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Anti-Arab Hate Crimes in the Aftermath of September 11, 2001: Assessing the Influence of Geographic and Situational Factors

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Anti-Arab Hate Crimes in the Aftermath of September 11, 2001:

Assessing the Influence of Geographic and Situational Factors

by

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ABSTRACT

This study investigates how hate crimes in general and anti-Arab hate crimes in particular were distributed across different regions of the United States during the 2001-2002 period. The study explores how a historical event – the terrorist attacks against the U.S. on September 11, 2001 – and county population demographics affect the rates of hate crime against Arabs, Muslims or Middle Easterners. It was hypothesized that anti-Arab or anti-Muslim hate crimes displaced other forms of hate crime and were characterized by open acts of violence. According to the contact hypothesis, anti-Arab and anti-Muslim hate crimes would be more likely to occur in counties with relatively high levels of poverty and economic inequality. The research materials were obtained from publicly available data. The hate crime data were obtained from the national hate crime incidents reported to the FBI Uniform Crime Reports (UCR) program. The population demographics were obtained from the U.S. Census 2000. The primary research methods employed in this study include descriptive and inferential statistical analyses, full and partial correlations, independent sample t-tests and continuation ratio logit models. The study indicates that hate crimes against Arabs, Muslims and people of Middle Eastern descent increased dramatically after September 11, 2001. The findings further reveal that anti-Arab hate crimes are more likely to occur in counties with relatively high racial diversity than in counties with low racial diversity. The study

shows that anti-Arab hate crimes do not follow the same patterns as anti-Black hate crimes and thus cannot be explained by the “defended neighborhood hypothesis.” Anti-Arab hate crimes, instead, are best explained as a response to larger cultural and political threats available in mainstream society.

INTRODUCTION

Even though hate-motivated violence has existed since the dawn of time, only recently – beginning about two decades ago – has such violence been referred to as a hate crime. Once the new concept of hate crimes was adopted, it became part of the rhetoric used among social movement activists, civil rights organizations such as Anti-Defamation League (ADL), and legislative institutions. Hate crimes gained even more prominence with the media coverage of particular incidents such as the murders of James Byrd Jr. and Matthew Shepherd in 1998, which slowly transformed hate crimes from isolated cases of discrimination into a social problem of national concern.[1]

As hate crimes have become a social problem of national concern (Jenness and Grattet, 2001), a lot of research has focused on the factors that contribute to the existence of such phenomena. Green, McFalls, and Smith (2001:485) suggest that most theoretical perspectives on hate crimes “distinguish between two broad levels of analysis: individual and societal.” Individual-level analyses seek to explain the psychological characteristics of people who commit hate crimes. Societal-level analyses, on the other hand, focus on the socio-structural conditions that favor the occurrence of hate crimes.

The current study is a societal-level analysis. Its purpose is to add to the existing literature by testing a variety of hypotheses typically used to explain the incidence of hate crimes in various geographic and situational contexts. Specifically, it will examine a variety of social, economical, and historical-cultural conditions believed to influence the incidence of hate crimes, including such things as a county’s racial and ethnic composition, a county’s income and poverty levels, and the overall historical, cultural, and political climate that resulted from the terrorist attacks on New York City and Washington, D.C. on September 11, 2001.

The terrorist attacks of September 11, 2001, and the subsequent revelations that those attacks were orchestrated and carried out by Arabs increased the social awareness among all Americans of a specific social group, Arab-Americans (Volpp, 2002; Hall, 2003). In the aftermath of September 11, because many Americans began to associate Arab-Americans with the perpetrators of the terrorist attacks, it is not surprising that many Arab-Americans became targets of hate-motivated violence. According to the Council on American Islamic Relations (CAIR, 2002), there were 2,042 reports of hate crime against Arabs, Muslims, and people of Middle Eastern descent. These acts of violence did not harm only Arab-Americans. Targeted groups extended beyond the Arab-Americans to include other individuals, such as Indian Sikhs, who were perceived to have a Middle Eastern descent.

However, despite the data gathered by civil rights organizations and despite the extensive research on hate crime victims focusing on African-Americans, Asians, Jewish people, and homosexuals, there are currently no rigorous studies that have investigated the characteristics of the geographic and situational factors in predicting the occurrence of anti-Arab hate crimes. In order to investigate the characteristics of hate crime directed against people of Arab, Muslim or Middle Eastern descent, I used the 2001 and 2002 national hate crime data gathered by the Federal Bureau of Investigation (FBI) as well as the hate crime data pertaining to a specific community in the United States, the city of Chicago. My rationale for selecting a specific community in addition to the national hate crime data was that the national data set did not provide a specific count of anti-Arab hate crimes. The national data set only provided specific counts of anti-Muslim hate crimes as a specific category under religious bias crimes. Anti-Arab hate crimes, according to the incident reports on the national hate crime data set, fall under hate crimes against "other" ethnic groups. The city of Chicago, on the other hand, used a specific category that recorded the anti-Arab hate crimes. Given the variation among the hate crime categories that determine which social groups deserve legal protection and which ones do not deserve any protection, it is necessary to discuss how hate crime laws and statistics are constructed through the different layers of governmental institutions.

SOCIAL CONSTRUCTION OF HATE CRIMES

Hate Crime Legislation: A Brief History

Although violent acts directed against individuals perceived to belong to certain groups have occurred throughout history, in the United States, the first federal law against motivated bigotry did not pass until the enactment of the Civil Rights Act of 1968. This law protected the civil rights of minority groups against crimes based on race, ethnicity, religion, and national origin of the victim (FBI, 2005). However, because the law protected minority groups against hate violence only upon infringement of their civil rights, such as their right to vote or to attend school, social movement activists, including members of civil rights, gay rights, and women's rights organizations, pressured the states and the federal government for the enactment of more comprehensive hate crime laws (Jenness and Grattet, 2001; Nolan III, Akiyama, and Berhanu, 2002). In the early years of the 1980s, after tracking anti-Semitic hate crime incidents, the Anti-Defamation League (ADL), a civil rights organization, developed a model of hate crime legislation, "Model Ethnic Intimidation Statute" (ADL, 2001; Gerstenfeld, 2004). Soon after, many states, starting with California, followed the ADL model and developed similar hate crime laws.

The most comprehensive federal hate crime law was developed in 1990. That year, the U.S. Congress passed the Hate Crime Statistics Act (HCSA), “which required the attorney general to establish guidelines and collect data about crimes that manifest evidence of prejudice based on race, religion, sexual orientation, or ethnicity…” (Nolan III, Akiyama, and Berhanu, 2002, p. 137). The Attorney General transferred the responsibility of implementing the law to the Federal Bureau of Investigation (FBI). The FBI devised the guidelines and procedures of data collection under the National Hate Crime Data Collection Program. (See Appendix I for a list of FBI guidelines). This program was implemented as an additional element of the existing Uniform Crime Report (UCR) program. Law enforcement agencies enter the hate crime data in either the Summary UCR or the National-Incident Based Reporting System (NIBRS) format[2]. Hate crime data entries from law enforcement agencies are sent to the FBI UCR program, which publishes the results annually under the National Hate Crime Data Collection Program.

The 1990 HCSA law, which had mandated data collection only on hate crimes that manifest racial, religious, ethnicity/national origin or sexual orientation bias, was expanded in 1994 by a new Act that made two important amendments to the existing legislation. The Hate Crime Sentencing Enhancement Act (HCSEA), as a part of the Violent Crime Control and Law Enforcement Act of 1994, enhanced the sentencing for perpetrators of hate crimes. Perpetrators would receive longer and harsher sentences for bias motivated crimes than they would for similar crimes that did not manifest any levels of prejudice (Civil Rights, 2002). In addition to provisions for harsher sentencing of perpetrators of hate, the Violent Crime Control and Law Enforcement Act of 1994 amended the HCSA of 1990 by incorporating hate crimes that manifested bias on the actual or perceived disability status of the victim (ADL, 2001; FBI, 2001).

In 2003, federal authorities contemplated the expansion of hate crime laws to include gender motivated hate crimes under the "Hate Crime Statistics Improvement Act of 2003" (National Criminal Justice Reference Service, NCJRS, 2003). In addition, federal legislation is trying to expand the federal jurisdiction on hate crime prosecution by considering hate crimes a social problem of federal concern. For this matter, Congress is trying to pass a bill called "Hate Crime Prevention Act of 2003," which would expand the federal intervention on hate crime prosecution (NCJRS, 2003).

However, these bills have not yet passed into law. Therefore, at the present time, the National Hate Crime Data Collection Program collects information only on incidents that manifest the following types of biases: racial, religious, ethnic/national origin, sexual orientation and disability bias. The FBI collects and tabulates hate crime data that fall in one of the above categories. The states, however, do not follow the same guidelines of hate crime classification. Each state operates independently and develops its own legislature pertaining to the social categories that need protection under law.

Hate Crime Legislation: Federal Laws and State Laws

At the present time, federal laws have limited ability in defining and prosecuting hate crime incidents. The federal government has limited interest in state-based hate crimes because most of these incidents do not affect federally protected interstate affairs or human civil rights such as voting rights or attending school. Gerstenfeld (2004:13) states: “As the law currently stands, then, the federal government’s power to prohibit bias-motivated crime is, at the very least, severely in question.” Because the role of the federal government is limited in addressing bias-motivated crime, it is up to the states to develop laws that address issues of hate violence. However, despite the fact that legal policies regarding hate crimes initially developed at the state level (beginning with the state of California’s adaptation of the ADL “Model Ethnic Intimidation Statute”), the federal government, as mentioned in the previous section, started to develop its legislation on hate-motivated crimes with the Hate Crime Statistics Act (HCSA) of 1990. This act mandated data collection from local law enforcement agencies with the purpose of publishing the results (Gerstenfeld, 2004). With the enactment of the Violent Crime Control and Law Enforcement Act of 1994 four years later, the federal government defined hate crimes as criminal acts against a person or property that evidence prejudice based on the racial affiliation, religious inclination, ethnic background, sexual orientation, or disability status of the victim(s) (FBI, 2005).

The federal law, more specifically the HCSA and HCSEA, only provides the guidelines that states need to follow in order to submit hate crime reports to the national hate crime data collection program. The federal law, however, does not require a mandatory participation from law enforcement agencies. Instead, it relies on the voluntary participation of law enforcement agencies in collecting and reporting the data to the national hate crime program. Yet, because the federal government cannot interfere into a state’s internal affairs with respect to state laws, most states and law enforcement agencies have developed relatively independent legislative policies regarding hate crimes.

The role of the federal government is limited in addressing hate crime issues. Therefore, the primary social actors dealing with the data collection, reporting, prosecution and criminalization of bias-crime perpetrators are the states and the law enforcement agencies within each state. This means that it is primarily the states' responsibility to determine bias motives, to choose which groups to include under lawful protection, and to identify and prosecute hate crime offenders (Gerstenfeld, 2004).

Research suggests that most hate crime laws are divided into three categories; laws that include a criminal penalty, laws that allow for civil action, and laws that "require the data collection of hate crimes" (Soule and Earl, 2001, p. 287). The first type of law has been adopted by the majority of the states (46) and provides for often enhanced legal sanctions for hate crime perpetrators. The second type of law (adopted by 31 states) provides for payment of damages victims incur as a result of hate crime incidents. The third type of law is adopted by less than half of the states (25). I am primarily interested in the states that have adopted this third type of law, the statutory mandate for data collection. In this study, I investigate the characteristics of hate crime incidents that are collected and reported by law enforcement agencies in states with a statutory mandate for data collection. (See Appendix II for a complete map of states with a statutory mandate for data collection). I argue that states that have adopted statutory mandates for data collection provide more comprehensive reports of hate crimes than states with no statutory mandate for data collection.

The previous discussion illustrates the variation and the discrepancies between federal and state hate crime laws. The federal and the state laws overlap in the protection of many vulnerable social groups such as the racial, religious, and ethnic minorities. Yet, certain states extend the hate crime law by protecting individuals and groups of individuals against hate crimes based on political affiliation, (District of Columbia and the states of Louisiana, Iowa, and West Virginia) or ageism, by protecting individuals against hate crimes based on the age of the victim (District of Columbia and the states Iowa, Louisiana and Vermont). However, hate crime laws are differently constructed not only between the federal and state legislatures, but also among many states' legislatures (Jenness and Grattet, 2001). Some states like Arkansas, Kansas, or South Carolina do not even have any criminal penalties for hate crime incidents and only less than half of the states (25) require their law enforcement agencies to report hate crime incidents to the state Attorney General. The remaining states rely on the voluntary participation of law enforcement agencies to send hate crime reports to the national hate crime data collection program. The lack of comprehensive hate crime laws among federal and state governments is thought to be a major contributing factor in reducing the reliability of national hate crime statistics (Grattet, Jenness, and Curry, 1998). How states develop and enforce hate crime laws directly influences how law enforcement officials define, collect and report bias crimes on a daily basis.

The Interpretation and Implementation of Hate Crime Laws by Law Enforcement Agents

The late 1980s and the early 1990s witnessed many efforts on the part of federal and state legislators to regulate hate crime laws. During the late 1990s and the beginning of the new century, legislators addressed problems related to hate crime policies at the level of law enforcement agencies (Grattet & Jenness, 2001). As the concept of hate crimes transferred from social movement activism to civil rights organizations to federal and state legislatures, it ultimately reached the realm of law enforcement officials who had to translate the legal definitions of hate crime laws into the routine practices of their daily work (Jenness and Grattet, 2001).

Research on how law enforcement agents make sense of hate crime incidents, although limited, has demonstrated how different agencies use different methods for identifying, collecting and reporting hate crime incidents (Gerstenfeld, 2004; Bell, 2002, Boyd, Berk, & Hamner, 1996). The hate crime incident represents a complex situation for law enforcement agents because they have to determine *the motive* behind the crime. Their task is twofold. Not only do they have to investigate and report the "objective" crime (e.g., church vandalism), but they also must evaluate the perpetrator's motives for committing the crime. Sometimes, the perpetrators are unknown and law enforcement agents must rely on victims' accounts to determine bias. But even when law enforcement agents know the perpetrators who committed the crime, their motives are often unclear, confusing, and ambiguous at best. The subjective evaluation of a perpetrator's bias is a major factor that accounts for the observed inconsistency of police officers' categorization, collection, and reporting of hate crimes.

Recent research on hate crime reports reveals at least four factors hindering successful hate crime reporting. The first one relates to the victims of bias violence. Victims themselves do not report, or at least underreport the hate crime incidents. Reasons for non-reporting include fear of revictimization, fear of police neglect, shame, or lack of knowledge on hate crime laws (Gerstenfeld, 2004).

Assuming that the victim has reported the incident, the second factor affecting successful hate crime reporting lies with the responding police officer. The police officer must determine whether the perpetrator who commits the actual crime carries any subjective motives that would transform the underlying criminal act into a hate-motivated crime. Boyd, Berk, and Hamner (1996) found that police officers, in order to reduce the amount of paperwork, would not record an offense as a hate crime despite its potential for being one. Another study by Nolan and Akiyama (1999) suggested that police officers might not record the offense as a hate crime because they do not believe in punishing the motivation behind the act. These studies suggest that police officers' own biases pertaining to hate crimes play a crucial role on accurate reporting.

A third factor preventing successful hate crime reporting relates to the structure of the police department. Police departments with a centralized bias unit are more likely to enforce hate crime laws than police departments with a diffused unit or a single detective per district (Bell, 2002). However, despite the advantages of centralized units, hate crime reporting encounters more difficulties generated from the two-step processes involving the responding patrol officer and the bias unit representative. As mentioned in the previous paragraph, patrol officers may have their own biases. They may not believe in the "legitimacy" of hate crime laws or they may disagree with the structural procedures of identifying and reporting the offense to the investigative bias unit. If hate crime investigating officers do not receive any reports from patrol officers, the accuracy of the police department's data suffers.

The fourth factor believed to contribute to poor hate crime reporting relates to the lack of training police officers receive in detecting and identifying an incident as a bias motivated crime (Gerstenfeld, 2004). Currently, there are only 11 states that provide training for law enforcement officials, and in all likelihood, the training that each unit receives varies greatly.

So far, I have argued that hate crime reports are constructed based on the type of laws a state adopts as well as on the social practices that local law enforcement units use for the detection, identification and reporting of incidents. Hate crime incident reports vary according to the type of state laws, the degree of structural differences among police departments, and the individual subjectivity of police officers pertaining to the enforcement of state or federal bias laws. Yet, even though researchers can never be completely confident about the consistency of national hate crime statistics, they nonetheless employ strategies that can increase the degree of confidence in the use of such data.

Validity of Hate Crime Statistics

Despite the variation in hate crime legislation and law enforcement procedures from state to state and agency to agency, recent research suggests that the national hate crime data, especially the data collected in recent years, are of sufficient quality to be used for data analysis (Nolan, Akiama and Berhanu, 2002; Grattet and Jenness, 2001; Grattet, Jenness and Curry, 1998). The theory of diffusion and convergence of policies and procedures presented by Grattet, Jenness and Curry, (1998) provides strong support for the validity of national hate statistics. This theory argues that although policymakers and law enforcement agents may initially disagree about how to interpret, implement, and enforce new social policies, over time these social actors will come to agreement on how to perform these tasks. Hate crimes represent a new social phenomenon whose policies and procedures are expected to diffuse and converge over time.

Like all new social policies, hate crime laws and guidelines are expected to become more homogeneous as policymakers and law enforcement officials become more familiar with the concept. Grattet and Jenness (2001) investigated how hate crime laws converge over time by adopting similar words and phrases in the definition of hate crimes. Most states after 1993 adopted criminal laws in their hate crime statutes that incorporated the "because of" definition of bias crimes instead of "intent to intimidate and harass," "maliciously and with specific intent to harass," or "prejudice, hostility, maliciousness" (Grattet and Jenness, 2001, p. 678-679). The convergence of legal hate crime definitions represents only one aspect of the diffusion and homogenization of the concept of bias among state legislatures. Most states (46) have developed similar statuses that protect individuals against hate motivated violence based on their race, religion, or ethnicity and close to 50% of the states have developed statutes protecting individuals under the newer hate crime categories of sexual orientation, gender, and disability (ADL, 2001; Grattet and Jenness, 2001; Soule and Earl, 1999).

As hate crime laws become more similar over time and as more vulnerable social groups find equal representation under a legally protected category, Grattet and Jenness (2001) argue that law enforcement practices are expected to converge and become more homogeneous as well. Grattet and Jenness (2001:691-692) state:

> "This research suggests that the ambiguity of the concept is decreasing over time in all of the spheres we have examined. Specifically, social movement players have generally reached agreement on how to operationalize the concept. A dominant model of hate crime has emerged in the legislative arena. Judicial interpretations of the law have largely converged. And, the law enforcement practices appear to be solidifying… In fact, given the efforts to improve the knowledge of law enforcement and to homogenize the data collection techniques currently under way by federal and some state law enforcement agencies, we

> expect data collection to become more systematic and reliable and, incidentally, more useful for traditional criminological analyses as well."

This argument implies that most of the controversy regarding the validity of national hate crime statistics involves law enforcement practices. Research in this area, as mentioned previously, has suggested that law enforcement practices vary from region to region, state to state, and district to district (Gerstenfeld, 2004; Bell, 2002; Boyd, Berk and Hamner, 1996). However, recent research on law enforcement agencies by Nolan, Akiyama and Berhanu (2002) and McDevitt, Balboni and Bennett (2000) provides some support about the diffusion and homogenization of the legal concept of hate crime among police officials. Nolan, Akiyama and Berhanu (2002) conducted research on the participation consistency of law enforcement agencies in the national hate crime data collection program. In their research, police agencies that consistently reported hate crime data to the national data collection program were referred to as "consistent contributors" (Nolan, Akiyama and Berhanu (2002, p.142). They noticed that hate crimes reported by consistent contributing agencies and hate crimes reported by all participating agencies followed similar trends. That is, if consistent contributing agencies reported a low number of hate crime incidents on an annual basis, all participating agencies reported low numbers as well; if consistent contributing agencies reported a high number of hate crimes, all participating agencies tended to report high incident rates of hate crime. This finding, they suggest, increases our confidence in the use of national hate crime statistics.

A more comprehensive study of law enforcement participation in the collection and reporting of hate crime incident data was conducted by McDevitt, Balboni and

Bennett (2000). Their findings support the argument of Grattet and Jenness (2001) who suggested that law enforcement practices should solidify as police officers become more familiar with the notion of hate crime. They found that 62% of law enforcement agencies in cities with a population of over 100,000 participated in the National Hate Crime Data Collection. Despite their personal beliefs and experiences, police officers in their participating jurisdictions understood the seriousness of bias motivated crime and followed institutional guidelines, procedures and practices.

Judging by these findings, it can be argued that police officers will follow institutional policies of hate crime when the state adopts laws that reflect the seriousness of hate violence. Therefore, it can be argued that states that have adopted statutory mandates for data collection will have a high participation rate from law enforcement officials who become increasingly dedicated to the following of hate crime policies and procedures. If law enforcement officials perceive state laws to be serious and intolerant of bias motivated crimes, these officials will try to enforce those standards. If they are required by a statutory mandate to collect and report the data to the state UCR program, they will be more likely to participate in this program than law enforcement officials in states with no statutory mandate for data collection. For these reasons, limiting the statistical analyses only on the data reported by states with a statutory mandate for data collection can arguably increase the confidence in the accuracy of reported data.

HATE CRIME INCIDENT CHARACTERISTICS

Perpetrators and Situations of Hate Crime

A hate crime is defined as: “A criminal offense committed against a person, property, or society which is motivated, in whole or in part, by the offender's bias against a race, religion, disability, sexual orientation, or ethnicity/national origin" (FBI, 2002). Hate crime incidents usually include three components, perpetrators of hate, situational factors and victims of hate. In this section, I will discuss the characteristics of typical hate crime offenders as well as the situational and structural factors related to hate crime incidents.

Who are the typical perpetrators of hate crimes? Research on hate crime offenders, even though limited, has demonstrated that typical perpetrators are usually non-poor, young, white males not involved in any hate groups (Craig, 2002; Nolan, Akiyama, and Berhanu, 2002; McDevitt, Levin, Bennett, 2001). Yet, this is not always the case because as Gerstenfeld, (2004:88) states: "A significant number of hate crimes occur not between poor whites and poor blacks, but rather between two minority groups." To complicate the matters even more, on the national hate crime reports, determination of hate crime offenders is usually based on the victims' accounts and is therefore, subject to victims' biases and law enforcement officer's biases (Nolan, Akiyama, and Berhanu, 2002). Research on hate crime offenders suffers from another shortcoming. Knowing who hate crime offenders are does not explain why they commit acts of bias-motivated violence.

What, then, explains why people commit hate crimes? Explanations focus on a variety of psychological and situational factors. Most of the research on bias-motivated violence suggests that the development of prejudice starts with our ability for social categorization (Gerstenfeld, 2004; Brown, 1995). As we group people into social categories, we learn the stereotypes associated with each group. Stereotypes refer to "[cognitive] overgeneralizations about a category of people" (Lindsey and Beach, 2003,

p. 237). Stereotypes are usually negative and it is the internalization of these negative generalizations about a social group that leads to negative attitudes (prejudice or biases) towards that social group (Allport, 1954). Psychological approaches focus on parenting styles and personality traits in order to explain how hate crime offenders learn their biases (Gerstenfeld, 2004; Ezekiel, 2002; Brown, 1995; Allport, 1954). Proponents of these approaches argue that families play a central role in the development of certain personalities such as authoritarian personalities who have a higher propensity for hate-motivated violence (Ezekiel, 2002; Allport, 1954). However, most of the research on bias-motivated behavior has shifted away from psychological explanations. The reason, as Brown (1995:31) suggests, "…is that it underestimates – or, even, in its strongest form completely ignores – the power and importance of the immediate social situation in shaping people's attitudes." Given the difficulty of determining hate crime offenders, and the inadequacy of psychological approaches, most research tends to explain why hate crimes occur by focusing on the situational factors and the social context of hate crime incidents (Wang, 2002; Green, McFalls and Smith, 2001).

Research investigating the situational factors that influence hate crime incidence has focused on small group dynamics, socio-economic conditions as well as on historical, cultural and political conditions (Gerstenfeld, 2004; Green, McFalls, and Smith, 2001). Hate crimes are usually committed by small groups of friends rather than by single individuals or organized hate groups (Gerstenfeld, 2004). This finding suggests that peer groups play an influential role on bias motivated violence. Small groups increase the level of anonymity (deindividuation) and identification with group's attitudes and behaviors enabling individuals to be more inclined towards conformist behaviors

(Aronson, 1999; Zimbardo, 1972). Studies on hate crime perpetrators by Franklin (2000) and Byers, Crider, and Biggers (1999) have found that the offenders were highly influenced by the attitudes their peers held towards a victim's social group.

A large body of research has also focused on the influence of socio-economic conditions on hate crimes. Research that takes into account the role of socio-economics relies on two traditional theories, conflict theory and scapegoat theory. Conflict theory argues that when groups compete over scarce resources, they are more likely to engage in hostile behaviors (Sherif, Harvey, White, Hood, and Sherif, 1961). Scapegoat theory suggests that in times of economic difficulty, people seek out and blame convenient targets for their inopportune conditions (Allport, 1954). Members of Jewish and African-American minority groups have historically been targets of blame and with the events of September 11, Arab-Americans, members of the Muslim community as well as liberal advocates or feminists have emerged as new targets of blame (Gerstenfeld, 2004; Gerstenfeld, 2002). Utilizing these theories, researchers have tried to establish a link between poverty and hate violence. Ezekiel's (1995) study on neo-Nazi hate group members found that most members came from lower class and poor families. Medoff (1999) found that hate crime rates are inversely related to market wages; as market wages increase, hate crime rates decrease. However, not all studies have found a relationship between hate crime activity and socio-economic conditions. Studies by Green, Strolovitch and Wong (1998), Green, Glaser and Rich (1998) and Hamm (1993) have found no relationship between economic statuses and hate crime activity.

Given the ambiguity that surrounds the relationship between socio-economic factors and hate crime activity, recent research has started to pay more attention to the overall social context in order to explain hate crime activity. Advocates of the historical and cultural approaches to hate crime argue that most theories of hate crime search for individual or social factors that enable an individual to commit such acts of deviance as bias-motivated violence. According to advocates of this perspective, instead of perceiving perpetrators of hate as deviant individuals, we should in fact look for cultural and historical processes that normalize hate-motivated violence (Wang, 2002; Perry, 2001, 2002). As Gerstenfeld (2004:99) concludes:

> "It is tempting to think of them as deviant or evil. In fact, doing so reinforces our own self-images as good people. Certainly, those who do commit these acts are responsible for the choices they make and should be held legally and morally accountable. However, we should not become too comfortable in our own ethical superiority because, by most accounts, the type of people who commit hate crimes are not 'them' – they're 'us.'"

In this view, therefore, hate-motivated acts of violence should not be perceived as merely isolated cases of deviance, but rather as normal responses to diffused cultural values of a given society. Perry (2001:37) reinforces the same concept regarding the normality of bias-motivated violence by stating that:

> "Hate crime is not abnormal; rather it is a normal (albeit extreme) expression of the biases that are diffused throughout the culture and history in which it is embedded."

Furthermore, studies by Craig (2002), Perry (2002), Wang (2002), and Petrosino (1999) provide some support for the claim that the United States has a long history and culture of hate. Although dominant cultural values are important for understanding the expression of biases, the dominant culture of a society becomes more visible during particularly salient historical events. Various studies have highlighted the importance of historical events in generating bias-motivated violence. A study by Petrosino (1999), for instance, argues that escalated violence against Native Americans, African Americans, and Asian Americans in the preceding centuries could be explained in terms of certain historical events such as Manifest Destiny, emancipation, or transcontinental railroad construction. A more recent study by Gerstenfeld (2002) implies that modern historical events like the first Gulf War or the historical events of September 11 acquire significant salience in a particular culture and become a contributing factor toward intergroup hostility. Historical events such as September 11 have the ability to shape the cultural climate of an entire society yet, with the exception of some newspaper articles, no rigorous studies have been conducted on the relationship between the historical events of September 11 and hate crime activity.

My review of the existing literature on hate crimes has pointed out some deficiencies regarding the investigation of the situational and structural factors contributing to hate crime incidence. This study attempts to address these deficiencies by exploring how the combination of county level population dynamics, levels of poverty and inequality, and the historical events of September 11 affects the rates of anti-Arab hate crimes as well as the overall rates of hate crime. However, before explaining the constructs of the present study, it is necessary to review the literature on the victims of bias-motivated hostility.

Victims of Hate: Anti-Arab Hate Crimes

Research on victims of hate has demonstrated that members of racial and ethnic minority groups, especially African Americans, are the most common targets of hate-motivated violence (Gerstenfeld, 2004; Nolan, Akiyama, and Berhanu, 2002; Torres, 1999). When combined, racially and ethnically motivated hate crimes account for about

70% of all reported hate crime incidents (Perry, 2002), and African Americans and Jews make up a large portion of these victims.

Although African Americans and Jews have historically been the most common targets of hate crimes, every historical moment has the ability to surface new potential victims. With the terrorist attacks of September 11, 2001, and the subsequent revelations that those attacks were orchestrated and carried out by Arabs, Arab Americans emerged as an ethnic minority that constituted a convenient target of hate. In order to understand how Arab Americans, as an ethnic group, emerged as a target of hate following September 11, it is helpful to examine what social analysts refer to as "ethnicity industry."

Viewing ethnicity as a social construct, Berbrier (2000) suggested that ethnicity is like a "vessel" with permeable boundaries. Adherence to a particular ethnic group is situationally determined by social agents of "ethnicity industry" – who refer to "heterogeneous networks of people and institutions… involved in promoting both the 'ethnic' status of their particular group along with – and inseparable from – promoting, maintaining, and/or modifying collective representations of ethnicity" (Berbrier, 2000, p.79). As defined by social agents of ethnicity industry, particularly after the events of September 11, Arab Americans are perceived as perpetual foreigners along with members of Hispanic and Asian descent (Gerstenfeld, 2004; Chen, 2000). They are typified as dangerous terrorists unworthy of being considered truly "American;" they are perceived as the opposition that defines the identity of the "American" citizen (Hall, 2003; Gerstenfeld, 2002; Perry, 2002; Volpp, 2002; Alexander, 1992). Volpp (2002:1575) states: "Members of this group are identified as terrorists and disidentified as citizens."

She continues by arguing that Arab-Americans are stigmatized even further in relation to other minority groups because, after the events of September 11, the typical American citizen expanded to include members of other races and ethnicities, such as African-Americans, Asians, and Hispanics, at the exclusion of Arabs, Muslims and Middle Easterners.

Arab Americans are an example of an ethnic minority group uncertain of federal protection against hate crimes. In the national hate crime data collection, anti-Arab hate crimes do not fall into a specific hate crime category but are rather diffused with "hate crimes against other ethnicity/national origin" (FBI, 2001). Not having a specific, lawfully protecting category has the potential implication of rendering hate violence against Arab Americans and members of Middle Eastern descent as a minor problem of not any serious social concern (Gerstenfeld, 2004).

Anti-Arab hate crimes represent an example of hate crimes against "the other" ethnicity/national origin. Hate crimes based on the ethnic affiliation of the victim acquire a special dimension not common to other types of hate crimes. Anti-ethnic hate crimes are viewed as "routine border patrol" activities that are used to defend white cultural boundaries in the name of preserving "American-ness" (Chen, 2000:69). Hate crimes against other ethnicities, including Arabs, Muslims and people of Middle Eastern descent, take on an additional symbolic nature. They are justified because they are protecting "American values" and citizenry from foreign aliens and terrorists.

The period following the terrorist attacks of September 11, 2001, does not represent the first time that anti- Arab hate crimes occurred. Gerstenfeld (2004) argues that hate crimes against Muslims increased during the first Gulf War of the early 1990s.

Yet, research on anti-Arab hate crimes prior to September 11, 2001 is nearly nonexistent. Even after the historical events of September 11, the serious study of anti-Arab hate crimes remains relatively sparse. However, after September 11, even though there exist no rigorous studies to accurately measure the degree of anti-Arab violence, statistics from the states of California, Colorado, and Illinois (Gerstenfeld, 2004) as well as hate crime data collected by advocacy groups like the Council on American-Islamic Relations (CAIR, 2002), American Arab Anti-Discrimination Committee (ADC, 2002), and Arab-American Institute (AAI, 2001), report an increased number of hate crime incidents against members of the Arab community. These findings, coupled with the lack of adequate investigation of situational factors that influence hate crimes, provide some justification for this study's attempt to identify and measure anti-Arab hate crimes.

The Present Study and Hypotheses

This study investigates the influence of societal factors on county-level hate crime incidents. The societal factors explored in this study include the historical events of September 11, 2001, the structural conditions such as a county's population dynamics or racial diversity, and a county's socio-economic levels. As argued in the section on the social construction of hate crimes, despite the large legislative discrepancies, despite the problems law enforcement agents face with hate crime reporting and data collection, and despite the hardships of investigative and prosecutorial procedures, the actual numbers of hate crime incidents reported to the FBI Uniform Crime Reports (UCR) are grounded in an objective reality (Gerstenfeld, 2004; Best, 2003; Kitsuse and Cicourel, 1963). As a result, they are still worthy of analysis because they can provide useful information about the characteristics and patterns of bias-motivated violence.

In the present study, I will investigate the effects of September 11 on hate crimes, particularly on anti-Arab hate crimes. The social identity of Arab-Americans has become particularly salient after the historical events of September 11. Research by Petrosino (1999) on previous historical events has alluded that such events have the potential to increase intergroup hostility. Given the prominence the Arab American identity received after the events of September 11, 2001, it is hypothesized that anti-Arab hate crimes increased after such historical events.

However, I will extend this theory a step further by investigating how other forms of bias changed as a result of changes in anti-Arab hate crimes. Research suggests that the overall volume of deviancy (Erikson, 1966) or the level of social problems (Mauss, 1975) tend to remain stable over time. What about the level of hate crimes? How do the levels of anti-Black, anti-Asian, anti-White, anti-Jewish hate crime change as the level of anti-Arab hate crime increases?

Previous literature on structural factors of hate crime incidents, like research on historical events, is incomplete and suffers from many shortcomings. The most comprehensive study to explore the influence of a county's structural factors on hate crime incident reports was conducted by McVeigh, Welch, and Bjarnason (2003). Their study relied on the FBI national hate crime reports for the year 2000. They conceptualized hate crimes as consequences of successful social movement activism and found that hate crime reports depended on several features of the social context. They took into account a number of county level structural factors such as county population size, the number of advocacy groups, the number of organized hate groups and the major political party affiliation. Their findings suggested that hate crime reports increased as the county population, the number of racist groups, the number of civil rights organizations, and democratic voting behavior increased. However, their research focused on the overall number of hate crime reports and did not look at the distribution of any particular categories of hate crime. The current study will build on their research and observe the patterns of anti-Arab and anti-Muslim hate crimes for a two-year period, from 2001-2002. In addition, borrowing from research on conflict theory and intergroup dynamics, the present study will investigate how the racial composition of a county influences hate crime incident reports. Using Allport's (1954) concept of contact hypothesis and Sherif et., al., (1961) model of conflict theory, it is hypothesized that a county's level of racial diversity affects the level of hate crime rates such that as racial diversity increases, hate crime rates increase accordingly.

Whereas McVeigh, Welch, and Bjarnason (2003) investigated how county-level structural factors influence hate crime reporting, a study by Green, Strolovitch and Wong (1998), focusing primarily on New York city neighborhoods, investigated how demographic change influenced racially motivated crimes (e.g., anti-Black, anti-Asian, anti-Latino[3]) during an eight-year period, from 1987-1995. They found that demographic change is a good predictor of racially motivated hate crimes. Their findings suggested that racially motivated crimes occur due to "[perceived] threats to turf (neighborhoods) guarded by a homogeneous group" (Green, et. al., 1998: 398). However, if these are the patterns of racially motivated crime occurring in New York City from 1987-1995, what kind of patterns do we observe for anti-Arab and anti-Muslim hate crimes occurring in 2001-2002? Do they occur in locations of low or high racial diversity, of high or low population change? In other words, does the "defended neighborhood hypothesis," presented by Green et., al. (1998), explain the patterns of anti-Arab and anti-Muslim hate crime occurrences? Do these incidents occur because perpetrators feel they need to "defend their neighborhood" from Arab intruders or because they must defend their city/country from foreign aliens/enemies (Volpp, 2002; Chen, 2000)?

Since previous research on hate crimes has reported ambiguous findings pertaining to the role of economics on hate crime incidents (Green, McFalls, and Smith, 2001), I decided to investigate the role that socio-economic conditions play on anti-Arab and anti-Muslim hate crimes. According to contact hypothesis, hate crime activity is more likely to occur among competing groups of differential socio-economic statuses (Allport, 1954). Therefore, I hypothesize that anti-Arab and anti-Muslim hate crimes occur more frequently in counties with a high income inequality rather than in counties with a low income inequality.

Following the above theoretical conceptions, this study will test the validity of the following hypotheses:

Hypothesis 1 – Triggering events

Trends in anti-Arab or anti-Muslim hate crimes have been neglected and remain largely unexplored. This study will investigate the effects of a major historical event, the terrorist attacks of September 11, 2001, on anti-Arab hate crimes. Historical events have the ability to shape or enable the social construction of binary oppositions such as "American citizen" and "foreign alien" (Volpp, 2002; Alexander, 1992). Because such constructions increase the likelihood of bias-motivated violence, it is hypothesized that anti-Arab and anti-Muslim hate crimes will increase after the historical events of September 11.

Hypothesis 2 – Volume of hate crime

Erikson (1966) argues that the volume of deviancy remains relatively stable across time and space. Mauss (1975) argues that society has a "normal" quota of social problems at any given time. Given the theoretical perspective on the volume of deviancy and social problems, it is hypothesized that the overall number of hate crimes remains relatively stable over time; that is, if anti-Arab hate crimes increase, other forms of bias crime such as anti-black, anti-gay, anti-Jewish, and anti-Asian hate crimes will decrease.

Hypothesis 3 – Defended Neighborhood

Green et., al. (1998), using longitudinal data from the U.S. Census, tested what they called the "defended neighborhood hypothesis" by examining how demographic change was associated with racially motivated hate crimes in New York neighborhoods. Does this hypothesis seem as applicable to Arab-Americans as it does to blacks, for whom there is a long history of residential segregation (Massey and Denton, 1993)? "Defended neighborhood hypothesis" concentrates on the level of demographic change in a neighborhood. Do changes in the neighborhood racial composition equally apply to hate crimes against actual or perceived members of Arab, Muslim, or Middle Eastern descent? Do such members pose a neighborhood threat like African-Americans do (e., g., low property values)? In this study, I will test the defended neighborhood hypothesis, which would argue that anti-Arab hate crimes will be more likely to occur in counties with significant increases in Arab population.

Hypothesis 4 – Contact hypothesis

Allport (1954) argued that sustained contact among conflicting groups is a fundamental step for reducing prejudice and discrimination. However, in order to experience low levels of prejudice and discrimination, social groups must attain similar or equal social statuses (Andersen and Taylor, 2003; Cook 1988); the smaller the gap between "rich" and "poor," the lower the prejudice and discrimination levels; the larger the gap between "rich" and "poor," the higher the prejudice and discrimination levels. Therefore, if this holds true, anti-Arab hate crimes will occur at higher frequencies in racially diverse counties with a high-income inequality and high poverty levels rather than in relatively homogeneous (mainly white) counties with a low-income inequality and low poverty levels.

Hypothesis 5 – Open aggression

I believe that anti-Arab hate crimes are characterized by an "open display of aggression" which may not be as prevalent for other discriminated social groups. The reason is because violence against certain stigmatized groups is not perceived as a deviant act but rather as a normal response that upholds acceptable cultural standards (Perry, 2002; Volpp, 2002). If Arab Americans are depicted as a stigmatized social group, then violence against them is justified and does not need to be hidden. Therefore, it is hypothesized that anti-Arab hate crimes tend to occur in open public spaces rather than in private ones.

RESEARCH METHODS

Research Materials

The incident level hate crime data set

To test these hypotheses, I used the FBI hate crimes data set collected by the Inter-University Consortium for Political and Social Research (ICPSR). The data are tabulated in SPSS (Statistical Package for Social Sciences) format. The data set includes the hate crimes reported to FBI for 2001and 2002.

The FBI hate crime data set is limited to only five major bias categories, which include race, religion, ethnicity/national origin, sexual orientation, and disability. In this study, I incorporated all these categories into statistical analysis but I predominantly focused on the first three categories, on hate crimes based on race, religion, and ethnicity/national origin. In order to increase the confidence in the validity of hate crime data reports, I focused only on states with a statutory mandate for data collection. States that have developed statutory mandates are more likely to enforce the federal guidelines for data collection than states with no statutory mandates. As I pointed out in the section on the social construction of hate crimes, according to the diffusion theory of social policies, it can be argued that over time, states with statutory mandates for data collection are likely to be influenced by the policies and guidelines adopted in other states leading to a convergence across states in how hate crime data are collected. As a consequence, it can be assumed that law enforcement agencies within such states are more likely to feel compelled to follow the state law and take the reporting of hate crimes more seriously than law enforcement agencies in states with no statutory mandate for data collection. These factors lead me to have more confidence in the quality and validity of data reported by these states than the data reported by all the states. Thus, by eliminating the states that do not have a statutory mandate, I assume that the remaining states adhere to similar hate crime laws and provide similar guidelines by equally enforcing the participation of law enforcement agencies in the collection and reporting of hate crime incidents (Nolan, Akiyama, and Berhanu, 2002; McDevitt, Balboni, and Bennett, 2000). Selection of states with a data collection mandate was determined based on a publication by the Anti-Defamation League (ADL, 2001). After the selection process, the file was reduced to 26 states with 672 counties reporting a total of 14,421 hate crime incidents to the FBI UCR program. [4]

Incident data variables of interest

The hate crime data set reported incident level data where each case represented a single incident report. The data set was constructed such that no single reported incident of hate crime could be classified as having more than one bias motivation. This meant that each case on the data set consisted of a single bias motivation. For example, incident case #1 was reported as anti-Black and anti-Black only; incident case #2 was reported as anti-Muslim and anti-Muslim only; incident case #3 was reported as anti-Asian and anti-Asian only and so on.

Using data reported on bias motivation, I computed several dummy variables that allowed me to measure the specific types of hate crime I intended to investigate. Table 1 represents the categories and sub-categories of the dependent variables of interest in the hate crime data set. Each reported incident of hate crime available in the data set falls into one of the categories presented in Table 1.

Each category and subcategory assumed two values, a “0” and a “1.” For example, if a particular incident was motivated by racial bias, the dummy variable representing racial bias was coded “1;” if not it was coded “0.” If a particular incident was motivated by religious bias, the variable representing religious bias was coded “1;” if not, it was coded “0” and so on. The same coding scheme was applied to each of the subcategories listed in Table 1.

Table 1. Computations of the Main Categories and Sub-categories of Dependent Variables Based on Bias Motivation.

Categories	Sub-categories
Racial bias	Anti-White, Anti-Black, Anti-Asian
Religious bias	Anti-Jewish, Anti-Muslim
Ethnic bias	Anti-Hispanic, Anti-Other/Arab
Sexual orientation bias[5]	Anti-Gay(male)
Disability bias[5]	No sub-category

Because each hate crime incident reported in these data included the date that the offense occurred, I was able to designate, again by using a dummy variable, whether the incident occurred before September 11, 2001, or after September 11, 2001. Incidents that occurred before September 11 were assigned the code "0"; those that occurred after were assigned the code "1."

As Table 1 shows, anti-Other/Arab[6] is the main variable used to measure the occurrence of anti-Arab hate crimes. Anti-Other/Arab represents a proximate measure of anti-Arab hate crimes. The rationale for equating anti-Arab hate crimes to hate crime reports against other ethnic groups is based on the following assumptions. The first assumption is based on a logical question. Hate crimes against which vulnerable social groups are assigned under the category of "other ethnicity/ national origin?" If we follow the logic of a process of elimination, hate crimes against Arab-Americans have the highest probability to be assigned into this category. The other types of hate crime have their own specific categories. Anti-White, anti-Black, and anti-Asian hate crimes have their own specific categories under racial bias. Anti-Jewish and anti-Hispanic hate crimes are assigned into specific categories under religious and ethnic bias, respectively.

Arab-Americans are the only major ethnic group with no representation under hate crime law.

The second assumption relates to the events of September 11. As mentioned previously, some data gathered by Arab-American civil organizations has suggested that hate crimes against Arab-Americans increased after September 11. If that is the case, we then, should expect increased reports of hate crime against other ethnicities in the early months following September 11. If anti-Other/Arab reports increase, it can be assumed that anti-Arab hate crimes are relatively equivalent to anti-Other hate crimes or at least represent a high percentage of anti-Other hate crimes.

The third assumption is based on some preliminary analyses. The city of Chicago in Cook County, Illinois, is one of the few regions that implemented a specific "Arab" category in order to monitor and report hate crimes against Arab-Americans and people of Middle-Eastern descent (Chicago Police Department, 2001). A preliminary analysis indicated that Cook County anti-Other hate crime reports (44) (available from the national hate crime data collection program) coincide with anti-Arab hate crime reports (45) generated from City of Chicago commission on Human Relations. Taken together, these assumptions increase the degree of confidence for using anti-Other/Arab hate crimes as a measure of anti-Arab hate crimes.

The county-level hate crime data set

The incident level data, however, does not allow the measurement of hate crime rates. According to Kitsuse and Cicourel (1963), measuring rates of crime rather than incidents of crime is a useful method that improves the validity and reliability of official crime statistics. Because of this fact, and my interest in exploring the degree to which certain demographic characteristics predict the incidence of hate crimes, I created a new data set by aggregating the incident level data into county level data. The county-level data set represents an advantage over incident level data because this type of data set allows for the incorporation of county population demographics from the U.S. Census. By combining these data sources, I am able to assess the degree to which certain county demographic characteristics predict the incidence of hate crimes in counties.

County-level variables of interest

The variables included in the aggregate, or county-level, data set are similar to those contained in the incident-level data set. My chief dependent variable, incidence of hate crime, was computed on the basis of the incident-level data in three different ways for this aggregate data set to allow for thorough analysis using multiple statistical techniques. First, I calculated a variable to represent simply the total number of hate crimes in each category. Next, I computed each county rate (percentage) of hate crimes by dividing the number of hate crimes in a particular category by the total number of county hate crimes, which was computed by adding all the categories of hate crime together. For example, to calculate the percentage of a county's hate crimes that were attributed to racial bias, I divided the total number of racially motivated hate crimes in the county by the total number of hate crimes overall and multiplied by one hundred. The same procedure was followed for each of the other categories and sub-categories. For example, the county rate of anti-Black hate crimes was computed by dividing the total number of anti-Black hate crimes into the total number of county hate crimes and multiplying by one hundred. Having variables representing both the county hate crime total and the county hate crime rate in each category permitted me to examine the distribution of these variables to determine which statistic procedures to use.

Finally, because hate crime incident reports against specific categories are relatively infrequent and do not occur in every county, I developed two dummy variables that allowed me to investigate and compare the county characteristics associated with anti-Other/Arab or anti-Muslim hate crimes and anti-Black hate crimes. Counties with at least one report of anti-Other/Arab or anti-Muslim hate crime were coded "1" and counties with no reports of anti-Other/Arab or anti-Muslim hate crimes were coded "0." The same coding took place for county reports of anti-Black hate crimes. Counties with at least one report of anti-Black hate crime were coded "1" and counties with no reports of anti-Black hate crimes were coded "0." Having this type of variable permitted me to conduct t-tests to examine how the characteristics of counties with at least one reported hate crime differed from the characteristics of counties with no reported hate crimes.

The U. S. Census file

Census data can be aggregated at many different levels of analysis, such as state, county, census tracts, etc. In order to match my county level of analysis, files from U.S. Census 2000 were aggregated at the county level and were merged with the county-level hate crime data set. The U.S. Census 2000 county-level data and the hate crime county-level data did not always match. In some cases (such as in the State of Virginia) the U.S. Census 2000 did not report any county level demographics but rather independent city demographics. However, in the U.S. Census 2000, the demographics for independent cities are treated as the equivalents of county demographics (Wikipedia, 2005). In other instances, the county FIPS (Federal Information Processing Standards assigned to various geographic US regions and territories) codes (such as in Miami-Dade County) were not the same between the census file and the hate crime dataset. In such instances, I had to change the FIPS codes in the hate crime dataset so that they would match the appropriate FIPS codes in the census file.

U.S. Census variables of interest

The census file variables included county characteristics such as population, age, gender, race, ethnic affiliation, reported ancestry, as well as county poverty and income levels. The census variables served as independent and control variables used to test the effect of county characteristics on hate crime incidence. I primarily focused on race variables because I was interested in investigating the role that the racial composition of a county had on hate crime incidence.

In order to better measure the effects of a county's racial composition, in particular the degree of racial diversity, on hate crime incidence, I developed a composite variable similar to Finke and Stark's (1988:44) "religious diversity index", but with respect to ethnic diversity. Whereas their composite variable measured the level of religious pluralism in a particular city, the racial diversity index in this study measures the level of racial diversity in a particular county. This composite variable was calculated using the basic equation:

$$1 - [(a/z)^2 + (b/z)^2 + (c/z)^2 + (d/z)^2 + (e/z)^2]$$

where a, b, c, d, and e represent the county population of Whites, Blacks, Asians, Native Indians, and Other races respectively and z represents the total county population.

Because Hispanic and Arab populations fall outside these racial categories, in order to measure the Arab population in a county, I incorporated U.S. Census 2000 data on ancestry. In this manner, I was able to include in my analysis not only the racial diversity of a county's population but also the percentage of that county's population that reported an Arab descent. Thus, the census file included all the major racial and ethnic group formations enabling the analysis of their effect on hate crime incidence.

In addition to a county's demographic composition, I included a measure of county's income and poverty level as well as a measure of its inequality level. The income and poverty variable, labeled "percent poor," represents the percentage of a county's population that reported an annual income below the poverty line. "Percent poor" was used as an independent variable assessing the effect of a county's poverty level on hate crime incidence.

The inequality measure used in this study is the "Gini Coefficient." The "Gini Coefficient" was borrowed from the U.S. Census 2000 and represents a county's income inequality gap calculated from the families' annual income reports. The "Gini Coefficient" assumes values from "0" to "1." A value of "0" implies perfect equality, no income differences, whereas a value of "1" implies perfect inequality, maximum income differences. As mentioned in the hypotheses, the variables of income inequality and poverty level serve as measures for the effect of socio-economic levels on the incidence of hate crimes.

The Chicago file

The Chicago file was developed by using hate crime reports entered by the Chicago Commission on Human Relations. The file was tabulated in SPSS format similar to the national hate crime data set. The Chicago file reported hate crime incidents for the seventy-seven community areas in the city of Chicago, which is included within the borders of Cook County, Illinois. I used hate crime reports from the city of Chicago Commission on Human Relations in order to provide a more accurate measure for anti-Arab bias crimes.

Similar to the national hate crime data set, the hate crime incident level data for the city of Chicago was aggregated at the level of the community area (from now on referred to as community-level data set). The community-level data were merged with U.S. Census 2000 data for Chicago city community areas available at Northeastern Illinois Planning Commission (2002).

The final Chicago data set included similar variables of interest as the national hate crime data set. It included a measure of a community area racial diversity as well as a measure of poverty. However, in the community-level data set, I was able to add a few more variables of interest. First, I was able to include a specific measure of anti-Arab hate crimes. Second, I was able to obtain information on Arab ancestry from both the U.S. Census 2000 and from the U.S. Census 1990. Having such information I was able to calculate a variable (as the difference between the percentage of Arab ancestry in 2000 and the percentage of Arab ancestry in 1990) that measured the change in the Arab population from 1990 to 2000 for each community area in the city of Chicago. The change in the population of Arab ancestry for each community area was used to test Green, Strolovitch, and Wong (1998) theory of "defended neighborhoods."

Data Analysis

Using the incident-level data set, I performed a variety of analyses. The analyses on the incident-level data included analysis of descriptive statistics through bar and pie charts, reports, and crosstabs. These analyses explored the effects of September 11 on each category and sub-category of hate crime incidents. Due to the highly skewed numbers of reported incidents of hate crime for each particular category, inferential statistics were not appropriate since most inferential statistics assume normal distributions of dependent variables.

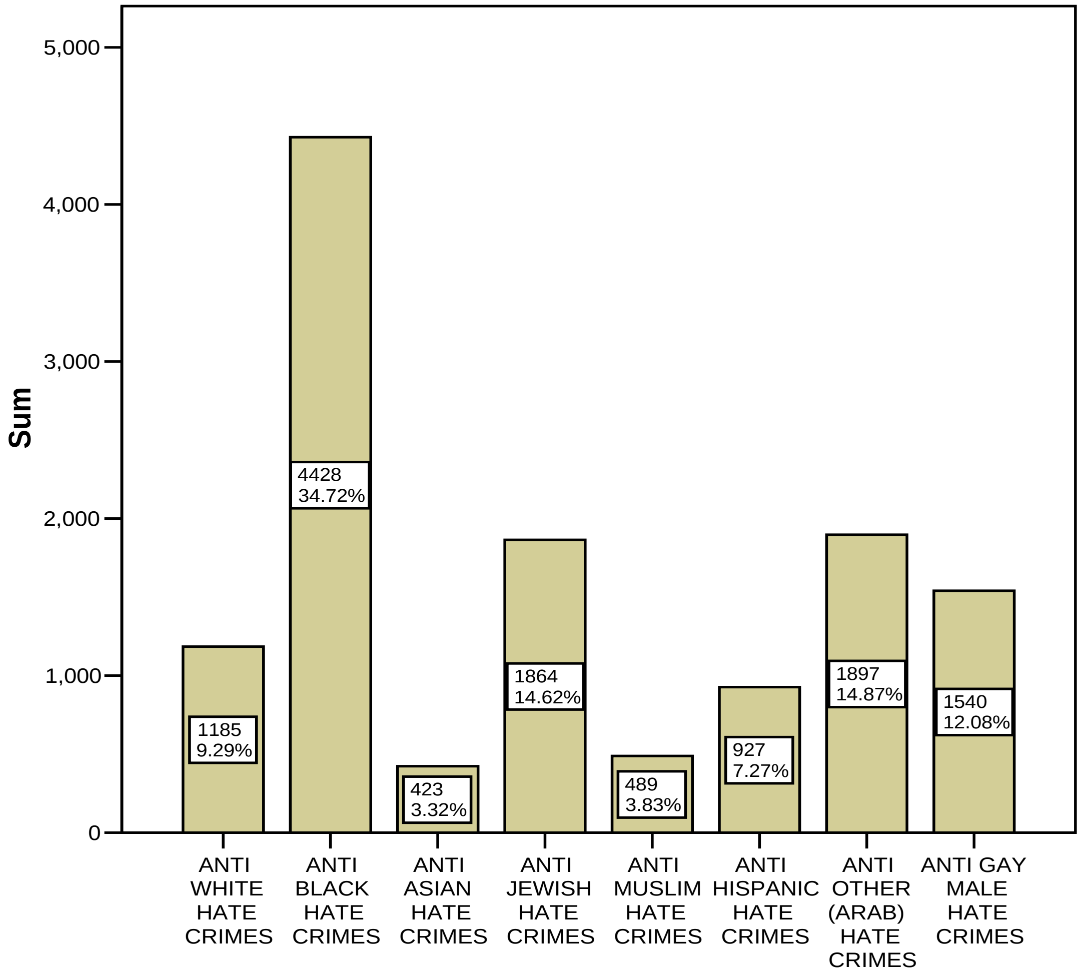
Most inferential statistics were performed on the aggregate data sets, on the county-level and community-level data sets. Because most of the independent variables were highly skewed, in order to achieve normal distributions, I often transformed the variables of interest by using the natural logarithm procedures. After ensuring that variables approximated normal distributions, I performed some correlation analyses and independent sample t-tests. However, the main method of analysis performed on these data sets, the Continuation-Ratio Logit Estimate, was borrowed from McVeigh, Welch, and Bjarnason (2003) as the best method for exploring highly skewed variables. The Continuation Ratio Logit Estimate is a statistical procedure that takes into account the degree of skewness on the dependent variable by treating it as a categorical variable.

FINDINGS

Incident-Level Findings

Who are the victims of hate crime in the 2001-2002 period? Analysis of data from the states with a statutory mandate for data collection demonstrates that the primary targets of hate crime violence are African-Americans. Anti-Jewish hate crimes, as Gerstenfeld (2004) had suggested, still represent a significant percentage (14.62%) of the overall hate crime reports, but the second highest percentage of overall hate crime incidents is the "Other Ethnicity," which includes members of Arab or Middle Eastern descent (see Figure 1.) It is assumed that anti-Other/Arab hate crime incident reports

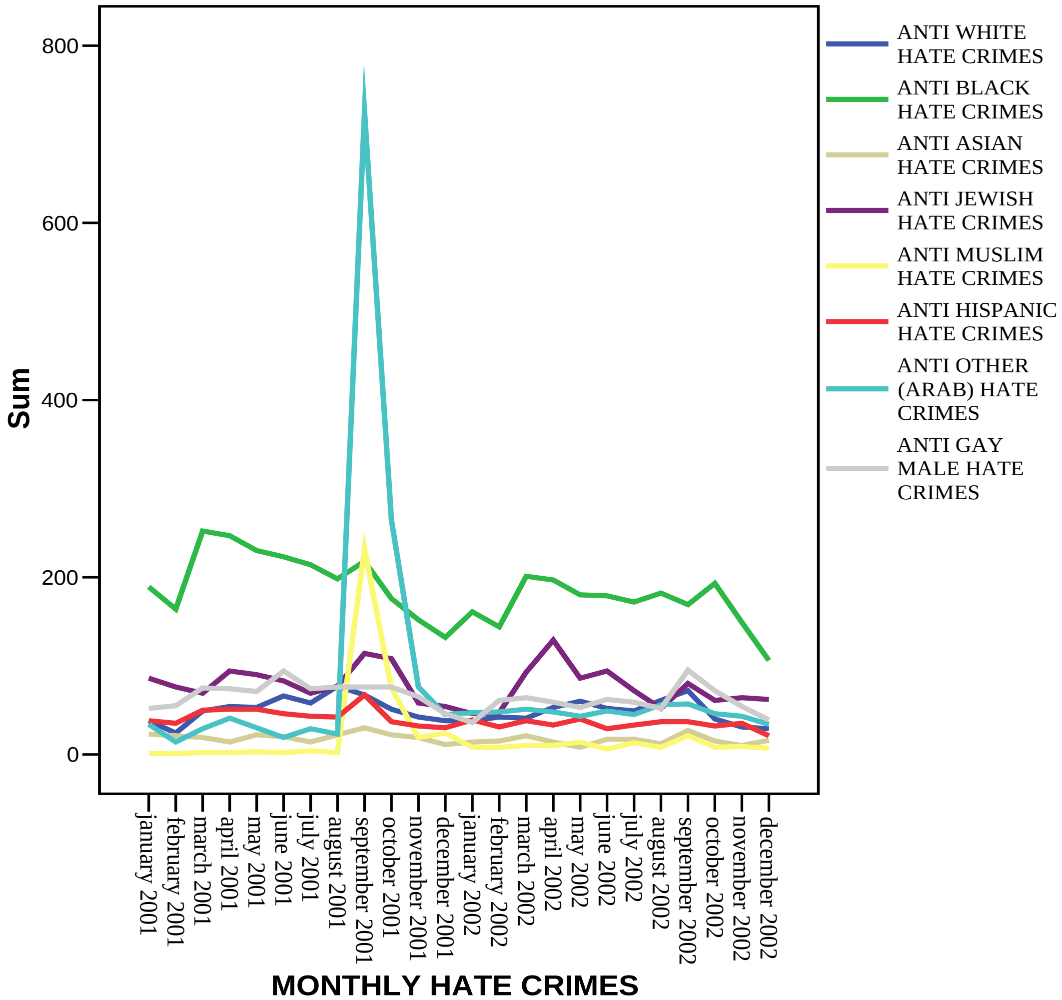
Figure 1. Sum of Reported Incidents per Hate Crime Category for 2001-2002 from the National Hate Crime Data Collection program.



constitute a large proportion of hate crimes against other ethnicities. The relatively high numbers of anti-Other/Arab incident reports become even more significant if we include the anti-Muslim hate crime incident reports. Together, anti-Other/Arab and anti-Muslim hate crime reports represent nearly 19% of the overall hate crime reports for the states with a statutory mandate for data collection during the 2001-2002 period.

As expected, anti-Other/Arab and anti-Muslim hate crimes increased significantly during the month of September 11, 2001. As Figure 2 illustrates anti-Other/Arab hate crimes were characterized by a sharp increase during this month. This finding increases our confidence in suggesting that anti-Arab hate crimes constitute a significant portion of (albeit not all) hate crimes against other ethnicities.

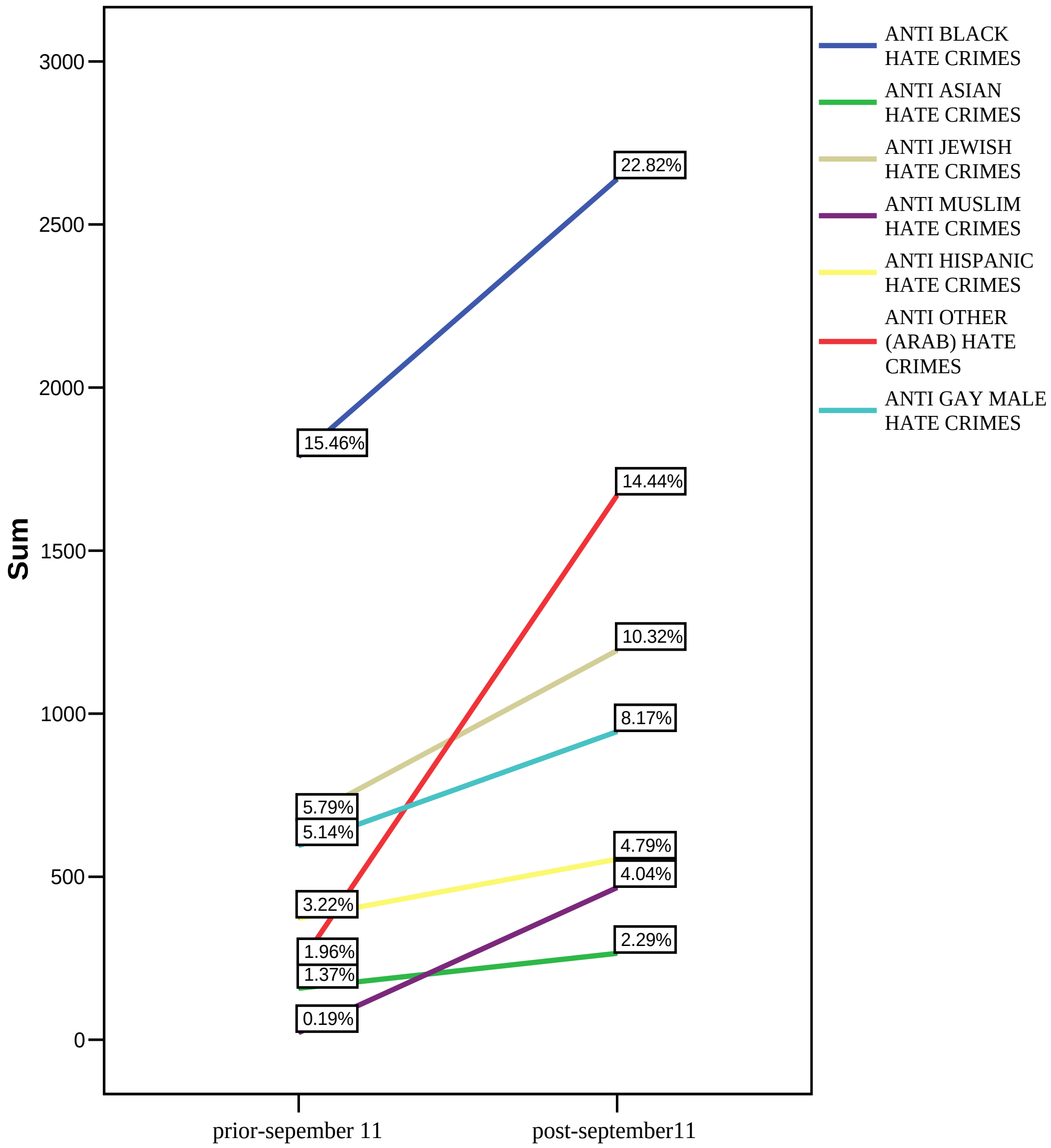
Figure 2. Hate Crime Incident Reports on a Monthly Basis for 2001-2002 Period.



Further descriptive analysis, taking into account the historical events of September 11, suggested that such events are positively related to all of the hate crime categories. The sharpest increases on hate crime incident reports occurred (1) among anti-Other/Arab hate crimes that increased from 227 (1.96% of total reports) prior-

September 11 to 1670 (14.44% of total reports) post-September 11 and (2) among anti-Muslim hate crime reports that increased from 22 (0.19% of total reports) prior-September 11 to 467 (4.04% of total reports) post-September 11 (see Figure 3). Figure 3

Figure 3. Sum of Reported Hate Crime Incidents for each Hate Crime Category Before and After September 11 for 2001-2002 from the National Hate Crime Data Collection Program.



Note: The graph does not include all the categories of hate crime. Therefore, the percentages may not add up to 100%.

also shows that other types of hate crimes increased after September 11 as well. The graph shows an increase in the number of hate crime reports in each represented category implying that the overall number of hate crime incident reports increased after September 11.

This finding does not support our hypothesis concerning the overall volume of hate crimes. According to Erikson (1966), and Mauss (1975), it was expected that other forms of hate crime such anti-Black, anti-Jewish, anti-Hispanic, anti-Gay hate crimes would decrease as anti-Other/Arab hate crimes increased. Probably one way to interpret such results is to suggest that the events of September 11 did not affect only anti-Other/Arab and anti-Muslim hate crimes but any form of bias-motivated violence. Given such an appropriate atmosphere of hate, any individual or group of individuals ascribing to a minority status could easily become a target.

Yet, another plausible explanation relates to the salience principle. Maybe it is not hate crime incidents that increased, but rather the law enforcement officials' awareness of such crimes and the importance of enforcing hate crime laws after the tragic events of September 11. If police officers become more aware of bias-motivated violence, there is reason to believe that they could be more inclined to report such incidents.

County Level Findings

The descriptive analysis of the incident-level data explored the effect of the events of September 11 on the overall number of hate crimes while focusing on anti-Other/Arab and anti-Muslim hate crimes. In order to explore the relationship between a county's demographic factors and anti-Other/Arab hate crimes, I examined correlations between these variables and then conducted multivariate analysis through the use of Continuation Ratio Logit Estimate models.

County-level correlation analysis, reported in Table 2, reveals that anti-Other/Arab hate crime rates are positively correlated with the racial diversity of the population ($p < .01$) , whereas anti-Black hate crimes are negatively correlated with such diversity ($p < .01$). These correlations suggest that anti-Other/Arab hate crimes are more likely to occur in counties with a high degree of racial diversity, whereas anti-Black hate crimes are more likely to occur in counties with a relatively homogeneous (mainly white) population. These correlations point out that anti-Arab and anti-Muslim hate crimes occur in different locations and follow different patterns than those observed for more traditional forms of bias such as anti-Black hate crimes.

Table 2. Correlations between Types of Hate Crime and County Characteristics for States with a Statutory Mandate for Data Collection.

	% anti-Other/Arab hate crimes	% anti-Muslim hate Crimes	% anti-Black hate crimes
County population	.151(**)	.033	-.080(*)
Racial diversity	.140(**)	.026	-.114(**)
% White population	-.101(**)	-.015	.119(**)
% Black population	.028	.012	.006
% Asian population	.198(**)	.056	-.114(**)
% Hispanic population	.093(*)	-.008	-.144(**)
% Multiracial population	.183(**)	.016	-.141(**)
% Arab Population	.204(**)	.090(*)	-.124(**)
% population in poverty	-.026	-.045	.043
Income inequality	.099(*)	.025	-.026

Note: Asterisks denote significance levels
* $p < .05$; ** $p < .01$

Given such differences, which particular county characteristics are most significantly associated with the overall, anti-Other/Arab, and anti-Muslim hate crime incidents? In order to investigate the relationship between the overall hate crime reports and county characteristics, I conducted Continuation Ratio Logit Estimates, the results of which are displayed in Table 3, Table 4, and Table 5.

As the results of Table 3 show, the overall incidence of hate crime is associated with multiple factors. Model 1 reveals that four county characteristics – population size, the population aged 20-24 years, the percentage of the population in poverty, and the racial diversity of the population -- are significant net predictors of hate crime incidents. Hate crimes occur more frequently in counties with large populations ($p < .001$), with high proportions of its population in the 20-24 year-old age bracket ($p < .001$), with lower levels of poverty ($p < .001$), and with higher levels of racial diversity ($p < .01$). Interestingly, neither the percentage of the population between ages 15-19 years old, nor the degree of inequality (as measured by the Gini coefficient) bears a significant net relationship to the number of hate crime incidents.

Because the "racial diversity index" is a composite variable calculated from the percentages of White, Black, Asian, and Native-American population, analyses were performed to determine which of these population categories displayed the strongest associations with the dependent variable. Models 2-7 present the results of these analyses. As the pseudo R-square values reported under each of these models show, out of all of the variables in these models, the percentage of the population that is White and percentage of the population that is Asian account for the highest proportions of explained variance, 14.2% and 14.3% respectively. Model 2 shows that the higher the percentage of a county's population that is white, the lower the number of reported incidents ($p < .001$). This is in contrast to Model 5 where we see that the higher the percentage of a county's population that is Asian, the lower its number of reported hate crime incidents ($p < .001$). Interestingly, the only other population category to display a significant relationship to hate crime incidents is the percentage of the population that Arab, as is reported in Model 7 of Table 3. As we might expect on this data set spanning the years 2001-2002, the larger the proportion of a county's population that is Arab, the higher the number of hate crime incidents ($p < .001$).

When we consider the findings presented in all of the models of Table 3 together, we see that, besides racial composition, the variables that emerge most consistently as predictors of the total number of hate crime incidents in a county are population size and the percentage of the population aged 20-24 years old. In none of the models is income inequality, as expressed by the Gini coefficient, significantly related to the number of hate crime incidents. Income inequality emerged as nonsignificant in all the statistical models.

The results of Continuation Ratio Logit Estimate analyzing the relationship between anti-Other/Arab hate crimes and county demographics are presented in Table 4. The results of Table 4 reveal that anti-Other/Arab hate crimes, like the overall numbers of hate crime, are associated with several county demographics. Anti-Other/Arab hate crimes in Model 1 occur more frequently in counties with a relatively large population size ($p < .001$), low percentage of population between the ages of 15-19 years old ($p < .01$), high percentage of population between the ages of 20-24 years old ($p < .001$), and high racial diversity index ($p < .05$). The results of Table 4 indicate that the percentage

Table 3. Continuation-Ratio Logit Estimates of the Total Reported Hate Crime Incidents in 2001-2002 for U.S. Counties and County Equivalents of the States with a Statutory Mandate for Data Collection

Independent variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
County population	1.982*** (.121)	1.992*** (.117)	2.130*** (.116)	2.132*** (.113)	1.806*** (131)	2.056*** (.123)	1.966** (.122)
population 15-19 years old	-.103 (.064)	-.087 (.065)	-.144* (.066)	-.140* (.063)	-.104 (.064)	-.149* (.063)	-.102 (.067)
population 20-24 years old	.098*** (.026)	.102*** (.027)	.105*** (.027)	.103*** (.027)	.048 (.029)	.111*** (.027)	.076** (.028
% in poverty	-.055*** (.015)	-.070*** (.016)	-.036* (.014)	-.034* (.015)	-017 (.015)	-.041** (.014)	-.026 (.014)
Income inequality (Gini coefficient)	.019 (2.093)	.685 (2.133)	-.043 (2.066)	-.130 (2.102)	-1.485 (2.105)	-125 (2.075)	-1.200 (2.117)
Racial diversity	1.194** (.369)	–	–	–	–	–	–
White population	–	-3.066*** (.721)	–	–	–	–	–
Black population	–	–	-.005 (.083)	–	–	–	–
Native-American population	–	–	–	-.026 (.119)	–	–	–
Asian population	–	–	–	–	.760*** (.156)	–	–
Hispanic population	–	–	–	–	–	.169 (.116)	–
Arab population	–	–	–	–	–	–	.639*** (.156)
Log likelihood	-1800.747	-1806.046	-1803.574	-1806.023	-1793.706	-1804.988	-1758.458
Pseudo R-square	.1397	.1418	.1371	.1372	.1430	.1376	.1330

Note: Numbers represent the coefficients and the standard error (in parentheses)
*p < .05; **p < .01; ***p < .001

Table 4. Continuation-Ratio Logit Estimates of the Anti-Other/Arab Reported Hate Crime Incidents in 2001-2002 for U.S. Counties and County Equivalents of the States with a Statutory Mandate for Data Collection

Independent variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
County population	2.851*** (.204)	2.928*** (.198)	3.090*** (.197)	3.021*** (.188)	2.537*** (.208)	2.858*** (.202)	2.778*** (.206)
population 15-19 years old	-.334** (.096)	-.330** (.097)	-.385*** (.097)	-.383*** (.096)	-.333** (.098)	-.380*** (.096)	-.309** (.098)
population 20-24 years old	.206*** (.038)	.206*** (.038)	.218*** (.039)	.223*** (.039)	.135** (.041)	.225*** (.039)	.177*** (.040)
% in poverty	-.037 (.023)	-.035 (.024)	-.015 (.021)	-.033 (.023)	.006 (.022)	-.030 (.022)	-.006 (.022)
Income inequality (Gini coefficient)	1.890 2.950	2.067 (2.962)	1.868 (2.949)	2.806 (3.006)	.821 (2.983)	1.486 (2.960)	.450 (2.991)
Racial diversity	1.179* (.537)	_	_	_	_	_	_
White population	_	-1.770 (1.060)	_	_	_	_	_
Black population	_	_	-.133 (.141)	_	_	_	_
Native-American population	_	_	_	.315 (.183)	_	_	_
Asian population	_	_	_	_	1.158*** (.219)	_	_
Hispanic population	_	_	_	_	_	.395* (.175)	_
Arab population	_	_	_	_	_	_	.808** (.275)
Log likelihood	-768.3443	-769.3513	-770.3183	-769.2839	-756.2499	-768.214	-760.705
Pseudo R-square	.2593	.2584	.2574	.2584	.2710	.2595	.2520

Note: Numbers represent the coefficients and the standard error (in parentheses)
*p < .05; **p < .01; ***p < .001

Table 5. Continuation-Ratio Logit Estimates of the Anti-Muslim Reported Hate Crime Incidents in 2001-2002 for U.S. Counties and County Equivalents of the States with a Statutory Mandate for Data Collection

Independent variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
County population	1.934*** (.219)	1.992*** (.208)	2.151*** (.204)	2.075*** (.191)	1.915*** (.235)	2.126*** (.216)	1.758*** (.206)
population 15-19 years old	-.228 (.116)	-.232* (.116)	-.297* (.116)	-.283* (.112)	-.240* (.115)	-.274* (.112)	-.178 (.117)
population 20-24 years old	.181*** (.048)	.184*** (.047)	.204*** (.048)	.201*** (.047)	.163** (.053)	.194*** (.047)	.138** (.050)
% in poverty	-.055 (.029)	-.054 (.029)	-.036 (.026)	-.052 (.029)	-.030 (.027)	-.036 (.028)	-.215 (.027)
Income inequality (Gini coefficient)	-2.517 (3.508)	-2.587 (3.523)	-2.938 (3.509)	-2.002 (3.588)	-3.099 (3.504)	-2.994 (3.511)	-4.273 (3.561)
Racial diversity	.949 (.666)	_	_	_	_	_	_
White population	_	-1.454 (1.231)	_	_	_	_	_
Black population	_	_	-.147 (.171)	_	_	_	_
Native-American population	_	_	_	.271 (.226)	_	_	_
Asian population	_	_	_	_	.340 (.269)	_	_
Hispanic population	_	_	_	_	_	-.068 (.206)	_
Arab population	_	_	_	_	_	_	1.094** (.322)
Log likelihood	-499.8395	-500.1457	-500.4859	-500.1394	-500.0578	-500.7979	-493.5964
Pseudo R-square	.1944	.1939	.1933	.1939	.1940	.1928	.1915

Note: Numbers represent the coefficients and the standard error (in parentheses)
*p < .05; **p < .01; ***p < .001

of the county population belonging to the age group from 15-19 years old and from 20-24 years old are significant predictors of anti-Other/Arab hate crimes. The findings however, suggest that as the percentage of population 15-19 years old increases, anti-Other/Arab hate crimes decrease, but as the percentage of population 20-24 increases, anti-Other/Arab hate crimes increase accordingly.

Model 5 and Model 7 in Table 4, like the respective models in Table 3 show that the percentage of population that is Asian ($p < .001$) and the percentage of the population that is Arab ($p < .01$) have a significant effect on the incidence of anti-Other/Arab hate crimes. Model 6 in Table 4 indicates that anti-Other/Arab hate crimes are influenced not only by the percentage of population that is Asian and Arab, but also by the percentage of population that is Hispanic ($p < .05$). Model 5 including the Asian population, Model 6 including the Hispanic population, and Model 7 including the Arab population account for the highest proportions of explained variance, 27.10%, 25.95%, and 25.20%, respectively.

The relationships between county characteristics and anti-Muslim hate crimes are presented in Table 5. The results of Model 1 reveal that only population size ($p < .001$) and the percentage of population between 20-24 years old ($p < .001$) are significantly related to anti-Muslim hate crimes. The racial diversity index appeared to be nonsignificant and out of the racial and ethnic categories included in the table, only the percentage of the population that is Arab ($p < .01$) appeared to be a good predictor of anti-Muslim violence.

Taken together, the findings suggest that poverty levels and income inequality levels may not be very good predictors of anti-Other/Arab or anti-Muslim hate crimes.

The findings seem not to support the hypothesis that anti-Other/Arab hate crimes occur more frequently in counties with high poverty levels and high income inequalities. However, if poverty levels did not emerge as significant in the models that measured anti-Other/Arab hate crimes in Table 4 or anti-Muslim hate crimes in Table 5, the percentage of a county population that is poor emerged as a significant predictor of hate crimes in Table 3, in the overall occurrence of hate crimes. Given the negative coefficients that emerged for the percentage of population that is poor, it can be argued that hate crime incidents do not share the same characteristics as the most "traditional" forms of street crime. Hate crimes do not occur among the poor like Merton's (1938) theory of blocked opportunity structure or Miller's (1958) theory of lower-class focal value would suggest, but they tend to occur in more affluent counties.

The results of Continuation Ratio Logit models that measured the incidence of anti-Other/Arab hate crimes presented in Table 4 or the incidence of anti-Muslim hate crimes presented in Table 5 suggest that a county's racial and ethnic composition is a better predictor of violence against Arab-Americans than a county's poverty and income inequality levels. The presence of a high percentage of racial and ethnic minorities such as Asian, Hispanic, and Arab populations increases the probability of Arab-American or Muslim victimization. This finding, as well as its potential causes, are further discussed in the following section pertaining to community-level findings for the City of Chicago.

Community-Level (Chicago City, Cook County) Findings

The results of the Continuation Ratio Logit Estimates for the community-level data set are shown in Tables 6 and 7. The findings on Table 6 corroborate the findings from the county-level analysis. In Model 1, the racial diversity index ($p < .05$) is

Table 6. Continuation-Ratio Logit Estimates of the Anti-Arab Reported Hate Crime Incidents in 2001-2002 for the 77 City of Chicago Community Areas

Independent variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
County population	.00002 (.000009)	.00002* (.000009)	.00002* (.000009)	.00001 (.000009)	.00002* (.000009)	.00001 (.000009)	.00003* (.00001)
population 15-19 years old	-.040 (.138)	.083 (.132)	.053 (.132)	-.009 (.139)	.202 (.149)	-.066 (.147)	.174 (.143)
population 20-24 years old	-.076 (.116)	-.079 (.119)	.029 (.106)	-.013 (.110)	-.092 (.120)	-.030 (.112)	-.030 (.112)
% in poverty	-.001 (.024)	.017 (.030)	-.022 (.028)	-.011 (.024)	-.009 (.023)	.004 (.026)	.002 (.024)
Racial diversity	2.721* (1.209)	–	–	–	–	–	–
White population	–	.928 (.499)	–	–	–	–	–
Black population	–	–	-.010 (.387)	–	–	–	–
Native-American population	–	–	–	1.151 (.832)	–	–	–
Asian population	–	–	–	–	.797* (.376)	–	–
Hispanic population	–	–	–	–	–	.768 (.422)	–
Arab population	–	–	–	–	–	–	1.699** (.603)
Log likelihood	-69.35496	-70.07556	-72.02487	-71.04812	-69.6457	-70.29421	-62.0215
Pseudo R-square	.0872	.0777	.0520	.0649	.0834	.0748	.1197

Note: Numbers represent the coefficients and the standard error (in parentheses)
*p < .05; **p < .01; ***p < .001

positively associated with higher incidence of anti-Arab hate crimes. Community area population size emerges as a significant predictor of anti-Arab hate crimes only in some of the models. Population size ($p < .05$) emerges as a significant predicting variable in Model 5 and Model 7. These models indicate that the percentage of Asian population ($p < .05$) and the percentage of Arab population ($p < .01$) continue to be significantly related to the number of anti-Arab hate crimes even at the community level. Model 5 and Model 7 account for 8.34% and 11.97% of the explained variance, respectively.

If the racial composition of a community area is an important factor in predicting the occurrence of anti-Arab hate crimes, changes in the Arab population do not seem to be good predictors of anti-Arab hate crimes. The findings from the Continuation Ratio Logit Estimate models presented in Table 7 were used in order to test Green, Strolovitch, and Wong (1998) “defended neighborhood” hypothesis. The defended neighborhood hypothesis argues that hate crimes occur as a consequence of perceived threats to neighborhoods from an influx of minority group members. As the population of minority groups in a neighborhood increases, bias-motivated violence from the earlier existing (usually the white) population of that neighborhood increases. According to their theory, as neighborhoods experience an influx of Black, Hispanic, and Asian population, the “old” neighborhood population responds by committing acts of bigotry in an attempt to protect their own “turf.” However, as suggested by the results of Table 7, the findings do not support the defended neighborhood hypothesis. As indicated in the table, the Arab population change in a community area seemed to have no effect on the occurrence of anti-Arab hate crimes. This finding suggests that anti-Arab hate crimes may not follow the same patterns as the more traditional forms of hate crime, such as racial bias crimes.

Table 7. Continuation-Ratio Logit Estimates of the Anti-Arab Reported Hate Crime Incidents in 2001-2002 for the 77 City of Chicago Community Areas, Accounting for Arab Population Change

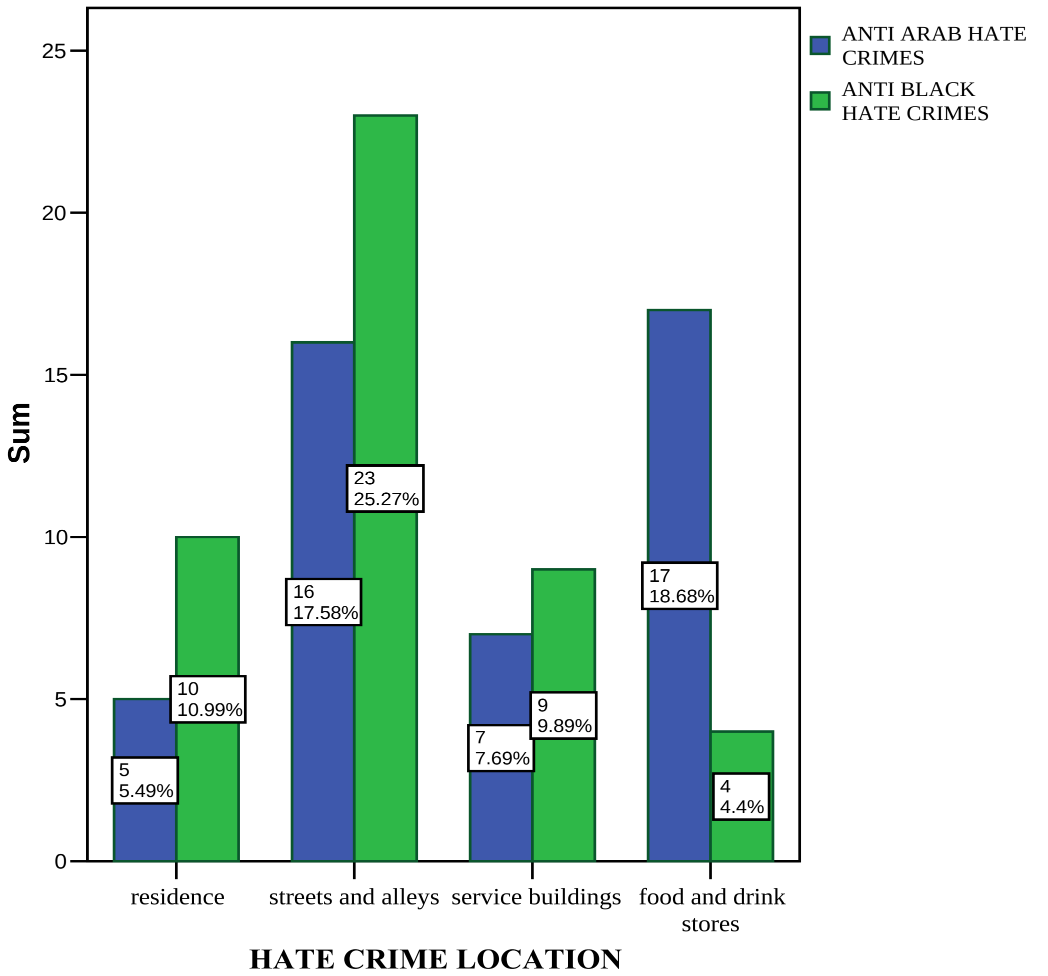
Independent variables	Model 1	Model 2
County population	.00002 (.000009)	.00003** (.00001)
Population 15-19 years old	-.035 (.144)	.218 (.169)
Population 20-24 years old	-.079 (.119)	-.063 (.126)
Percent population in poverty	-.002 (.023)	.003 (.025)
Racial diversity	2.758* (1.244)	_
Arab population change from 1990 – 2000	.032 (.253)	.0289 (.268)
Arab population	_	1.574* (.648)
Asian population	_	.261 (.461)
Log likelihood	-69.347	-61.85751
Pseudo R-square	.0873	.1220

Note: Numbers represent the coefficients and the standard error (in parentheses)
*p < .05; **p < .01; ***p < .001

Anti-Arab hate crimes may not be a response of threatened or devalued neighborhoods (an economical response) but rather a response of "threatened citizens" (a cultural response).

A better illustration of the differences between anti-Arab and anti-Black hate crimes can be seen by comparing the physical locations where such forms of hate crime took place. The patterns and locations of anti-Arab and anti-Black hate crime are shown in Figure 4. Figure 4 suggests that anti-Arab hate crimes tend to occur in relatively open

Figure 4. Locations of anti-Arab and anti-Black hate crimes for Chicago community areas during 2001-2002 period



public spaces such as food and drink stores whereas anti-black hate crimes tend to occur in relatively "hidden" places such as streets and alleys. Anti-Arab hate crimes tend to occur more frequently in food and drink stores, which include bars, restaurants, convenience stores and supermarkets; in places that are usually characterized by high levels of business activity, public life, and face-to-face social interactions. These findings validate Perry's (2002) argument and indicate that discriminatory acts of violence directed at members of the Arab and Muslim community display a degree of open public aggression that reflects the hidden cultural codes of the acceptance and justification of hate-motivated violence against members of these minority groups.

DISCUSSION AND CONCLUSION

As the findings illustrate, reports of anti-Other/Arab and anti-Muslim hate crimes increased after the events of September 11. This finding is consistent with previous research on the effects of historical events on hate crime activity (Gerstenfeld, 2004). The events of September 11, however, seemed to have a similar affect on the number of hate crimes reported by members of other racial and ethnic groups. According to Erikson's (1966) theory on the volume of deviance and Mauss's (1975) theory on the level of social problems, historical events have the ability to stigmatize a social group while de-stigmatizing previously discriminated social groups. Therefore, following this logic, as Arab Americans became a prominent stigmatized group and experienced higher levels of biased hostility after the events of September 11, other forms of bias-motivated violence were expected to decrease. However, as anti-Other/Arab and anti-Muslim hate crime reports increased, other types of hate crime reports, including the most prominent anti-Black and anti-Jewish hate crimes, increased as well. As the results of this analysis illustrate, anti-Black and anti-Jewish hate crimes continued to increase along with anti-Other/Arab and anti-Muslim hate crimes. Whether such results are an artifact of police officers' increased sensitivity towards hate crimes after the events of September 11, an outcome of more efficient law enforcement practices in detecting and reporting biased violence, or an actual increase of the overall number of hate crime incidents, may be impossible to pull apart. We can see here, however, that hate crimes do not remain stable over time. They are a fluctuating social phenomenon influenced by historical moments.

The events of September 11, 2001, affected not only people of Arab, Muslim or Middle Eastern descent, but also people of other racial and ethnic minority groups. Clearly, an event such as September 11, has the ability to increase the vulnerability of many ethnic minority groups, not just the ones perceived to be "responsible" for the catastrophic event.

Even though the findings reveal that the events of September 11 affected many social groups, Arab-Americans clearly experienced the most dramatic increase in hate crime rates following September 11. The results from county-level statistical analyses show that reports of anti-Other/Arab and anti-Muslim hate crimes were more likely to occur in counties with a large population and with a high degree of racial diversity. This finding corroborates the finding, presented by McVeigh et al. (2003), that population size is a significant predictor of the overall hate crimes reported in counties across the United States. The current study found a significant relationship not only between population size and hate crimes, but also between a county's or a community's racial diversity and anti-Arab hate crimes.

Anti-Arab hate crimes occurred more frequently in racially diverse counties and community areas. More specifically, anti-Arab hate crimes were associated with a higher percentage of Asian or Arab population in a county or community area. Two theories that might provide some insights for explaining these findings are scapegoat theory and conflict theory. Scapegoat theory suggests that in times of struggle and confusion, people seek out individuals and groups of individuals on whom to blame their experienced hardships. After the events of September 11, Arab-Americans became an easy target to blame for the general social anxiety. Arab-Americans were constructed as dangerous terrorists deserving constant monitoring and discrimination because they threatened the cultural values of good, law-abiding American citizens (Volpp, 2002; Gerstenfeld, 2002). However, in times of chaos, it is not only members of dominant culture who aspire to be Americans of a good, moral character, but minority group members consider chaos an opportune moment to adhere to the social norms of the dominant social group. Striking convenient scapegoats is a rational choice minority group members may use in order to improve their status in the social hierarchy.

According to conflict theory, competition among ethnic minorities over scarce resources could also be a contributing factor towards intergroup violence. Asian minorities and Arab minorities could be competing over the domination of small business ownership. Given the role of economics, of favorable social, cultural, and historical conditions that justify discrimination against members of the Arab-American community, it is conceivable to expect higher rates of anti-Arab hate crimes in counties with a high percentage of Asian population. Gerstenfeld (2004:88) illustrates this argument by stating:

> "A significant number of hate crimes occur not between poor whites and poor blacks, but rather between two minority groups. Examples of this include the conflict between blacks and Jews in Crown Heights; between blacks, Hispanics and Asian Americans in Los Angeles, New York, and Washington D. C.; and between people of color and gays throughout the United States (Perry, 2001). Often, these groups are in competition for the second-lowest rung on the social and economic ladder. It makes sense that attack by minorities might be targeted not at whites, whose position on that ladder is several steps ahead and perhaps viewed as unattainable, but instead at the attackers closest rivals. In addition, as Perry (2001:134) points out, members of minority groups, too, have 'internalized the dominant aspects of white masculine supremacy' and thus might choose white culture's traditional scapegoats."

The fact that anti-Arab hate crimes occur more frequently in racially diverse counties and community areas does not support Allport's (1954) contact hypothesis, where he argued that sustained contact among conflicting groups reduces negative attitudes among the groups. Sustained contact, however, under conditions of poverty or economic inequality may produce reverse effects (Eitle and Eitle, 2003; Cook, 1988). Even though poverty and income inequality were not significantly related to anti-Arab hate crimes, judging by the significant relationship between poverty levels and the overall hate crimes, it can be argued that status differences may play a functional role in hate crime occurrence. The findings pertaining to contact hypothesis need to be treated with caution because while it is safe to say that anti-Arab hate crimes occurred in relatively heterogeneous counties and communities, measures of socio-economic status were not significant predictors of such crimes.

What makes the relationship between hate crimes and poverty even more complex is the result that hate crimes are associated with more affluent layers of society. The results of this study corroborate the findings of McVeigh et al. (2003) where they find that hate crime are reported more frequently in counties with a higher per capita income. Similarly, this study suggested that hate crime activity is more prevalent in counties with a low percentage of people in poverty. Even though this finding cannot be extended to anti-Arab or anti-Muslim hate crimes, it can be assumed from the negative coefficients for the variable that measures the poverty level that such forms of bias may occur more frequently among the privileged rather than among the lower social layers.

As the findings from community-level data analysis in the City of Chicago, Cook County suggest, anti-Arab hate crimes follow different patterns from the more traditional forms of racially motivated crime. Contrary to the results of the study conducted by Green, Strolovitch, and Wong (1998) on “defended neighborhoods”, where they found racially motivated crimes to occur more frequently in relatively homogeneous neighborhoods that experienced a high influx of racial minorities, the statistical analyses of the current study indicate that anti-Arab hate crimes occur more frequently in racially diverse community areas. Changes in the percentage of Arab population in a community seemed to have no effect on the incidents of hate crime. These findings imply that Arab-Americans do not pose a territorial threat but a cultural threat. In the public imagination, Arab-Americans are equated with Islamic fundamentalists, are equated with terrorists, and are equated with the “enemy.” This type of social identity, despite having little or no resemblance to real people, becomes a symbolic characteristic with real consequences for Arab-Americans. Perceiving them as dangerous terrorists justifies the violence and the more prominent “public displays of hate” associated with anti-Arab hate crimes, a characteristic not as visible for other types of crime, such as anti-Black hate crimes. Having anti-Arab hate crimes occur in relatively open public locations implies that such acts may be a culturally acceptable response to the symbolic representations of Arab-Americans (Perry, 2002; Volpp, 2002; Chen, 2000). In other words, constructing the social identity of Arabs, Muslims, and people of Middle Eastern descent as foreigners, fundamentalists, terrorists, justifies their discrimination and transforms their victimization into an acceptable social act.

Anti-Arab and anti-Muslim hate crimes constitute an objective reality. Yet, in very real ways, a hate crime “does not exist” if there is no category for such crime. The statistical analysis, no matter how powerful, cannot capture anti-Arab violence if such a phenomenon is not categorized as a social problem in the first place. Anti-Arab hate crimes represent a social reality that is difficult to measure. They possess all the characteristics associated with the problems of hate crime ranging from social movement activism to legal issues to identification, collection, and reporting from law enforcement officials. In addition, they suffer even more shortcomings generated by the fact of not having a specific category in the legislative classification of vulnerable social groups. Anti-Arab hate crimes suffer from political, as well as statistical misrepresentation. Therefore, before improving the statistical quality of hate crime statistics, it is necessary to identify anti-Arab hate crimes as a specific category of hate-motivated violence instead of simply clustering them as crimes against “insignificant others.”

This study points out some of the difficulties in conducting statistical analyses on anti-Arab hate crimes and suggests that researchers need to devise better methods for investigating vulnerable social groups such as Arab Americans. Hate crimes represent a social problem of national concern and Arab-Americans could be the primary victims of this problem today.

Endnotes

1. James Byrd Jr. was an African-American who was murdered by being dragged behind a pick-up truck by three white men in the state of Texas and Matthew Shepherd was a gay college student who was brutally beaten and murdered in the state of Wyoming (Soule and Earl, 2001). Both incidents received national attention and broad coverage from the media.

2. For an explanation of the FBI UCR program on hate crime data collection and its two subsections, Summary UCR and National Incident-Based Reporting System (NIBRS), refer to www.fbi.org. Also, see Nolan, Akiama, and Berhanu, 2002.

3. In their study, Green, Strolovitch and Wong (1998) included anti-Hispanic hate crimes as racially motivated crimes however, anti-Hispanic hate crimes fall under ethnically motivated crimes in the UCR FBI reports for 2001-2002.

4. ADL reports only 25 states with a statutory mandate for data collection. New York is the only state included in the analysis that does not have a statutory mandate for data collection. The reason for including New York is the fact that the events of September 11 directly affected this state and are thought to have had a direct effect on the engaging participation of law enforcement agencies.

5. Racial, religious and ethnically motivated hate crimes are legally protected categories for all the states included in the analysis. However, sexorientationbias and disabilitybias represent legally unprotected categories in some of the states with a statutory mandate for data collection (ADL, 2001). Use caution when interpreting these data.

6. Anti-Other is the variable used for the measurement of anti-Arab hate crimes. Anti-Other represents a proximate measure of anti-Arab hate crimes. It should be treated with caution because the FBI dataset does not provide a specific anti-Arab category. Anti-Arab hate crimes are included into hate crimes against "anti-other ethnicity/National Origin."

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APPENDICES

Appendix I: The FBI Guidelines to Law enforcement Officials for the Identification of Hate Crime Incidents

1. The offender and the victim were of different race, religion, disability, sexual orientation, and/or ethnicity/national origin. For example, the victim was black and the offender was white.
2. Bias-related verbal comments, written statements, or gestures were made by the offender, which indicate his/her bias. For example, the offender shouted a racial epithet at the victim.
3. Bias-related drawings, markings, symbols, or graffiti were left at the crime scene. For example, a swastika was painted on the door of a synagogue.
4. Certain objects, items, or things, which indicate bias, were used. For example, the offenders wore white sheets with hoods covering their faces or a burning cross was left in front of the victim's residence.
5. The victim is a member of a racial, religious, disability, sexual-orientation, or ethnic/national origin group, which is overwhelmingly outnumbered by other residents in the neighborhood where the victim lives and the incident, took place. This factor loses significance with the passage of time; i.e., it is most significant when the victim first moved into the neighborhood and becomes less and less significant as time passes without incident.
6. The victim was visiting a neighborhood where previous hate crimes were committed against other members of his/her racial, religious, disability, sexual-orientation, or ethnic/national origin group and where tensions remained high against his/her group.
7. Several incidents occurred in the same locality, at or about the same time, and the victims were all of the same race, religion, disability, sexual orientation, or ethnicity/national origin.
8. A substantial portion of the community where the crime occurred perceived that the incident was motivated by bias.
9. The victim was engaged in activities promoting his/her race, religion, disability, sexual orientation or ethnicity/national origin. For example, the victim was a member of the NAACP or participated in gay rights demonstrations.
10. The incident coincided with a holiday or a date of particular significance relating to a race, religion, disability, sexual orientation, or ethnicity/national origin, e.g., Martin Luther King Day, Rosh Hashanah.
11. The offender was previously involved in a similar hate crime or is a hate group member.
12. There were indications that a hate group was involved. For example, a hate group claimed responsibility for the crime or was active in the neighborhood.
13. A historically established animosity existed between the victim's and the offender's groups.
14. The victim, although not a member of the targeted racial, religious, disability, sexual-orientation, or ethnic/national origin group, was a member of an advocacy group supporting the precepts of the victim group.

Appendix II: State Hate Crime Laws as Reported by the Anti-Defamation League (ADL).

Alabama - Idaho

	AL	AK	AZ	AR	CA	CO	CT	DC	DE	FL	GA	HI	ID
Bias-Motivated Violence and Intimidation	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓		✓
Civil Action				✓	✓	✓	✓	✓		✓	✓		✓
Criminal Penalty	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓		✓
Race, Religion, Ethnicity [1]	✓	✓	✓		✓	✓	✓	✓	✓	✓			✓
Sexual Orientation			✓		✓		✓	✓	✓	✓			
Gender		✓	✓		✓			✓					
Other [2]	✓	✓	✓		✓			✓	✓				
Institutional Vandalism	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	
Data Collection [3]			✓		✓		✓	✓		✓			✓
Training for Law Enforcement Personnel [4]			✓		✓								

Illinois - Missouri

	IL	IN	IA	KS	KY	LA	ME	MD	MA	MI	MN	MS	MO
Bias-Motivated Violence and Intimidation	✓		✓		✓	✓	✓	✓	✓	✓	✓	✓	✓
Civil Action	✓		✓			✓			✓	✓	✓		✓
Criminal Penalty	✓		✓		✓	✓	✓	✓	✓	✓	✓	✓	✓
Race, Religion, Ethnicity [1]	✓		✓		✓	✓	✓	✓	✓	✓	✓	✓	✓
Sexual Orientation	✓		✓		✓	✓	✓		✓		✓		
Gender	✓		✓			✓	✓			✓	✓	✓	
Other [2]	✓		✓			✓	✓		✓		✓		
Institutional Vandalism	✓	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Data Collection [3]	✓		✓		✓	✓	✓	✓	✓	✓	✓		
Training for Law Enforcement Personnel [4]	✓		✓		✓	✓			✓		✓		

Montana - Pennsylvania

	MT	NE	NV	NH	NJ	NM	NY	NC	ND	OH	OK	OR	PA
Bias-Motivated Violence and Intimidation	✓	✓	✓	✓	✓		✓[5]	✓	✓	✓	✓	✓	✓
Civil Action		✓	✓		✓					✓	✓	✓	✓
Criminal Penalty	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓
Race, Religion, Ethnicity [1]	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	✓
Sexual Orientation		✓	✓	✓	✓		✓					✓	
Gender		✓		✓	✓		✓		✓				
Other [2]		✓	✓	✓	✓		✓				✓		
Institutional Vandalism	✓		✓		✓	✓		✓		✓	✓	✓	✓
Data Collection [3]		✓	✓		✓						✓	✓	✓
Training for Law Enforcement Personnel [4]												✓	

Rhode Island - Wyoming

	RI	SC	SD	TN	TX	UT	VT	VA	WA	WV	WI	WY
Bias-Motivated Violence and Intimidation	✓		✓	✓	✓[6]	✓[7]	✓	✓	✓	✓	✓	
Civil Action	✓		✓	✓			✓	✓	✓		✓	
Criminal Penalty	✓		✓	✓	✓	✓	✓	✓	✓	✓	✓	
Race, Religion, Ethnicity [1]	✓		✓	✓			✓	✓	✓	✓	✓	
Sexual Orientation	✓			✓			✓		✓		✓	
Gender	✓						✓		✓	✓		
Other [2]	✓						✓		✓	✓	✓	
Institutional Vandalism	✓	✓		✓	✓			✓	✓		✓	
Data Collection [3]	✓				✓			✓	✓			
Training for Law Enforcement Personnel [4]	✓								✓			

[1]. The following states also have statutes criminalizing interference with religious worship: CA. DC. FL. ID, MD. MA, MI, MN, MS, MO, NV, NM, NY, NC, OK, RI, SC, SD, TN, VA, WV.

[2]. "Other" includes mental and physical disability or handicap (AL, AK, A IL, IA, LA, ME, MA, MN, NE, NV, NH, NJ, NY, OK, RI, VT WA WI), p affiliation (DC, IA, LA, WV) and age (DC, IA, LA, VT).

[3.] States with data collection statues which include sexual orientation are A
DC, FL, IL, IA ,MD, NV, OR, and WA; those which include gender are A
MN, WA.

[4.] Some other states have regulations mandating such training.

[5.] New York State law provides penalty enhancement limited to the crime
harassment.

[6.] The Texas Statute refers to victims selected "because of the defendant's
prejudice against a person or group."

[7.] The Utah Statute ties penalties for hate crimes to violations of the victim
or civil rights.

Appendix III: Variable Distributions: Frequency Tables of Anti-Arab and Anti-Muslim Hate Crimes.

antiother ANTI OTHER (ARAB) HATE CRIMES

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	12404	86.8	86.8	86.8
	1	1890	13.2	13.2	100.0
	Total	14294	100.0	100.0	

antimuslim ANTI MUSLIM HATE CRIMES

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	0	13809	96.6	96.6	96.6
	1	485	3.4	3.4	100.0
	Total	14294	100.0	100.0	