

Analysis of Factors Related to Hate Crime and Terrorism

Final Report to the National Consortium for the Study of Terrorism and Responses to Terrorism

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About This Report

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The views and conclusions contained in this document are those of the authors and should not be interpreted as necessarily representing the official policies, either expressed or implied, of START.

About START

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Executive Summary

The objective of this project was to empirically assess the association between hate crime and terrorism in the United States and evaluate whether these behaviors share common determinants. Prior research has suggested that hate crime can be thought of as a "close cousin" to terrorism and that the two behaviors may be correlated and share common determinants. Yet theories of crime and political violence gave us reason to question the assumption of a hate crime-terrorism nexus. To examine the relationship between terrorism and hate crime we integrated several data sources at both the county and national levels covering a period of seventeen years (1992-2008).

Our analysis produced several key findings. First, and on a methodological note, the data **show that** "double counting" of hate crimes and terrorist acts is uncommon. We estimate that between 3% and 5.3% of the terrorist attacks included in the Global Terrorism Database are duplicated in the FBI hate crime statistics. Second, at the national level of analysis, we find evidence that hate crimes are likely to *follow* terrorist attacks, but this relationship is specific to particular types of terrorism and hate crime. Attacks on symbols of core American values (e.g., the Pentagon) and those perpetrated by groups with a religious motivation were followed by a sizeable increase in the number of hate crimes targeting minorities during the first week after an attack. Hate crimes remained at an elevated level for about four weeks in some cases. Further analysis indicates that much of this effect is driven by the 9/11 attacks. In addition, the hate crimes were not confined to the immediate geographic location of the terrorist attack.

At the county level we examined: a) the statistical relationship between hate crimes and terrorism; b) whether hate crime and terrorism were associated with the demographic characteristics of counties in which they occurred; and c) the sequencing of hate crime and terrorism by day for counties that experienced at least one terrorist attack between 1992 and 2008. We found no robust correlation between terrorism and hate crime at the county level. We also found very little similarity in the demographic nature of counties where terrorism and hate crimes took place. We did find evidence of an impact of the timing of hate crimes and terrorism on each other, but our analysis was very sensitive to model specification. As such, we interpret the latter association cautiously. In the end our research points in the direction that the relationship between terrorism and hate crimes is best understood at the national level and that hate crimes are more likely to follow than precede terrorist attacks.

In future work we plan to examine the relationship between hate crimes in the United States and terrorist attacks against U.S. interests that take place abroad, which account for approximately 70 percent of attacks against U.S. interests. Second, we plan to examine single-actor terrorist attacks and assess whether they are more similar to terrorism or hate crimes.



Introduction and Background

During the past two decades social scientists have amassed a sizeable body of research on the topic of hate crime in the United States (see Green et al. 2001 for review of literature). At the same time, an independent body of empirical scholarship has emerged on the topic of terrorism, particularly since the creation of the Global Terrorism Database (GTD; see LaFree 2010). Although these respective criminal behaviors – hate crime and terrorism – share some general similarities, such as their shared objective of expressing aggression and seeking to intimidate a larger group rather than victimize a single individual, little research to date has investigated whether these types of offending are related. We also don't know whether they share common determinants and occur in the same types of places or around the same time.

The overarching objective of this project was to analyze existing quantitative data at the national and county levels to identify potential risk factors for hate crime and terrorism and to assess whether there is an empirical association between hate crime and terrorism. Prior research has suggested that hate crime can be thought of as a "close cousin" to terrorism and that the two behaviors may be correlated and share common determinants (Krueger and Malečková 2002, p.28). Yet theories of social control and political violence gave us reason to question the assumption of a hate crime-terrorism nexus. For instance, hate crime incidents are frequently perpetrated by young offenders who have criminal records and are oftentimes under the influence of alcohol or drugs at the time of the incident (Dunbar 2003; Messner et al. 2004), which makes the typical offender more like the average criminal than the prototypical terrorist. Also unlike terrorism, many hate crime perpetrators lack strong political affiliations or ideological commitments and seem to shun formal organizations (Willems et al. 1993). Finally, hate crimes are disproportionately perpetrated by members of the majority or powerful group in society with the modal victim being a racial, religious, or other minority, and hence we might think of them as 'downward offenses.' On the other hand, terrorism is often considered an 'upward offense' with the attacks frequently involving perpetrators of a lower social standing than the target or victim, which is often a government entity (Black 2004, building on Senechal de la Roche 1996). Unlike hate crimes, terrorist acts are more apt to be planned, part of a sustained effort, and in many cases associated with organized groups that draw attention to a political or social cause through publicity of the terrorist event (LaFree and Dugan 2004). Prior to this study no empirical research has assembled the data and conducted the analyses to assess the relationship between hate crime and terrorism.

This project was largely motivated by three research questions. First, we took this opportunity to investigate a methodological issue that could bear on our research as well as future work on this topic. To what extent are hate crimes 'double counted' by appearing in both hate crime and terrorism databases? Specifically, we examine how likely it is for a single event to be listed in both the Global Terrorism Database (GTD) and the Federal Bureau of Investigation's annual hate crime statistics. The FBI defines hate crimes as "criminal offenses that are motivated, in whole or in part, by the offender's bias against a race, religion, sexual orientation, ethnicity/national origin, or disability that are committed against persons, property, or society." Following the methodology of the GTD, we define terrorism as "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." The two behaviors are thus defined differently, but they are not by definition mutually exclusive. For instance, the August 2012

¹ See FBI *Hate Crime Statistics* (2010) at http://www.fbi.gov/about-us/cjis/ucr/hate-crime/2010/resources/hate-crime-2010-methodology.

² See GTD Data and Methodology description at http://www.start.umd.edu/gtd/using-gtd/.



shooting at a Sikh Temple in Oak Creek, Wisconsin may be considered a hate crime with an anti-Sikh or perhaps anti-Islamic motive (if the perpetrator mistook Sikhs for Muslims), or it could be categorized as an act of domestic right-wing terrorism. We must ensure that any empirical investigation of these behaviors does not include the same event as both an act of terrorism and a hate crime since we will be examining them as separate phenomena. Our first analytic endeavor is thus to identify duplicate cases.

Second, we asked whether the perpetration of hate crimes foreshadows future domestic terrorist events. In other words, can we think of hate crime as a 'poor man's terrorist attack' that predicts more serious and potentially lethal acts of terrorism? This hypothesis is largely exploratory in nature and, as such, theoretical and empirical work on this topic is noticeably thin and rarely entails systematic data analysis. The notion that a spike in hate crimes may foreshadow future terrorist acts is premised on the idea of 'radicalization.' Although a rather nebulous concept, we follow McCauley and Moskalenko (2008) and view radicalization as a change in belief, feeling or behavior toward increased support for intergroup conflict. To date, most work on radicalization has consisted of case studies or has speculated about the association between attitudinal and behavioral measures of extremist behavior. For instance, Turk (2004) draws on the work of Hamm (1997) to suggest that in some cases individuals develop negative attitudes towards minority groups or the government that may graduate in severity over time. We investigate whether the perpetration of hate crimes against minorities in a given geographic area constitutes a 'yellow flag' indicating terrorism may be in the offing.

Third, we examined whether terrorist attacks foreshadow future hate crimes. Theoretical work on crime and social control posits that many criminal offenses can be thought of as forms of "self-help" - "the expression of a grievance by unilateral aggression such as personal violence or property destruction" (Black, 1983, p.34). Many crimes satisfy a desire for justice, particularly among those who cannot easily turn to law enforcement agencies for help. This proposition resonates with what gang researchers label 'generalized violence,' "in which innocent victims (nondisputants) serve as proxies for past wrongs" committed by others (Papachristos, 2009, p.81). This idea also aligns with recent theoretical work in the social psychology of aggression, namely Lickel and colleagues' (2006) work on "vicarious retribution." These authors suggest that vicarious retribution occurs when "a member of a group commits an act of aggression toward members of an out-group for an assault or provocation that had no personal consequences for him or her, but did harm a fellow in-group member" (Lickel et al. 2006, pp.372-3). In other words, aggression is vicarious when a member of group A is aggressive toward an innocent member of group B for the actions of a third party who also belonged to group B. Importantly, this work also draws explicit attention to the role of provocation. Interracial violence in U.S. history has often taken the form of reactions to perceived provocations (Myrdal, 1944), as was the case with much violence in Northern Ireland (LaFree, Dugan and Korte, 2009). Pertinent to the present case, violent or discriminatory acts that are seen as committed by members of one group against another, and especially acts that stoke a sense of group pride in the victimized group, are likely to incite retribution that is vicarious in nature (Lickel et al. 2006). The case of post 9/11 hate crimes appears to be an exemplar of this phenomenon. A violent act was perpetrated, a definable out-group was identified shortly afterward, the emotion of anger was thick and widespread in American society after the attacks, justice through legal channels may have been viewed as impossible by certain individuals due to the suicidal nature of the attack, and hate crimes against innocent third parties followed (Disha et al., 2011). We might then

³ This notion is also premised on the assumption that terrorism is more violent than hate crime. Unlike hate crime, terrorism by definition entails the threatened or actual use of force (see definition above). Data on hate crime and terrorism corroborate the assumption that terrorism is proportionately more lethal. For instance, nearly 8% of terrorist attacks examined in this analysis were lethal (resulting in one or more deaths). By comparison, about one tenth of one percent of hate crimes during the 1992-2008 period was classified as murder or manslaughter.



understand some crime and aggression as retributive, moralistic, and aimed at innocent third parties. These circumstances could be particularly helpful for understanding hate crimes, which are inherently moralistic because, by definition, they entail a degree of prejudice or hatred against the victim's group.

In this project we tested whether hate crimes spike in the days or weeks following a terrorist attack in the United States. In addition, we disaggregated terrorist attacks by ideology of the perpetrators and also disaggregated hate crimes based on the type of bias involved in the crime. We also investigated whether attacks against institutions that might be thought of as representing core American values result in a backlash in which some minority groups are at higher risk of victimization after the attack.⁴ Our working hypothesis is that hate crimes against minority groups will increase following particular types of terrorist attacks. We suspect that individuals who share certain racial, ethnic or religious characteristics with the perpetrators of a terrorist attack are at a particularly high risk (e.g., Muslims after a terrorist attack by Islamist militants), yet there are reasons to look at minority groups more generally. For instance, Sikhs or North Africans may be targeted because in the eyes of hate crime offenders they may *appear* to share key characteristics with the perpetrators, even if this is not actually the case.

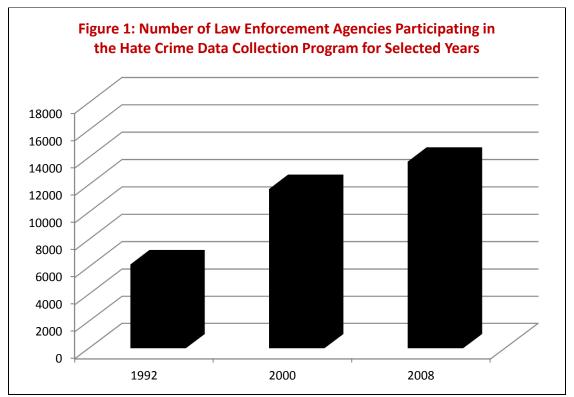
Data Sources and Integration

This project necessitated the integration of several data sources that had to be organized at both the county and national levels over a period of seventeen years (1992-2008). Our analysis begins in 1992 because this is the first year in which hate crime data were available and we end with the year 2008, the last year for which the raw hate crime data were available at the beginning of this project.

The original source of the hate crime data was the Federal Bureau of Investigation's annual hate crime statistics files. As stated above, the FBI states that "a hate crime... is a criminal offense committed against a person, property, or society that is motivated, in whole or in part, by the offender's bias against a race, religion, disability, sexual orientation, or ethnicity/national origin." Law enforcement agencies throughout the U.S. have been asked to submit counts of hate crime incidents in their respective jurisdictions, and to the extent possible record information on the nature of the offense, the characteristics of the victim (e.g., person, business), offenders (e.g., race, if known), and location, among other data pertinent to the offense under the Hate Crime Statistics Act (HCSA) of 1990. Under-reporting of incidents has been a persistent problem since the onset of the data collection endeavor, although participation by local law enforcement agencies has steadily improved over the life of the program. For instance, approximately 6,181 law enforcement agencies participated in the hate crime data collection program in its first year (1992). Importantly, these participating agencies were disproportionately from large population centers and hence accounted for a large proportion of the U.S. population. By 2008 the number of participating agencies climbed to 13,690 agencies covering approximately 89% of the nation's population (see Figure 1).

⁴ We examined both any anti-minority hate crimes and hate crimes that were specifically anti-Muslim or anti-Islamic. The latter results were consistent with those reported in this document.





Sources: Data for 1992 are from the Anti-Defamation League's report on the Hate Crime Statistics Act (see http://www.adl.org/issue_government/hate_crime_statistics_act.asp). Data for 2000 and 2008 are from the FBI's annual Hate Crime Statistics Reports (http://www.fbi.gov/about-us/cjis/ucr/ucr#cius_hatecrime).

Failure to report hate crime data is not random, and prior research shows that compliance is associated with demographic characteristics of cities (King 2007) and with social movement mobilization and the political environment of counties (McVeigh et al. 2003), among other factors. While the problematic nature of the data warrants caution and consideration in any analysis, these issues do not render the data unusable. In our national level analysis, our data files are organized at the weekly and even the daily level, and our objective is to assess the temporal proximity of hate crimes in relation to terrorist attacks. As such, reporting bias across states and over the long term is less of an issue. In the national-level analysis the cross-sectional differences in compliance with the HCSA are a minimal problem because our time-series units (days and weeks) are smaller than the reporting periods (quarters), and thus it is unlikely that increases in hate crimes in the days after a terrorist attack could be attributable to a sudden onset of hate crime reporting by many law enforcement agencies. As discussed below, we also account for growth in reporting over time by controlling for linear time in models with hate crime offending as a dependent variable.

In county-level analyses our concerns about underreporting are more severe since there are differences in reporting both over time and across counties. In order to ensure that our results are not driven by underreporting we conducted several sensitivity analyses. In some models we restricted our analysis to counties that complied with the HSCA 90 percent of the time. In other models we made use of a zero-inflated negative binomial estimator that allows us to model 'zero-counts' (counties reporting no hate crimes) and those reporting one or more hate crimes simultaneously, which effectively enables us to control for reporting differences over time and across counties. In short, we are mindful of the limitations of the data, yet when attentive to these limitations and when employing models to account for underreporting we see the hate crime data as suitable for an inquiry of this nature.



The FBI provides summary statistics for each year on its website, yet our inquiry required more finely grained temporal units than annual estimates. Accordingly, we retrieved the raw data from the Inter-University Consortium for Political and Social Research (ICPSR). These incident-level hate crime files include the date and place of the incident, which allowed us to aggregate the data to both the county and national levels. These data also enabled us to examine hate crimes over time (e.g., on a daily or weekly basis). Using combinations of date and place information, the hate crime data were then merged with data from the Global Terrorism Database (GTD) on terrorist attacks taking place on U.S. soil. According to GTD, a terrorist attack must be an intentional act or threat of violence whose perpetrators are subnational actors. Additionally, two of the following three criteria must be met: there must be a political, economic, religious or social goal, the perpetrators must be trying to coerce or intimidate a group larger than the immediate victims of the attack, and the event must not be an act of legitimate warfare (GTD). This merger resulted in two files. The first included data on terrorism and hate crime at the national level organized by day, which enabled us to assess the temporal order of hate crime and terrorism. Second, we constructed a dataset that included information on hate crimes and terrorism by county and by year. This enabled us to examine whether there were associations between hate crime and terrorism at the county level.

For the latter analysis of counties over time it was also necessary to control for a number of demographic and crime indicators. For instance, an initial analysis might indicate a significant correlation between hate crime and terrorism, yet the statistical association may be attributable to a third factor such as population size or the percentage of the county living in an urban area. If we failed to adequately control for such characteristics then results of the regression models would be biased because of critical omitted variables. Incorporating data from the U.S. Census also allowed us to model hate crimes and terrorism separately so that we could ascertain whether they shared common determinants. Accomplishing this necessitated the extraction of census data for approximately 3,000 counties in the United States for multiple data points between 1990 and 2010. The majority of our data were taken from three censuses (1990, 2000, and 2010) and from the American Community Survey five-year aggregated files.⁵ Although some economic indicators and core population measures were available annually from the Census Bureau and the Bureau of Labor Statistics, for many variables we had to interpolate for non-census years.⁶ This effort resulted in a file with approximately 156 variables covering five general demographic areas: population structure, ancestry and languages, area and density, economic and educational measures, and family structure.

Finally, we integrated the census, terrorism, and hate crime data with crime information from the FBI's Uniform Crime Reports (UCR). The UCR contains county-level estimates for the number of violent and property crimes in counties during the time period under investigation.⁷ These data, like all other

⁵ The American Community Survey samples the American population each year. Given that the survey is based on a sample rather than full population counts (as is done with the decennial U.S. Census), data from a single year are too sparse to provide reliable estimates for small geographic units, such as counties with small populations. This can be remedied by taking three-year or five-year estimates. The former provide estimates for geographic areas with more than 20,000 people while the five-year estimates include information for all counties.

⁶ Interpolation was based on the assumption of linear growth. Consider as an example the age structure of the population. If a county's population over the age of 25 was 50,000 in 1990 and 51,000 in the 2000 Census, then we assume an annual growth of 100 per year. The interpolated value for 1991 would be 50,100, the estimate for 1992 would be 50,200, and so on.

⁷ Violent crimes include murder and non-negligent manslaughter, forcible rape, robbery, and aggravated assault. Property crimes include burglary, larceny-theft, motor vehicle theft, and arson. The combined total, often referred to as Part I offenses or index crimes, was divided by the total population and then multiplied by 100,000 to calculate the index crime rate for each county. The FBI uses an imputation algorithm to adjust for incomplete reporting by some law enforcement agencies. For



information, were integrated into the master file using county-specific Federal Information Processing Standards (FIPS) codes and year variables.

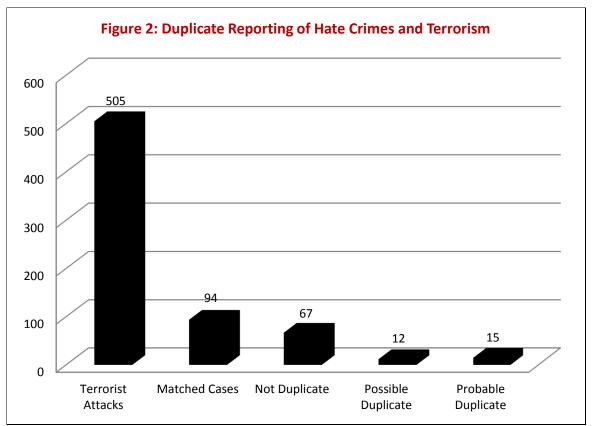
Key Findings

Overlap between the GTD and Hate Crime Data

As mentioned above, a methodological question of interest was whether hate crimes and terrorism are frequently "double-counted." To assess the degree of overlap we examined whether the same incidents were included in both the GTD and the annual FBI hate crime data. With few exceptions this is not the case. To identify duplicates in the respective files we first created a variable in each database that combined information about the date of the incident and the county in which it took place. This variable was then used to merge the two datasets, which yielded a total of 94 matched cases. Following the merger of the two datasets, information was used from the summary description, attack type, target type. weapon type, group affiliation, and 'additional notes' variables from the GTD and the number of victims and offenders, offender race, bias motivation, and location variables from the hate crime data to further examine if these matched cases were indeed duplicates. Based on this information, the matched cases were then coded into one of three categories: 1) "Not Duplicate" 2) "Possible Duplicate" and 3) "Probable Duplicate." Cases were coded as "Not Duplicate" if information about the incidents in the hate crime data was substantively different from the information in the GTD. Cases were coded "Possible Duplicate" if ambiguous or insufficient information prevented the exclusion of a matched case as a duplicate. Cases were coded "Probable Duplicate" if all available information about the incidents from the GTD matched all available information from the hate crime data. Of the 94 matched cases, 67 cases were determined not to be duplicates, 12 were determined to be possible duplicates, and 15 were determined to be probable duplicates (See Figure 2). There were 505 terrorist attacks listed in GTD during our time period of interest (1992-2008) and more than 130,000 hate crimes. The 15 probable duplicates amount to 3% of all domestic terrorism acts in the GTD and 0.005% of hate crimes during the period of study. Duplication was not an issue in our analyses that used lagged measures of hate crime or terrorism (e.g., the association between hate crime in 2000 and terrorism in 2001) because cases could not be doublecounted if they occurred in different years. When looking at the contemporaneous correlation between the two behaviors we counted the 15 probable duplicates as terrorism events and *not* as hate crimes.

more information and an assessment of the FBI imputation procedures, see Lynch and Jarvis (2008). We also note that some violent and property crimes that were motivated by hatred or bias (i.e., hate crimes) may be included in the index crime rate, but hate crimes constitute such a small proportion of index crimes that their inclusion does not introduce significant bias into statistical models. For instance, in 2008 there were approximately 11.2 million violent and property crimes and 7,783 hate crimes reported across the nation, and thus only a fraction of a percentage of the reported violent and property crimes were hate crimes.





Sources: Global Terrorism Database and FBI Hate Crime Statistics.

National-Level Analyses: Terrorism and Hate Crime

We examined the association between terrorism and hate crime at the national level using time series data organized at the daily and weekly level. The key questions here were whether, at the national level, hate crimes and terrorism were correlated over time, and of particular interest was whether hate crimes tended to foreshadow or follow terrorist attacks (i.e., lagged effects). We coded each variable in multiple ways. For instance, we began our analysis by looking at all hate crimes and all terrorist attacks, and successively broke down each behavior by target (hate crimes) or motivation (terrorism). To determine the motivation of the terror attack, we examined Terrorist Organization Profiles (TOPS) originally collected by the Memorial Institute for the Prevention of Terrorism. TOPS codes and organizes groups by ideology. An attack was determined to have a right-wing motivation (being either reactionary or conservative in their ideology) if it was carried out by a group that was categorized as right-wing conservative or right-wing reactionary by TOPS.⁸ Additionally, groups categorized as racist, religious, or nationalist/separatist were examined closely for right-wing ideological beliefs. Attacks carried out by groups with these beliefs were also classified as right-wing.⁹ Anti-abortion attacks were consistently carried out by individuals or groups with a right-wing motivation, and thus were coded as right-wing. Attacks perpetrated by groups with an environmental, animal rights, or other left-wing ideologies as

⁸ As a point of clarification, this does *not* imply that groups are terrorist organizations because they have right-wing beliefs. Rather, when looking at the terrorist attack, TOPS codes the group responsible as having beliefs that might be classified as right-wing, or other motivation.

⁹ Groups with racist, religious or nationalist/separatist ideologies that were headquartered in the United States were categorized as right-wing, although not all groups with these types of ideologies located outside of the United States fell into this category. For instance, al-Qa'ida is a religious organization but was not categorized as ideologically right-wing.



identified by TOPS (being communist, Marxist or socialist in nature) were coded as having a left-wing motivation. We also coded attacks that appeared to target core American ideals as a distinct category. These attacks are mostly carried out by international groups and violent Islamist groups, which we label 'anti-American terrorism' in the present research. Additionally, there were some attacks that did not fit neatly into any of the categories and were labeled as "other." These attacks mostly consisted of anti-communist groups and groups protesting the current regime in Vietnam. Finally, some attacks lacked sufficient information on both the group perpetrating the attack and the motivation of the attack. These attacks were unable to be classified into any of the categories listed above and were grouped into their own category, which was labeled unknown. Of the 505 attacks in our dataset (1992-2008), 29 percent were coded as having a right-wing motivation, 33 percent had a left-wing motivation, 2 percent were attacks on symbols of core American ideals, 34 percent had unknown motivation, the remaining 2 percent of attacks were listed as other.

As a robustness check, we also used data from the Profiles of Perpetrators of Terrorism in the U.S. (PPT-US) to categorize terrorism by ideology. During our period of study, 282 of the 505 terrorist attacks had enough information to be covered by the PPT, while 223 were coded as having an 'unknown' ideology. Typically an ideology was coded as 'unknown' because the group or individual carrying out the attack was not present in the PPT database or because the PPT database explicitly lists an unknown ideology for the group. Also, 227 attacks were carried out by groups characterized simply as "single issue," which leaves 55 attacks, or just over 10% of the sample, that were carried out by groups with a known and unique ideology. We present the results using both the TOPS and the PPT-US coding below, mindful that the former includes fewer unknowns and the latter has more detailed data on perpetrator ideologies.

Most of the analyses looked specifically at hate crimes against minority groups. ¹⁰ This variable includes attacks in which the motivation was aggression against the victims because they were black, Asian, Hispanic, multi-racial, Jewish, Catholic, Muslim, agnostic/atheist, members of another non-Protestant religion, or another ethnicity. Each of these groups has been the target of hate groups at various points in recent history.

Due to concerns that the attacks of September 11th may have fundamentally changed the level of aggression towards specific groups (namely Muslims and Arabs), which could influence the frequency of hate crimes and terrorism, a post-9/11 dummy variable is included in all models. In addition, compliance with the HCSA has generally improved over time (see Figure 1 above). As such, an indicator of time (week) is included to account for trending in the data on hate crimes.

We employ two basic modeling strategies. First, hate crimes at one time point are modeled as a function of past terrorism and other control variables:

$$HateCrime_t = \beta_0 + \ \beta_1 terrorism_{t-1} + \beta_2 terrorism_{t-2} + \beta_3 terrorism_{t-3} + \ \beta_4 Z_t + \ \epsilon_t$$

where Z_t denotes other control variables. We also examine variations of this model using different types of terrorism – e.g., right-wing, left-wing, attacks targeting core American institutions or ideals – and the measure of reported hate crimes specifically refers to anti-minority hate crimes (defined above;

 $^{^{10}}$ The results presented are based on any anti-minority hate crimes. The results maintained their sign and significance when examining only anti-Muslim or anti-Islamic hate crimes. These regressions are available upon request.



measured as count data). In an average week, 148 hate crimes were reported in the U.S. A negative binomial regression is used to assess the above relationship.¹¹

In the second strategy, terrorism is modeled as a function of past hate crime and other control variables:

$$Terrorism_t = \alpha_0 + \alpha_1 HateCrime_{t-1} + \alpha_2 HateCrime_{t-2} + \alpha_3 HateCrime_{t-3} + \alpha_4 X_t + v_t$$

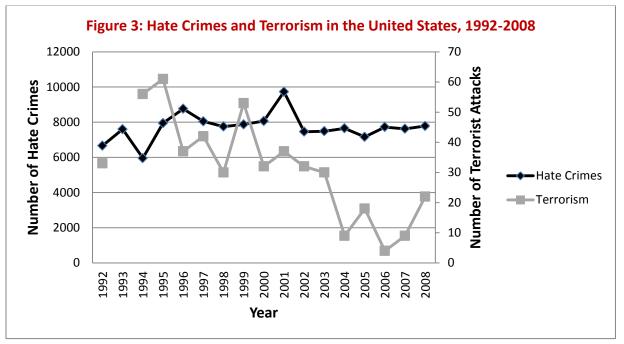
where X_t denotes other control variables. This equation allows us to determine whether terrorism follows hate crimes. Again, iterations of this model examine subgroups of terrorist attacks, such as those perpetrated by groups with left-wing or right-wing ideologies. Terrorism is also count data, with an average of 0.56 attacks each week and more than half of the weeks included in the dataset registering no attacks. Given this distribution in the data, we again rely on a series of negative binomial regression models. Additionally, robustness checks were run using a logit analysis, where the variable of interest was whether or not any terrorist attacks had occurred in that week.

We began our national-level analysis by first assessing the trends in each type of behavior over time using annual data from the GTD and the FBI hate crime reports. As evidenced by the trends in Figure 3 below, the two behaviors do not appear to trend together during our time period of interest (1992-2008). There has been a general decline in the number of terrorist attacks on U.S. soil since 1992, although the trend is by no means linear and the 2001 attacks on the World Trade Center and the Pentagon obviously resulted in a significant number of casualties. The hate crime data indicate less of a decline over time, and indeed the correlation between terrorism and hate crime for the years in question is quite weak (Pearson correlation is -0.02). However, two additional points are noteworthy with respect to Figure 3. First, there appears to be a spike in hate crimes in 2001, the same year as the most deadly terrorist attack in U.S. history. Second, the theoretical work cited above indicates that annual data may be too crude to detect short-term covariance between the two behaviors, and as such we conducted our analyses using weeks as the temporal unit of analysis.

¹¹ This is a variant of a regression model that is suitable for analyzing counts of events, such as the number of hate crimes.

¹² Terrorism data for the year 1993 are missing in the figure because of missing data in the Global Terrorism Database.

 $^{^{13}}$ We note that the 9/11 terrorist attacks were not counted as hate crimes in the data.



Sources: Global Terrorism Database and FBI Hate Crime Statistics.

Regression coefficients for our weekly analysis of anti-minority hate crimes and terrorism (disaggregated by ideology) are reported in Table 1 below. Model 1 in Table 1 indicates that non-right-wing terrorist attacks a week prior are significantly associated with a spike in anti-minority hate crime incidents (b=.045; p<.001). The coefficient indicates that each additional terror attack carried out by a non-right-wing group leads to a 4.5 percent increase in the number of anti-minority hate crimes in the following week. This effect weakens considerably and quickly over time, as the coefficients for non-right-wing terrorism in the prior 2 and 3 weeks were not statistically significant.



	Model 1	Model 2
	Anti-Minority Hate Crimes	Right-Wing Terrorism
Non-Right-Wing	•	-
Terrorism		
1 week prior	.045***	
	(.010)	
2 weeks prior	.016	
	(.010)	
3 weeks prior	.010	
_	(.010)	
Anti-Minority		
Hate Crimes		
1 week prior		019**
1 West prior		(.007)
2 weeks prior		.006
		(.007)
3 weeks prior		002
r		(.007)
Post 9/11 Period	049	-1.212***
1 05t // 11 1 CHOU	(.032)	(.259)
	(.032)	(.237)
Week	.0002**	
	(.00007)	
Constant	4.562***	.107
Combunit	(.024)	(.599)

Note: Standard errors are in parentheses. All tests are two-tailed.

^{*}p<.05 **p< .01 ***p< .001



In Model 2 of Table 1 we regress right-wing terrorism on a measure of anti-minority hate crime occurring in the prior week. The negative and significant coefficient on the one-week lagged variable provides no evidence that anti-minority hate crimes serve as a warning sign that right-wing terrorism is likely in the future. Indeed, the coefficient suggests quite the opposite.

We next disaggregate the results in model 1 of Table 1 by different types of non-right-wing terrorism. It would be consistent with our argument if different types of terrorism yielded unique responses, particularly with respect to hate crimes. We would expect a strong effect for what we coded above as attacks on symbols of core American ideals but small or null effects for the other types of terrorism. To this end, in Table 2 we examine the impact of four different classifications of non-right-wing terrorism on anti-minority hate crimes. As described above, the four classifications are left-wing, attacks on symbols of core American ideals, other, and unknown.

The results are generally consistent with the results from Model 1 in Table 2, although the magnitude of the coefficient appears weaker. For instance, each additional left-wing terrorist attack increases the expected number of anti-minority hate crimes one week later by about 3.4 percent (b=.034, p<.05). Model 2 shows the relationship between attacks on symbols of core American ideals and anti-minority hate crimes, which is where we would expect the most substantial backlash. The results indicate that terrorism of this nature in the prior weeks is strongly associated with an increase in the number of anti-minority hate crimes in the following time period. Two points warrant particular attention in model 2. First, anti-minority hate crimes remain associated with terrorist attacks against core American social, political or economic institutions for four weeks, although the effect dissipates over time. Second, the magnitude of the coefficients, particularly in the first week or two following the terrorist attack, is substantially larger than what we find for any other type of terrorism. One attack against symbols of core American ideals increases the expected number of hate crimes a week later by a large margin – 28 percent (b=0.247, p<.001). Additionally, one attack of this nature increases the expected number of hate crimes four weeks in the future by 12 percent (b=0.114, p<.05).

As mentioned above, we also test our model using data on perpetrator groups from the PPT-US. The PPT coding differs from the TOPS, and hence the categories are different in Table 3 compared to Table 2. Still, we would expect two results to remain consistent. First, as with Table 2 we anticipate that terrorism perpetrated by groups with a right-wing motivation would not be correlated with anti-minority hate crimes that occur in prior weeks. Second, we think that attacks perpetrated by groups that the PPT would categorize as 'religious' will have a positive and statistically significant association with anti-minority hate crimes. That is, hate crimes of this sort will increase during the week or weeks following a terrorist attack that was perpetrated by a group with a religious motivation, akin to the effect we observed for attacks on core American values above.



 $\label{thm:condition} \begin{tabular}{ll} Table 2: Negative Binomial Regression Coefficients: Anti-Minority Hate Crime on Disaggregated Non-Right-Wing Terrorism (N=832) \\ \end{tabular}$

Tion right iting for				
	Model 1	Model 2	Model 3	Model 4
Left-Wing				
1 week prior	.034*			
	(.016)			
2 weeks prior	.015			
	(.017)			
3 weeks prior	001			
1	(.016)			
Attack Core	. ,			
American Ideals				
1 week prior		.247***		
1		(.042)		
2 weeks prior		.136**		
2 weeks prior		(.043)		
3 weeks prior		.139**		
5 weeks prior		(.044)		
A wooks prior		.114*		
4 weeks prior				
O4l N D!-1.4		(.046)		
Other Non-Right-				
Wing			0.40	
1 week prior			.048	
			(.094)	
2 weeks prior			.020	
			(.093)	
3 weeks prior			050	
			(.094)	
Unknown				
1 week prior				.029
_				(.016)
2 weeks prior				.010
•				(.016)
3 weeks prior				.006
r				(.016)
Post 9/11 Period	044	100**	050	050
	(.032)	(.032)	(.033)	(.032)
	(.032)	(.032)	(.055)	(.552)
Week	.0002*	.0003***	.0002*	.0002**
,, JOR	(.0002)	(.0007)	(.0002)	(.0002)
	(.00007)	(.00001)	(.00007)	(.00007)
Constant	4.604***	4.576***	4.611***	4.595***
	(.022)	(.022)	(.022)	(.024)
	(.044)	(.044)	(.044)	(.024)

Note: Standard errors are in parentheses. All tests are two-tailed.

^{*}p<.05 **p< .01 ***p< .001



Table 3: Negative Binomial Regression Coefficients: Anti-Minority Hate Crime on Disaggregated Terrorism Using PPT-US Coding (N=832)

1 week prior		Model 1	Model 2	Model 3	Model 4	Model 5
1 week prior	Single Issue					
Contain Cont		007				
2 weeks prior	1 Week prior					
(.013) 3 weeks prior 001 (.013)	2 wooks prior	· ·				
3 weeks prior	2 weeks prior					
Right-Wing 1 week prior 1 week prior 1 week prior 2 weeks prior 3 weeks prior 1 week prior 2 weeks prior 3 weeks prior 1 week prior 2 weeks prior 3 weeks prior 1 week prior 1 week prior 2 weeks prior 3 weeks prior 1 week prior 2 weeks prior 3 weeks prior 1 week prior 2 weeks prior 3 weeks prior 1 week prior 2 weeks prior 3 weeks prior 1 week prior 2 weeks prior 3 weeks prior 1 week prior 2 weeks prior 3 weeks prior 1 week prior 2 weeks prior 3 weeks prior 1 week prior 2 weeks prior 3 weeks prior 1 week prior 2 weeks prior 3 weeks prior 1 week prior 2 weeks prior 3 weeks prior 4 week						
Right-Wing 1 week prior	3 weeks prior					
1 week prior		(.013)				
Counting	Right-Wing					
Counting the counting to the	1 week prior		.009			
2 weeks prior	1		(.026)			
(.026) 3 weeks prior	2 weeks prior					
3 weeks prior Left-Wing 1 week prior	2 weeks prior					
Left-Wing 1 week prior	2 1 .					
Left-Wing 1 week prior	3 weeks prior					
1 week prior 2 weeks prior 2 weeks prior 3 weeks prior 185 (.178) 3 weeks prior 073 (.176) Religious 1 week prior 2 weeks prior 339* (.041) 3 weeks prior 339* (.041) 3 weeks prior 240* (.043) Nationalist 1 week 070 (.087) 2 weeks prior 124 (.087) 2 weeks prior 124 (.087) 3 weeks prior 080 (.085) Post 9/11 Period049050045045149*052 (.029) (.028) Week .0002* (.029) (.028) Week .0002* (.00007) (.00007) (.00007) (.00007) (.00007) (.00007) Constant 4.608* 4.613* 4.618* 4.559* 4.617*			(.026)			
1 week prior 2 weeks prior 2 weeks prior 3 weeks prior 185 (.178) 3 weeks prior 073 (.176) Religious 1 week prior 2 weeks prior 339* (.041) 3 weeks prior 339* (.041) 3 weeks prior 240* (.043) Nationalist 1 week 070 (.087) 2 weeks prior 124 (.087) 2 weeks prior 124 (.087) 3 weeks prior 080 (.085) Post 9/11 Period049050045045149*052 (.029) (.028) Week .0002* (.029) (.028) Week .0002* (.00007) (.00007) (.00007) (.00007) (.00007) (.00007) Constant 4.608* 4.613* 4.618* 4.559* 4.617*	Left-Wing					
(178) 2 weeks prior -185 (.178) 3 weeks prior -073 (.176) Religious 1 week prior -507* (.040) 2 weeks prior 339* (.041) 3 weeks prior 3 weeks prior -070 (.043) Nationalist 1 week -070 (.087) 2 weeks prior -124 (.087) 3 weeks prior -080 (.087) 3 weeks prior -080 (.085) Post 9/11 Period -049 -050 -045 -149* -052 (.085) Post 9/11 Period -049 -050 -045 -149* -052 (.085) Week -0002* -002* -002* -0007 -0007 -000007 -000007 -000007 -00				216		
2 weeks prior 3 weeks prior 185 (.178) 3 weeks prior 073 (.176) Religious 1 week prior 2 weeks prior 339* (.040) 3 weeks prior 3 weeks prior 3 weeks prior 3 weeks prior 070 (.087) 2 weeks prior 2 weeks prior 124 (.087) 3 weeks prior 3 weeks prior 087) 2 weeks prior 124 (.087) 3 weeks prior 080 (.085) Post 9/11 Period049050045149*052 (.085) Post 9/11 Period049050045149*052 (.085) Week0002*002*002*0007000700007	F					
(178) 3 weeks prior Religious 1 week prior 2 weeks prior 339* (.040) 3 weeks prior 339* (.041) 3 weeks prior 2 40* (.043) Nationalist 1 week	2 vyoolea maion					
3 weeks prior Religious 1 week prior 2 weeks prior 3 weeks prior 3 weeks prior 3 weeks prior 3 weeks prior Nationalist 1 week 1 week 1 week 1 week 2 weeks prior 3 weeks prior 1 week 2 weeks prior 2 weeks prior 3 weeks prior 2 weeks prior 2 weeks prior 2 weeks prior 3 weeks prior 2 weeks prior 2 weeks prior 3 weeks prior 2 weeks prior 2 weeks prior 3 weeks prior 2 weeks prior 2 weeks prior 3 weeks prior 2 weeks prior 3 weeks prior 2 weeks prior 3 weeks prior 4 week 1 week 2 woon 1 week 2 weeks prior 2 weeks prior 2 weeks prior 3 weeks prior 2 weeks prior 3 weeks prior 2 weeks prior 3 weeks prior 4 weeks prior 2 weeks prior 3 weeks prior 2 weeks prior 3 weeks prior 2 weeks prior 3 weeks prior 4 weeks prior 2 weeks prior 3 weeks prior 4 weeks prior 2 weeks prior 3 weeks prior 4 weeks prior 2 weeks prior 4 weeks prior 2 weeks prior 3 weeks prior 4 weeks prior 2 weeks prior 2 weeks prior 3 weeks prior 4 weeks prior 2 weeks prior 4 weeks prior 2 weeks prior 3 weeks prior 4 weeks prior 2 weeks prior 4 weeks prior 4 weeks prior 4 weeks prior 5 weeks prior 6 weeks prior 9 weeks prior 9 weeks prior 1 weeks prior 9 weeks prior 1 weeks prior 2 weeks	2 weeks prior					
Religious 1 week prior 2 weeks prior 339* (.041) 3 weeks prior 240* (.043) Nationalist 1 week 1 week 2 weeks prior 1 week 2 weeks prior						
Religious 1 week prior 2 weeks prior 3 weeks prior 3 weeks prior Nationalist 1 week 2 weeks prior 2 weeks prior Nationalist 1 week 070 (.087) 2 weeks prior 3 weeks prior 124 (.087) 3 weeks prior 124 (.0887)124 (.0887)124 (.0887)124 (.0885) Post 9/11 Period 049050045149*052 (.085) Post 9/11 Period049 (.029) (.028) Week .0002* (.029) (.028) Week .0002* (.00007) (.00007) (.00007) (.00007) Constant 4.608* 4.613* 4.618* 4.559* 4.617*	3 weeks prior					
1 week prior 2 weeks prior 3 339* (.041) 3 weeks prior 2 240* (.043) Nationalist 1 week				(.176)		
1 week prior 2 weeks prior 3 339* (.041) 3 weeks prior 2 240* (.043) Nationalist 1 week	Religious					
(.040) 2 weeks prior 339* (.041) 3 weeks prior 240* (.043) Nationalist 1 week					507*	
2 weeks prior 3 weeks prior 3 weeks prior 2 weeks prior 2 weeks prior Nationalist 1 week 2 weeks prior 2 weeks prior 3 weeks prior 3 weeks prior 4 week 5 weeks prior 6 weeks prior 7 weeks prior 9 weeks prior 1 week 1 week 1 week 1 week 1 week 1 week 2 weeks prior 3 weeks prior 4 weeks prior 4 weeks prior 5 weeks prior 6 weeks prior 7 weeks prior 8 weeks prior 9 weeks prior 1 week 2 weeks prior 2 wee	1 week prior					
(.041) 3 weeks prior (.043) Nationalist 1 week	21				, ,	
3 weeks prior	2 weeks prior					
Nationalist 1 week 2 weeks prior 3 weeks prior Post 9/11 Period 049050050045049 (.087)052 (.029)050045149*052 (.029)050045149*052 (.029)050045149*052 (.029)052 (.0028)045149*052 (.0027)052 (.0028) Week0002*0002*0001*0003*0002*00007)00007)00007)00007)00007)00007)00007)00007)00007)00007)00007)						
Nationalist 1 week 2 weeks prior 3 weeks prior Post 9/11 Period 049049050045049052 (.029)045149*052 (.029)048)045149*052 (.029)048)049050045149*052 (.027)052 (.028) Week0002*0002*00007	3 weeks prior				.240*	
Nationalist 1 week 2 weeks prior 3 weeks prior Post 9/11 Period 049049050045049052 (.029)045149*052 (.029)048)045149*052 (.029)048)049050045149*052 (.027)052 (.028) Week0002*0002*00007					(.043)	
1 week 2 weeks prior 2 weeks prior 3 weeks prior020080 (.087)080 (.085)080 (.085)080 (.085)080 (.085)080 (.085)080 (.085)080 (.085)080 (.085)080 (.085)080 (.085)080 (.085)080 (.085)080 (.085)080 (.085)080 (.087)080 (.085)080 (.085)080 (.087)080 (.087)080 (.087)080 (.087)080 (.087)080 (.087)080 (.087)080 (.087)080 (.087)080 (.085)080 (.085)090 (.0027) (.0027) (.0028)090	Nationalist				,	
2 weeks prior 2 weeks prior 3 weeks prior Post 9/11 Period 049 050 (.028) 045 149* 052 (.029) (.028) Week .0002* .0002* .00007) .00007) .00007) Constant 4.608* 4.613* 4.618* 4.559* 4.617*						070
2 weeks prior 3 weeks prior Post 9/11 Period 049 (.029) 050 (.028) 045 (.032) (.027) (.028) Week .0002* .0002* .00007) .00007) .00007) Constant 4.608* 4.613* 4.618* 4.559* 124 (.087) 080 (.085) 045 149* 052 (.027) (.028) .0002* .0003* .0002* .00007) .00007)	1 WCCK					
(.087) 3 weeks prior Post 9/11 Period049 (.029)050 (.028)045 (.032)149*052 (.027) (.028) Week052 (.029)045 (.032)045 (.027)052 (.028) Week052 (.027)045 (.027)052 (.028) Constant049 (.029)045149*052 (.027)052 (.028) Constant045149*052 (.027)052 (.028) Constant045149*052 (.027)045045149*052 (.027)045045045045049052 (.027)052 (.028) Constant080 (.085)045149*052 (.027)052 (.028) Constant080 (.085)045149*052 (.027) (.028) Constant045045149*052 (.027)052 (.028)0003*0002* (.00007) (.00007) (.00007)00007)00007)00007)00007)00007)00007	2 1 .					· ·
3 weeks prior 080 (.085) Post 9/11 Period049050045149*052 (.029) (.028) (.032) Week052 (.029)045149*052 (.027) (.028) Week0002*0002*0001*0003*0002*00007)00007)00007) Constant080 (.085)045149*052 (.027)028) 4.617*	2 weeks prior					
Post 9/11 Period049050045149*052 (.029) (.028) (.032) (.032) (.027) (.028) Week .0002* .0002* .0001* .0003* .0002* (.00007) (.00007) Constant 4.608* 4.613* 4.618* 4.559* 4.617*						(.087)
Post 9/11 Period049050045149*052 (.029) (.028) (.032) (.032) (.027) (.028) Week .0002* .0002* .0001* .0003* .0002* (.00007) (.00007) Constant 4.608* 4.613* 4.618* 4.559* 4.617*	3 weeks prior					080
Post 9/11 Period049050045149*052 (.029) (.028) (.032) (.032) (.027) (.028) Week .0002* .0002* .0001* .0003* .0002* (.00007) (.00007) Constant 4.608* 4.613* 4.618* 4.559* 4.617*	•					
(.029) (.028) (.032) (.027) (.028) Week .0002* .0002* .0001* .0003* .0002* (.00007) (.00007) (.00007) Constant 4.608* 4.613* 4.618* 4.559* 4.617*	Post 9/11 Period	049	050	045	- 149*	
Week .0002* .0002* .0001* .0003* .0002* (.00007) (.00007) (.00007) (.00006) (.00007) Constant 4.608* 4.613* 4.618* 4.559* 4.617*	2 330 7/11 1 01100					
(.00007) (.00007) (.00007) (.00006) (.00007) Constant 4.608* 4.613* 4.618* 4.559* 4.617*		(.043)	(.020)	(.034)	(.027)	(.020)
(.00007) (.00007) (.00007) (.00006) (.00007) Constant 4.608* 4.613* 4.618* 4.559* 4.617*	XX7 1	00024	00004	00014	00024	0000*
Constant 4.608* 4.613* 4.618* 4.559* 4.617*	week					
		(.00007)	(.00007)	(.00007)	(.00006)	(.00007)
	Constant	4.608*	4.613*	4.618*	4.559*	4.617*
(.0/2) (.0/2) (.0/2) (.0/3) (.0/2)		(.023)	(.023)	(.023)	(.018)	(.022)

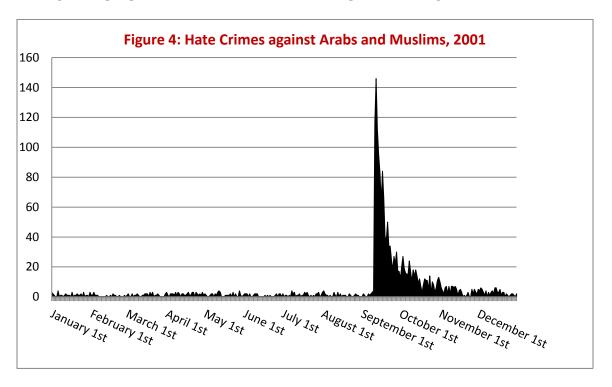
Note: Standard errors are in parentheses. All tests are two-tailed.

^{*}p<.05 **p< .01 ***p< .001



The results of this analysis are reported in Table 3 above, and they are quite consistent with what we found when using the TOPS coding. Namely, hate crimes rise in the week immediately following an attack conducted by a group that is categorized by PPT-US as religious in nature. The size of the effect decays rather quickly (e.g., the slope is .507 in week 1 and .240 by week 3; a drop of more than 50%), but clearly there is a climate conducive to perpetrating hate crime during the weeks immediately following terrorist attacks of this type.

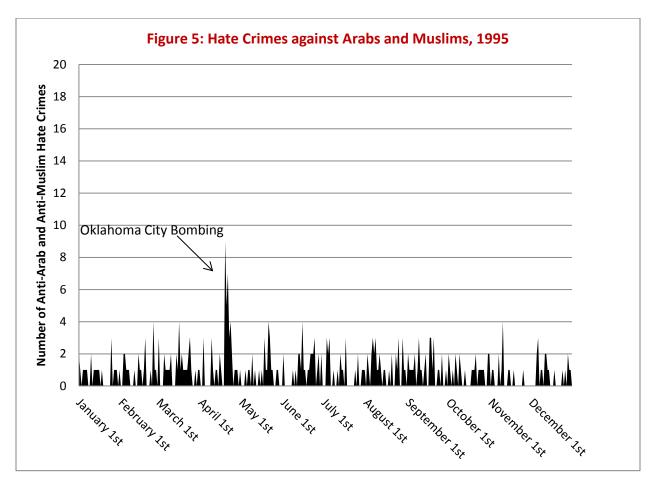
One commonality between the 'religious' category in the PPT coding and the 'core American values' category derived from the TOPS data is that each includes the September 11th terrorist attacks. We reestimated the models when omitting the year 2001 from analysis and in other models we restrict the data to the pre-9/11 era (no attacks on 'core American ideals' were perpetrated since 9/11). The results of those analyses are not shown in tables in this report, but the results can be summarized rather succinctly. The associations for particular types of terrorism and hate crime depicted in Tables 2 and 3 are no longer positive and statistically significant when we omit the year 2001 or when analyzing the pre-9/11 era. It is difficult to conclude whether the results without the 9/11 attacks in the model are different because the effect is driven by these attacks or because omitting these cases gives us far less statistical power to detect effects (e.g., the events of September 11th account for 40 percent of all attacks on core American values during our observation period). We suspect each carries some weight, although a closer inspection of hate crimes targeting two particular minority groups - Arabs and Muslims - after 9/11 supports the notion that these attacks have serious leverage in the statistical models. For instance, anti-Arab and anti-Islamic hate crimes increased dramatically following the attacks of September 11th (see Figure 4 below).¹⁴ Given the regression results and the pattern depicted in Figure 4, we tentatively suggest that more lethal attacks will yield a more widespread and intense backlash that is longer in duration, although this proposition warrants additional empirical testing.



¹⁴ For more information on the calculation of anti-Arab hate crimes, see Disha et al. (2011, pp.28-30).



The September 11th attacks most vividly capture the association between violent terrorist attacks and subsequent hate crimes, although it is not the only case in which hate crime followed a terrorist attack. For instance, initial reports following the bombing of the Alfred P. Murrah Federal Building in Oklahoma City in 1995 indicated that it may have been perpetrated by violent Islamists (see Hamm 1997, e.g., pp.54-5), an assertion that was quickly dispelled but nonetheless made its way into the first reports about the attack. Consistent with our time-series analysis, there was indeed a short-term spike in hate crimes against Arabs and Muslims in the United States beginning on the day of the attack (see Figure 5), although the increase was extremely short in duration, likely because Timothy McVeigh was apprehended and the facts of the case became known within days of the bombing. When considering the results of our statistical analysis along with the graphical depictions of hate crimes following the September 11th and Oklahoma City attacks, the weight of the evidence points to a higher likelihood of hate crimes against minorities, particularly victims that appear to resemble the actual or *alleged* perpetrators, in the days or weeks following the attack.



County-Level Analysis

We next examined the association between hate crime and terrorism at the county level. This set of analyses unfolded in three stages. We first assessed the correlation between the respective types of crime using the "county-year" as the unit of analysis. That is, unlike the analyses above that looked at the entire nation over time, these analyses drill down to the county level for each year of data. Second, we independently examined whether hate crime and terrorism were associated with the demographic characteristics of counties in which they occurred. Third, we created a dataset that allowed us to look at



the sequencing of hate crime and terrorism by day within counties. The latter analysis closely examined only those counties that had experienced at least one terrorist event at any time in the 17-year time period covered by this study. More than 230 counties in the United States experienced at least one terrorist attack between 1992 and 2008. For these 230 counties, we examined the timing of terrorist attacks and hate crimes at the daily and weekly level.

Our statistical analysis began by assessing the bivariate correlation between right-wing terrorism (as defined above) and anti-minority hate crime. 15 We focus on these respective types of hate crime and terrorism because the radicalization perspective discussed earlier in this document suggests an association that is type-specific. Moreover, we expected more commonality between these behaviors than, for instance, left-wing terrorism and anti-minority hate crime. This initial analysis allows us to answer a straightforward question: without taking into account other factors, do places with more antiminority hate crime have a higher probability of experiencing a right-wing terrorist attack? The answer is ves, as indicated by the statistically significant regression coefficient for anti-minority hate crime (see Model 1 of Table 4 below). However, we find no evidence of a robust or causal association. As indicated in Model 2 of Table 4, the coefficient reduces to nearly zero and is no longer statistically significant once we control for a single demographic measure: county population size. Model 2 tells us that large population centers are more likely to be targets of right-wing terrorism and provide more opportunity for anti-minority hate crime, but anti-minority hate crimes do not necessarily predict the likelihood of right-wing terrorism once we take population size into account. This result was consistent when employing various strategies to account for underreporting of hate crime data, for instance by restricting data to counties that regularly reported hate crimes or when controlling for the percentage of the population in the county covered by law enforcement agencies that regularly complied with the Hate Crimes Statistics Act.

The second analysis, which independently modeled anti-minority hate crime and right-wing terrorism, further suggested that the two behaviors share practically no common determinants. In other words, variables that are statistically associated with right-wing terrorism in the United States are by and large not the same as those associated with anti-minority hate crimes. As shown in Model 3 of Table 4, four variables were significantly associated with the likelihood of right-wing terrorism in this model – population size, region, percent citizens, and percent owner-occupied residences. In short, the probability of a right-wing terrorist attack is higher in counties with larger populations, a higher proportion of residents who are citizens, and in the West and Midwest relative to the Northeast. The risk is slightly lower in places with a higher proportion of owner-occupied homes. In contrast, analysis of hate crimes against minority groups revealed several other statistically significant associations (see Model 4 of Table 4). 16 For instance, controlling for reporting differences, hate crimes against minority groups were more common in counties located in the Northeast relative to other regions of the country (indicated by the negative coefficient for all other regions in Model 4). They were also more common in counties with higher crime rates and a larger proportion of younger males, major population centers, and counties with a larger proportion of non-Hispanic whites. Fewer anti-minority hate crimes were reported in counties where a larger proportion of residents were citizens, where home ownership was higher, and where a larger proportion of residents were on public assistance.

¹⁵ Estimates are based on a random effects logit model using the xtlogit procedure in Stata.

¹⁶ Here we estimated a zero-inflated negative binomial regression model. This model simultaneously estimates whether or not any hate crimes were reported in the county and, for those with one or more hate crimes, provides estimates of the effect of predictor variables on the number of hate crimes.



	Model 1	Model 2	Model 3	Model 4
	Terrorism	Terrorism	Terrorism	Hate Crime
Anti-minority hate crime	.014***	.00004	007***	1 000***
Population size (logged)		1.016***	.997***	1.080***
West			1.823***	193***
South			.825	548***
Midwest			1.910***	400***
Crime rate			.000	.0001***
% Non-Hispanic White			.012	.012***
% Citizens			.106*	023***
% Owner occupied esidences			092***	019***
% on public assistance			014	040***
% age 15-24			072	.013***
Predictors of zero-hate crimes Regular hate crime compliance				038***
% Non-Hispanic Black				.019***
% urban				031***
South				.262*
Midwest				388**
Year (linear)				019*
N	49,799	49,678	49,648	49,611

*p<.05 **p<.01 ***p<.001

Note: Constant terms omitted from table. Year dummy variables were included in models 3 and 4 but omitted from the table. 1993 omitted from models because of missing data in the GTD.



The third analysis (results not shown in a table), which examined the timing of hate crimes and terrorism at the county level, proved sensitive to the choice of model specification. Using a negative binomial regression, we found that anti-minority hate crimes tend to follow terrorist attacks at the county level. The analysis showed that terrorist attacks against core American ideals were followed by a sizeable escalation in this type of hate crime during the first week after an attack (the expected number of hate crimes increased by over 500 percent during the first seven days). A terror attack occurring two weeks earlier was associated with a 700 percent increase in anti-minority hate crimes. The number of anti-minority hate crimes remained at an elevated level for only two weeks before returning to pre-terrorist attack levels. However, we stress that when changing the model specification to a random effects model the results were not robust. Given the differences across model specification we are reluctant to make inferences and we think further work must be done to examine the results on the timing of terrorist attacks and hate crimes at the county level.

Conclusions

This project began with three primary research questions in mind. To what extent are hate crimes also counted as terrorism events? To what extent does the perpetration of hate crimes foreshadow future domestic terrorist events? And does the perpetration of terrorist attacks foreshadow future hate crimes? In addition, our analysis allowed us to assess whether hate crimes and terrorism share common determinants in a panel analysis of counties between 1992 and 2008.

We find no evidence that hate crimes serve as an indicator of future terrorist events. That is, we should not view an escalation in hate crimes as a warning sign that violent terrorist attacks are in the offing. However, we found evidence that anti-minority hate crimes follow acts of terrorism. Additionally, attacks against symbols of core American ideals (based on TOPS coding) and those perpetrated by groups with a religious motivation (based on the PPT coding) tended to be associated with the largest increases in anti-minority hate crimes. It is possible that some hate crimes constitute a form of "vicarious retribution" in which perpetrators seek retribution against members of a group that they view as responsible for the act of terrorism. As noted above, this pattern was particularly evident following the 9/11 attacks, and indeed that event appears to have substantial leverage in the model; much of the association between hate crime and terrorism is attributable to 9/11. Finally, we found that very few acts, approximately 15 but perhaps as many as 27 in a 17-year time period, were counted in both the FBI hate crime statistics and the Global Terrorism Database.

In order to complete the analysis necessary for this project, we have established two main datasets. The first links hate crimes and terrorist attacks by day at the national level. The second links hate crimes, terrorist attacks, and county characteristics at the county-year observation level. There are two additional questions that this team plans to examine with the data we collected. The first question returns to the national-level analysis of the relationship between hate crimes and terrorism. The analysis presented in this report discovered that hate crimes are likely to follow a terrorist attack taking place inside the United States. We are interested in extending this analysis to examine responses to terrorist attacks against U.S. interests which take place abroad (approximately 70 percent of attacks against U.S. interests take place abroad). The second question expands the examination of terrorism and hate crimes at the county level. One of the frontiers of terrorism research lies in investigating single-actor terrorists and how they compare to members of terrorist groups. The GTD dataset identifies attacks carried out by individuals who are not known to belong to any terrorist organization. By comparatively examining



single-actor terrorism, terrorism carried out by groups, and hate crimes, we can determine whether single actors behave more like terrorist groups or individuals who carry out hate crimes. While expanding our understanding of single-actor terrorists, this research could also benefit law enforcement and homeland security practitioners.



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