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Why Do Some Terrorist Attacks Receive More Media Attention Than Others?

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ABSTRACT

Terrorist attacks often dominate news coverage as reporters seek to provide the public with information. Yet, not all incidents receive equal attention. Why do some terrorist attacks receive more media coverage than others? We argue that perpetrator religion is the largest predictor of news coverage, while target type, being arrested, and fatalities will also impact coverage. We examined news coverage from LexisNexis Academic and CNN.com for all terrorist attacks in the United States between 2006 and 2015 ($N = 136$). Controlling for target type, fatalities, and being arrested, attacks by Muslim perpetrators received, on average, 357% more coverage than other attacks. Our results are robust against a number of counterarguments. The disparities in news coverage of attacks based on the perpetrator's religion may explain why members of the public tend to fear the "Muslim terrorist" while ignoring other threats. More representative coverage could help to bring public perception in line with reality.

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Introduction

On February 6, 2017, President Trump stated that media neglect to report some terrorist attacks.[1] His administration released a list of purportedly underreported attacks. The list included attacks that occurred in many countries and the perpetrators were overwhelmingly Muslim. Reporters and academics were quick to dismiss President Trump's claim and demonstrate that these attacks were covered, often extensively.[2] As we will show here, it turns out that President Trump was correct: media do not cover some terrorist attacks at all, while others receive disproportionate coverage. This

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[1]https://www.washingtonpost.com/news/politics/wp/2017/02/06/president-trump-is-now-speculating-that-the-media-is-covering-up-terrorist-attacks/?utm_term=.b23ffe5a9113

[2]https://www.theatlantic.com/politics/archive/2017/02/trump-centcom-media-terror-cover-up/515823/; http://time.com/4489405/americans-fear-of-foreign-terrorists/

project addresses the question: Why do some terrorist attacks[3] receive more media coverage than others?

Media are naturally drawn to covering ongoing or potential conflicts, especially those which are shocking or sensational (Tuman, 2010). Research has demonstrated that terrorism is most effective at spreading fear when given widespread media coverage (Powell, 2011). Most research on media coverage of terrorism has focused on framing and its impact on public opinion (Norris, Kern, & Jost, 2003; Powell, 2011; Ruigrok & van Attevelt, 2007). While framing impacts perceptions, the underlying assumption here is that coverage exists in the first place. A few studies have focused on the *quantity* of media coverage rather than the context. From this small body of research, it is clear that incident-level factors can impact the amount of media coverage that terrorist attacks receive (Chermak & Gruenewald, 2006; Nacos, 2002; Persson, 2004). Weimann and Brosius (1991) also found that perpetrator nationality impacts the amount of media coverage that international terrorist attacks receive. Yet, these works are largely focused on the pre-9/11, pre-digital media age factors that may impact the extent and nature of coverage disparities. Additionally, these studies do not focus on perpetrator religion as a key predictor of coverage in the context of domestic terrorism.

The amount of coverage that an incident receives increases public awareness, while signifying that the event is worthy of public attention. Media frames matter but can only have influence if they reach an audience. To understand the reach of coverage, we must examine *how much* media covers terrorist attacks in addition to examining *how* terrorism is covered. This study addresses two gaps in the literature: 1) factors that explain differences in the *quantity* of media coverage that terrorist attacks receive post-9/11 and in the digital media age and 2) how perpetrator religion impacts these coverage disparities.

We examined media coverage of terrorist attacks in the United States to understand why some receive *more* coverage than others. Our paper is organized as follows: First, we engage with the literature on media coverage of violence, crime, and terrorism, and discuss factors that impact why some events receive more coverage than others. Following this, we discuss our methodological approach to examining media coverage of terrorism, our sample, and our analyses. Lastly, we conclude with the results of this study, how they pertain to policy and public perception, and avenues for future research.

Media coverage

Why media coverage matters

Most of the information we get about the world outside of our local context comes from media. As such, media play a vital role in how we form ideas about people, places, and things which we have not personally experienced (McCombs, 2003). Media attention lends legitimacy to the voices and frames – the conceptions and

[3]In the current study, the definitional criteria for what constitutes terrorism have been established in the development of the Global Terrorism Database (GTD) by the National Consortium for the Study of Terrorism and Responses to Terrorism (2016). According to the GTD Codebook, terrorism is "the 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." Additional details about the definition of terrorism used in the GTD are available at http://www.start.umd.edu/gtd/using-gtd/. See Schmid (2013) for a more detailed discussion of the challenges related to defining terrorism, along with consideration of over 250 definitions that have been applied over time.

organizations of information that help us understand the world around us – that are chosen to be featured (Bekkers, Beunders, Edwards, & Moody, 2011). Media coverage also amplifies incidents and ideas by providing a platform to spread certain positions and perspectives to a broader audience (Bekkers, Beunders, Edwards, and Moody, 2011). This platform is further expanded by members of the public disseminating media amongst themselves (Nacos, 2002). In a recent study, King, Schneer, and White (2017) found that media coverage of subjects of the researchers' choosing significantly increased online discussion of that topic immediately and this effect persisted for nearly a week. People also discuss news media content in various forums, resulting in further – not necessarily accurate – analysis of the information provided.

The rapid spread of information – regardless of its veracity – is especially common when focusing events occur. A focusing event is a sudden, attention-grabbing event that draws public awareness to an issue (Kingdon, 1995). In addition to being attention-grabbing and easy to politicize, focusing events are also relatively uncommon, reveal a cause of harm or potential harm, and are depicted as being particular to certain areas or groups (Kingdon, 1995). When something becomes a focusing event, debates and discussions surrounding certain policy topics markedly increase and receive greater media attention (Kingdon, 1995). Media coverage does not necessarily determine how we feel about these issues, but it sets the tone for which issues we discuss and how we discuss them (McCombs, 2003).

Particularly when discussing an issue that people do not directly experience, media creates a perspective for viewers that may be incongruent with reality (Gerbner, 1998). Media are primarily responsible for providing information, and thus frames, to the public in the aftermath of a terrorist attack (Altheide, 1987). There is clear evidence that media coverage impacts public perception across a host of topics including civic engagement (McCarthy, McPhail, & Smith, 1996), mental health issues (Stack, 2003), and national security threats (Slone, 2000). Further, both news media (Graziano, Schuck, & Martin, 2010; Miller & Davis, 2008; Weitzer & Tuch, 2005) and entertainment media (Callanan & Rosenberger, 2011; Donahue & Miller, 2006; Donovan & Klahm, 2015; Eschholz, Blackwell, Gertz, & Chiricos, 2002; Kearns & Young, 2017) impact the public's views of crime and justice. When people do not have direct experience with a topic – as is almost always the case for terrorism – media depictions are especially impactful (Adoni & Mane, 1984). Moreover, media are primarily responsible for providing information to the public, who use that information to contextualize and understand terrorism.

When news media spend time on an issue, this suggests to the public that the topic is valid and important for understanding the world around them. The amount of attention that a story gets is an indicator of its importance (McCombs, 2003). The "CNN effect" – whereby media influence politics and government during conflict and natural disasters – suggests that media framing can impact public opinion and potentially sway policy decisions (Gilboa, 2005). Exposure to media coverage of terrorist attacks is positively correlated to perceived personal risk for being victimized, fear of others (Nellis & Savage, 2012), and short-term anxiety levels (Slone, 2000). Media are especially impactful at setting public discourse and, as a result, influencing public opinion in regard to limiting or protecting personal freedoms and civil liberties, as they feature and prioritize certain political viewpoints and narratives over others

(Guasti & Mansfeldova, 2013; Hall, 2012; Norris, Kern, & Just, 2003). Political organizations use media to set the priorities of the public (Chermak, 2003), which means that biases in media reporting can have real-world consequences. In short, media coverage influences public opinion and perceptions of the world, which can, in turn, influence how the public perceives relevant people, policies, and groups.

Media coverage of violence

In the United States, violent crime has been declining steadily for the past twenty years,[4] yet public perceptions of violent crime do not reflect this.[5] In fact, as the violent crime rate in the United States decreases, people still perceive that it is increasing (Gramlich, 2017). Media may influence this disparity in perceptions of violence. For example homicides receive a disproportionate amount of news coverage relative to both the actual risk of being victimized and the frequency of the crime (Paulsen, 2003; Peelo, Francis, Soothill, Pearson, & Ackery, 2004; Sorenson, Manz, & Berk, 1998). Violence, broadly construed, is one of the most prominent topics in the news media, and enjoys something of a privileged position, yet it is rare in day-to-day life for much of the audience. Slone (2000) argues that media influence increases as actual experience with a problem decreases, which could explain this discrepancy between real and perceived violent crime rates. Taking this into account, perhaps it is unsurprising that half of Americans are concerned that they or a family member will be the victim of a terrorist attack, despite the actual risk being minuscule (Jones & Cox, 2015).

Of course, media covering a topic does not necessarily indicate its subjective (or, indeed, objective) relevance for a given individual or the public at large. An event may be attention-grabbing but lose relevance quickly. For a topic to maintain relevance, it must receive ongoing coverage by the media for approximately one to eight weeks (Coleman, McCombs, Shaw, & Weaver, 2009). The perceived relevance of an incident fades as time passes without the media referring to it (Coleman et al., 2009). Given the current "infotainment" format of news media, stories are selected for coverage based on how much attention they can potentially attract (Xiang & Sarvary, 2007). Coverage of violence fills that role, while also potentially providing useful information to the viewer.

Media coverage of terrorism

While some terrorist attacks are sensationalized and extensively covered, the majority receive little to no media attention (Chermak & Gruenewald, 2006). An issue's relevance influences the amount of media coverage that it receives (McCarthy et al., 1996). Some terrorist attacks may be deemed more relevant than others due to their inherently political, attention-grabbing nature, and potential to be a focusing event. Terrorism lends itself to being used as a focusing event, as it is uncommon and can raise awareness of potential weak points in national security. To give a few recent examples, media coverage of Dylann Roof's terrorist attack against the congregation

[4]https://ucr.fbi.gov/crime-in-the-u.s/2013/crime-in-the-u.s.-2013/violent-crime/violent-crime-topic-page/violentcrimemain_final
[5]http://www.pewresearch.org/fact-tank/2016/11/16/voters-perceptions-of-crime-continue-to-conflict-with-reality/

of the Emanuel African Methodist Episcopal Church sparked fierce debates about the Confederate Flag and gun control policy in the United States. Robert Lewis Dear's attack on a Planned Parenthood facility was used to argue that promoting misleading information could have deadly consequences. In short, these attacks are used as focusing events, shifting the public discourse to political topics secondary to terrorism itself and often facilitating or inspiring new policy.

Brian Jenkins (1974, p. 4) stated that "terrorism is theater," a metaphor reflecting that perpetrators engage in violence to communicate with an audience. Media coverage of attacks amplifies a group's messaging and sensationalizes the event (Picard, 1993). In this respect, media and terrorist groups have a mutually reinforcing relationship. Yet, media do not cover all terrorism equally. Focusing on terrorism in the United States between 1980 and 10 September 2001, Chermak and Gruenewald (2006) found that attacks received more coverage if there were casualties, if it was a hijacking, if an airline was targeted, or if domestic groups were involved. In this study, perpetrator identity was not considered as a factor that would impact the amount of coverage an attack receives. Even minor attacks may receive coverage if the target, location, or groups involved are of high symbolic or political significance to the public (Nacos, 2002). Further, evidence suggests that a terrorist attack will receive less coverage if it is framed as a crime (Persson, 2004). Whether an attack is framed as terrorism or a crime is complicated by the fact that there is no one accepted definition of terrorism to rely on, even among experts (Schmid, 2013; Spaaij & Hamm, 2015). Indeed, there are myriad potential factors that can impact why a particular terrorist attack receives more news coverage than others. We are interested in how the following factors influence the amount of news coverage that a given terrorist attack will receive: who committed the attack, what the target was, and how many people were killed.

Who is the perpetrator?

Events are more newsworthy if they can be typified as reflecting current beliefs and social structure, and can be scripted in ways that reinforce stereotypes (Lundman, 2003). Consistent with the social identity perspective (Tajfel & Turner, 1986), media in the predominantly white, Christian United States may portray members of this in-group in a more favorable way than people who are not members of the majority race or religion. In the context of entertainment media, such as *24* or *Homeland*, we generally see Muslim or Arab actors portraying terrorists while white actors play the hero (Alsultany, 2012). In fact, Shaheen (2012) found clear evidence that most Arab movie characters are portrayed as dangerous stereotypes – as sub-human or villains – while Arab protagonists often have surprisingly Caucasian features. Similarly, in news media, perpetrators of terrorism are disproportionately non-white (Gilliam & Iyengar, 2000).

While perhaps not intentional, it seems unlikely that disparities in entertainment media coverage based on race and religion are coincidental. Media coverage may explain public perceptions of terrorism and identity. Evidence suggests that, to Americans, there is an implicit association between terrorism, people of Middle Eastern descent, and Islam (Alsultany, 2012; Gottschalk & Greenberg, 2008; Park, Felix, & Lee, 2007; Saleem & Anderson, 2013). In the United Kingdom, Muslims – particularly those who are foreign-born – are increasingly viewed as a national security threat

(Allouche & Lind, 2010). Huff and Kertzer (2017) found that members of the public are more likely to consider an attack terrorism when the perpetrator is Muslim. Similarly, when presented with news stories about real crimes, incidents committed by Muslims were more likely to be labeled as terrorism and were also judged more harshly (West & Lloyd, 2017).

Turning to media coverage of terrorism and identity, similar patterns emerge. Dixon and Williams (2015) found that Muslims were vastly overrepresented in broadcast media coverage of terrorism. Similarly, in two prominent Australian newspapers, news stories about Middle Eastern people often focused on terrorism, asylum seekers, and cultural practices that are alien to Western cultures (Akbarzadeh & Smith, 2005). Even in cases where the depictions of Muslims were sympathetic or neutral, media still positioned stories almost exclusively in ways that emphasized their otherness and dealt with the topic of terrorism (Akbarzadeh & Smith, 2005).

Media may frame terrorism as a specifically Muslim problem because that is a dominant narrative (Sultan, 2016). Domestic terrorism is often portrayed as a minor threat committed by mentally ill perpetrators, whereas terrorism influenced by radical interpretation of Islam is framed as a hostile outside force (Powell, 2011). If the perpetrators were Muslim and the victims Christian, the innocence and goodness of the victims and their spirituality will often be presented in juxtaposition with Islam (Powell, 2011). When the perpetrator(s) of a terrorist attack are members of an out-group or "other," we should expect to see more media coverage. Since discussions of terrorism and counterterrorism often overly focus on Muslim perpetrators,[6] we expect the following:

> H1: Terrorist attacks will receive more media coverage when the perpetrator is Muslim than when the perpetrator is not Muslim.

While we expect that the perpetrator's identity will be the strongest predictor of the amount of media coverage an attack receives, we anticipate other factors will have significant influence as well. Perpetrators of terrorist attacks may be apprehended, killed, or escape capture or identification. Perpetrators who are arrested provide more opportunities for media coverage as they are charged, stand trial, and, if found guilty, sentenced. Accordingly, we expect the following:

> H2: Terrorist attacks will receive more media coverage when the perpetrator is arrested than the perpetrator is not arrested.

What is the target?

The relative sociological relationship between a victim and offender influence the way in which law is applied for punishment (Black, 1976). Stemming from this dyadic perspective, the target type may influence media coverage of violence. In a study of international terrorism, attacks against politically significant targets received more coverage (Zhang, Shoemaker, & Wang, 2013). Members of the public are also more inclined to label an attack as "terrorism" when the target is governmental (Lemieux, Masyn, Betus, Karampelas, Garzon, Saleem, Lane & Kearns 2016). In so far as terrorism is a tactic to

[6]https://www.start.umd.edu/pubs/START_ECDB_IslamistFarRightHomicidesUS_Infographic_Feb2017.pdf

influence politics, attacks on governmental facilities or employees may generate increased media coverage. From this, we expected that:

H3: Terrorist attacks will receive more media coverage when the target is a governmental facility or employee(s) than when the target is non-governmental.

How many people were harmed?

The adage "if it bleeds it leads" suggests that news coverage focuses on violent or gory stories (Miller & Albert, 2015). When more people are killed in an attack, this can increase the shock value to viewers and increase fear of terrorism (Zhang Shoemaker, & Wang, 2013). Therefore, when there are more death and destruction, we should see more coverage (Nacos, 2002). As Chermak and Gruenewald (2006) found in a study of media coverage on domestic terrorism pre-9/11, at least one casualty led to both an increase in the number of articles written about that attack and the length of that article. Media may cover higher fatality count attacks more because death is both newsworthy and draws readers in. We expect that:

H4: Terrorist attacks will receive increased media coverage as the number of fatalities caused by the attack increases.

Alternative explanations

There are many potential idiosyncratic factors that impact media coverage of an event. We identify five testable counterarguments. First, white homicide victims receive more media coverage than minority victims (Gruenewald, Chermak, & Pizarro, 2013). Drawing from the disparities in homicide coverage, the discussion on out-groups, and the societal position of the victim(s), it is also possible that attacks against an out-group receive less media coverage. Second, symbolism can be important in terrorism. Certain dates, such as Hitler's birthday and the anniversary of 9/11, attract more violence.[7] When attacks occur within close proximity to these symbolic dates, they may receive more media coverage. Third, we may expect to see less media coverage when responsibility for the attack is unknown (Weimann & Brosius, 1991; Weimann & Winn, 1994). Fourth, we may expect to see more coverage when the individual(s) responsible are connected with a larger group that uses terrorism. Lastly, when classifying whether or not a violent incident is terrorism there can be insufficient or contradicting information that makes it difficult to make a definitive determination. If experts question whether or not an incident should be considered terrorism, members of the media may have similar difficulties. It is possible that classification differences can explain variation in coverage, potentially resulting in ambiguous cases receiving less media attention. We tested our argument on why some attacks received more media coverage than others against these alternatives. Additionally, some factors, such as a major event occurring at the same time to crowd out the news cycle, are difficult to operationalize and model. Whether or not a manhunt occurred plausibly could impact

[7] https://www.washingtonpost.com/local/the-strange-seasonality-of-violence-why-april-is-the-beginning-of-the-killing-season/2016/04/03/4e05d092-f6c0-11e5-9804-537defcc3cf6_story.html?utm_term=.ca9fc4cd77e8

coverage of a terrorist attack. Unfortunately, it is infeasible to operationalize a manhunt in a consistent way across attacks.[8]

Methods

Data

The data for this study consisted of media coverage for terrorist attacks in the United States between 2006 and 2015,[9] as listed in the GTD.[10] While the GTD lists 170 terrorist attacks during this ten-year span, several of the attacks were perpetrated by the same individual(s), and thus are reported together in media. We collapsed multiple attacks with the same perpetrator(s) into a single terrorism episode to avoid counting the same articles numerous times. In total, there were 136 terrorism episodes in the United States during this time.

To measure media coverage, we focused on two sources: LexisNexis Academic and CNN.com[11] LexisNexis Academic searches through the full text of thousands of news publications. For the purpose of this study, we limited the search results to newspaper coverage[12] from US-based sources between the date of the attack and the end of 2016.[13] LexisNexis searches news articles from national sources such as *The New York Times*, *Wall Street Journal*, *The Washington Post*, and *USA Today,* as well as local newspapers from around the country. To supplement these results, we searched CNN.com's archives to obtain additional news coverage that is solely in digital format. For each incident, we searched for the perpetrator(s) (if known), the location, and other keywords about the attack. In this initial stage, our goal was over-inclusion of potential articles. From this, we culled the final list to only include articles where the attack, perpetrator(s), or victim(s) were the primary focus. We removed the following types of articles most frequently: lists of every attack of a given type; political or policy-focused articles where the attack or perpetrators were an anecdote to a larger debate, such as abortion or gun control;[14] and discussion of vigils held in other locations. In total, we

[8]If this were binary, it would assume an hours-long foot search and a month-long hunt through the wilderness are the equivalent. If we count duration, then that implies the few days-long search for the Tsarnaev brothers that shut down Boston is less meaningful than the 48-day search for Eric Frein through the Pennsylvania wilderness. Given the diversity of what a manhunt can entail, we do not think it is advisable to control for this in a regression model.

[9]Starting in 2006, an increasing percentage of Americans used the Internet as their main source of news. http://www.pewresearch.org/fact-tank/2013/10/16/12-trends-shaping-digital-news/ Since the news sources used for this study include both print and online newspaper articles, we started our analysis in 2006. In years prior to 2006, we may see fewer articles overall since print was more common and is subject to space constraints.

[10]The Global Terrorism Database is a systematic and unbiased source that codes terrorism at the incident-level around the world from 1970 to 2017. The GTD is the most comprehensive and complete dataset available on terrorism. At the time of data collection, 2015 was the most recent year of data released by the GTD.

[11]While we wanted to include searches from sources across the political spectrum, such as Fox News and Huffington Post, neither has a searchable archive going back to 2006 and email requests for archive access were not answered.

[12]It is beyond our current scope to conduct a systematic study of television and radio coverage from both national and local stations across a decade span. Furthermore, broadcast media have a fixed amount of airtime so coverage disparities should be exacerbated. Including TV and radio coverage in our study would likely bias the results in favor of larger or more sensational events that dominate news coverage.

[13]By the end of 2016, all known perpetrators had either pled guilty or gone to trial with the exception of Robert Lewis Dear. Dear is currently not competent to stand trial, so we expect occasional coverage of this going forward. Otherwise, we do not expect any ongoing coverage of the incidents, perpetrators, or victims listed in this dataset.

[14]For example: Dylann Roof's attack sparked debate about the Confederate Flag and gun control; Robert Lewis Dear's attack led to discussion about gun control and abortion rights; the Boston Bombing increased discussions about immigration; and, the San Bernadino attack generated a discussion about immigration, gun control, and Apple refusing to unlock the perpetrator's iPhone.

included 3541 news articles in our dataset. A full list of terrorism episodes and the amount of coverage each received can be found in the appendix. The dataset generated and analyzed for the current study is available from the corresponding author on reasonable request.

Variables

Dependent variable

The outcome variable for all hypotheses was the number of news stories about the incident. We added the number of relevant articles from LexisNexis Academic and CNN.com to yield the total number of articles for each terrorism series. National media outlets may cover terrorism differently than outlets primarily focused on a local audience. To examine differences in coverage by audience, we also estimate models with the total number of articles from major sources[15] only (35.6% of the articles) and with the total number of articles from other sources only (64.4% of the articles). The key independent variables fall into three categories: perpetrator-level factors, target type, and casualties.[16] Information to code these variables came from news reports and the GTD.

Independent variables

Three binary perpetrator-level variables were coded: perpetrator Muslim, perpetrator arrested, and unknown perpetrator. When there were multiple perpetrators, we coded the variable as 1 if any of the perpetrators fell into a category. When the perpetrator was unknown, we coded both perpetrator Muslim and perpetrator arrested as a 0.[17] In this dataset, the individual person(s) responsible for the attacks is unknown 40.4% of the time.[18]

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[15]There are five major, national media outlets in our dataset: *CNN.com*, *The New York Times*, *Wall Street Journal*, *The Washington Post*, and *USA Today*.

[16]All variables were double coded, inconsistencies in coding were discussed, and final codes were agreed upon for all variables in each incident. In a few instances where coding could be disputed, we estimated models both ways and the results were unchanged.

[17]In terrorism, the perpetrator is often unknown so treating these as missing data and dropping the incidents is not appropriate. We recognize that for incidents where the perpetrator is unknown, it is possible that some were committed by Muslims but there is no way to know this. Essentially, there are three categories of perpetrator: Perpetrator Known & Muslim; Perpetrator Known & Not Muslim; and Perpetrator Unknown. Even when the individual perpetrator is unknown, we often know the group responsible so "perpetrator unknown" is not a theoretically sound category on its own, though we account for these incidents in robustness checks. In the models reported, we collapsed Perpetrator Unknown and Perpetrator Known & Not Muslim into a single category (0) and compared to Perpetrator Known & Muslim (1). To ensure that our results are not an artifact of whether or not the perpetrator is known, we also estimated all models where Perpetrator Unknown or Perpetrator Known & Muslim are collapsed into a single category (0) and compared to Perpetrator Known & Not Muslim (1). Across all models reported in the main text and the appendix, attacks where the perpetrator is known and not Muslim do not receive a significantly different amount of news coverage. In contrast, incidents where the perpetrator is known and Muslim receive significantly more coverage in all models. These findings give us additional confidence in our conclusions.

[18]This is common for terrorism: approximately 13% of incidents globally are claimed (Kearns, Conlon, & Young, 2014) and 40% are attributed to a particular group (GTD, 2016). Even when the individual perpetrator is unknown, we often know the group or movement responsible. For example, attacks claimed by the Animal Liberation Front still send a clear message even in the absence of an arrest or identification of the individual(s) responsible. Thus, simply considering attacks where the perpetrator is unknown is not appropriate in terrorism studies. Instead, we control for unknown responsibility in two ways. First, we created a dummy variable for incidents where neither the perpetrator nor group are known. Second, we created a dummy variable for incidents where the perpetrator, group, and motive are all unknown.

Three binary target type variables were coded: law enforcement/governmental target, Muslim target,[19] and minority target. We measured fatalities as the number of people killed – excluding the perpetrator(s) – in each terrorism series.[20] Lastly, we included a binary indicator to denote whether or not the attack occurred near a symbolically significant event in the United States as a control for another factor that could increase the amount of coverage that an attack receives. If an attack occurred within a week of Hitler's birthday (20 April), 4 July, 11 September, or Christmas (25 December), this was coded as 1. When there were multiple incidents in a terrorism series, this was coded as 1 if any of the events take place within a week of a significant date.

On average, each of the 136 terrorism incidents was covered in 26 news articles. However, the distribution is highly skewed. Over one quarter of the incidents received no coverage from the sources that we searched while other attacks received disproportionate coverage. In this dataset, Muslims perpetrated 12.5% of the attacks yet received 50.4% of the news coverage. The perpetrator was arrested in about half (47.1%) of the incidents. Attacks targeted law enforcement or government 20.6% of the time. On average, less than one person was killed per attack, though this again is highly skewed with the vast majority of attacks (81.6%) having no fatalities. See Table 1 for descriptive information about each variable.

Results

Negative binomial regression models[21] are most appropriate[22] since the dependent variable is a non-negative count of news articles per attack. In Table 2, we display the results of six models. As expected in hypothesis 1, Model 1 shows that attacks by Muslims receive significantly more coverage than attacks by non-Muslims. Of course, factors other than the perpetrator's religion impact the amount of coverage the attack receives. As Model 2 shows, all of our hypotheses are supported. If the perpetrator is Muslim, we see 357% more news stories about the attack. Model 2

[19]We include the 2012 Sikh temple shooting in Oak Creek, Wisconsin and the 2015 attack on the Sikh bus driver in Los Angeles in this calculation. Evidence suggests that these attacks were Islamophobia-inspired and the perpetrators were unaware of the difference between Sikhs and Muslims.

[20]The number of people wounded may also impact the amount of coverage that an attack receives. The vast majority (96.3%) of attacks wounded fewer than 10 people. Five attacks had more than 10 wounded: the Austin IRS attack, San Bernadino, Fort Hood, the West Texas Explosion, and the Boston Bombing. While casualties likely impact coverage, injuries are not of the same magnitude as fatalities. If we were to include the counts of both, this would assume that fatalities and casualties have the same impact on media coverage and that the relationship is linear. Rather, to account for the non-linear relationship between casualties and coverage, we logged the number wounded. The correlation between the number of fatalities and the log of number wounded is 0.63 so including both variables in a model introduces concerns of multicollinearity. We created an additive variable (number killed plus log of number wounded) to bluntly account for the impact of casualties on coverage, though this measure is difficult to substantively interpret. As shown in the appendix (Models A1-A20), results are substantively and statistically similar across all models.

[21]All models are estimated with bootstrapped standard errors to minimize the impact of outliers with the small number of observations. Akaike Information Criterion (AIC) and Baysian Information Criterion (BIC) are presented to compare model fit where lower values suggest greater congruence with the true model. The extent to which one model is preferred to another depends on the magnitude of difference between model fit statistics (Raftery, 1995). Models discussed in text have either a weak or positive difference between alternatives.

[22]A high proportion (N = 36, 26.5%) of the attacks in these data did not receive any news coverage. Thus zero-inflated negative binomial regression models were also estimated. Vuong tests of the zero-inflated negative binomial versus a standard negative binomial indicate that the negative binomial models are preferred.

Table 1. Descriptive statistics ($N = 136$).

Variable	Frequency (*N*)	Mean (SD)	Median	Range
Dependent variable				
Articles per incident	–	26.0 (62.3)	3.5	0–460
Articles per incident (from NYT, WSJ, WaPo, USA today, or CNN)	–	9.28 (28.1)	0	0–256
Articles Per Incident (from all other media outlets)	–	16.8 (36.9)	3	0–277
Independent variables				
Perpetrator Muslim	12.5% ($N = 17$)	–	–	–
Perpetrator and group unknown	26.5% ($N = 36$)	–	–	–
Perpetrator, group, and motive unknown	6.6% ($N = 9$)	–	–	–
Perpetrator arrested	47.1% ($N = 64$)	–	–	–
Target LE/government	20.6% ($N = 28$)	–	–	–
Number killed	–	0.7 (2.4)	0	0–15
Number wounded (log)	–	0.4 (0.9)	0	0–5.0
Signification date	13.2% ($N = 18$)	–	–	–
Target Muslim	15.4% ($N = 21$)	–	–	–
Target minority	33.1% ($N = 45$)	–	–	–

also shows a 287% increase in coverage when the perpetrator is arrested, a 211% increase if the target is governmental, and a 46% increase per fatality, on average. Models 3 through 6 include variables to test counterarguments about the target type, significant dates, and the perpetrator being unknown, but the fundamental results remain unchanged.

We suggested five possible alternative explanations for the amount of news coverage that a terrorist attack receives. First, it is possible that some targets receive less media coverage than others. When the target is an out-group member – such as a Muslim target or a minority target in general – the attack may receive less coverage. As we see, however, neither targeting Muslims (Models 3 and 5) nor minorities (Models 4 and 6) impact coverage. Second, when an attack occurs in close temporal proximity to a significant date, the attack may receive more coverage. Yet, Models 3 through 6 show that symbolic timing does not impact the amount of coverage that an attack receives. Third, when the perpetrating individual(s) or group is unknown, this may impact coverage. In Models 3 and 4, we see that attacks where both the individual(s) and group responsible are unknown received about 70% less coverage. In these models, the other variables remain significant but the impact is reduced for all factors except the number of fatalities. Fourth, all models reported were estimated to account for attacks connected with a larger group. As shown in the appendix (Models A21–A40), incidents connected to a group do not receive more coverage and accounting for this factor does not impact the effect of other variables on coverage.

Differences in coverage may be explained by whether or not there is doubt about classifying the attack as terrorism. To test this, we estimated the models reported in Table 2 with only cases where there is "essentially no doubt as to whether the incident is an act of terrorism" (GTD Codebook, p. 14).[23] As shown in Table 3, our results largely hold. One exception is that targeting the government is no longer significant, though this is unsurprising since the vast majority of those

[23]Descriptive statistics for each variable are relatively unchanged, as shown in the appendix.

Table 2. News coverage by terrorism episode ($N = 136$).

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Perpetrator Muslim	**1.96*** (0.41) [611%]**	**1.52*** (0.42) [357%]**	**1.20** (0.39) [233%]**	**1.14** (0.41) [214%]**	**1.47** (0.49) [334%]**	**1.34** (0.47) [283%]**
Perpetrator arrested	–	**1.35*** (0.27) [287%]**	**0.85* (0.36) [135%]**	**0.96** (0.35) [162%]**	**1.32*** (0.32) [273%]**	**1.40*** (0.28) [307%]**
Target law enforcement/government	–	**1.13** (0.42) [211%]**	**0.79* (0.36) [121%]**	**0.77* (0.38) [116%]**	**1.04* (0.40) [182%]**	**0.94* (0.41) [156%]**
Number killed	–	**0.38** (0.12) [46%]**	**0.34** (0.11) [40%]**	**0.34** (0.13) [41%]**	**0.39** (0.14) [48%]**	**0.40** (0.12) [49%]**
Significant date	–	–	0.14 (0.31) [15%]	0.08 (0.33) [8%]	−0.12 (0.34) [−12%]	−0.16 (0.35) [−15%]
Target Muslim	–	–	−0.46 (0.31) [−37%]		−0.40 (0.37) [−33%]	–
Target minority	–	–	–	−0.42 (0.28) [−35%]	–	−0.53**** (0.31) [−41%]
Perpetrator and group unknown	–	–	**−1.23** (0.44) [−71%]**	**−1.16** (0.45) [−69%]**	–	–
Perpetrator, group, and motive unknown	–	–	–	–	−0.21 (3.36) [−19%]	−0.30 (0.82) [−26%]
AIC	968.9632	923.6827	919.5945	919.0597	928.4819	926.8268
BIC	977.7011	941.1586	945.8084	945.2736	954.6958	953.0407

Negative binomial regression models. Constants not reported.
Coefficients are presented with bootstrapped standard errors in parentheses.
Percent change in expected count reported in brackets.
*$p<.05$.
**$p<.01$.
***$p<.001$.
****$p<.10$.

attacks are clearly terrorism. For the variables that remain significant, the magnitude of each's impact on the outcome is similar and the effect of a Muslim perpetrator is stronger.

Across this ten-year period, two terrorist attacks dominated news coverage. The Boston Marathon and Fort Hood attacks together account for over a quarter of media coverage on terrorism (13.0 and 11.3%, respectively). Hyper-salient events like this drive media coverage and may also be driving our results.[24] To test this, we estimated all models with these two cases excluded. As shown in Table 4, our hypotheses are still supported. The magnitude of our main predictor – the perpetrator being Muslim – was slightly stronger with 369% more coverage when these two attacks are removed from the analyses (Model 14). The impact of the other key variables remains roughly the same.

[24]The next most covered attack, Faisal Shahzad's attempted bomb in Times Square, received less than half the coverage of these. By the statistical definition, 17% of the cases are outliers due to the skewed distribution of coverage. Yet, there is not a sound argument for dropping all of these observations from the dataset since this is the reality of media coverage for these attacks.

Table 3. News coverage by terrorism episode when all GTD terrorism criteria met ($N = 113$).

	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Perpetrator Muslim	**2.07*** (0.47) [694%]**	**1.58*** (0.40) [384%]**	**1.29** (0.49) [264%]**	**1.23** (0.46) [242%]**	**1.49** (0.47) [344%]**	**1.38** (0.47) [298%]**
Perpetrator arrested	–	**1.28*** (0.28) [261%]**	**0.88* (0.36) [141%]**	**1.00* (0.40) [172%]**	**1.23** (0.36) [243%]**	**1.32*** (0.35) [274%]**
Target law enforcement/government	–	0.58 (0.37) [79%]	–0.38 (0.40) [-46%]	0.37 (0.40) [45%]	0.48 (0.42) [62%]	0.42 (0.41) [52%]
Number killed	–	**0.41** (0.13) [50%]**	**0.37** (0.12) [45%]**	**0.38** (0.14) [46%]**	**0.42** (0.14) [52%]**	**0.43** (0.14) [53%]**
Significant date	–	–	0.23 (0.40) [26%]	0.18 (0.40) [19%]	0.11 (0.41) [12%]	0.07 (0.39) [7%]
Target Muslim	–	–	–0.55 (0.36) [–42%]	–	–0.47 (0.49) [–38%]	–
Target minority	–	–	–	–0.51 (0.35) [–40%]	–	–0.58 (0.36) [–44%]
Perpetrator and group unknown	–	–	**–0.97* (0.42) [–62%]**	–0.87**** (0.47) [–58%]	–	–
Perpetrator, group, and motive unknown	–	–	–	–	0.05 (6.14) [5%]	–0.04 (6.48) [–4%]
AIC	797.3354	758.7131	758.2688	757.5781	763.54	761.9215
BIC	805.5176	775.0775	782.8153	782.1246	788.0865	786.468

Negative binomial regression models. Constants not reported.
Coefficients are presented with bootstrapped standard errors in parentheses.
Percent change in expected count reported in brackets.
*$p<.05$.
**$p< .01$.
***$p<.001$.
****$p<.10$.

Furthermore, Table 5 shows that when we remove the Boston Marathon bombing and the Fort Hood shooting *and* only include cases where there is no doubt that it is terrorism, the results remain unchanged. Again, the magnitude increased to an expected 405% more coverage when the perpetrator is Muslim (Model 20). In this model, the impact of a perpetrator being arrested is slightly lower and the impact of each additional fatality is slightly higher.

We estimated the models previously discussed by disaggregated the outcome variable to compare results between major and non-major sources. Figure 1 compares the results of our main model across: 1) the whole sample, 2) only non-major sources, and 3) only major sources. Across source type, whether or not the perpetrator was arrested, whether or not the attack targeted government or law enforcement, and the number of fatalities has approximately the same impact on coverage (Models A41-A60). Importantly, there is no meaningful difference in the impact of these three independent variables by source type. However, we see clear differences in the extent to which a Muslim perpetrator generates additional media coverage. Across the whole sample, attacks receive 357% more coverage on average when the perpetrator is

Table 4. News coverage by terrorism episode without Boston Bombing or Fort Hood ($N = 134$).

	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18
Perpetrator Muslim	**1.43***** **(0.34)** **[317%]**	**1.54**** **(0.47)** **[369%]**	**1.22*** **(0.50)** **[239%]**	**1.16*** **(0.48)** **[220%]**	**1.50**** **(0.51)** **[348%]**	**1.38**** **(0.44)** **[298%]**
Perpetrator arrested	–	**1.35***** **(0.28)** **[286%]**	**0.88*** **(0.36)** **[142%]**	**0.99*** **(0.39)** **[170%]**	**1.33***** **(0.30)** **[280%]**	**1.42***** **(0.29)** **[314%]**
Target law enforcement/government	–	**1.18**** **(0.39)** **[224%]**	**0.86*** **(0.40)** **[136%]**	**0.83*** **(0.36)** **[130%]**	**1.09*** **(0.44)** **[198%]**	**1.00*** **(0.40)** **[170%]**
Number killed	–	**0.42*** **(0.18)** **[53%]**	**0.37*** **(0.15)** **[45%]**	**0.38*** **(0.15)** **[46%]**	**0.43**** **(0.16)** **[54%]**	**0.44**** **(0.16)** **[55%]**
Significant date	–	–	0.03 (0.34) [3%]	−0.02 (0.33) [−2%]	−0.20 (0.33) [−18%]	−0.23 (0.36) [−21%]
Target Muslim	–	–	−0.45 (0.35) [−36%]	–	−0.40 (0.38) [−33%]	–
Target minority	–	–		−0.43 (0.28) [−35%]	–	−0.53**** (0.29) [−41%]
Perpetrator and group unknown	–	–	**−1.16**** **(0.41)** **[−69%]**	**−1.09*** **(0.48)** **[−66%]**	–	–
Perpetrator, group, and motive unknown	–	–	–	–	−0.15 (3.46) [−14%]	−0.24 (1.67) [−21%]
AIC	934.58	890.3033	886.9415	886.3227	894.95	893.2618
BIC	943.2736	907.6904	913.022	912.4033	921.0305	919.3424

Negative binomial regression models. Constants not reported.
Coefficients are presented with bootstrapped standard errors in parentheses.
Percent change in expected count reported in brackets.
*$p<.05$.
**$p< .01$.
***$p<.001$.
****$p<.10$.

Muslim. Among non-major sources, the expected increase in coverage is 228% whereas the increase in coverage among major sources is 758%. Across the 24 main models reported in text, incidents perpetrated by a Muslim receive between 1.81 and 4.93 times more coverage from major sources relative to non-major sources.

In sum, we find strong evidence to support all of our hypotheses. Attacks receive significantly more coverage when: the perpetrator is Muslim, the perpetrator is arrested, the target is law enforcement or government, and there are more fatalities. While most factors have a similar impact on the extent of additional media coverage between major and non-major sources, attacks by Muslims received drastically more coverage in national media sources than in sources focused on more local audiences.

Discussion

The motivating questions for this project were whether there are quantitative differences in the amounts of coverage, and why some terrorist attacks receive more media coverage than others. Research on media and terrorism has largely focused on framing

Table 5. News coverage by terrorism episode when all GTD terrorism criteria met without Boston Bombing or Fort Hood ($N = 111$).

	Model 19	Model 20	Model 21	Model 22	Model 23	Model 24
Perpetrator Muslim	**1.54***** **(0.38)** [366%]	**1.62***** **(0.41)** [405%]	**1.34**** **(0.49)** [284%]	**1.28**** **(0.44)** [261%]	**1.55**** **(0.49)** [373%]	**1.44**** **(0.48)** [324%]
Perpetrator arrested	–	**1.27***** **(0.31)** [257%]	**0.91*** **(0.39)** [149%]	**1.03**** **(0.39)** [181%]	**1.25***** **(0.34)** [250%]	**1.34***** **(0.33)** [281%]
Target law enforcement/government	–	0.62**** (0.36) [86%]	0.45 (0.42) [56%]	0.43 (0.39) [54%]	0.54 (0.41) [72%]	0.47 (0.40) [61%]
Number killed	–	**0.47**** **(0.17)** [60%]	**0.42**** **(0.15)** [53%]	**0.44**** **(0.15)** [55%]	**0.48**** **(0.17)** [62%]	**0.49*** **(0.20)** [63%]
Significant date	–	–	0.14 (0.39) [15%]	0.09 (0.36) [10%]	0.05 (0.39) [5%]	0.01 (0.37) [1%]
Target Muslim	–	–	–0.53 (0.38) [–41%]	–	–0.46 (0.40) [–37%]	–
Target minority	–	–	–	–0.52 (0.36) [–40%]	–	–0.58**** (0.34) [–44%]
Perpetrator and group unknown			**–0.90*** **(0.44)** [–59%]	–0.80**** (0.43) [–55%]	–	–
Perpetrator, group, and motive unknown	–	–	–	–	0.11 (6.62) [12%]	0.02 (6.34) [2%]
AIC	762.952	725.4446	725.7583	724.8874	730.2868	728.5586
BIC	771.0806	741.7018	750.1441	749.2732	754.6726	752.9444

Negative binomial regression models. Constants not reported.
Coefficients are presented with bootstrapped standard errors in parentheses.
Percent change in expected count reported in brackets.
$^{*}p<.05$.
$^{**}p<.01$.
$^{***}p<.001$.
$^{****}p<.10$.

within articles and the impact this has on public opinion (Norris et al., 2003; Powell, 2011; Ruigrok & van Attevelt, 2007). Since some attacks are not covered at all while others receive the bulk of media coverage, the quantity of articles is also important for public perception of terrorism. In a study using pre-9/11 data, attack-level factors impacted coverage but the perpetrator's identity was not included among them (Chermak & Gruenewald, 2006). To our knowledge, this is the first post-9/11 and digital media age study focused on the *quantity* of coverage that terrorist attacks receive. Additionally, this is the first study to explicitly examine how perpetrator religion impacts coverage across such a wide range of terrorism cases.

Myriad factors may impact why a particular terrorist attack receives more coverage than another. By modeling coverage over all terrorist attacks in the United States during a ten-year period, we are able to identify trends in coverage. As we see here, perpetrator religion matters for the *quantity* of coverage that an attack receives. We found clear evidence that terrorist attacks perpetrated by Muslims receive drastically more media coverage than attacks by non-Muslims. This finding is consistent with the

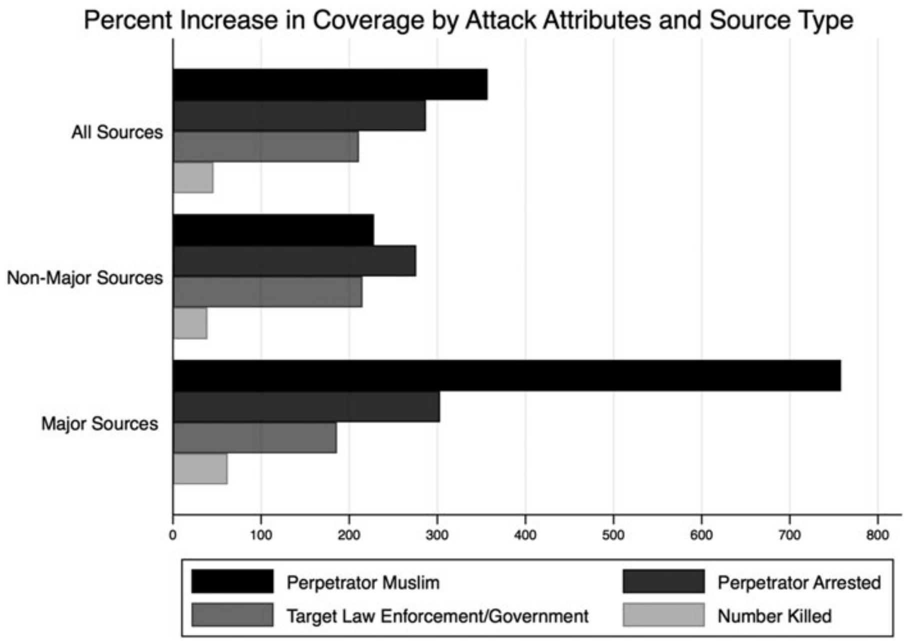

Figure 1. Percent increase in coverage by attack attributes and source type ($N = 136$).

literature on social identity (Tajfel & Turner, 1986) that highlights in-group and out-group dynamics whereby people who are perceived as "others" are portrayed and perceived more negatively. Research has shown similar media bias against Muslims and Arabs in the context of entertainment media (Shaheen, 2012). Our findings clearly show that similar biases against Muslims exist in media coverage of terrorism. In part, this may explain why people implicitly connect terrorism and Islam (Park et al., 2007; Saleem & Anderson, 2013) and view Muslims as a threat to national security (Allouche & Lind, 2010). Coverage disparities may also explain why people are more likely to consider an incident to be "terrorism" when the perpetrator is Muslim (Huff & Kertzer, 2017), which can create a feedback loop that perpetuates biases in both media coverage and public perception.

Each of our other hypotheses was supported. Specifically, when a perpetrator of an attack is arrested we find significantly more coverage. This may be driven in part by the fact that an arrest is a newsworthy event in its own right, and especially so when linked to a terrorist attack. If indeed "terrorism is theatre" as Jenkins (1974) posits, then an arrest made in a terrorism case provides another opportunity to spark audience interest, thereby extending the show.

We also find that attacks against the government receive more coverage. Terrorism inherently has a political dimension. As such, attacks that target the government send a clearer signal about intent, which may result in media coverage. However, this result is inconsistent with Chermak and Gruenewald's (2006) finding that pre-9/11 attacks against government targets received less coverage when contrasted with airline hijackings. Consistent with Chermak and Gruenewald's (2006) analyses, the number of fatalities in a given attack has a significant impact on the extent of coverage. Because fatal events tend to be covered more in general, we anticipated that higher numbers of casualties would generate additional focus in instances of terrorism as well.

Across most of the models, the variables testing other counterarguments were not significant. Attacks that targeted either Muslims specifically or minorities in general did not receive less media coverage. Although Moeller (2009, 70) notes “coverage of victims, the dead and the survivors, is not egalitarian,” the current findings do not suggest a clear distinction in coverage based on whether an attack primarily targeted members of a minority group. While minority homicide victims receive less media coverage (Gruenewald et al., 2013), our results may suggest that terrorism coverage is more strongly driven by other factors. It is also possible that target identity impacts coverage in certain media outlets but not others, though this is beyond the scope of this study. Further, we found that incidents that occurred near significant dates did not receive more coverage. While it stands to reason that the symbolic value of particular dates might add context or additional interest to coverage of an attack thereby generating more coverage, this was not supported. Surprisingly and contradicting previous scholarship (Weimann & Brosius, 1991; Weimann & Winn, 1994), there was no difference in the amount of coverage for attacks connected to a larger group versus those without this connection. While attacks connected to larger groups automatically have name recognition, our results show that this does not drive coverage. In some models, attacks received less coverage when neither the perpetrator nor group responsible was known, though the other key variables were still significant.

In sum, our results and the robustness of our models demonstrate the strength of the conclusion that media give disproportionate coverage to terrorism when the perpetrator is Muslim, though other factors also matter. We find that the identity of a perpetrator as Muslim has primacy as the key driver of the amount of coverage, relative to each of the other factors. Thus, the findings reported here empirically establish perpetrator religion as the most substantial element of what drives overall coverage.

We demonstrate that our findings are robust against a number of alternative explanations. In all of the models we estimated, attacks where the perpetrator was Muslim received significantly more media coverage. This result was strengthened when we only included incidents that clearly met all criteria on the definition of terrorism. Similarly, our results were strengthened when we excluded the Boston Marathon bombing and the Fort Hood shooting. This demonstrates that the two most high-profile events in the dataset were not driving our results. Somewhat surprisingly, Muslim perpetrated attacks receive the most coverage – by far – from major, national news sources. The five major sources in our study provided over a third (35.6%) of the articles we analyzed. Taken together, this suggests that sources with the broadest readership make up a sizeable proportion of terrorism coverage in the United States and this coverage tends to focus on attacks by Muslims. It is not clear – and beyond the scope of the project to determine – what impact this has on public perceptions of terrorism. Yet, it is reasonable to think that coverage disparities may help explain why people are more likely to define violence as “terrorism” when the perpetrator is Muslim (Lemieux, Masyn, Betus, Karampelas, Garzon, Saleem, Lane & Kearns, 2018; Huff & Kertzer, 2018). To date, research on terrorism media coverage has not examined differences in the amount of coverage that attacks receive based on the source. As this study suggests, however, these differences do exist between national and local outlets.

When people think about terrorism, events like the Boston Marathon bombing and the Fort Hood shooting are what come to mind. This is not surprising considering that these two incidents received over a quarter of the coverage in the United States over the last decade. Yet, so much is missed. Based on fatalities, there are a few attacks in the dataset that received less coverage than we would expect. Wade Michael Page's attack on the Sikh Temple in Wisconsin killed six people and it only received 1.9% of the total coverage. Frazier Glenn Miller's attack on a synagogue in Kansas killed three people and it only received 2.0% of the coverage. Dylann Roof killed nine people in an African–American church in Charleston and received 4.5% of the coverage. These attacks have two things in common: the perpetrator was a white man and the targets were both religious and minority groups. These instances highlight disparity in media coverage of terrorism.

Conclusions

Limitations and future directions

From this study, we see that characteristics of a terrorist attack and its perpetrator(s) impact the amount of coverage that it receives from media. When something is covered more extensively, it is in the public's eye more often. This can connote significance and can skew public perceptions. While our findings are clear and robust, they are not without limitation. First, our study is limited to print and online media. Since broadcast media has space constraints with airtime, it is reasonable to expect that coverage disparities would be further exacerbated in television and radio coverage. To explore this, future research could replicate our project with broadcast coverage. Second, our dataset is limited to the United States so the extent to which our findings are generalizable more broadly is unclear. In the future, we plan to conduct similar analyses in other countries to address concerns with generalizability. Third, we are focused on terrorism and media coverage since 2006. As we have discussed, there are methodological reasons to limit our study of print and online media coverage to this timeframe. Exploring these differences using print media only or using select broadcast media over a longer time-span is another avenue for future research. Finally, some media outlets may selectively cover certain attacks more than others in a way that reflects the ideological perspective of the news organization. If this occurs, we would see uneven coverage of attacks both within and across news sources. In such cases, the source of coverage and select factors of interest (i.e. targeting a minority group) may interact in ways that provide a finer-grained perspective on how *particular* news organizations cover and label such attacks, rather than the aggregate level of coverage across *many* news organizations. While this level of analysis is beyond the scope of the current research, it presents an interesting avenue for future research.

Beyond just the quantity of coverage, it is also important to analyze the content of what is said. Research on media frames and terrorism reporting tend to focus on a few key events, such as the London and Madrid bombings (Ruigrok & van Attevelt, 2007). Insights derived from such work help us to understand media coverage, but limit our ability to compare how numerous different attacks are framed. Powell (2011) focused on media coverage of 11 terrorist attacks in the US from 9/11 through 2009 and found qualitative differences in how attacks are framed based on the perpetrator's identity. One of her selection criteria for inclusion, however, is that the attack was reported on as "terrorism" in media. However, media might be reticent to use the term "terrorist" to describe some attackers relative to others, particularly to the extent that the term carries the connotation of making a value judgment (Maguire, 2007).

Policy implications

When President Trump asserted that the media does not cover some terrorist attacks enough,[25] he was correct. However, his assertion that attacks by Muslim perpetrators received less coverage is unsubstantiated. All attacks in this study are considered terrorism by experts and should be covered as such. Yet, media do not cover these events equally. Even when controlling for other factors that may impact coverage, attacks perpetrated by Muslim receive a disproportionate amount of media coverage. In this data, Muslims perpetrated 12.5% of the attacks yet received half of the news coverage.

The way in which media frames an issue can impact public perception (Tversky & Kahneman, 1981). Whether the disproportionate coverage is a conscious decision on the part of journalists or not, this stereotyping reinforces cultural narratives about what and who should be feared. By covering terrorist attacks by Muslims dramatically more than other incidents, media frame this type of event as more prevalent. These findings help explain why half of Americans fear that they or someone they know will be a victim of terrorism[26] and implicitly link terrorism and Islam (Saleem & Anderson, 2013). Reality demonstrates, however, that these fears are misplaced.

One way to combat misplaced fears about terrorism is to change the public narrative on terrorism to cover attacks more evenly and based on consistently applied criteria. A robust body of research shows that media coverage impacts perceptions across a range of issues (Callanan & Rosenberger, 2011; McCarthy et al., 1996; Stack, 2003), including terrorism and security threats (Norris et al., 2003; Slone, 2000). While we see media's impact broadly, this connection is particularly strong for topics with which people lack direct experience (Gerbner, 1998). We see that people think crime rates are going up when the opposite is true, and that media coverage likely drives this incorrect perception. From this, it is reasonable to expect that media coverage of terrorism has a similar impact on the public. When attacks perpetrated by Muslims receive drastically more coverage, audiences may think these attacks are more common and become more afraid of Muslim terrorists. This misperception can create a feedback loop of incorrect information fueling prejudice and discrimination. Moreover, such misperceptions may prevent the acknowledgment and addressing of other pressing security threats that have a factually rooted basis.

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[25]https://www.washingtonpost.com/news/politics/wp/2017/02/06/president-trump-is-now-speculating-that-the-media-is-covering-up-terrorist-attacks/?utm_term=.b23ffe5a9113
[26]http://www.gallup.com/poll/4909/terrorism-united-states.aspx

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No potential conflict of interest was reported by the authors.

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Appendix

Table A1. News coverage by attack.

GTD Event ID	Perpetrator(s)	# of articles	% of dataset
200601170007	Unknown	0	0.00
200603030013	Mohammed Reza Taheri-azar	42	1.19
200606300004	Unknown	0	0.00
200607120007	Unknown	0	0.00
200607280004	Naveed Afzal Haq	59	1.67
200609110007	David Robert McMenemy	0	0.00
200703180002	Grant Barnes	3	0.08
200704250006	Paul Ross Evans	15	0.42
200705090002	Unknown	0	0.00
200706240004	Unknown	1	0.03
200710200003	Unknown	5	0.14
200710260003	Unknown	5	0.14
200712060011	Chad Altman, Sergio Baca	2	0.06
200802090004	Eric Ian Baker, Michael Corey Golden, Jonathan Edward Stone	2	0.06
200802170007	Unknown	1	0.03
200803020012	Unknown	11	0.31
200803060004	Unknown	0	0.00
200804070005	Unknown	0	0.00
200804220011	Unknown	2	0.06
200804250010	Eric Reginald Robinson, Rachelle Carlock, Ella Louise Sanders	4	0.11
200805260017	Gary David Moss	0	0.00
200806140008	Unknown	0	0.00
200807250030	Unknown	0	0.00
200807270001	Jim David Adkisson	25	0.71
200808020023	Joseph Buddenberg, Maryam Khajavi, Nathan Pope, Adriana Stump	19	0.54
200811050008	Benjamin Haskell, Michael F. Jacques Jr., and Thomas Gleason Jr.	14	0.40
200811140015	Justin Tyme Hayes, Derek Shane O'Brien, Darrin Peter Thibault, Crystal Lee McCann,	0	0.00
200903070010	Unknown	2	0.06
200905300002	Shawna Forde, Jason Eugene Bush, Albert Robert Gaxiola	17	0.48
200905310017	Scott Roeder	123	3.47
200906010028	Abdulhakim Muhammad	51	1.44
200906100003	James W. von Brunn	49	1.38
200907030004	Bret MacDonald Hicks, Michael Aaron Powell, Brian Charles Hanson, Erin Lee Brooks	1	0.03
200908240016	Alex Youshock	36	1.02
200909040003	Unknown	1	0.03
200911060002	Nidal Malik Hasan	400	11.30
200912250024	Umar Farouk Abdulmutallab	115	3.25
201002170017	Brad A. Saari, Timothy Dean, Nicholas A. Halverson, Jared D. Hubbuch	6	0.17
201002180013	Joseph Stack	36	1.02
201002250007	Roosevelt Terry	1	0.03
201003040016	John Patrick Bedell	21	0.59
201004300006	Walter Edmund Bond	18	0.51
201005010001	Faisal Shahzad	194	5.48
201005100042	Sandlin Matthews Smith	12	0.34
201007270013	Unknown	0	0.00
201009010022	James Lee	21	0.59
201010000001	Yonathan Melaku	72	2.03
201011160004	Unknown	2	0.06
201101060018	Unknown	15	0.42

(*continued*)

Table A1. (*Continued*)

GTD Event ID	Perpetrator(s)	# of articles	% of dataset
201101170018	Kevin Harpham	27	0.76
201102220009	Unknown	4	0.11
201104230010	Unknown	1	0.03
201105060004	Unknown	0	0.00
201109260012	Unknown	0	0.00
201110120003	Unknown	0	0.00
201111110020	Oscar Ramiro Ortega – Hernandez	59	1.67
201201010020	Bobby Joe Rogers	17	0.48
201201030019	Ray Lazier Lengend	8	0.23
201204010018	Francis Grady	1	0.03
201205200024	Unknown	0	0.00
201205200025	Jean – Claude Bridges	0	0.00
201205230034	Unknown	0	0.00
201206180029	Anson Chi	1	0.03
201207040032	Jedediah Stout	11	0.31
201208050006	Wade Michael Page	67	1.89
201208120012	Unknown	1	0.03
201208150059	Floyd Lee Corkins II	22	0.62
201209300041	Randolph Linn	13	0.37
201211300009	Abdullatif Aldosary	0	0.00
201301170006	Unknown	0	0.00
201302030025	Christopher Dorner	132	3.73
201302260036	Unknown	3	0.08
201304150001	Tamerlan Tsarnaev, Dzhokhar Tsarnaev	460	12.99
201304160051	Unknown	6	0.17
201304170041	Unknown	48	1.36
201304180010	Unknown	0	0.00
201305200073	Shannon Guess Richardson	33	0.93
201307250065	Unknown	0	0.00
201308220053	Unknown	0	0.00
201311010046	Paul Anthony Ciancia	33	0.93
201403180089	Unknown	0	0.00
201403250090	Unknown	0	0.00
201404130060	Frazier Glenn Cross	72	2.03
201404270057	Ali Muhammad Brown	6	0.17
201405050073	David Patterson	1	0.03
201406060065	Dennis Marx	11	0.31
201406080071	Jerad and Amanda Miller	21	0.59
201406110089	Unknown	0	0.00
201408110060	Douglas Leguin	0	0.00
201409110001	Eric King	2	0.06
201409120032	Eric Frein	109	3.08
201410030065	Unknown	0	0.00
201410230047	Zale H. Thompson	5	0.14
201410240071	Unknown	0	0.00
201411040086	Michael C. Sibley	2	0.06
201411040087	Unknown	2	0.06
201411230071	John Hugo Scherzberg	3	0.08
201411230072	Jeremiah Mauer, Gregory Tinnell, Warren Gerald Browning	1	0.03
201411280018	Larry Steven McQuilliams	7	0.20
201412180047	Justin Nojan Sullivan	12	0.34
201412200060	Ismaaiyl Brinsley	90	2.54
201501060024	Thaddeus Cheyenne Murphy	7	0.20
201502100004	Craig Stephen Hicks	64	1.81
201502170127	Unknown	1	0.03
201502180067	Dominick T. Johnson, Nathan Deshawn	0	0.00
201502230104	Unknown	0	0.00
201503100045	Unknown	0	0.00
201503200036	Richard White	8	0.23

(*continued*)

Table A1. (*Continued*)

GTD Event ID	Perpetrator(s)	# of articles	% of dataset
201505030003	Nadir Soofi, Elton Simpson	62	1.75
201506170035	Dylann Roof	158	4.46
201506220069	Unknown	0	0.00
201506230056	Unknown	1	0.03
201506240051	Unknown	1	0.03
201506260046	Unknown	1	0.03
201507150077	Unknown	0	0.00
201507160061	Muhammad Yousef Abdulazeez	100	2.82
201507190097	Unknown	1	0.03
201507230080	John Russell Houser	23	0.65
201508010105	Unknown	0	0.00
201508020114	Unknown	12	0.34
201508190040	Unknown	6	0.17
201509040048	Unknown	4	0.11
201509130079	Rasheed Abdul Aziz	4	0.11
201509300082	Unknown	4	0.11
201511010076	Marshall W. Leonard	1	0.03
201511040056	Faisal Mohammad	19	0.54
201511060053	K.C. Tard Jr.	1	0.03
201511150043	Ted Hakey Jr.	8	0.23
201511190054	Chester H. Gore	0	0.00
201511230084	Nathan Gustavsson, Allen Lawrence, Daniel Thomas Macey, Joseph Martin Backman	14	0.40
201511270001	Robert Dear	178	5.03
201512020012	Syed Rizwan Farook, Tashfeen Malik	152	4.29
201512050031	Piro Kolvani	2	0.06
201512080038	Matthew Gust	3	0.08
201512110031	Carl James Dial Jr.	10	0.28
201512260016	Unknown	2	0.06

Table A2. Descriptive statistics for terrorism episodes when all GTD terrorism criteria met ($N = 113$).

Variable	Frequency (N)	Mean (SD)	Median	Range
Dependent variable	–			
Articles per incident	–	27.0 (66.8)	3	0–460
Articles per incident (from NYT, WSJ, WaPo, USA today, or CNN)	–	10.2 (30.5)	0	0–256
Articles per incident (from all other media outlets)	–	16.8 (38.9)	3	0–277
Independent variables				
Perpetrator Muslim	15.0% ($N = 17$)	–	–	–
Perpetrator and group unknown	25.7% ($N = 29$)	–	–	–
Perpetrator, group, and motive unknown	4.4% ($N = 5$)	–	–	–
Perpetrator arrested	45.1% ($N = 51$)	–	–	–
Target LE/government	21.2% ($N = 24$)	–	–	–
Number killed	–	0.7 (2.2)	0	0–14
Number wounded (log)	–	0.4 (0.8)	0	0–4.9
Signification date	12.4% ($N = 14$)	–	–	–
Target Muslim	15.0% ($N = 17$)	–	–	–
Target minority	31.0% ($N = 35$)	—	—	—

Table A3. News coverage by terrorism episode, with alternative operationalization of casualties ($N = 136$).

	Model A1	Model A2	Model A3	Model A4	Model A5
Perpetrator Muslim	**1.36****	**1.10***	**1.04***	**1.33***	**1.22****
	(0.44)	**(0.49)**	**(0.52)**	**(0.52)**	**(0.44)**
	[290%]	**[199%]**	**[184%]**	**[280%]**	**[240%]**
Perpetrator arrested	**1.35*****	**0.88***	**0.97****	**1.33*****	**1.40*****
	(0.28)	**(0.37)**	**(0.33)**	**(0.32)**	**(0.33)**
	[286%]	**[142%]**	**[164%]**	**[280%]**	**[304%]**
Target law enforcement/government	**1.05****	**0.76***	0.73****	**0.99***	**0.90***
	(0.39)	**(0.36)**	(0.38)	**(0.44)**	**(0.40)**
	[185%]	**[113%]**	[108%]	**[169%]**	**[145%]**
Number killed + log wounded	**0.31*****	**0.27****	**0.28*****	**0.31*****	**0.32*****
	(0.08)	**(0.09)**	**(0.08)**	**(0.09)**	**(0.09)**
	[36%]	**[31%]**	**[32%]**	**[36%]**	**[38%]**
Significant date		0.07	0.03	−0.16	−0.18
		(0.32)	(0.36)	(0.39)	(0.32)
		[7%]	[3%]	[−15%]	[−16%]
Target Muslim		−0.35		−0.28	
		(0.32)		(0.41)	
		[−30%]		[−24%]	
Target minority			−0.35		−0.44
			(0.27)		(0.32)
			[−29%]		[−36%]
Perpetrator and Group Unknown		**−1.17****	**−1.11***		
		(0.41)	**(0.49)**		
		[−69%]	**[−67%]**		
Perpetrator, group, and motive unknown				−0.15	−0.24
				(4.48)	(2.75)
				[−14%]	[−21%]
AIC	919.5436	916.4742	916.0118	924.7762	923.3711
BIC	937.0196	942.6881	942.2257	950.9901	949.585

Negative binomial regression models. Constants not reported.
Coefficients are presented with bootstrapped standard errors in parentheses and are in bold if significant.
Percent change in expected count reported in brackets.
*$p<.05$.
**$p< .01$.
***$p<.001$.
****$p<.10$.

Table A4. News coverage by terrorism episode when all GTD terrorism criteria met, with alternative operationalization of casualties (N =113).

	Model A6	Model A7	Model A8	Model A9	Model A10
Perpetrator Muslim	**1.46****	**1.22***	**1.18***	**1.40****	**1.32****
	(0.45)	**(0.47)**	**(0.46)**	**(0.43)**	**(0.46)**
	[332%]	**[237%]**	**[226%]**	**[305%]**	**[276%]**
Perpetrator arrested	**1.28*****	**0.91***	**1.01****	**1.25*****	**1.32*****
	(0.32)	**(0.38)**	**(0.37)**	**(0.34)**	**(0.35)**
	[261%]	**[148%]**	**[174%]**	**[247%]**	**[274%]**
Target law enforcement/government	0.44	0.28	0.29	0.35	0.32
	(0.35)	(0.37)	(0.37)	(0.36)	(0.36)
	[55%]	[32%]	[33%]	[42%]	[38%]
Number killed + log wounded	**0.34*****	**0.31****	**0.31*****	**0.34*****	**0.35*****
	(0.08)	**(0.09)**	**(0.08)**	**(0.09)**	**(0.10)**
	[40%]	**[36%]**	**[37%]**	**[41%]**	**[42%]**
Significant date		0.20	0.14	0.12	0.08
		(0.41)	(0.38)	(0.38)	(0.38)
		[22%]	[16%]	[12%]	[8%]
Target Muslim		−0.47		−0.39	
		(0.39)		(0.43)	
		[−38%]		[−32%]	
Target minority			−0.37		−0.43
			(0.36)		(0.34)
			[−31%]		[−35%]
Perpetrator and group unknown		**−0.90***	−0.83****		
		(0.44)	(0.49)		
		[−60%]	[−56%]		
Perpetrator, group, and motive unknown				0.08	0.03
				(7.31)	(7.03)
				[9%]	[3%]
AIC	753.8595	754.2013	754.1748	758.9512	758.1872
BIC	770.2238	778.7478	778.7213	783.4977	782.7337

Notes. Negative binomial regression models. Constants not reported.
Coefficients are presented with bootstrapped standard errors in parentheses and are in bold if significant.
Percent change in expected count reported in brackets.
*$p<.05$.
**$p<.01$.
***$p<.001$.
****$p<.10$.

Table A5. News coverage by terrorism episode without Boston Bombing or Fort Hood, with alternative operationalization of casualties ($N = 134$).

	Model A11	Model A12	Model A13	Model A14	Model A15
Perpetrator Muslim	**1.45****	**1.18***	**1.13***	**1.42****	**1.30****
	(0.52)	**(0.50)**	**(0.49)**	**(0.45)**	**(0.49)**
	[326%]	**[225%]**	**[208%]**	**[313%]**	**[269%]**
Perpetrator arrested	**1.36*****	**0.93****	**1.02***	**1.36*****	**1.42*****
	(0.31)	**(0.35)**	**(0.40)**	**(0.31)**	**(0.31)**
	[291%]	**[153%]**	**[176%]**	**[288%]**	**[314%]**
Target law enforcement/government	**1.06***	**0.80***	**0.76***	**1.01***	0.90****
	(0.44)	**(0.35)**	**(0.36)**	**(0.41)**	(0.47)
	[190%]	**[122%]**	**[115%]**	**[174%]**	[147%]
Number killed + log wounded	**0.36****	**0.31****	**0.32****	**0.36****	**0.37****
	(0.11)	**(0.10)**	**(0.11)**	**(0.11)**	**(0.11)**
	[43%]	**[37%]**	**[38%]**	**[43%]**	**[45%]**
Significant date		0.05	0.01	−0.16	−0.17
		(0.34)	(0.34)	(0.39)	(0.33)
		[5%]	[1%]	[−14%]	[−16%]
Target Muslim		−0.35		−0.29	
		(0.34)		(0.35)	
		[−29%]		[−25%]	
Target minority			−0.37		−0.47
			(0.29)		(0.33)
			[−31%]		[−37%]
Perpetrator and group unknown		**−1.09***	**−1.02***		
		(0.43)	**(0.48)**		
		[−66%]	**[−64%]**		
Perpetrator, group, and motive unknown				−0.09	−0.19
				(1.67)	(3.67)
				[−9%]	[−17%]
AIC	886.2738	884.312	883.6645	891.5244	889.9159
BIC	903.6608	910.3925	909.7451	917.6049	915.9964

Notes. Negative binomial regression models. Constants not reported.
Coefficients are presented with bootstrapped standard errors in parentheses and are in bold if significant.
Percent change in expected count reported in brackets.
*$p<.05$.
**$p<.01$.
***$p<.001$.
****$p<.10$.

Table A6. News coverage by terrorism episode when all GTD terrorism criteria met without Boston Bombing or Fort Hood, with alternative operationalization of casualties ($N = 111$).

	Model A16	Model A17	Model A18	Model A19	Model A20
Perpetrator Muslim	**1.56****	**1.33****	**1.28***	**1.50****	**1.42****
	(0.48)	**(0.47)**	**(0.52)**	**(0.54)**	**(0.45)**
	[376%]	**[276%]**	**[261%]**	**[347%]**	**[313%]**
Perpetrator arrested	**1.29*****	**0.95****	**1.05***	**1.26*****	**1.34*****
	(0.31)	**(0.36)**	**(0.43)**	**(0.33)**	**(0.37)**
	[263%]	**[159%]**	**[187%]**	**[253%]**	**[280%]**
Target law enforcement/government	0.42	0.27	0.27	0.34	0.30
	(0.34)	(0.37)	(0.40)	(0.38)	(0.35)
	[52%]	[32%]	[32%]	[40%]	[35%]
Number killed + log wounded	**0.41*****	**0.37****	**0.38*****	**0.41*****	**0.42*****
	(0.10)	**(0.11)**	**(0.09)**	**(0.11)**	**(0.10)**
	[50%]	**[45%]**	**[46%]**	**[51%]**	**[52%]**
Significant date		0.21	0.16	0.14	0.11
		(0.40)	(0.39)	(0.42)	(0.44)
		[23%]	[17%]	[16%]	[11%]
Target Muslim		−0.46		−0.39	
		(0.39)		(0.46)	
		[−37%]		[−32%]	
Target minority			−0.39		−0.45
			(0.35)		(0.39)
			[−32%]		[−36%]
Perpetrator and group unknown		−0.80****	−0.72		
		(0.47)	(0.45)		
		[−55%]	[−52%]		
Perpetrator, group and motive unknown				0.15	0.09
				(6.93)	(7.21)
				[16%]	[10%]
AIC	720.2493	721.4975	721.2439	725.2698	724.3359
BIC	736.5065	745.8833	745.6297	749.6556	748.7217

Notes. Negative binomial regression models. Constants not reported.
Coefficients are presented with bootstrapped standard errors in parentheses and are in bold if significant.
Percent change in expected count reported in brackets.
*$p<.05$.
**$p< .01$.
***$p<.001$.
****$p<.10$.

Table A7. News coverage by terrorism episode, including measure for known group affiliation ($N = 136$).

	Model A21	Model A22	Model A23	Model A24	Model A25
Perpetrator Muslim	**1.55***** **(0.42)** **[370%]**	**1.32*** **(0.51)** **[273%]**	**1.24*** **(0.52)** **[246%]**	**1.50**** **(0.48)** **[349%]**	**1.38**** **(0.44)** **[297%]**
Perpetrator arrested	**1.36***** **(0.27)** **[289%]**	**0.84*** **(0.36)** **[131%]**	**0.96**** **(0.32)** **[162%]**	**1.32***** **(0.31)** **[273%]**	**1.42***** **(0.32)** **[312%]**
Target law enforcement/government	**1.12**** **(0.39)** **[207%]**	0.70**** (0.38) [102%]	0.69**** (0.39) [99%]	**1.00*** **(0.45)** **[172%]**	**0.89*** **(0.40)** **[144%]**
Number killed	**0.37**** **(0.13)** **[45%]**	**0.31*** **(0.13)** **[36%]**	**0.32**** **(0.10)** **[37%]**	**0.38**** **(0.13)** **[46%]**	**0.39**** **(0.13)** **[47%]**
Known group	−0.13 (0.36) [−12%]	−0.49 (0.41) [−39%]	−0.47 (0.41) [−38%]	−0.20 (0.35) [−18%]	−0.26 (0.37) [−23%]
Significant date		0.18 (0.35) [19%]	0.11 (0.41) [11%]	−0.10 (0.40) [−10%]−	−0.15 (0.32) [−14%]
Target Muslim		−0.53**** (0.32) [−41%]		−0.44 (0.42) [−36%]	
Target minority			−0.47**** (0.27) [−37%]		−0.57**** (0.33) [−44%]
Perpetrator and group unknown		**−1.34**** **(0.42)** **[−74%]**	**−1.25*** **(0.52)** **[−72%]**		
Perpetrator, group and motive unknown				−0.26 (3.54) [−23%]	−0.36 (2.78) [−31%]
AIC	925.5687	920.126	919.6467	930.2168	928.4033
BIC	945.9572	949.2525	948.7733	959.3434	957.5298

Notes. Negative binomial regression models. Constants not reported.
Coefficients are presented with bootstrapped standard errors in parentheses and are in bold if significant.
Percent change in expected count reported in brackets.
$^{*}p<.05$.
$^{**}p< .01$.
$^{***}p<.001$.
$^{****}p<.10$.

Table A8. News coverage by terrorism episode when all GTD terrorism criteria met, including measure for known group affiliation ($N = 113$).

	Model A26	Model A27	Model A28	Model A29	Model A30
Perpetrator Muslim	**1.60*****	**1.37****	**1.29****	**1.52****	**1.40****
	(0.41)	**(0.49)**	**(0.45)**	**(0.52)**	**(0.50)**
	[394%]	**[292%]**	**[263%]**	**[355%]**	**[307%]**
Perpetrator arrested	**1.29*****	**0.87***	**1.01****	**1.24*****	**1.34*****
	(0.33)	**(0.35)**	**(0.34)**	**(0.34)**	**(0.33)**
	[264%]	**[138%]**	**[174%]**	**[244%]**	**[280%]**
Target law enforcement/government	0.57	0.30	0.31	0.45	0.38
	(0.38)	(0.39)	(0.39)	(0.40)	(0.39)
	[77%]	[35%]	[36%]	[57%]	[47%]
Number killed	**0.40****	**0.34****	**0.35****	**0.41****	**0.42****
	(0.14)	**(0.12)**	**(0.12)**	**(0.14)**	**(0.13)**
	[49%]	**[40%]**	**[42%]**	**[50%]**	**[52%]**
Known group	−0.11	−0.45	−0.40	−0.19	−0.21
	(0.33)	(0.42)	(0.36)	(0.40)	(0.41)
	[−11%]	[−36%]	[−33%]	[−17%]	[−19%]
Significant date		0.27	0.19	0.13	0.07
		(0.39)	(0.36)	(0.42)	(0.43)
		[30%]	[21%]	[13%]	[8%]
Target Muslim		−0.64		−0.51	
		(0.40)		(0.47)	
		[−47%]		[−40%]	
Target minority			−0.54		−0.61****
			(0.33)		(0.37)
			[−42%]		[−46%]
Perpetrator and group unknown		**−1.09***	**−0.97***		
		(0.50)	**(0.46)**		
		[−66%]	**[−62%]**		
Perpetrator, group and motive unknown				−0.004	−0.09
				(6.11)	(7.09)
				[−0.4%]	[−9%]
AIC	760.6306	759.0815	758.5581	765.3155	763.6192
BIC	779.7223	786.3554	785.832	792.5894	790.893

Notes. Negative binomial regression models. Constants not reported.
Coefficients are presented with bootstrapped standard errors in parentheses and are in bold if significant.
Percent change in expected count reported in brackets.
*$p<.05$.
**$p<.01$.
***$p<.001$.
****$p<.10$.

Table A9. News coverage by terrorism episode without Boston Bombing or Fort Hood, including measure for known group affiliation ($N = 134$).

	Model A31	Model A32	Model A33	Model A34	Model A35
Perpetrator Muslim	**1.57****	**1.34***	**1.27***	**1.53****	**1.42****
	(0.46)	**(0.62)**	**(0.54)**	**(0.58)**	**(0.53)**
	[380%]	**[281%]**	**[254%]**	**[363%]**	**[313%]**
Perpetrator arrested	**1.36*****	**0.87***	**1.00****	**1.33*****	**1.43*****
	(0.27)	**(0.37)**	**(0.37)**	**(0.31)**	**(0.31)**
	[288%]	**[139%]**	**[171%]**	**[280%]**	**[319%]**
Target law enforcement/government	**1.17****	**0.78***	0.76****	**1.06***	**0.95***
	(0.39)	**(0.37)**	(0.40)	**(0.44)**	**(0.40)**
	[221%]	**[118%]**	[114%]	**[190%]**	**[159%]**
Number killed	**0.42***	**0.35****	**0.36***	**0.42***	**0.43****
	(0.16)	**(0.12)**	**(0.14)**	**(0.17)**	**(0.16)**
	[52%]	**[42%]**	**[43%]**	**[53%]**	**[54%]**
Known group	−0.09	−0.43	−0.42	−0.16	−0.22
	(0.38)	(0.43)	(0.40)	(0.39)	(0.42)
	[−9%]	[−35%]	[−34%]	[−14%]	[−19%]
Significant date		0.09	0.02	−0.18	−0.21
		(0.38)	(0.36)	(0.36)	(0.36)
		[9%]	[2%]	[−16%]	[−19%]
Target Muslim		−0.52****		−0.43	
		(0.30)		(0.40)	
		[−41%]		[−35%]	
Target minority			−0.47		−0.57****
			(0.30)		(0.30)
			[−38%]		[−44%]
Perpetrator and group unknown		**−1.26****	**−1.18***		
		(0.48)	**(0.45)**		
		[−72%]	**[−69%]**		
Perpetrator, group, and motive unknown				−0.19	−0.29
				(2.81)	(2.40)
				[−17%]	[−25%]
AIC	892.245	887.8346	887.2319	896.7967	894.9642
BIC	912.5299	916.813	916.2103	925.7751	923.9426

Notes. Negative binomial regression models. Constants not reported.
Coefficients are presented with bootstrapped standard errors in parentheses and are in bold if significant.
Percent change in expected count reported in brackets.
*$p<.05$.
**$p<.01$.
***$p<.001$.
****$p<.10$.

Table A10. News coverage by terrorism episode when all GTD terrorism criteria met without Boston Bombing or Fort Hood, including measure for known group affiliation ($N = 111$).

	Model A36	Model A37	Model A38	Model A39	Model A40
Perpetrator Muslim	**1.63****	**1.41****	**1.34***	**1.58****	**1.46****
	(0.51)	**(0.53)**	**(0.55)**	**(0.48)**	**(0.50)**
	[412%]	**[311%]**	**[282%]**	**[383%]**	**[333%]**
Perpetrator arrested	**1.28*****	**0.90***	**1.04****	**1.26****	**1.35*****
	(0.34)	**(0.35)**	**(0.37)**	**(0.36)**	**(0.33)**
	[259%]	**[147%]**	**[184%]**	**[251%]**	**[286%]**
Target law enforcement/government	0.62	0.38	0.38	0.52	0.44
	(0.40)	(0.41)	(0.39)	(0.43)	(0.42)
	[85%]	[46%]	[46%]	[68%]	[56%]
Number killed	**0.47****	**0.40****	**0.42****	**0.47****	**0.48***
	(0.16)	**(0.15)**	**(0.16)**	**(0.17)**	**(0.21)**
	[60%]	**[49%]**	**[52%]**	**[60%]**	**[62%]**
Known Group	−0.07	−0.38	−0.35	−0.14	−0.18
	(0.37)	(0.47)	(0.42)	(0.44)	(0.42)
	[−6%]	[−32%]	[−29%]	[−13%]	[−16%]
Significant date		0.18	0.12	0.06	0.02
		(0.47)	(0.41)	(0.41)	(0.38)
		[20%]	[13%]	[6%]	[2%]
Target Muslim		−0.61		−0.49	
		(0.42)		(0.50)	
		[−46%]		[−39%]	
Target minority			−0.55		−0.62****
			(0.36)		(0.37)
			[−43%]		[−46%]
Perpetrator and group unknown		**−1.00***	−0.88****		
		(0.47)	(0.47)		
		[−63%]	[−59%]		
Perpetrator, group, and motive unknown				0.07	−0.03
				(7.08)	(6.51)
				[8%]	[−3%]
AIC	727.4156	726.8947	726.1247	732.1616	730.3527
BIC	746.3823	753.99	753.22	759.2569	757.448

Notes. Negative binomial regression models. Constants not reported.
Coefficients are presented with bootstrapped standard errors in parentheses and are in bold if significant.
Percent change in expected count reported in brackets.
*$p < .05$.
**$p < .01$.
***$p < .001$.
****$p < .10$.

Table A11. News coverage by terrorism episode – comparing major and non-major media outlets ($N = 136$).

	Model A41		Model A42		Model A43		Model A44		Model A45	
	Major	Non-major	Major	Non-major	Major	Non-major	Major	Non-major	Major	Non-major
Perpetrator Muslim	**2.15*****	**1.19****	**1.92*****	**0.89***	**1.96****	**0.81***	**2.20****	**1.12***	**2.15****	**0.99***
	(0.53)	**(0.38)**	**(0.51)**	**(0.36)**	**(0.58)**	**(0.38)**	**(0.64)**	**(0.45)**	**(0.66)**	**(0.43)**
	[758%]	[228%]	[579%]	[144%]	[611%]	[124%]	[807%]	[208%]	[759%]	[168%]
Perpetrator arrested	**1.39*****	**1.32*****	**1.00***	**0.81***	**1.07****	**0.92***	**1.43*****	**1.27*****	**1.50*****	**1.35*****
	(0.35)	**(0.27)**	**(0.40)**	**(0.36)**	**(0.39)**	**(0.35)**	**(0.39)**	**(0.32)**	**(0.38)**	**(0.30)**
	[303%]	[276%]	[171%]	[126%]	[190%]	[150%]	[319%]	[256%]	[347%]	[286%]
Target law enforcement/ government	**1.05***	**1.15****	0.74****	**0.81***	0.77****	**0.77***	**0.96***	**1.05***	**0.91***	**0.94***
	(0.42)	**(0.44)**	(0.41)	**(0.36)**	(0.42)	**(0.38)**	**(0.41)**	**(0.41)**	**(0.46)**	**(0.46)**
	[186%]	[215%]	[109%]	[126%]	[117%]	[116%]	[160%]	[187%]	[149%]	[156%]
Number killed	**0.48****	**0.33****	**0.43****	**0.30****	**0.43***	**0.30****	**0.50****	**0.34***	**0.50****	**0.35****
	(0.16)	**(0.11)**	**(0.15)**	**(0.10)**	**(0.17)**	**(0.12)**	**(0.19)**	**(0.13)**	**(0.16)**	**(0.11)**
	[62%]	[39%]	[55%]	[34%]	[54%]	[35%]	[65%]	[41%]	[64%]	[42%]
Significant date			−0.31	0.21	−0.40	0.16	−0.55	−0.03	−0.61	−0.07
			(0.54)	(0.31)	(0.53)	(0.33)	(0.53)	(0.35)	(0.57)	(0.36)
			[−27%]	[24%]	[−33%]	[17%]	[−42%]	[−3%]	[−45%]	[−7%]
Target Muslim			−0.65	−0.38			−0.60	−0.33		
			(0.43)	(0.32)			(0.46)	(0.37)		
			[−48%]	[−31%]			[−45%]	[−28%]		
Target minority					−0.27	−0.46			−0.44	−0.55
					(0.45)	(0.28)			(0.44)	(0.37)
					[−23%]	[−37%]			[−35%]	[−42%]
Perpetrator and group unknown			**−1.34***	**−1.21****	**−1.24***	**−1.16***				
			(0.56)	**(0.43)**	**(0.57)**	**(0.45)**				
			[−74%]	**[−70%]**	**[−71%]**	**[−69%]**				
Perpetrator, group, and motive unknown							−0.32	−0.24	−0.36	−0.35
							(4.75)	(3.53)	(6.00)	(3.27)
							[−27%]	[−22%]	[−30%]	[−30%]
AIC	591.522	852.725	589.286	849.245	590.434	847.940	594.831	857.948	595.074	855.75
BIC	608.998	870.201	615.500	875.459	616.648	874.154	621.045	884.162	621.288	881.964

Notes. Negative binomial regression models. Constants not reported.
Coefficients are presented with bootstrapped standard errors in parentheses.
Percent change in expected count reported in brackets.
*$p<.05$.
**$p< .01$.
***$p<.001$.
****$p<.10$.

Table A12. News coverage by terrorism episode when all GTD terrorism criteria met – comparing major and non-major media outlets (N=113).

	Model A46		Model A47		Model A48		Model A49		Model A50	
	Major	Non-major	Major	Non-major	Major	Non-major	Major	Non-major	Major	Non-major
Perpetrator Muslim	2.13***	1.28**	1.81**	1.02*	1.87**	0.93*	2.06***	1.20**	2.05**	1.06*
	(0.51)	(0.37)	(0.61)	(0.47)	(0.63)	(0.42)	(0.52)	(0.43)	(0.65)	(0.43)
	[742%]	[259%]	[512%]	[178%]	[552%]	[152%]	[682%]	[231%]	[675%]	[189%]
Perpetrator arrested	1.30**	1.26***	0.93*	0.86*	1.07*	0.95*	1.32**	1.19**	1.43***	1.26**
	(0.40)	(0.27)	(0.42)	(0.35)	(0.43)	(0.41)	(0.43)	(0.37)	(0.40)	(0.36)
	[267%]	[254%]	[153%]	[136%]	[193%]	[159%]	[273%]	[230%]	[316%]	[252%]
Target law enforcement/government	0.43	0.62	0.17	0.43	0.25	0.38	0.32	0.51	0.36	0.42
	(0.40)	(0.38)	(0.41)	(0.41)	(0.43)	(0.40)	(0.50)	(0.41)	(0.49)	(0.40)
	[54%]	[85%]	[19%]	[54%]	[29%]	[46%]	[38%]	[67%]	[43%]	[52%]
Number killed	0.50**	0.36**	0.46**	0.33**	0.46*	0.34**	0.52**	0.37**	0.52**	0.38**
	(0.17)	(0.12)	(0.17)	(0.12)	(0.19)	(0.12)	(0.19)	(0.13)	(0.19)	(0.12)
	[64%]	[44%]	[58%]	[39%]	[59%]	[41%]	[68%]	[45%]	[68%]	[47%]
Significant date			0.03	0.29	−0.12	0.25	−0.14	0.20	−0.27	0.16
			(0.65)	(0.39)	(1.83)	(0.39)	(0.59)	(0.41)	(1.64)	(0.39)
			[4%]	[33%]	[−12%]	[28%]	[−13%]	[22%]	[−24%]	[18%]
Target Muslim			−1.07	−0.38			−0.98****	−0.33		
			(1.43)	(0.37)			(0.56)	(0.50)		
			[−66%]	[−32%]			[−62%]	[−28%]		
Target minority					−0.39	−0.54			−0.50	−0.61****
					(0.55)	(0.35)			(0.55)	(0.36)
					[−32%]	[−42%]			[−39%]	[−46%]
Perpetrator and group unknown			−1.08*	−0.94*	−0.92	−0.88****				
			(0.51)	(0.43)	(0.61)	(0.46)				
			[−66%]	[−61%]	[−60%]	[−58%]				
Perpetrator, group, and motive unknown							0.16	−0.02	0.17	−0.14
							(6.88)	(5.69)	(6.01)	(5.99)
							[17%]	[−2%]	[19%]	[−13%]
AIC	498.871	694.514	498.406	694.780	500.815	692.912	501.890	699.816	503.288	697.297
BIC	515.236	710.878	522.953	719.326	525.362	717.459	526.437	724.362	527.834	721.843

Notes. Negative binomial regression models. Constants not reported.
Coefficients are presented with bootstrapped standard errors in parentheses.
Percent change in expected count reported in brackets.
*p<.05.
**p< .01.
***p<.001.
****p<.10.

Table A13. News coverage by terrorism episode without Boston Bombing or Fort Hood – comparing major and non-major media outlets ($N = 134$).

	Model A51		Model A52		Model A53		Model A54		Model A55	
	Major	Non-major	Major	Non-major	Major	Non-major	Major	Non-major	Major	Non-major
Perpetrator Muslim	**2.22*****	**1.21****	**1.95****	**0.92***	**1.99****	0.83****	**2.26*****	**1.16***	**2.20*****	**1.03***
	(0.62)	**(0.41)**	**(0.75)**	**(0.46)**	**(0.64)**	(0.45)	**(0.65)**	**(0.48)**	**(0.55)**	**(0.42)**
	[816%]	**[237%]**	**[603%]**	**[150%]**	**[633%]**	[130%]	**[854%]**	**[219%]**	**[805%]**	**[180%]**
Perpetrator arrested	**1.39*****	**1.33*****	**1.03***	**0.85***	**1.09***	**0.95***	**1.45*****	**1.29*****	**1.51*****	**1.37*****
	(0.38)	**(0.28)**	**(0.42)**	**(0.36)**	**(0.44)**	**(0.40)**	**(0.38)**	**(0.30)**	**(0.39)**	**(0.29)**
	[302%]	**[277%]**	**[181%]**	**[133%]**	**[199%]**	**[159%]**	**[327%]**	**[264%]**	**[355%]**	**[295%]**
Target law enforcement/government	**1.11****	**1.19****	0.82****	**0.88***	**0.86***	**0.83***	**1.03***	**1.11***	**0.99***	**0.99***
	(0.42)	**(0.40)**	(0.44)	**(0.40)**	**(0.39)**	**(0.37)**	**(0.44)**	**(0.45)**	**(0.45)**	**(0.41)**
	[204%]	**[229%]**	[128%]	**[140%]**	**[136%]**	**[129%]**	**[180%]**	**[202%]**	**[168%]**	**[169%]**
Number killed	**0.55***	**0.37***	**0.47***	**0.33***	**0.47***	**0.34***	**0.54****	**0.38***	**0.54****	**0.39****
	(0.23)	**(0.17)**	**(0.21)**	**(0.14)**	**(0.21)**	**(0.14)**	**(0.21)**	**(0.15)**	**(0.21)**	**(0.14)**
	[73%]	**[45%]**	**[60%]**	**[39%]**	**[60%]**	**[40%]**	**[72%]**	**[47%]**	**[72%]**	**[48%]**
Significant date			−0.47	0.12	−0.56	0.07	−0.66	−0.10	−0.72	−0.13
			(0.64)	(0.35)	(0.59)	(0.34)	(0.63)	(0.34)	(0.76)	(0.35)
			[−38%]	[13%]	[−43%]	[7%]	[−48%]	[−10%]	[−51%]	[−12%]
Target Muslim			−0.63	−0.37			−0.60	−0.33		
			(0.51)	(0.36)			(0.51)	(0.40)		
			[−47%]	[−31%]			[−45%]	[−28%]		
Target minority					−0.26	−0.46			−0.43	−0.55****
					(0.46)	(0.29)			(0.45)	(0.29)
					[−23%]	[−37%]			[−35%]	[−43%]
Perpetrator and group unknown			**−1.27***	**−1.15****	−1.18****	**−1.09***				
			(0.54)	**(0.42)**	(0.61)	**(0.49)**				
			[−72%]	**[−68%]**	[−69%]	**[−67%]**				
Perpetrator group and motive unknown							−0.25	−0.18	−0.29	−0.29
							(4.46)	(3.04)	(5.37)	(1.55)
							[−22%]	[−17%]	[−26%]	[−25%]
AIC	560.702	822.478	558.689	819.829	559.748	818.457	563.667	827.640	563.904	825.405
BIC	578.089	839.865	584.769	845.909	585.828	844.537	589.748	853.720	589.985	851.485

Notes. Negative binomial regression models. Constants not reported.
Coefficients are presented with bootstrapped standard errors in parentheses.
Percent change in expected count reported in brackets.
*$p<.05$.
**$p< .01$.
***$p<.001$.
****$p<.10$.

Table A14. News coverage by terrorism episode when all GTD terrorism criteria met without Boston Bombing or Fort Hood – comparing major and non-major media outlets ($N = 131$).

	Model A56		Model A57		Model A58		Model A59		Model A60	
	Major	Non-major	Major	Non-major	Major	Non-major	Major	Non-major	Major	Non-major
Perpetrator Muslim	2.20***	1.32***	1.89**	1.08*	1.95**	0.98*	2.14**	1.26**	2.13***	1.13*
	(0.52)	(0.37)	(0.61)	(0.47)	(0.56)	(0.41)	(0.69)	(0.43)	(0.61)	(0.45)
	[804%]	[274%]	[560%]	[194%]	[600%]	[167%]	[750%]	[254%]	[739%]	[208%]
Perpetrator arrested	1.29**	1.26***	0.98*	0.89*	1.11*	0.99*	1.35**	1.21***	1.44**	1.28***
	(0.41)	(0.32)	(0.45)	(0.38)	(0.44)	(0.39)	(0.42)	(0.34)	(0.44)	(0.33)
	[264%]	[252%]	[167%]	[145%]	[205%]	[169%]	[286%]	[236%]	[324%]	[260%]
Target law enforcement/government	0.48	0.65****	0.26	0.49	0.34	0.43	0.40	0.57	0.43	0.46
	(0.42)	(0.37)	(0.46)	(0.42)	(0.45)	(0.39)	(0.47)	(0.42)	(0.52)	(0.39)
	[62%]	[92%]	[30%]	[63%]	[40%]	[54%]	[50%]	[76%]	[53%]	[59%]
Number killed	0.58**	0.43**	0.52**	0.38**	0.53*	0.40**	0.59**	0.44**	0.59*	0.45*
	(0.22)	(0.16)	(0.18)	(0.15)	(0.21)	(0.14)	(0.21)	(0.16)	(0.30)	(0.17)
	[78%]	[53%]	[68%]	[47%]	[70%]	[49%]	[80%]	[55%]	[81%]	[56%]
Significant date			−0.08	0.21	−0.25	0.18	−0.22	0.14	−0.36	0.12
			(2.22)	(0.40)	(2.05)	(0.37)	(0.77)	(0.39)	(0.64)	(0.38)
			[−8%]	[24%]	[−22%]	[20%]	[−20%]	[15%]	[−30%]	[12%]
Target Muslim			−1.06	−0.37			−0.97****	−0.32		
			(1.16)	(0.39)			(0.52)	(0.42)		
			[−65%]	[−31%]			[−62%]	[−28%]		
Target minority					−0.40	−0.56			−0.50	−0.62****
					(0.53)	(0.37)			(0.53)	(0.36)
					[−33%]	[−43%]			[−39%]	[−46%]
Perpetrator and group unknown			−0.98*	−0.88****	−0.83	−0.81****				
			(0.49)	(0.47)	(0.53)	(0.45)				
			[−63%]	[−58%]	[−56%]	[−55%]				
Perpetrator group and motive unknown							0.24	0.04	0.25	−0.09
							(6.77)	(6.55)	(6.81)	(6.25)
							[28%]	[4%]	[29%]	[−8%]
AIC	468.252	664.330	468.275	665.400	470.483	663.400	471.101	669.703	472.411	667.092
BIC	484.509	680.587	492.661	689.786	494.869	687.785	495.487	694.088	496.797	691.478

Notes. Negative binomial regression models. Constants not reported.
Coefficients are presented with bootstrapped standard errors in parentheses.
Percent change in expected count reported in brackets.
*$p<.05$.
**$p<.01$.
***$p<.001$.
****$p<.10$.