetrators may be framed differently in different articles, but closer inspection suggests that in most cases, a dominant framing tends to emerge.

Terms	Type
first second next former last lone prime high unknown recent final senior	procedural
active unclear alleged former potential small confident suspected	procedural
dead pronounced relative nearby loose armed civilian open former adult	procedural
clear able deranged bizarre unable self-inflicted murderous innocent	mental / behavioural
good different strange late bad difficult nice last odd unclear dangerous	mental / behavioural
able mental young much little intelligent likely psychiatric bright afraid	mental / behavioural
quiet calm sorry former polite smart shy respectful guilty reserved real	mental / behavioural
white black young male suspect unemployed stocky recent crucial racist	identity
muslim american immigrant religious multiple gay fifth possible naturalized	identity

Table 6: Set of example dimensions (ways of characterizing perpetrators) learned using the Scholar framework. Note that "black" here more often refers to clothing than to race.

However, we are interested in whether the framing of perpetrators differs between those conceptualized as "white" or not. For example, if we compare the two shootings that took place at Fort Hood (2009 and 2014), both resulted in articles using a multitude of different dominant framings (as identified by our model). The later event, perpetrated by a white shooter, was clearly dominated by a mental health frame (`able mental young much little intelligent likely psychiatric bright afraid`). The earlier event, by contrast, was dominated by reporting which emphasized the perpetrator's identity (`muslim american immigrant religious multiple gay fifth possible naturalized`).

In order to analyze this at a broader scale, we experiment with a model in which we include this information as a label to be predicted (y_i in equation (4)). If we re-run the same model, but include whether or not an individual could be characterized as *white*, this information exerts a subtle influence on the model, and encourages it to learn topics that are useful in predicting this attribute.

Figure 7 shows an updated set of dimensions, along with the predicted probability of a perpetrator being white, if the description were given entirely in terms of that dimension.

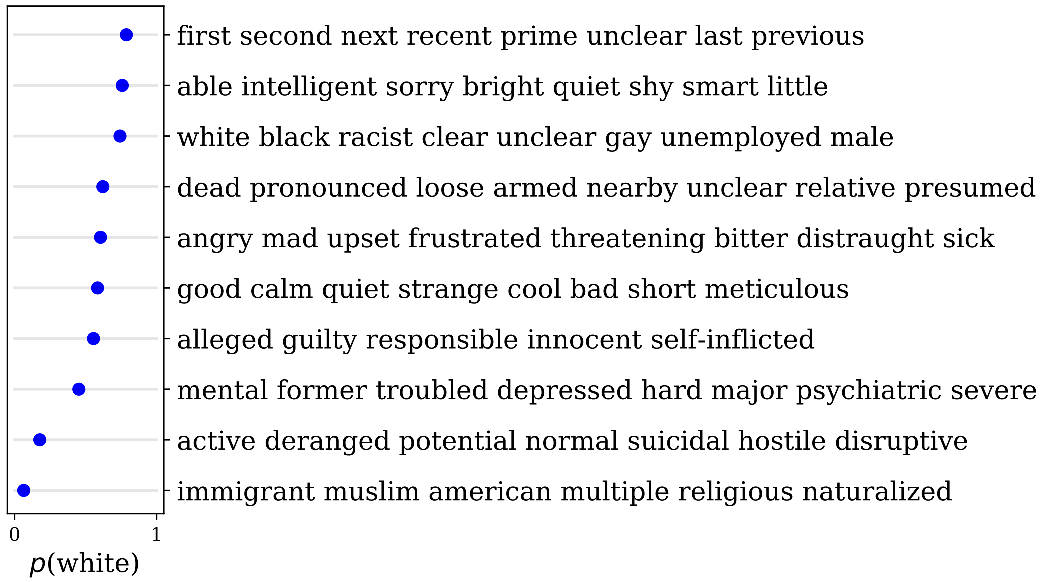

Figure 7: Latent dimension learned by the Scholar framework when using white/non-white as a label to be predicted, along with predicted probability of a perpetrator being white per dimension.

If we examine two the topics most associated with "whiteness", we find a procedural topic and a topic that has a notable sympathetic slant - `able intelligent sorry bright quite shy smart little`. However, if we examine the two topics most likely to be associated with being *non*white, we see a more nefarious frame: one racialized topic about islam and immigrant status and one with a decidedly *un*sympathetic frame: `active deranged potential normal suicidal hostile disruptive`.

Noise in the process at various stage (data collection, identifying entity mentions, and coreference), and relative lack of data (which means that the results of the unsupervised model are not completely stable) make these findings preliminary. Nevertheless, these broader patterns are highly suggestive of a relationship between the perpetrator's racialization and the language used to describe the incident.

5 Conclusion

While preliminary, the above results present suggestive evidence there there may be a relationship between the social construction of a perpetrator's race and their likelihood of being considered a terrorist in the news. Preliminary regression analysis and results from the Scholar model, as well as anecdotal qualitative evidence, appear to demonstrate that a) a perpetrator being cast as Middle Eastern or Muslim appears to correlate with an event being considered terrorism; b) negative frames are more likely to be associated with people of color; and c) there is some evidence that sympathetic frames may be more likely to be associated with the shooter's probability of being white. Finally, some preliminary statistical models demonstrate an inverse relationship between mentions of terrorism and mental health in the news: those who are considered terrorists are less likely to be talked about as having mental health problems, and those who are talked about as having mental health problems are unlikely to be called terrorists.

There are necessary caveats to any study in with a limited universe of events, and particularly a limited universe of "positive" observations of an event (in our case, mass shootings that are also terrorism). As well, we hesitate to make to large of generalizations to other sorts of violence from the universe of mass shooting events, and plan to extend this study to include other types of violent events in the United States (e.g. bombings or attempted bombings). Likewise, the methods presented here, particularly the unsupervised methods and lexical matching, have a chance of both false positive and negatives. However, the triangulation of three different methods (qualitative analysis, statistics and unsupervised methods) gives us confidence in our findings. Finally, we believe further research is necessary to understand how these dynamics work when dealing with groups, rather than individuals alone. We plan to evaluate both violent and nonviolent groups (e.g. Black Lives Matter protests vs. KKK protests) and determine which groups are most likely to be referred to as terrorist in the news.

This study has important implications for the academic study of terrorism (and violence more generally), policy makers inferences from academic and think-tank reports about terrorism's causes and consequences, news caster's future discussion of violent events, and most especially, for people of color, members of minority religions and immigrants in the United States. Our preliminary findings indicate that there is racial and religious bias in how events become counted as terrorism in the news. If these preliminary findings hold, the racial identity of the perpetrator may influence which violent acts get officially designated as terrorism by experts as well. This may mean that the some 379 studies on google.scholar which cite the GTD (LaFree and Dugan, 2007) or other terrorism databases may also have racial, religious and anti-immigrant bias in their findings. Policy inferences drawn from those studies may likewise be geared towards disproportionately criminalizing people of color.

We therefore close by identifying troubling policy implications of these results. Terrorist designations can justify policies that encourage national security profiling, punitive approaches to law enforcement, and racially discriminatory criminal justice policies. When racialized, terrorism designations produce disproportionately severe penalties for non-white perpetrators.[51] Furthermore, policymakers use terrorist designations to justify policies which disproportionately target minorities and immigrants as national security threats[52] despite dubious evidence (Barrett, 2018).[53] Meanwhile, white-perpetrated mass shootings generate advocacy for mental health reforms (Steinberg, 2012; Turndorf, 2012), which induce sympathy for white perpetrators (Dixon and Linz, 2000b; Mingus and Zopf, 2010), reinforce existing racial and gender stereotypes (Metzl and MacLeish, 2015) that link criminality to racialized perpetrators (Gilliam Jr et al., 1996; Paulsen, 2003; Walker et al., 2018), and erroneously stigmatizes people who face mental illness as predisposed to violence (Fox and Fridel, 2016). Emphases on terrorism disproportion-

[51] Because terrorism as a federal charge (thus more severe), while other violent crimes (shootings, homicides) are the purview of the states, terrorism carries particular policy weight. On the other hand, federal charges can be harder to prosecute, which can dissuade police from treating an an event as terrorism (Reilly, 2018).

[52] Because of the severity of the required in response to terrorism, such events can be used to create "states of exception" (Agamben, 2005) and also provide effective fodder for threat construction: state use terrorism to shore up their own security (Hodges, 2011).

[53] This has life-and-death consequences for immigrants and refugees hoping to escape violence in their home countries and build a safe, prosperous life in the United States (Powell, 2011). However, the Trump Administration (like others before it) have rallied perceptions of immigrant violence to justify excessively harsh immigration policy (BERENSON, 2018; Davis and Nixon, 2018; June 18 et al., 2018; Valverde, 2018).

ately elevate terrorist threats and redirect federal funds to fight terrorism rather than addressing U.S. quotidian violence,[54] which kills exponentially more Americans—especially among minority communities (Ferdman, 2014; Fingerhut et al., 1998)—every year (BBC, 2016).[55]

This study serves as a framework for considering how racism can insidiously sneak into policy making at the national and international level. Such subtle bias can perpetuate a system of state-based punitive measures that racializes and disproportionately targets immigrants and people of color. In short, we believe racial bias continues to permeate national and international policy, and with real, felt implications for the lives of communities of color.

10215 (errors:1) words

References

Giorgio Agamben. *State of exception*, volume 2. University of Chicago Press, 2005.

David Bamman, Brendan O'Connor, and Noah A. Smith. Learning latent personas of film characters. In *Proceedings of ACL*, 2013.

Devlin Barrett. Trump administration links terrorism and immigration, but an expert doubts the math. 2018. ISSN 0190-8286. URL https://www.washingtonpost.com/world/national-security/trump-administration-links-terrorism-and-immigration-but-an-expert-doubts-the-math/2018/01/16/1b9d41ae-fac8-11e7-a46b-a3614530bd87_story.html.

James R Barrett and David Roediger. How white people became white. *White privilege*, pages 29–34, 2002.

BBC. Statistics behind US violence. 2016. URL https://www.bbc.com/news/world-us-canada-34996604.

TESSA BERENSON. 'they're permanently separated.' president trump compares people killed by undocumented immigrants to border separations, 2018. URL http://time.com/5320128/trump-undocumented-violence-border-separation/.

Gerlof Bouma. Normalized (pointwise) mutual information in collocation extraction. In *From Form to Meaning: Processing Texts Automatically, Proceedings of the Biennial GSCL Conference 2009*, 2009. URL https://svn.spraakdata.gu.se/repos/gerlof/pub/www/Docs/npmi-pfd.pdf.

Alex Braithwaite and Quan Li. Transnational terrorism hot spots: Identification and impact evaluation. *Conflict Management and Peace Science*, 24(4):281–296, 2007.

Daniel José Camacho. Why mark anthony conditt – a white christian – isn't called a terrorist | daniel josé camacho. 2018. ISSN 0261-3077. URL http://www.theguardian.com/commentisfree/2018/mar/23/mark-anthony-conditt-terrorism-christianity.

[54] The United States has spent more a trillion dollars since 911 defending against terrorism, which by any measure kills a fraction of the number of people that quotidian gun violence does (BBC, 2016).

[55] The U.S. homicide rate is significantly higher than that of any other industrialized democracy, and roughly 60 percent of those are gun deaths. There were approximately 1.4 million firearm deaths between 1968 and 2011, compared with 1.2 million U.S. casualties in all wars the U.S. has fought since its independence from Britain.

Dallas Card, Justin H. Gross, Amber E. Boydstun, and Noah A. Smith. Analyzing framing through the casts of characters in the news. In *EMNLP*, 2016.

Dallas Card, Chenhao Tan, and Noah A. Smith. Neural models for documents with metadata. In *Proceedings of ACL*, 2018.

Erica Chenoweth. Yes, mass shootings tend to produce copycats. so do terror attacks. 2015. ISSN 0190-8286. URL https://www.washingtonpost.com/news/monkey-cage/wp/2015/12/04/yes-mass-shootings-tend-to-produce-copycats-so-do-terror-attacks/.

Steven M Chermak and Jeffrey Gruenewald. The media's coverage of domestic terrorism. *Justice Quarterly*, 23(4):428–461, 2006.

Hsiang Iris Chyi and Maxwell McCombs. Media salience and the process of framing: Coverage of the columbine school shootings. *Journalism & Mass Communication Quarterly*, 81(1): 22–35, 2004.

Craig Considine. The racialization of islam in the united states: Islamophobia, hate crimes, and "flying while brown". *Religions*, 8(9):165, 2017.

Martha Crenshaw. The psychology of terrorism: An agenda for the 21st century. *Political psychology*, 21(2):405–420, 2000.

Francisco Cribari-Neto and Achim Zeileis. Beta regression in r. 2009.

Julie Hirschfeld Davis and Ron Nixon. White house fuels immigration debate with terrorism statistics. 2018. ISSN 0362-4331. URL https://www.nytimes.com/2018/01/16/us/politics/trump-immigration-terror-convictions.html.

Travis L Dixon. 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, 2017.

Travis L Dixon and Daniel Linz. Overrepresentation and underrepresentation of african americans and latinos as lawbreakers on television news. *Journal of communication*, 50(2):131–154, 2000a.

Travis L Dixon and Daniel Linz. Race and the misrepresentation of victimization on local television news. *Communication research*, 27(5):547–573, 2000b.

David Domke. Racial cues and political ideology: An examination of associative priming. *Communication Research*, 28(6):772–801, 2001.

David Domke, Kelley McCoy, and Marcos Torres. News media, racial perceptions, and political cognition. *Communication Research*, 26(5):570–607, 1999.

William Edward Burghardt Du Bois. The souls of white folk. In *Darkwater: Voices from Within the Veil*, chapter 2. Harcourt, Brace and Company, New York, 1920.

Jacob Eisenstein, Amr Ahmed, and Eric P. Xing. Sparse additive generative models of text. In *Proceedings of ICML*, 2011.

Roberto A. Ferdman. The racial divide in america's gun deaths. 2014. ISSN 0190-8286. URL https://www.washingtonpost.com/news/wonk/wp/2014/09/19/the-racial-divide-in-americas-gun-deaths/.

Lois A Fingerhut, Deborah D Ingram, and Jacob J Feldman. Homicide rates among us teenagers and young adults: differences by mechanism, level of urbanization, race, and sex, 1987 through 1995. *JAMA*, 280(5):423–427, 1998.

John R. Firth. *Papers in Linguistics 1934-–1951*. Oxford University Press, 1957.

James Alan Fox and Emma E Fridel. The tenuous connections involving mass shootings, mental illness, and gun laws. *Violence and gender*, 3(1):14–19, 2016.

Paul Foy. Utah mall reopens after deadly shooting, February 2007. URL http://www.washingtonpost.com/wp-dyn/content/article/2007/02/14/AR2007021400102.html.

Emily Kalah Gade. Defining the non-combatant: How do we determine who is worthy of protection in violent conflict? *Journal of Military Ethics*, 9(3):219–242, 2010.

Jürgen Gerhards and Mike S Schäfer. International terrorism, domestic coverage? how terrorist attacks are presented in the news of cnn, al jazeera, the bbc, and ard. *International Communication Gazette*, 76(1):3–26, 2014.

Franklin D Gilliam Jr, Shanto Iyengar, Adam Simon, and Oliver Wright. Crime in black and white: The violent, scary world of local news. *Harvard International Journal of press/politics*, 1(3):6–23, 1996.

Sandra Graham and Brian S Lowery. Priming unconscious racial stereotypes about adolescent offenders. *Law and human behavior*, 28(5):483, 2004.

Kory Grow. Mass shootings dramatically on the rise, fbi says, 2014. URL https://www.rollingstone.com/culture/culture-news/mass-shootings-dramatically-on-the-rise-fbi-says-67878/.

William L. Hamilton, Jure Leskovec, and Dan Jurafsky. Diachronic word embeddings reveal statistical laws of semantic change. In *Proceedings of ACL*, 2016.

Michael Harriot. If the texas church shooter wasn't white, 2018. URL https://www.theroot.com/if-the-texas-church-shooter-wasnt-white-1820203320.

Adam Hodges. *The" War on terror" narrative: discourse and intertextuality in the construction and contestation of sociopolitical reality*. OUP USA, 2011.

Jacqueline S. Hodgson and Victor Tadros. The impossibility of defining terrorism. *New Criminal Law Review: In International and Interdisciplinary Journal*, 16(3):494–526, 2013.

Bruce Hoffman. Defining terrorism. *Social Science Record*, 24(1):6–7, 1986.

John Horgan. Leaving terrorism behind: An individual perspective. *Terrorists, victims and society: Psychological perspectives on terrorism and its consequences*, pages 109–130, 2003.

Connor Huff and Joshua D Kertzer. How the public defines terrorism. *American Journal of Political Science*, 62(1):55–71, 2018.

CBS/AP June 18, 2018, and 10:00 Am. U.n. rights chief: Migrant family separations "unconscionable", 2018. URL `https://www.cbsnews.com/news/trump-policy-migrant-family-separation-parents-children-unconscionable-un-says/`.

Daniel Kahneman and Patrick Egan. *Thinking, fast and slow*, volume 1. Farrar, Straus and Giroux New York, 2011.

Daniel Kanstroom. Criminalizing the undocumented: Ironic boundaries of the post-september 11th pale of law. *NCJ Int'l L. & Com. Reg.*, 29:639, 2003.

Erin Kearns, Allison Betus, and Anthony Lemieux. Why do some terrorist attacks receive more media attention than others? *Justice Quarterly*, 2018.

Diederik P Kingma and Max Welling. Auto-encoding variational bayes. In *Proceedings of ICLR*, 2014.

Audrey Kobayashi and Linda Peake. Racism out of place: Thoughts on whiteness and an antiracist geography in the new millennium. *Annals of the association of American geographers*, 90(2):392–403, 2000.

Vivek Kulkarni, Rami Al-Rfou, Bryan Perozzi, and Steven Skiena. Statistically significant detection of linguistic change. In *Proceedings of the 24th International Conference on World Wide Web*, 2015.

Andrew H Kydd and Barbara F Walter. The strategies of terrorism. *International Security*, 31 (1):49–80, 2006.

Gary LaFree and Laura Dugan. Introducing the global terrorism database. *Terrorism and Political Violence*, 19(2):181–204, 2007.

Robin Tolmach Lakoff. *The Language War*. University of California Press, Berkeley, CA, 2000.

Richard R Lau and David P Redlawsk. Advantages and disadvantages of cognitive heuristics in political decision making. *American Journal of Political Science*, pages 951–971, 2001.

Kenton Lee, Luheng He, Mike Lewis, and Luke Zettlemoyer. End-to-end neural coreference resolution. In *Proceedings of EMNLP*, 2017.

Omer Levy and Yoav Goldberg. Neural word embedding as implicit matrix factorization. In *Advances in Neural Information Processing Systems 27*, 2014. URL `http://papers.nips.cc/paper/5477-neural-word-embedding-as-implicit-matrix-factorization.pdf`.

Brendan Maguire, Georgie Ann Weatherby, and Richard A Mathers. Network news coverage of school shootings. *The Social Science Journal*, 39(3):465–470, 2002.

Jenna McLaughlin. Why wasn't dylann roof charged with terrorism?, 2015. URL `https://theintercept.com/2015/07/22/department-justice-didnt-charge-dylan-roof-domestic-terrorism/`.

Jonathan M Metzl and Kenneth T MacLeish. Mental illness, mass shootings, and the politics of american firearms. *American journal of public health*, 105(2):240–249, 2015.

Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg S Corrado, and Jeff Dean. Distributed representations of words and phrases and their compositionality. In *Advances in neural information processing systems*, pages 3111–3119, 2013.

Teresa A Miller. Blurring the boundaries between immigration and crime control after september 11th. *BC Third World LJ*, 25:81, 2005.

William Mingus and Bradley Zopf. White means never having to say you're sorry the racial project in explaining mass shootings. *Social Thought & Research*, pages 57–77, 2010.

Glenn W Muschert. Research in school shootings. *Sociology Compass*, 1(1):60–80, 2007.

Brigitte L Nacos. Revisiting the contagion hypothesis: Terrorism, news coverage, and copycat attacks. *Perspectives on Terrorism*, 3(3):3–13, 2009.

Joane Nagel. Constructing ethnicity: Creating and recreating ethnic identity and culture. *Social problems*, 41(1):152–176, 1994.

Paul S Nelson and John L Scott. Terrorism and the media: An empirical analysis. *Defence and Peace Economics*, 3(4):329–339, 1992.

Julie Netherland and Helena Hansen. White opioids: Pharmaceutical race and the war on drugs that wasn't. *BioSocieties*, 12(2):217–238, 2017.

Julie Netherland and Helena B Hansen. The war on drugs that wasn't: wasted whiteness,"dirty doctors," and race in media coverage of prescription opioid misuse. *Culture, Medicine, and Psychiatry*, 40(4):664–686, 2016.

Michael Omni, Howard Winant, et al. Racial formation in the united states. *N. York: Routledge*, 1994.

Zizi Papacharissi and Maria de Fatima Oliveira. News frames terrorism: A comparative analysis of frames employed in terrorism coverage in us and uk newspapers. *The International Journal of Press/Politics*, 13(1):52–74, 2008.

Robert Anthony Pape. *Dying to win: The strategic logic of suicide terrorism.* Random House Incorporated, 2006.

Derek J Paulsen. Murder in black and white: The newspaper coverage of homicide in houston. *Homicide Studies*, 7(3):289–317, 2003.

Brian J. Phillips. Was what happened in charleston terrorism? 2015. ISSN 0190-8286. URL `https://www.washingtonpost.com/news/monkey-cage/wp/2015/06/18/was-what-happened-in-charleston-terrorism/`.

Vincent Pouliot. Practice Tracing. In Andrew Bennett and Jeffry T. Checkel, editors, *Process Tracing: From Metaphor to Analytic Tool*, pages 237–259. Cambridge University Press, New York, 2015.

Kimberly A Powell. Framing islam: An analysis of us media coverage of terrorism since 9/11. *Communication Studies*, 62(1):90–112, 2011.

Ryan J. Reilly. There's a good reason feds don't call white guys terrorists, says DOJ domestic terror chief. 2018. URL https://www.huffingtonpost.com/entry/white-terrorists-domestic-extremists_us_5a550158e4b003133ecceb74.

Paul B. Rich. Understanding terror, terrorism, and their representations in media and culture. *Studies in Conflict & Terrorism*, 36:255–277, 2013.

Molly Roberts, Brandon Stewart, Dustin Tingley, Christopher Lucas, Jetson Leder-Luis, Shana Gadarian, Bethany Albertson, and David Rand. Structural topic models for open ended survey responses. *American Journal of Political Science*, 58:1064–1082, 2014.

LA Rotenberg and Robert L Sadoff. Who should have a gun? some preliminary psychiatric thoughts. *American Journal of Psychiatry*, 125(6):841–843, 1968.

Charles L Ruby. The definition of terrorism. *Analyses of social issues and public policy*, 2(1): 9–14, 2002.

Nel Ruigrok and Wouter Van Atteveldt. Global angling with a local angle: How us, british, and dutch newspapers frame global and local terrorist attacks. *Harvard International Journal of Press/Politics*, 12(1):68–90, 2007.

Sarah Ruiz-Grossman. The double standard in how the media is portraying the las vegas shooter. 2017. URL https://www.huffingtonpost.com/entry/double-standard-white-privilege-media-las-vegas-shooting_us_59d3da15e4b04b9f92058316.

Evan Sandhaus. The new york times annotated corpus, 2008. URL https://catalog.ldc.upenn.edu/ldc2008t19.

Jaclyn Schildkraut and Glenn W Muschert. Media salience and the framing of mass murder in schools: A comparison of the columbine and sandy hook massacres. *Homicide studies*, 18(1): 23–43, 2014.

Frank Schimmelfennig. Efficient Process Tracing: Analyzing the causal mechanisms of European integration. In Andrew Bennett and Jeffry T. Checkel, editors, *Process Tracing: From Metaphor to Analytic Tool*, pages 98–125. Cambridge University Press, New York, 2015.

Alex P Schmid. Frameworks for conceptualising terrorism. *Terrorism and political violence*, 16 (2):197–221, 2004.

Anne Schneider and Helen Ingram. Social construction of target populations: Implications for politics and policy. *The American Political Science Review*, 87(2):334–347, 1993.

Sameer Singh, Sebastian Riedel, Brian Martin, Jiaping Zheng, and Andrew D McCallum. Joint inference of entities, relations, and coreference. In *AKBC@CIKM*, 2013.

Stephen Speckman, Ben Winslow, and Deborah Bulkeley. Cannon takes back 'allah' quote, 2007. URL https://www.deseretnews.com/article/660197676/Cannon-takes-back-Allah-quote.html.

Paul Steinberg. Opinion | our failed approach to schizophrenia. 2012. ISSN 0362-4331. URL https://www.nytimes.com/2012/12/26/opinion/our-failed-approach-to-schizophrenia.html.

Jeff Stone, W Perry, and John M Darley. " white men can't jump": Evidence for the perceptual confirmation of racial stereotypes following a basketball game. *Basic and Applied Social Psychology*, 19(3):291–306, 1997.

Jeffrey W Swanson, E Elizabeth McGinty, Seena Fazel, and Vickie M Mays. Mental illness and reduction of gun violence and suicide: bringing epidemiologic research to policy. *Annals of epidemiology*, 25(5):366–376, 2015.

Jamie Turndorf. Was adam lanza an undiagnosed schizophrenic?, 2012. URL `http://www.psychologytoday.com/blog/we-can-work-it-out/201212/was-adam-lanza-undiagnosed-schizophrenic`.

Miriam Valverde. Trump admin. misleads tying terrorism report to immigration, 2018. URL `http://www.politifact.com/truth-o-meter/article/2018/jan/22/donald-trumps-team-misleads-tying-international-te/`.

Baldwin Van Gorp. Strategies to take subjectivity out of framing analysis. In Paul D'Angelo and Jim A. Kuypers, editors, *Doing News Framing Analysis: Empirical and Theoretical Perspectives*, chapter 4, pages 84–109. Routledge, 2010.

Hannah Walker, Loren Collingwood, and Tehama Bunyasi. White response to black death: How group empathy shapes responses to gun violence. 2018.

Gabriel Weimann and Hans-Bernd Brosius. The newsworthiness of international terrorism. *Communication Research*, 18(3):333–354, 1991.