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Religious Motivated Hate Crimes: Reporting to Law Enforcement and Case Outcomes

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Abstract Relative to non-bias motivated crimes, hate crimes have much graver consequences for victims and their community. Despite the large increase in religious hate crimes over the past decade relative to all other hate crime, little is known about these types of crimes and the factors associated with both reporting to law enforcement and case outcomes. Utilizing the National Crime Victimization Survey and National Incident-Based Reporting System datasets, this study examines the relationship between victim, offender, and incident characteristics on reporting to law enforcement and case outcomes. Most religious hate crimes are not reported (41.3 %) in part due to perceptions of law enforcement's perceived response. Of the violent incidents that are reported, the vast majority do not result in the arrest of an offender (22.2 %). Whereas only a small number of variables related to the seriousness of the offense are associated with both reporting and arrest, these exhibited large effect sizes.

Keywords Hate crimes · Religious bias · Reporting to law enforcement · Arrest

Bias crimes are considered especially heinous because offenders are motivated by a prejudice against a particular group of people and choose victims based on their characteristics.[1] In 2012, estimates from the National Crime Victimization Survey

[1]The terms 'hate crime' and 'bias crime' are used interchangeably.

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(NCVS) indicated there were 293,800 nonfatal violent and property hate crime victimizations in the United States (Wilson, 2014). This is important, as these crimes have the potential to polarize and divide communities, and negatively impact social stability and cohesion (Abramovsky, 1991; Iganski & Lagou, 2015; Levin, 1999; Martin, 1995; Wexler & Marx, 1986). In addition to the targeted victim, members of the group also suffer from changes in behavior due to both a perceived increase of in terrorem effects (e.g., shock, helplessness, depression), and perceived vulnerability from the message sent about their immutable characteristics, regardless of the seriousness of the crime (see Iganski & Lagou, 2015; Leicester Centre for Hate Studies, 2014; Martin, 1995; Perry & Alvi, 2011). As a result of the increased harm to both the victim and the group relative to similar non-biased offenses, referred to as "parallel crimes," perpetrators of hate crimes may be subjected to penalty enhancements or additional charges (Levin, 1999; McDevitt, Balboni, Garcia, & Gu, 2001; Wisconsin *v.* Mitchell, 1993). Generally, hate crimes often start with what is typically perceived as minor crimes, tend to be serial in nature, and escalate in severity (see Levin, 1999; Martin, 1996; McDevitt et al., 2001; Wexler & Marx, 1986). Yet despite public concerns over hate crimes, this area remains largely understudied (Nelson, Wooditch, Martin, Hummer, & Gabbidon, 2015).

Most research on hate crimes has focused on race/ethnicity, as it comprises the majority of bias-motivated crime, and sexual orientation (Levin, 1999; Sandholtz, Langton, & Planty, 2013). Conversely, much less research has focused on religiously-motivated bias crimes. Findings from the NCVS indicate the proportion of hate crimes motivated by religious bias doubled from 10 % in 2003–2006 to 21 % in 2007–2011 (Sandholtz et al., 2013). The following year, Wilson (2014) reported the percentage of hate crimes motivated by a religious bias had increased to 28 %. This increasing proportion of religious hate crimes is concerning, yet little is known about the current state of these crimes, as much of the existing research is descriptive and/or outdated.

Terrorist attacks, especially those committed against symbolic American institutions domestically and globally, are considered antecedent events and result in an immediate spike in hate crimes committed against members belonging to the same group as the perpetrators, regardless of where the attack took place (Deloughery, King, & Asal, 2012; King & Sutton, 2013; Levin & Reichelmann, 2015). For instance, following the 9/11 terrorist attacks, the FBI indicated more than half (58 %) of the anti-Islamic crimes committed that year occurred within just two weeks (Disha, Cavendish, & King, 2011; King & Sutton, 2013). Similarly, there was a wave of anti-Jewish[2] hate crimes following Israel's armed conflicts with Hamas and Hezbollah in 2006 and 2008, respectively, while anti-Islamic crimes increased in the aftermath of the Oklahoma City bombing[3] and the start of the Iraqi War (Deloughery et al., 2012; Disha et al., 2011; Levin & Reichelmann, 2015). These findings are particularly

[2] While "anti-Semitic" is more common, we use anti-Jewish to be consistent with the terminology used by the FBI.

[3] Despite being committed by a white right-wing extremist, Muslims were initially presumed to be behind the attack.

important given the current state of affairs in the Middle East, the increase in international terrorist attacks, and sectarian violence that has led to the commission hate crimes in the United States.

The extent that these crimes are reported to police and are successfully cleared (i.e., result in the arrest of at least one offender) may influence perceptions of police competency and legitimacy with far reaching implications (see Sunshine & Tyler, 2003). In a national survey, Reisig, Bratton, & Gertz, (2007) found procedural justice was positively associated with police legitimacy which increased the likelihood respondents would cooperate with police; individuals who trusted law enforcement were more likely to cooperate as well. Successfully clearing a case may have enhanced benefits by preventing retaliatory attacks and improving police-public relations, particularly as the victimized group(s) may be weary of law enforcement (Levin, 1999; Martin, 1996). As King, Messner and Baller (2009, p. 291) note, "the state can serve dominant group interests not only by administering punitive sanctions against a subordinate group, but also by 'looking the other way' when civilians discriminate against subordinate group members." Specifically, an arrest conveys to individuals and the community that hate crimes are taken seriously by the criminal justice system, a salient symbolic message which helps to "protect the equal status of the victim's group" (Kauppinen, 2015, p. 1735; see also Bell, 2002). Conversely, the lack of an arrest has detrimental effects, as it may create an "us versus them" mentality for the victimized group (Perry, 2002), and increases the likelihood of further social conflict. For example, one study in Boston found that the small number of victims who reported racialized hate crimes believed that police sided with the offenders or acted indifferently (Wexler & Marx, 1986).

The current study examines how victim and situational (i.e., offender and incident) factors are related to religious motivated hate crimes being reported to law enforcement and resulting in the arrest of an offender. This study contributes to the literature in two important ways. First, by examining a decade worth of recent data from two sources, it allows for the examination of a large number of crimes while using advanced statistical analyses. Second, this study helps address the dearth of research examining the correlates relating to reporting and case outcomes for religious hate crimes (e.g., Lyons & Roberts, 2014; Wilson & Ruback, 2003).

Occurrence and Characteristics of Anti-Religious Motivated Crime

A significant portion of what is known on anti-religious motivated crime is a result of the special reports released by the Bureau of Justice Statistics' *Hate Crime Series* (Langton & Planty, 2011; Sandholtz et al., 2013; Strom, 2001; Wilson, 2014). When combined with other general hate crime studies across a number of bias types, most of which are limited to a small number of jurisdictions, a rudimentary picture of religious crime begins to form (Bell, 2002; Martin, 1996; Messner, McHugh, & Felson, 2004; cf. Lyons & Robets, 2014).

Data from the Uniform Crime Report's (UCR) Summary Program and the National Incident Based Reporting System (NIBRS) offer an initial examination of religious-bias crimes. Utilizing UCR data, researchers have found that after anti-Black bias crimes, anti-Jewish bias is the second most frequent bias type though per capita, anti-Jewish bias crimes are much more prevalent (Cheng, Ickes, & Kenworthy, 2013). Across the United States, anti-Jewish crime represented the majority of religious cases for every year except 2001 as a result of the spike in anti-Islamic crimes following the 9/11 terrorist attacks, though New York City *still* experienced more anti-Jewish crimes that year (Cheng et al., 2013; Levin & Amster, 2007). Indeed, prior to 9/11, anti-Islamic crimes were less prevalent than either anti-Catholic or anti-Protestant crimes. While these crimes have dropped significantly compared to 2001, they remain higher than pre-2001 rates, and Muslims remain the second most frequently targeted religious group per capita.

A study of Muslims living in New York City post 9/11 found that while none personally suffered a violent attack, the majority of participants knew an individual who had been harassed (62.8 %) or were themselves victimized in some form (70.6 %; Abu-Ras & Suarez, 2009). Importantly, while none of the respondents reported any physical injuries, these hate crimes still resulted in significant long-term negative symptoms (e.g., PTSD, hopelessness, anxiety), changes in behavior, and greater fear for their safety, findings substantiated by studies on victims of other different types of bias crimes (e.g., Garofalo, 1997; Herek, Gillis, & Cogan, 1999; Levin, 1999; McDevitt et al., 2001). Research conducted in England and Wales generally supports these findings; victims of hate crimes are affected much more emotionally and are less satisfied with the police response, regardless of the bias, than victims of parallel crimes (Corcoran, Lader, & Smith, 2015; Leicester Centre for Hate Studies, 2014; Ministry of Justice, 2013).

In 2014, the most recent year for which official data are available from the UCR *Hate Crime Statistics*, 18.6 % of the single bias incidents were due to a religious bias. Of these, 60 % were anti-Jewish, the majority of which (about 3 in 4) involved property crimes (Federal Bureau of Investigation, 2015). While this is a start, UCR summary data lacks victim information, relies on reported crimes, and includes only 11 offense types, which limits the depth of any analyses performed. NIBRS, while not yet universally adopted by law enforcement agencies in the U.S., represents a much more comprehensive and detailed data collection system, with information collected on each incident (see Roberts, 2009 for a review). Of the 2976 bias incidents reported to NIBRS-participating law enforcement agencies between 1997 and 1999, Strom (2001) reported that 14.4 % (n = 431) were motivated by a religious bias. Of these, nearly half (41 %) occurred due to an anti-Jewish prejudice, though this may be a conservative estimate, as an unnamed religious group was reported in 31 % of the religious-bias incidents (Strom, 2001). The majority of offenders were young, often committing the offense in a public location, and committed these crimes with multiple offenders, which is similar to findings from the NCVS and other studies (e.g., Harlow, 2005). Supporting this, in one of the earliest studies, Martin (1996) found the majority of the *religious* motivated crimes were anti-Jewish, which was the second most reported overall bias type to both the Baltimore County and New York City police departments between 1982 and 1996.

To summarize, the prior research suggests that perhaps 15 to 20 % of bias crimes involve religious bias, with the overall number of these crimes decreasing over the last few years. While anti-Jewish bias is consistently the most prevalent form, anti-Muslim crimes have the highest per-capita rate, and spiked following the 9/11 attacks. Situationally, the majority of these are property crimes, involve multiple offenders, juvenile offenders, and occur out in public.

While informative, these and other prior studies on bias crimes have been hampered by methodological issues (e.g., small samples and/or lack of generalizability). For instance, Messner et al. (2004) utilized a single year of NIBRS (1999), to examine the differences in assaults based on bias motivation. Due to the small sample sizes for religious (n = 43), ethnic (n = 83), and sexual orientation (n = 91) motivated bias crimes, they were unable to estimate their effects separately, and instead created an "other" category to capture these cases. Thus, any reliable interpretation for these cases is confounded. Studies using earlier years of NIBRS have been limited by the slow implementation of departments. For example, in 1999, only a third of the states, representing less than 20 % of agencies in the U.S., had been certified and reported data to NIBRS (Strom, 2001). Because of these problems, more recent and more extensive research on this topic is warranted at this time.

Theoretical Perspectives

Researchers have proposed various theories to explain the variation in the covariates associated with reporting crime and crime clearance. This has often been interpreted through two competing perspectives: *victim-devaluing* (Blalock, 1967; Black, 1971, 1976; King et al., 2009) and *solvability* (Addington & Rennison, 2008; Briggs & Opsal, 2012; Gottfredson & Hindelang, 1979; Laub, 1981; Skogan, 1984).

Emerging from a conflict perspective, the victim-devaluing perspective argues that victims from the dominant classes are more likely to report and utilize law enforcement resources and, in return, receive more attention and greater allocation of resources towards solving their crimes. Given the amount of discretion law enforcement has in investigating the crimes, and their roles as the initial gatekeepers from being the first point of contact with the criminal justice system (Kerstetter, 1990), this means certain crimes may receive more attention. For instance, crimes involving white, Christian, and male victims might have a greater likelihood of being reported *and* having the case result in arrest. This is particularly important for bias crimes, as victims tend to be members of minority groups. Specifically, members of these groups may be hesitant to report either as a result of past discriminatory experiences and/or as a result of animosity within the community (Levin, 1999; Martin, 1996).

Other researchers argue that the seriousness of the crime is more important than extralegal characteristics, particularly when the victim recognizes the seriousness of the offense (Addington & Rennison, 2008; Skogan, 1984). Crimes with aggravating features such as victim injury, weapon use, being committed by a stranger, and involving co-occurring crimes would thus be afforded more resources and investigatory time due to its perceived seriousness and impact on the victim. Research on crime clearance for non-lethal crimes has generally found more support for the solvability perspective (e.g., Addington & Rennison, 2008; Briggs & Opsal, 2012; Lyons & Roberts, 2014).

Factors Affecting Reporting and Arrest for Hate Crimes

The vast majority of crimes come to the attention of law enforcement due to victim and third party reporting. Given that the majority of hate crimes go unreported, and reporting rates have declined in the past decade, understanding the factors and context associated with reported crimes is important (Sandholtz et al., 2013). The lack of reporting ensures the offender(s) remains free, and any general or specific deterrent effect that the criminal justice system may impose is negated. This is important given the serial nature of hate crimes and the escalation in severity over time. Furthermore, when crime goes unreported, victims are less likely to receive medical and/or mental health treatment in addition to victim compensation.[4] As the impact of hate crimes is widespread and affects members of the victim's sub-group as well, this may contribute to increased conflict in the community, deteriorating relationships between the minority group and law enforcement, and amongst other societal consequences (Bell, 2002; Iganski & Lagou, 2015; Perry, 2002; Wexler & Marx, 1986).

Research has found various characteristics are related to the decision to report a hate crime to law enforcement. For instance, whereas juveniles are less likely to report, females are more likely, in addition to cases involving either the use of a weapon or serious violence resulting in medical attention (Harlow, 2005; Sandholtz et al., 2013). In exploring reasons for victim non-reporting, a quarter of non-reporting victims believed that police would not or could not help, whereas 18 % believed the crime was not important enough to report (Sandholtz et al., 2013). Anecdotal evidence suggests officers are less likely to bring bias charges in more ambiguous cases in which they judge there to be a greater potential for a non-guilty verdict, as officers believe this would weaken the hate crime statutes and their power to enforce anti-bias legislation (Bell, 2002; Boyd, Berk, & Hamner, 1996). In other words, some officers' decision to arrest is influenced by their estimate of the likelihood of a guilty finding, which supports the solvability perspective (Gottfredson & Hindelang, 1979). Other officers, however, indicated hate crimes are "really not that different" (Boyd et al., 1996, p. 842) from parallel crimes, and therefore do not deserve extra attention or resources.

Because hate crimes have only recently begun to receive increased attention, and the rate of these victimizations is small, most studies are limited to qualitative examinations of a small number of jurisdictions. These studies typically focus on the processes and investigations by law enforcement personnel, some of whom work in bias units, to determine if a crime was motivated by hate; less emphasis is placed on how this affects the decision to arrest the offender(s) (e.g., Bell, 2002; Boyd et al., 1996; Cronin, McDevitt, Farrell, & Nolan, 2007; Martin, 1995; 1996).

This growing body of literature suggests officers rely on certain pieces of evidence when investigating and arresting an offender. For instance, in a study of a Midwestern police department, Bell (2002) reported investigators in a bias unit relied on several indicators to determine if the crime was motivated by bias. These included the difference between the victim and offender for a protected group; words, writing, or gestures; problematic location; and the offenders outnumbering the victim(s) (Bell 2002). The victim-offender relationship is also considered important for the arrest

[4] Importantly, victims may receive compensation even if the case does not result in arrest or conviction.

decision, as a preexisting relationship may indicate to law enforcement that the crime may be a result of jealousy, anger, or some other non-bias reason (Bell, 2002; Boyd et al., 1996). Boyd et al. (1996) found the police perceived crimes committed by juveniles as acts of irresponsibility rather than legitimate hate crimes. As Black (1976) would argue, these crimes would be less likely to result in arrest.

Unfortunately, much of the existing research on crime clearance is outdated (e.g., Martin, 1995; 1996; Walker & Katz, 1995). Recent studies have found that relative to racial/ethnic motivated crimes and non-bias crimes, religious crimes are less likely to be cleared (Lyons & Roberts, 2014; Wilson & Ruback, 2003). Specifically, utilizing NIBRS data restricted to violent offenses, Lyons and Roberts (2014) found that when the types of bias were disaggregated into five general categories (i.e., racial, ethnic, religious, sexual orientation, and disability), a religious motivation *decreased* the odds of arrest compared to non-bias incidents, while ethnically and racially motivated incidents were as likely as non-bias incidents to be cleared. However, when conducting multivariate analysis on the likelihood of arrest, cases were limited to racial and ethnic motivated bias crimes due to the focus of their study. Results supported the solvability perspective. Specifically, serious violent crimes (e.g., aggravated assault, kidnapping), injury, co-occurring crimes, weapon (other than a firearm), and multiple victims increased the likelihood of arrest.

Current Study

Research Questions

The current study focuses on bias crimes that the police have classified as motivated by a religious bias. Three research questions are examined: (1) What are the characteristics associated with an individual reporting a hate crime to law enforcement? (2) What factors influence the likelihood of arrest in religious motivated bias crimes? (3) Do the same correlates that influence reporting also affect arrest likelihood?

Methodology

Data

To test these research questions, the data in the study are derived from two datasets: the National Crime Victimization Survey and the National Incident-Based Reporting System. Due to the rarity of religious motivated hate crimes, several steps are taken in order to have an adequate sample of incidents to perform advanced statistical analyses. The NCVS is a nationally representative crime survey of persons ages 12 and older, and uses a stratified, multistage cluster of households in the United States. While hate crime questions were first added in 1999, data were not included in the public use file until 2003; all available years since then are utilized in the present study (2003–2014; Bureau of Justice Statistics, 2014). NIBRS is a voluntary system which collects extensive information on victim, offender, and incident characteristics supplied by police departments for each verified crime, including the resulting case outcome (i.e., open, arrest, or exceptionally cleared). NIBRS now covers approximately 33 % of the U.S. population, and while it remains the best source of information about founded hate crimes, it relies on the accuracy and comprehensiveness of law enforcement reporting. NIBRS agencies tend to be smaller jurisdictions, with a greater proportion located in the South and Midwest. This study pools the most recent years of NIBRS data (2003–2014) to match the years covered by the NCVS data.

By comparing the NCVS and NIBRS datasets in the current study, it allows for benefits not available when using them separately. Specifically, the NCVS includes crimes that are not reported to the police and, importantly, reasons why victims do and do not report, whereas NIBRS provides much more comprehensive incident data for the crimes that *are* reported, allowing for analysis of what influences arrest.

Dependent Variables

Two dependent variables are utilized, both of which are binary coded. The first, from the NCVS, measures whether the hate crime incident was reported to law enforcement (either by the victim or a third party) contrasted to cases which are unreported. All crimes in which the victim believed the incident occurred due to their religious beliefs are included, resulting in an unweighted sample of 218 victims, which serves as the unit of analysis. Three cases which were missing data on the dependent variable were removed. It is important to note that these incidents are not necessarily confirmed by law enforcement to be hate crimes, but instead are "perceived by victims to be motivated by an offender's bias against them for belonging to or being associated with a group largely identified by these characteristics" (Sandholtz et al., 2013, p. 1).[5]

For NIBRS data, the second dependent variable indicates whether a hate religious crime (the unit of analysis), resulted in the arrest of an offender or not. As approximately 6 % (n = 71) of the incidents were exceptionally cleared, these were omitted prior to conducting the analysis.[6] The majority of these were either due to prosecutors declining to press charges for reasons other than probable cause, or from the victim refusing to cooperate with the prosecution. This results in a final sample size of 1162 incidents across 557 agencies.

Independent Variables

Three blocks of independent variables are included in the analyses: victim, offender, and situational characteristics. Predictor variables common to both datasets are coded similarly when possible. As some hate crimes involve multiple victims and/or offenders, various strategies (noted below) are utilized to control for these complex relationships, as not doing so may bias the results (Roberts, 2009).

[5] In 2010, the NCVS was modified to include additional questions on evidence of a hate crime (e.g., presence of hate symbols, whether the police confirmed it).

[6] The UCR Handbook (Federal Bureau of Investigation, 2004, pp. 149) allows a crime to be cleared by arrest or exceptional means. While the latter is rare, it occurs as a result of some element beyond law enforcement control which prevents the filing of formal charges against the offender (e.g., victim refuses to cooperate with prosecution, extradition is denied, death of the offender).

NCVS Variables

Juvenile victim is measured as a binary variable indicating if any of the victims are juveniles (i.e., younger than 18). Note that the NCVS is limited to respondents over the age of 12. *Male* indicates the sex of the victim as male (1), with female (0) serving as the comparison group. *College degree* indicates whether the victim has completed a college degree (1) or not (0). *Renter* is a binary variable contrasting individuals who reside in an owned dwelling (0) with those renting (1). *Rural* indicates whether the victim resides in an urban (0) or rural (1) location.

Offense type is measured as *violent crimes* (1), contrasted with property crimes (0). *Multiple incidents* is a dichotomous variable which indicates if a similar offense occurred within the past six months. *Residence* indicates if the crime occurred as the victim's dwelling (1) or other location (e.g., school, open the street, on public transportation; 0). *Injury* captures if the victim suffered any injuries (e.g., broken bones, knocked unconscious). *Medical care* indicates if the victim received any medical care (or not) following the incident. *Weapon* is recoded as a binary variable indicating the presence of a weapon (e.g., gun, knife, blunt object). A dichotomous variable is used to indicate the presence of *multiple offenders.* To capture the victim-offender relationship, a dichotomous measure, *stranger*, is used to indicate whether the victim and offender were strangers (1) or known to each other prior to the crime (0). For incidents involving multiple offenders and both types of relationships, these cases are categorized as being committed by a known offender. *Juvenile offender*(*s*) indicates if any of the offenders were juveniles.

NIBRS Variables

Religion indicates the specific motivation type and is measured using four categories: anti-Jewish, anti-Islamic, anti-Christian, and anti-'other' groups, which combine multi-religious groups, atheism/agnosticism, and other religious groups due to low cell counts. Anti-Jewish bias serves as the reference category. While NIBRS collects data for up to 10 offenses per incident, it follows the hierarchy rule in that the most serious offense is listed first, which is used to classify the type of crime; only violent (i.e., person) crimes are included in the analyses.

Of the incident-based predictor variables, three indicators of crime seriousness are included: *weapon*, *co-occurring*, and *injury. Weapon* is measured similarly to the NCVS measure. *Co-occurring* is a dichotomous variable that indicated if there were multiple offenses committed within a single incident (e.g., aggravated assault and kidnapping; 1) or one offense (0). *Injury* is recoded as an ordinal variable indicating whether a minor or major injury was sustained (with no injury serving as a reference category). Major injuries often require hospitalization, and include broken bones, possible internal injury, loss of teeth, and unconsciousness (see Messner et al., 2004). *Location* is a categorical variable that measured if an incident occurred at an individual's residence, a religious institution (i.e., church, synagogue, or temple), or other location (e.g., school, work, parking garage; reference category). *Multiple offenders*, *juvenile offender*, and *stranger* are coded similarly to NCVS, as is *juvenile victim*, though NIBRS does include victims younger than 12.

As NIBRS includes some information at the macro-level, two variables were utilized in the analysis. To control for geographic variability, *region* identifies where the incident is located, and was based on the U.S. Census categories (South [reference category], Northeast, Midwest, and West). *Population* is an ordered variable with three categories: municipalities with a population less than 24,999 (reference category), a population between 25,000 and 99,999, and a population greater than 100,000.

Analytic Procedure

Two sets of analyses were conducted with all data preparations performed in *R* 3.2.4 (R Core Team, 2015). The first utilizes the NCVS data to examine reporting to law enforcement and the second uses the NIBRS data to examine case outcomes. As both dependent variables are binary, logistic regression was utilized for both models. While the NIBRS data is clustered (i.e., incidents within departments) and contains data on both the micro- and macro-level, a single-level model was estimated due to the small number of incidents per department as approximately two-thirds of the agencies report only one incident. This may introduce bias into the estimation of fixed effects and when calculating the intra-class correlation (ICC), which is used to determine if multilevel modeling is necessary, and is particularly problematic for logistic regression (see Clarke, 2008 for a review; McNeish & Stapleton, 2014; Theall et al., 2011). As such, robust standard errors (RSE) were computed for the NIBRS model using the package “miceadds” (Robitzsch, Grund, & Henke, 2016) and model diagnostics were utilized with the package “rms” (Harrell, 2016).[7] Due to the complexity of the models and number of categorical covariates included in each, an alpha level of .10 is used to determine statistical significance and as such, 90 % confidence intervals were estimated and presented.

Missing Data

As the data utilized from the NCVS has minimal missing data, listwise deletion was utilized.[8] However, for NIBRS, there was a non-trivial amount of data missing at the incident level, with more missingness for offender related variables (i.e., offender age, victim-offender relationship) and cases that did not result in arrest; this is referred to as non-ignorable missing data (Graham, 2009). As the vast majority of incidents were missing data on only one or two variables, listwise deletion in this context is more consequential, as it biases the results since cases with missing data were less likely to result in arrest, and it further reduces the lack of power, thereby increasing the probability of a Type II error (Allison, 2001). Multiple imputation, which uses observed data to impute missing values, was used. As Graham (2009, p. 55) argues, multiple imputation of data missing not at random is “always at least as good as the old procedures (e.g., listwise deletion, except in artificial, unrealistic circumstances), and are typically better than old methods, and often very much better.” This has also been used by other researchers using the NIBRS data when examining arrest (e.g. Roberts,

[7] Results from the estimated multilevel model were consistent concerning their direction, effect size, and significance.

[8] Three cases were removed for the analysis due to missing data on the dependent variable.

2009). The package "mice" was used multiple imputes data by chained equations via Markov chain Monte Carlo techniques to produce twenty "complete" datasets (van Buuren & Groothuis-Oudshoorn, 2011). Descriptive statistics presented were from the last imputed dataset; regression results pool the parameter estimates across all twenty datasets using Rubin's rule.

Results

Descriptives of Reporting and Case Closure

Tables 1 and 2 present the frequencies of the dependent and independent variables for reporting to law enforcement and case closure, respectively. When considering reporting outcomes (Table 1), of the 218 religious hate crimes, only 41.3 % (*n* = 90) were reported to law enforcement. Slightly more incidents were violent crimes (56.0 %). More than one in four respondents indicated a similar crime had occurred within the past six months, supporting prior findings on repeat attacks. A similar percentage of cases involved a weapon (25.4 %), resulted in injury to the victim (21.3 %), or was committed by strangers (23.0 %). Almost a third (31.1 %) was committed by multiple offenders.

Of the 1162 violent offenses reported to NIBRS, only 22.2 % (*n* = 258) resulted in the arrest of an offender (Table 2). There were similar numbers of anti-Jewish and anti-Islamic crimes (36.0 % and 34.2 %, respectively). About two-thirds of attacks took place away from the victim's residence, with a small number occurring at a religious institution (6.6 %). Whereas slightly more crimes involved a stranger (39.8 %) relative to the NCVS, there were fewer which had multiple offenders (13.1 %). Crimes involving multiple victims were slightly more common (17.3 %). Finally, whereas approximately one third (34.2 %) of incidents had a weapon present, only 21.1 % of cases resulted in any injury, and just 3.6 % of cases involved major injuries.

Predictors of Reporting to the Police & Reasons for the Reporting Decision

Table 3 presents two models predicting reporting outcomes due to the inclusion of offender variables for violent offenses which are either absent or unknown for property crimes (e.g., weapon and offender age, respectively). Model 1 considers both violent and property crimes (*n* = 218), while Model 2 considers only violent crimes with complete data (*n* = 121). As shown on Model 1, a number of victim and incident characteristics were significantly related to reporting, though surprisingly, the type of offense was not statistically significant. Juveniles and college graduates had decreased odds of reporting (78 % and 53 %, respectively). Respondents who had experienced a similar victimization within the previous six months were 49 % less likely to report compared to those without recent prior victimizations. Incidents occurring at the victim's residence were 69 % more likely to be reported than those occurring elsewhere.

When examining only reporting for violent crimes (Model 2), due to multicollinearity, as measured using the variance inflation factor (VIF), two variables were omitted from the model: injury and juvenile offender. Two of the effects from the

Table 1 NCVS scale and frequencies of dependent and predictor variables (N = 218)

Variable	Scale	*N*	%
Report	0 = *No report*	128	58.7
	1 = *Report*	90	41.3
Victim Characteristics			
Juvenile	0 = *Adult*	178	81.7
	1 = *Juvenile*	40	18.3
Male	0 = *Female*	119	54.6
	1 = *Male*	99	45.4
Education	0 = *High school/some college*	156	71.6
	1 = *College degree*	62	28.4
Renter	0 = *Own*	124	56.9
	1 = *Rent*	94	43.1
Rural	0 = *Urban*	182	83.5
	1 = *Rural*	36	16.5
Incident Characteristics			
Violent Crime	0 = *Property*	96	44.0
	1 = *Violent*	122	56.0
Multiple Incidents	0 = *Single*	156	71.6
	1 = *Multiple*	62	28.4
Residence	0 = *Other*	99	45.4
	1 = *Residence*	119	54.6
Weapon†	0 = *None*	90	73.8
	1 = *Weapon present*	31	25.4
Injury†	0 = *No injury*	95	77.9
	1 = *Injury*	26	21.3
Medical Care†	0 = *None*	104	85.2
	1 = *Medical care*	17	13.9
Multiple Offenders†	0 = *Single*	83	68.0
	1 = *Multiple*	38	31.1
Stranger†	0 = *Known*	93	76.2
	1 = *Stranger*	28	23.0
Juvenile Offender(s)†	0 = *Adult*	87	71.3
	1 = *Juvenile*	34	27.9

†Only includes complete data from violent crimes

previous model remained statistically significant: juvenile victims and incidents occurring at a residence. Whereas the odds of reporting increased slightly for cases involving juvenile victims (0.28), those occurring at a residence exhibited a large effect, increasing the odds of reporting by 134 %. Similarly, crimes committed by a stranger increased the odds of reporting by 160 %, and receiving medical care increased the odds of reporting by 323 %. However, due to the small sample size in both models (218 and 121, respectively), interactions could not be tested due to insufficient power. The R^2 measures, .154 and .205, respectively, while low, cannot be interpreted similarly as

Table 2 NIBRS scale and frequencies of dependent and predictor variables (*N* = 1162)

Variable	Scale	*N*	%
Arrest	0 = *No arrest*	904	77.8
	1 = *Arrest*	258	22.2
Micro-level			
Religious Bias	*Anti-Jewish*†	418	36.0
	Anti-Islamic	397	34.2
	Anti-Christianity	106	9.1
	Anti-other	241	20.7
Juvenile Victim(s)	0 = *Adult*	965	83.0
	1 = *Juvenile*	197	17.0
Juvenile Offender(s)	0 = *Adult*	933	80.3
	1 = *Juvenile*	229	19.7
Multiple Victims	0 = *Single victim*	961	82.7
	1 = *Multiple victims*	201	17.3
Multiple Offenders	0 = *Single offender*	1010	86.9
	1 = *Multiple offenders*	152	13.1
Co-occurring Crimes	0 = *Single*	1058	100.0
	1 = *Concomitant*	104	9.0
Location	*Other*†	666	57.2
	Residential	417	36.2
	Religious institution	79	6.6
Stranger	0 = *Known*	700	60.2
	1 = *Stranger*	462	39.8
Weapon	0 = *None*	765	65.8
	1 = *Weapon present*	397	34.2
Injury	*No injury*†	917	78.9
	Minor injury	207	17.8
	Major injury	39	3.3
Macro-level			
Population	*Small*†	352	30.3
	Medium	431	37.1
	Large	379	32.6
Region	*South*†	298	25.6
	Northeast	178	15.3
	Midwest	486	41.8
	West	200	17.2

Categorical variables are included in the models as dummy variables. Variable categories with a "†" are the comparison group

ordinary least squares regression and shows the models explain a moderate amount of variation in the decision to report to law enforcement. Model diagnostics for models 1 and 2 indicated a suitable fit.

As shown in Table 4, there is significant variation in the reasons why victims themselves decide to report or not to report the incident to law enforcement. Of the victims who reported, nearly half (47.6 %) indicated they did so to apprehend the offender, in order to prevent future crimes against the respondent or others. Interestingly, only one in five indicated they reported to let the police know, in order to improve police surveillance in the area or feeling it was their duty to make police aware of the incident, and only a quarter (23.8 %) reported to seek recovery for their loss.

Of those who did not report, (39.1 %) did not report due to their perception of how law enforcement would (or would not) respond, with nearly twice as many indicating they believed the police would not help (25.8 %, not shown), relative to those who believed the police could not do anything to help (13.3 %, not shown). Only one in four (23.4 %) indicated it was not important enough to them personally to justify reporting. One in ten respondents (9.4 %) indicated they did not report for fear of retaliation.

Table 3 Summary of logistic regression analysis predicting reporting to law enforcement

	Incident Reported to Law Enforcement							
	Model 1 (All Crimes)				Model 2 (Violent Crimes)			
Variables	*B*	*SE*	*OR*	90 % CI	*B*	*SE*	*OR*	90 % CI
Constant	−0.005	.454	0.99	[0.47, 2.11]	−0.797	.596	0.45	[0.16, 1.18]
Victim Characteristics								
Juvenile	−1.501	.586	0.22*	[0.08, 0.56]	−1.282	.685	0.28†	[0.08, 0.82]
Male	−0.419	.311	0.66	[0.39, 1.10]	−0.162	.431	0.85	[0.42, 1.73]
College Degree	−0.753	.345	0.47*	[0.26, 0.83]	−0.407	.454	0.67	[0.31, 1.40]
Renter	−0.163	.322	0.85	[0.50, 1.44]	−0.172	.450	0.84	[0.40, 1.76]
Rural	0.586	.401	1.80	[0.93, 3.50]	0.139	.609	1.15	[0.42, 3.15]
Incident Characteristics								
Violent Crime	0.229	.320	1.26	[0.74, 2.14]	–	–	–	–
Multiple Incidents	−0.677	.339	0.51*	[0.29, 0.88]	0.284	.458	1.33	[0.33, 1.69]
Residence	0.526	.320	1.69†	[1.01, 2.89]	0.852	.480	2.34†	[1.07, 5.25]
Juvenile Offender	−0.121	.570	1.13	[0.44, 2.94]	–	–	–	–
Weapon Present	–	–	–	–	−0.276	.493	0.76	[0.33, 1.69]
Medical Care	–	–	–	–	1.443	.626	4.23*	[1.56, 12.51]
Multiple Offenders	–	–	–	–	0.018	.472	1.02	[0.46, 2.21]
Stranger	–	–	–	–	0.955	.529	2.60†	[1.10, 6.33]
Model diagnostics								
AIC	287				167			
Model χ^2	26.50***				19.98*			
Nagelkerke pseudo R^2	.154				.205			
N	218				121			

Two variables, injury and juvenile offender, were omitted from model 2 due to multicollinearity. *CI* = Confidence intervals for odds ratio (*OR*). *AIC* Akaike information criterion

†$p < .10$. *$p < .05$. **$p < .01$. ***$p < .001$

Predictors of Case Outcomes

Table 5 presents the NIBRS model that examines the correlates of arrest for founded religious hate crimes reported to law enforcement. One variable, weapon, was omitted due to multicollinearity. Relative to anti-Jewish crimes, anti-Christian crimes were 78 % more likely to result in arrest, whereas ‘other’ religions were 45 % more likely. Crimes involving multiple victims and concomitant crimes increased the odds of an arrest by 69 % and 75 %, respectively. The location of the incident was significantly related to the case outcome. Compared to ‘other’ locations, incidents occurring at a religious institution were 73 % less likely to result in arrest. The strongest predictor of arrest was injury to the victim. Cases involving victims with minor or major injuries increased the odds of arrest by 138 % and 263 %, respectively, compared to those with no injuries. Of the macro-level variables, incidents occurring in the West (relative to the South) were more likely to result in arrest, increasing the odds by 99 %. Model diagnostics indicated a suitable model fit.

Discussion

This exploratory study sought to answer three research questions. Due to the dearth of research on anti-religious crimes, we set out to investigate the characteristics of these crimes, correlates to reporting and arrest, and similarities between religious hate that are reported and result in arrest. While only a small number of covariates were significantly related to both dependent variables, those that were exhibited large effect sizes, suggesting a handful of case characteristics that are extremely important for both reporting *and* investigational purposes.

While slightly less than half of religious hate crimes come to the attention of law enforcement, only one in five resulted in arrest. This is troubling, and when considered

Table 4 Reasons for the reporting decision

	N	%
Panel A. Reasons for Reporting		
To get offender	30	47.6
Other	24	38.1
To get help with this incident	21	33.3
To recover loss	15	23.8
Let police know	13	20.6
Panel B. Reasons for Not Reporting		
Police could not/would not help	50	39.1
Dealt with another way	38	29.7
Other	31	24.2
Not important enough to respondent	30	23.4
Afraid of reprisal by offender or others	12	9.4

Total percentages within panels exceed 100 because respondents can select multiple reasons in light of prosecutorial decision-making and post-arrest case attrition, the vast majority of cases and offenders are not prosecuted. For instance, in a study of hate crimes in New Jersey, of the 643 cases investigated for bias crimes by investigators and prosecutors, only 30 (4.6 %) were suitable for prosecution, and were the least ambiguous and

Table 5 Summary of logistic regression analysis predicting arrest with robust standard errors (RSE)

	Arrest made			
Variables	*B*	*RSE*	*OR*	90 % CI
Constant	−1.741	.286	0.18***	[0.11, 0.28]
Religion				
Anti-Semitic (reference)				
Anti-Islamic	0.192	.186	1.21	[0.89, 1.65]
Anti-Christian	0.579	.292	1.78*	[1.10, 2.88]
Anti-Other	0.374	.215	1.45†	[1.02, 2.07]
Juvenile Victim	0.088	.250	1.09	[0.62, 1.65]
Juvenile Offender	−0.092	.252	−0.91	[0.60, 1.38]
Multiple Victims	0.525	.217	1.69**	[1.18, 2.42]
Multiple Offenders	0.014	.239	1.01	[0.68, 1.50]
Stranger	−0.134	.208	0.87	[0.62, 1.23]
Co-occurring	0.558	.285	1.75*	[1.09, 2.79]
Location				
Other (reference)				
Residence	−0.187	.171	0.83	[0.63, 1.10]
Religious Institution	−1.320	.417	0.27**	[0.13, 0.53]
Injury				
None (reference)				
Minor	0.868	.199	2.38***	[1.72, 3.31]
Major	1.288	.361	3.63***	[2.00, 6.57]
Region				
South (reference)				
Northeast	0.392	.309	1.48	[0.89, 2.46]
Midwest	−0.138	.238	0.87	[0.59, 1.29]
West	0.690	.235	1.99**	[1.35, 2.94]
Population				
Small (reference)				
Medium	−0.064	.203	0.94	[0.67, 1.31]
Large	−0.366	.233	0.69	[0.47, 1.02]
Model Diagnostics				
AIC	1157			
Model χ^2	28.87***			
N	1162			

One variable, weapon, was omitted due to multicollinearity. *CI* = Confidence intervals for odds ratio (*OR*)
†$p < .10$, *$p < .05$, **$p < .01$, ***$p < .001$

most stereotypical cases (Phillips, 2009). Overall, we find that evidentiary factors that are comparable to the prototypical crime involving evidence of violence (i.e., requiring medical care), and committed by a stranger, are critical to the likelihood that it is reported. Similar to the NCVS findings, suffering any injury, regardless of severity, improves the likelihood the case results in arrest, and was the strongest predictor in the NIBRS model.

Indeed, in support of the solvability perspective, crime seriousness was important in both reporting and arrest likelihood (Gottfredson & Hindelang, 1979; Laub, 1981; Skogan, 1984). Crimes involving victim injury are typically perceived as more serious and more worthy of police attention relative to low level, minor crimes, and also tend to have greater victim/witness cooperation; yet these violent crimes tend to be quite rare. This supports prior findings from Lyons and Roberts (2014, p. 268) who note, "hate crimes that fit popular constructions of 'normal victims and offenders' receive investigative outcomes comparable with otherwise similar nonbias offenses." Individuals may also hold similar views of what a typical crime entails, and may base their decision to report on the characteristics of the incident and its perceived seriousness as judged by law enforcement. Recall that among the victims that did not report, 39 % perceived police could not/would not help, and 23 % did not perceive it to be serious enough to report. However, these minor crimes still have significant ramifications for victims and members of the respective community, as prior research has shown.

For those who decide not to report, a plurality indicated a lack of faith in law enforcement (39.1 %). This is similar to results from the 2011–2012 Crime Survey for England and Wales, which is comparable to the NCVS. Indeed, the Crime Survey found that 40 % of hate crimes were reported to law enforcement, and of those who did not report, the most common reason cited (43 %) was "because the victim believed that the police would not or could not do much about it" (Ministry of Justice, 2013, p. 6). Religious hate crimes were also much more likely to occur at the victim's home than anywhere else according to NCVS, but more likely to occur outside of a home (or religious institution) according to NIBRS. This suggests a mismatch between where most religious hate crimes occur and where most *reported* religious hate crimes occur. Further, religious hate crimes occurring in a residence were more likely to be reported compared to other locations, but were also less likely to involve an arrest. While crimes involving a stranger are more likely to be reported, these cases are much more difficult for law enforcement to investigate and solve. Unfortunately, NIBRS does not collect the data needed to determine if an offender had been identified.

These results are troubling, given that research has shown hate crimes tend to start as a minor crime, such as intimidation, tend to be serial, and escalate in severity with significant consequences extending beyond the victim to the group (Garcia, McDevitt, Gu, & Balboni 2002; Martin, 1996; Wexler & Marx, 1986). As prior findings have indicated, religious hate crimes have been steadily increasing (Sandholtz et al., 2013; Wilson, 2014). If the response to the initial reported crime is seen as inadequate or lacking (i.e., the lack of arrest), this may have important implications, including mistrust towards law enforcement, additional attacks, acts of retaliation, and vigilantism, while implicitly sending the message these crimes are condoned (Bell, 2002; McDevitt et al., 2001; Wexler & Marx, 1986). As McDevitt et al. (2001) reported, the psychological well-being of victims is associated with the level of satisfaction with law enforcement's response. A lack of an arrest may not only affect the emotional and psychological well-being and recovery of the victims, but also affect their feelings of safety and security in society, and may actually lead to minority groups leaving their neighborhoods and changing their behavior (Abu-Ras & Suarez, 2009; Wexler & Marx, 1986). A lack of an arrest may also be perceived as police inaction, further discouraging victims from reporting future incidents or participating in investigations, even if minor crimes persist or escalate, as the findings involving multiple crimes suggest.

In support of the existing research on clearance and incidents with co-occurring crimes (i.e., homicide, rape, and assault), and recent findings specifically regarding bias crimes (Lyons & Roberts, 2014), co-occurring crimes increase the likelihood of arrest for violent crimes. This may provide additional evidence to assist the police, although NIBRS data does not allow for testing this assertion (see Addington & Rennison, 2008; Lyons & Roberts, 2014). Alternatively, it may convey to the police that these incidents are more serious, and thus are more deserving of time and attention, despite being relatively rare (Bell, 2002). Similarly, the involvement of multiple victims increases the odds of arrest for violent crimes.

Limitations and Future Research

Four important limitations must be considered when interpreting the results of this study. First, hate crime data suffers from two sources of biases which are absent from non-bias-motivated crime. Bias-motivated crimes are less likely to be reported, especially for the more common low-level types of criminal activity such as intimidation or vandalism (Lawrence, 2002). Law enforcement also has significant discretion at categorizing an incident as a bias crime, and may be under either organizational or community pressures to not classify it as such. A large number of these crimes may suggest a community is more bigoted, when in reality an increase may be due to better relations with law enforcement and/or more transparency (Jenness & Grattet, 2001).

Second, both NCVS and NIBRS datasets have some inherent weaknesses, as prior studies have indicated (e.g., Lyons & Roberts, 2014; Messner et al., 2004). For instance, as Bell (2002) notes, when law enforcement searches for evidence of bias motivation, the actions and words by the offender(s) are important. However, the NCVS only began collecting data in 2010 (e.g., presence of hate language or symbols), and it is completely absent from NIBRS; this could result in model misspecification due to omitted variable bias.

Third, there are two issues concerning the classification of certain religious hate crimes that must be considered. Specifically, the NCVS does not capture the subcategory of the hate crime, and some NIBRS participating states have recorded anti-Islamic crimes as anti-Arab, even though the FBI only began to officially collect data on this category in 2015 (Federal Bureau of Investigation, 2015).[9] The FBI also doubled the number of religious bias categories to 14 (e.g., anti-Sikh, anti-Jehovah's Witness); recall in this study, there were a large number of 'other' religious hate crimes. As a result, these types of crimes were categorized as 'other', and this may under-count anti-Islamic crimes in this study, given the different ways it could be classified by agencies. While time-intensive, research using police reports provides an alternative source of

[9] For instance, Nelson et al. (2015) combined the categories of anti-Arab and anti-Muslim.

data that may contain this information. Even with these limitations, NIBRS still represents the best source of data to examine the research questions due to the extensive information collected for each incident.

Future research should examine the mechanisms behind these effects to see if the findings here concerning religious crimes are generalizable across the various types of hate crimes, and in comparison to parallel crimes. As the current study aggregated victim and third-party reporting, future research should examine these separately, though only the NCVS contains data on who reported the crime.[10] Furthermore, NIBRS can be linked to other datasets, such as the American Community Survey (ACS) or Law Enforcement Management and Administrative Statistics (LEMAS), the latter of which would allow researchers to examine the impact of police department characteristics, such as the presence of a bias unit, on crime clearance within a multi-level framework.

Conclusion

The results reported here indicate religious-bias crimes are highly unlikely to be reported and cleared, which may negatively impact social stability and police-public relations. Only a few characteristics relating to offense severity are important for *both* reporting and clearing these hate crimes (e.g., injury, co-occurring crimes, victim-offender relationship). The combination of low reporting and arrest rates is troubling, given prior research on the negative consequences these crimes have on both the victim and others in the community who share the victim's characteristics (Perry & Alvi, 2011; Wexler & Marx, 1986). To combat hate crimes and increase reporting and arrest likelihood, law enforcement departments must improve their police-community relations and outreach to marginalized groups. Further, efforts must be made to carefully consider all bias crimes, regardless of how minor the incident may appear to be for police.

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[10] The authors would like to thank an anonymous reviewer for noting this limitation.

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