BIAS CRIME INCIDENCE IN UNITED STATES COUNTIES, 2000-2009: AN APPLICATION OF SOCIAL DISORGANIZATION THEORY

By

Ryan Brevin Martz

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Criminal Justice – Doctor of Philosophy

2014

ABSTRACT

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This goal of this dissertation is to identify predictors of bias criminality in the United States at the county level from 2000 - 2009. There is relatively little known about bias crime occurrence in the United States. In addition, increased public attention to bias criminality requires additional social science research examining the predictors of bias crime in American communities. By examining traditional indicators of social disorganization theory, this dissertation seeks to explore the likelihood of bias crime occurrence at the macro-level. As such, the unit of analysis is United States counties. The N is 3,141. The data upon which this dissertation is based come from the Federal Bureau of Investigation (FBI), the United States Census Bureau (USCB), the Association of Religious Data Archives (ARDA), and *Congressional Quarterly's* Voting and Elections Collection.

From the data, measures of economic deprivation, social heterogeneity (diversity), social cohesion, and residential mobility were created. These measures represent traditional indicators of social disorganization theory. Four models are introduced in this dissertation in order to answer several research questions that explore the differences between how these predictors affect various types of bias crime. Negative binomial regression and OLS regression are used to analyze the data and address the research questions. Specifically, anti-race motivated bias crime, anti-sexual orientation motivated bias crime, and anti-religion motivated bias crime types are considered.

Although the findings were not resoundingly supportive of the application of social disorganization theory to the understanding of bias criminality, there are remarkable conclusions nonetheless. Measures of social heterogeneity – or diversity – seem to yield the most conclusive evidence toward predicting the risk of bias crime occurrence. Specifically, a county's (higher) percentage of Muslim residents was the strongest predictor of bias criminality across the United States from 2000 – 2009. Similarly, the percentage of Jewish residents, the percentage of non-White residents, and the percentage of foreign-born persons were positively related. Individual measures of residential mobility and social cohesion were also helpful to predicting bias crimes. In addition, county population was useful in predicting bias criminality. Urban areas and urbanized clusters were more likely to experience bias crime occurrence than were rural areas. In addition, results are inconclusive on whether hate crime legislation decreases the risk of bias crime occurrence. The findings indicate that more research is needed. Specifically, understanding a community's level of diversity seems to be important to the prediction of bias criminality in American counties.

This dissertation is dedicated to my parents, Eric and Brenda Martz, who have always encouraged and supported my education and inquisitive nature, and to my grandmother, Betty Carraway, who continues to inspire me daily.

ACKNOWLEDGMENTS

I would like to acknowledge the efforts of those who have contributed toward the completion of this dissertation. From Bloomington to East Lansing, Dr. Steve Chermak has supported my educational goals the entire way. He inspired me to pursue a career in academia and has always provided support to that end. He has reviewed countless drafts and has always been available to guide my academic growth. I am extremely grateful for his efforts, his mentorship, and the education he has provided me. I would also like to thank Dr. Tim Bynum, Dr. Ed McGarrell, and Dr. Steve Gold for serving on my committee. Their expertise and guidance were instrumental in my completion of this project.

I would like to acknowledge and recognize my friends and colleagues from Michigan State University and Saginaw Valley State University. Without them, I could not have begun or completed this journey. Dr. Carol Zimmermann provided encouragement, support, and her theoretical and methodological expertise throughout the dissertation process. I am infinitely grateful for her guidance, kindness, and friendship. Dr. Joni Boye-Beaman and Dr. Bob Lane provided institutional support and patiently guided me through numerous challenges.

Dr. Eric Grommon provided guidance with research design and was my go-to data consultant. His friendship and academic support are much appreciated. Dr. Mary Braz contributed her methodological advice when I was designing this dissertation. Dr. Tim Rowlands read drafts and provided feedback throughout the writing process. Dr. Jennifer McCullough offered much methodological and statistical support. Her assistance is much appreciated. Dr. Sher Ratnabalasuriar was always there for a cup of coffee and to discuss the many angles from which this research could be considered. In addition, Dr. James Bowers shared his SPSS and statistical expertise on a regular basis. I am grateful for all of the generous efforts so many friends and colleagues have provided.

I would also like to thank my family for their unrelenting support of my education. Brenda Martz, Eric Martz, and Lauren Martz have each encouraged me during frustrating points in the writing process and have been patient with my reactions to the many ups and downs of the dissertation process. In addition, they have listened to hours of discussion about the many unrealized research ideas I have had. Lynn Michelsen, George Michelsen, Jeff Michelsen, and Jeanine Michelsen have been supportive in helping me identify my contributions to the field of criminal justice. They have also encouraged me to move forward during times of doubt. I am lucky to have such a supportive family; this dissertation would not have been possible without their efforts.

Dr. Melissa Garmo has been by my side during my entire doctoral program at MSU. I cannot thank her enough for the daily encouragement and friendship. She has been there for me in so many ways throughout many challenging times during the Ph.D. program. For that, I cannot express my gratitude enough.

Christopher Michelsen has sacrificed greatly so that I could earn my degree. From East Lansing, to Ann Arbor, to Saginaw, to Washington, and back to Saginaw again – he has been present throughout my entire doctoral program. He has not wavered in his confidence in me, even when I could not muster the same. Chris has listened to hundreds of hours of discussion about my academic life, including the process of completing this dissertation. In addition, his expertise with data organization and analyses in Microsoft Excel was helpful and much appreciated during the data collection process. I cannot express enough appreciation as Chris is

the person who has sacrificed the most so I could achieve my goal of completing a Ph.D. and beginning a career in academia. I could not have completed this degree without him.

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CHAPTER 1: INTRODUCTION

This dissertation investigates various factors influencing the occurrence of bias crimes in United States counties. By examining traditional indicators of social disorganization theory, this dissertation seeks to explore the likelihood of bias crime occurrence in United States counties. The data upon which this dissertation is based come from the Federal Bureau of Investigation (FBI), the United States Census Bureau (USCB), the Association of Religious Data Archives (ARDA), and *Congressional Quarterly's* Voting and Elections Collection.

However, before engaging in further research on bias crime in the United States, it is important to review the breadth of bias crime knowledge available in the literature and to understand the risks such crimes create for communities. The remainder of Chapter One is devoted to the descriptive analysis of bias-motivated crime as well as an introduction to this dissertation.

Understanding the Risk of Bias Crime in the United States

The risk associated with bias crime is usually focused on the individual victims of said crimes. In order to have a complete picture of the nature of bias crime risk, however, it is imperative to investigate the nature of the crime itself. This information will inform the current study as it relates to the risk and subsequent harm imposed on United States counties. The following discussion uncovers this understanding by introducing discussion on the scope of bias crime in the United States, the nature of bigotry and hate, and the social construction of difference and the impact of power.

Although the United States government has a relatively broad definition of what constitutes a bias crime, not all states have adopted policies protecting all oppressed social groups. Michigan, for instance, protects individuals based on race, religion, color, gender, or national origin (Michigan Legislature, 2011), but not on sexual orientation, gender identity, disability, or ethnicity. These omissions are not uncommon. Traditionally, with regard to sexual orientation and gender identity, fewer than half of all states with bias crime laws include sexual orientation and gender identity in the definition of bias crimes (Wang, 1994). However, according to Gerstenfeld (2011), as of 2009, the National Gay and Lesbian Task Force (2009) reports that only fifteen states with bias crime legislation omit sexual orientation from inclusion in the definition. Although there is much debate as to which groups should and should not be protected by bias crime legislation, sexual orientation is often omitted as legislators are reluctant to lend political legitimacy the circumstances of the lesbian, gay, and bisexual community (Jenness & Broad, 1997). Women and persons with a disability are also groups that face an uphill battle in gaining protection via bias crime legislation. Many individuals do not view gender (i.e. females) to be a minority[1], and thereby overlook that women retain an oppressed status in society. Additionally, there are those who would argue that persons who have physically or mentally disabilities are not often victims of bias crime (Jenness & Broad, 1997). Nevertheless, according to Gerstenfeld (2011), as of 2009, there were still five states with no bias crime laws on the books at all. Given the political difficulty of bias crime legislation, even limited progress in providing protection to marginalized groups is notable.

As stated, bias crime has traditionally been defined as a criminal act motivated by animus toward the victim's affiliation with an oppressed social group (Gerstenfeld, 2004). Definitions of bias crime vary by time and location – even the concept itself has numerous frequently used terms such as hate crime, ethnic intimidation, ethnoviolence, and civil rights crimes. Hate crime is really about prejudice, or bias, and less about hate; therefore, bias crime appears to be a more

[1] Although 'minority' is a commonly used word to describe subordinate social groups, 'oppressed social group' is used to more accurately reflect the situation of a marginalized group of people.

accurate designation of the phenomenon (Jacobs & Potter, 1998). Publicly, the two terms are frequently used interchangeably; however, bias crime is largely considered by scholars to be a more accurate term.

Regardless of the debate as to which groups should be protected by bias crime legislation, it is clear that any crime based on bigotry is particularly hurtful to the victim, both physically and psychologically, and consequently is important as a topic of investigation (Iganski, 2001). Moreover, Iganski (2001) suggests that bias crime not only affects the individual victim, but also distresses the oppressed - and thereby subordinate - social group to which the victim belongs. For instance, in the case of James Byrd, an African American individual who was murdered in Texas in 1998, Byrd was not randomly selected as a victim; he was chosen as a victim because of his racial identification. The message of hatred and intolerance was meant not only for Byrd, but for the entire African American community in Jasper, Texas and the United States alike. In this way, messages of hate and intolerance terrorize the entire group with which the victim identifies (Tsesis, 2003; Boekmann & Turpin-Petrosino, 2002; Green, McFalls, & Smith, 2001; Iganski, 2001). Consequently, the African American community, particularly in Jasper, Texas, was left with feelings of insecurity, fear, and terror following the murder. For this reason, many scholars argue that crimes of this type warrant legislative, social, and scholarly attention.

The Scope of Bias Crime in the United States

Since the Hate Crimes Statistics Act of 1990, whereby the Federal Bureau of Investigation (FBI) was required by Congress to collect bias crime data from local law enforcement agencies, scholars and government officials have gained a better understanding of the frequency of reported bias crimes. As reported by the FBI and is evident in Table 1, total reported bias crimes for the United States were 10,706 in 1996 and by 2008 amounted to 7,783.

Overall, the majority of reported bias crimes were motivated by bias toward a victim's race, religion, or sexual orientation. This fact informs the current research in that it forms the basis for understanding the context of bias crime occurrence.

Table 1.1: Bias Crime Incidents by Year (1996-2010)

	1996	***2000***	***2004***	***2008***	***2010***
Total Incidents	10,706	8,063	7,649	7,783	6,628
Race	6,767	4,337	4,042	3,992	3,135
Ethnicity/National Origin	1,163	911	470	894	847
Religion	1,500	1,472	1,374	1,519	1,322
Sexual Orientation	1,256	1,299	1,197	1,297	1,277
Disability	-	36	57	78	43
Multiple Bias	20	8	7	3	4

*Hate Crime Statistics (Federal Bureau of Investigation, (1996); (2000); (2004); (2008); (2010)

Understanding Bigotry and Hate

Bigotry is difficult to comprehend for many; however, it is often described by scholars as being a thinking disorder (Beck, 1999). As a thinking disorder, or even as a strong emotion, bigotry can be very destructive to those who encounter it. Moreover, the causes of bigotry can also be difficult to discern. Similar to other social phenomena, there is great variability in a person's reasons for falling into a pattern of bigoted thinking or behavior.

Many scholars argue that one of the more influential components to bigoted thinking is ignorance. Similarly, the lack of experience with difference can be attributed to bigotry as well. For instance, Jacobs and Potter (1997) explain that the fear of social diversity propels some individuals to feel bigoted toward another person based on that person's identification with a subordinate social group. Specifically, the socially "undesirable" groups tend to be those of oppressed statuses such as race, ethnicity, sexual orientation, and religion (Perry, 2003b). Moreover, the fear of diversity can lead to prejudice, whereby a person comes to have a negative opinion about someone based on a preconceived idea of a group with which the person may identify (Jacobs & Potter, 1997).

Although bigotry is generally not considered to be a positive personal characteristic, it is not as detrimental as the criminal act it sometimes supports - that of a bias crime. Moreover, it is important to note that bigotry is itself not criminal in the United States; it is protected by the First Amendment of the United States Constitution (Iganski, 2001). However, as Steinberg, Brooks, and Remtulla (2003) suggest, bias crime is defined as learned aggressive behavior completely motivated by prejudice, bigotry, or racism.

Other scholars differentiate between bigotry and hate in how the concepts inform bias crime offending. For instance, Gordon Allport's (1954) book *The Nature of Prejudice* introduces the concept of prejudice as relevant to the understanding of the construction of hate. In this seminal work, Allport (1954) suggests that though it is possible to hate individuals and groups, it is often easier to hate social groups. After all, it is easier to the see humanity in an individual.

Allport (1954) continues to discuss prejudice as being influential in the commission of five certain actions: 1) antilocution, 2) avoidance, 3) discrimination, 4) physical attack, and 5) extermination. These five actions can be viewed as scalar, with antilocution being the least serious. In this case, individuals are able to identify an out-group and participate in negative discourse related to that group. More seriously, persons may choose to create social distance between those whose group identification is viewed as undesirable and themselves. There is no direct harm inflicted here. Discrimination is yet more serious, with social groups experiencing the deprivation of certain opportunities or rights. Allport (1954) continues to explain that physical attack is generally more serious than discrimination, as individuals are often gravely harmed. At this point, it is evident that prejudice has contributed toward criminal victimization of someone identified with an out-group. The most severe level is extermination. At this stage, Allport (1954) explains that the out-group's complete annihilation is the goal. Examples of this include the Holocaust in Europe (Allport, 1954) or the Rwandan genocide in Africa in the 1990s.

With regard to hatred, it is perhaps a common misunderstanding that love and hate are opposite in nature. To combat this notion, Sternberg and Sternberg (2008) introduce a multifaceted structural theory of hate. The authors use a triangular explanation of love to explain the closely related central tenets of hate. Sternberg and Sternberg (2008) suggest love can be explained by the convergence of three factors: commitment, passion, and intimacy. Conversely, hate is constructed by the melding of commitment, passion, and a negation of intimacy. In effect, there is relatively little difference between love and hate. Given the concepts are similar in nature, Sternberg and Sternberg (2008) suggest that the hatred held toward individuals and groups can, in part, be attributed to the convergence of the three pillars of the structural theory of hate.

The Impact of Bias Crime on Victims

Across the United States, when a bias crime occurs, organized hate groups such as the Ku Klux Klan, skinheads, or neo-Nazis are often suspected of perpetrating the crime and are thereby blamed. However, in general, organized hate groups do not commit the majority of bias crimes. Although bias crime offenders generally commit their crimes in groups, they are not usually affiliated with an organized hate group (Craig, 2002). Bias crime offenders tend to be young, Caucasian males with no prior criminal record from backgrounds that are generally not impoverished (Craig, 2002). Moreover, in many cases, the offender may even be a neighbor or live in close proximity to the victim (McDevitt, Levin, & Bennett, 2002). Rather than blatant extremists dressed in regalia, the bias crime offender may be living next door and be seemingly otherwise harmless.

Bias crime offenders' motives can vary. As such, this dissertation focuses on exploring the individual motives related to bias crime occurrence. Currently, there is little macro-level research capable of providing context for such incidents. Therefore, it is important to remember that the underlying factor found in all bias crimes is bigotry (Levin & McDevitt, 1993). McDevitt, Levin, and Bennett (2002) explain the various motivating factors involved with bias crime offending. For instance, in certain bias crimes the offender is in search of a sense of power and excitement. These crimes are considered thrill crimes and are the most common. Other bias crime offenders feel the need to protect their territory or resources and are called defensive offenders. Yet others that commit bias crimes in a reactive manner avenging a perceived wrong are regarded as retaliatory criminals. Those that victimize based on a desire to "cleanse the world of evil" are known as mission offenders.

During the 1980s and 1990s, a series of celebrated crimes involving victims of subordinate status invigorated much interest and disagreement by American legislators and scholars alike. Since that time, many resources – scholarly, financial, and legislative - have been allocated toward the understanding and remedy of bias crime. While some consensus exists on the detriment of bias crime offending, disagreement still surrounds the causes of bias crime victimization and the policy actions that should be taken to combat such crimes. Although bias crime occurs across a wide range of groups – from political affiliation to race – this study is limited to the three most frequently occurring types of bias crimes: those motivated by bias against the victim's race, religion, and sexual orientation.

Race

African Americans are the most common victims of bias crime in the United States (Gerstenfeld, 2004). This should not be surprising as African Americans have been subjected to intolerance, violence, racism, and inequality for centuries. American slavery is perhaps the most massive bias crime in history (Gerstenfeld, 2004), and therefore it set the stage for the occurrence of more recent bias criminality. For decades after slavery, African Americans endured lynchings and other forms of violence nationwide, though arguably much of it occurred in the South. Historically these crimes were not necessarily recorded or viewed as bias crimes. As an example, Nolan, Akiyama, and Berhanu (2002) point out that though the South has the second highest number of index crimes and the second highest crime rate in the four regions of the United States, it somehow reports the lowest number of bias crimes. Prejudicial views of African Americans are present today and are made painfully visible every time a bias crime against an African American occurs. Incidents occur more frequently than one would presume, though they are not always as brutal as the James Byrd murder. For example, in the South hundreds of black churches have been bombed or burned in recent years (Gerstenfeld, 2004). Numerous cross burnings have occurred in the front lawns of African Americans as well. According to Green (1998) although considered free speech, these cross burnings, usually carried out by whites, often predict more direct and violent attacks. These incidents are equally as troubling given that they are motivated by the same bigotry and intolerance that took James Byrd's life.

Religion

Although religiously-motivated bias crime can happen to a member of any subordinate religious group, the Jewish community has long endured bias-based criminal victimization.

Anti-Semitism is perhaps among one of the oldest and deepest forms of prejudice and intolerance in existence. Historically, Jewish persons were persecuted by the Egyptians, Greeks, and Romans and have been confined to ghettoes without the ability to own land (Gerstenfeld, 2004). The most well-known account of anti-Semitism occurred in Nazi Germany where six million Jewish persons perished throughout Europe. On the American front, anti-Semitism often involves the extremist beliefs that blame Jewish persons for economic troubles, communism, and disloyalty to the United States (Gerstenfeld, 2004). Additionally, many fringe Americans believe that a Jewish conspiracy runs the country and that Jewish persons have led various social movements, such as the feminist and Civil Rights movements (Gerstenfeld, 2004). When these extremist beliefs are acted upon, anti-Jewish incidents ranging from swastika spray paintings on synagogues to harassment and more violent assaults occur across the United States (Gerstenfeld, 2004). For instance, as Altschiller (1999) describes, in 1994 a Lebanese immigrant shot at a van carrying fifteen Hasidic Jewish students in New York. One student died and three were injured.

Sexual Orientation

Individuals in the lesbian, gay, and bisexual community experience acts of intolerance and violence, both criminal and non-criminal, at a rate similar to members of other oppressed social groups (Gerstenfeld, 2004), yet attention to these injustices is often overlooked and ignored. Although there are numerous reasons for this, the sentiment that members of the LGB community are deviant, abnormal, and unworthy of legitimacy and concern is widely accepted in American society (Gerstenfeld, 2004). Taking this assumption into consideration, it should come as no surprise that there is a limited availability of information about, and therefore a significant gap exists in the literature, the effects of bias crime on the LGB community (Comstock, 1991).

Specifically, anecdotal evidence exists that suggests bias crime may affect LGB individuals in a manner that differs from other bias crime or non-bias crime. It is frequently noted that a theme of anti-LGB violence is the presence of an elevated level of severity and brutality of attack. Many scholars argue that anti-LGB bias crimes tend to be the most brutal and physically severe of all bias crimes (Comstock, 1991; Levin & McDevitt, 1993; Miller & Humphries, 1980; Rayburn & Davison, 2002). Certainly, there are numerous examples of bias crimes committed against other oppressed subordinate groups that result in equally brutal and severe injuries. The difference seems to be that bias crime against the LGB community tends to be particularly brutal and are often considered to be overkill (Bufkin, 1999), sending a particularly strong message of intolerance to victims and to the entire LGB community.

As research and anecdotal accounts suggest, whether an assault or homicide, the effects of attacks against those persons who identify as part of the LGB community tend to be severe in nature. Police officers are often witnesses to the aftermath of an anti-LGB bias crime. One Miami, Florida police officer noted that anti-LGB attacks have been among the worst beatings that he has seen (Comstock, 1991). In more severe cases, Comstock (1991) references a psychiatrist as stating, "Multiple and extensive wounds are not uncommon in the fury of anti-homosexual murder." (p. 47). In their 1980 study of anti-LGB assaults and homicides, Miller and Humphreys remarked that, "An intense rage is present in nearly all homicide cases involving gay male victims. A striking feature... is their gruesome, often vicious nature. Seldom is the homosexual victim simply shot. He is more apt to be stabbed a dozen or more times, mutilated, and strangled" (p. 179). According to Berrill (1992), yet another example of anti-LGB bias crime brutality comes from, Melissa Mertz, a hospital employee in New York City, "Attacks against gay men were the most heinous and brutal I encountered. They frequently involved torture, cutting, mutilation, and beating, and showed the absolute intent to rub out the human being because of his [sexual] preference" (p. 25).

The Impact of Bias Crime on Communities

Although there are various perspectives on the immediate outcomes of bias crime offending, many scholars have focused on concept of interchangeability. McDevitt, Balboni, Garcia, and Gu (2001) suggest that bias crime offending is conceptually different from non-bias based crimes given the victim potentially could have been any member of the targeted group. For example, in the event that an African American individual is the victim of a bias crime, the larger African American community realizes this act of criminality could have been targeted toward them as well. In effect, people are left thinking, "It could have been me." In this way, bias crime offenders are inherently sending a negative message to oppressed subordinate groups. This message is largely based on the sentiment that these individuals are viewed as different and thereby not welcome to be part of the community. Subsequently, other members of the affected subordinate groups may experience secondary victimization (McDevitt J. , Balboni, Garcia, & Gu, 2001).

Likewise, Iganski (2001) suggests the harm of bias crime victimization can be considered to have a wave-like effect. Others have discussed this as being a "ripple effect" (Noelle, 2001). When one person is victimized, the result is a wave of victimization throughout the community – affecting not only the victim, but others in the subordinate group. Moreover, it is certain that a bias crime victim is generally subjected to physical harm; however, bias crime victims also experience psychic harm (Iganski, 2001). Although Iganski (2001) notes that the findings are not unanimous, emotional and psychological impacts usually follow bias-based criminal events. Moreover, victims generally do experience what Iganski (2001) considers an "in terrorem" effect. Essentially, "in terrorem" refers to the threatened state a victim and community experience after the occurrence of a bias crime. In addition, this terror, or psychological trauma, for victims can last over five years past the criminal event – a time period that is double that of non-bias motivated crimes (Craig, 2002). In their study of effects of ethnoviolence, Ehrlich, Larcom, and Purvis (1994) compare the psychophysiological symptoms resulting from post-traumatic stress of ethnoviolence victims, personal violence victims, and non-victims. The results of this nationwide survey suggest that 18 of the 19 stress items occurred for a higher percentage of ethnoviolence victims than others in the study. Among some of the most common reported symptoms were sleep difficulties, anxiety, hardships at work and with concentration, anger, fear, and feelings of unexplained exhaustion (Ehrlich, Larcom, & Purvis, 1994). As is evident, the violent message of intolerance that meets the victims of bias-based victimization is quite accurately considered to be a form of domestic terrorism.

As suggested, bias crime is harmful to individuals and to society alike – both physically and emotionally to individuals and entire subordinate social communities; however, this dissertation seeks to focus attention on the effects of bias crime on Unites States counties. All types of criminal activity are detrimental for communities; there is no doubt. However, bias crime presents a unique challenge. Given the complexities of bias criminality, public policy options are much debated. It is certain, that the motive behind one policy option - bias crime laws – is to publically acknowledge the ill effects bias crime has on the community. Jacobs (1998) calls this symbolic denunciation. In effect, society has recognized that a certain type of crime – in this case, bias crime – is particularly harmful to the community and takes action to state its collective recognition of and condemnation for the problem.

The Importance of Research on Bias Crime

Although bias crime is a relatively new topic of study in the discipline of sociology and field of criminal justice, there has been significant research conducted on this type of crime from the policing, legal, behavioral, and political perspectives. Moreover, various contemporary theories have been explored to help explain bias crime offending.

The effects of intolerance, bigotry, and bias are numerous; however, bias-motivated criminal acts invoke fear and confusion that disturb entire communities (Iganski, 2001), leading many to understand that bias-related crimes warrant increased attention. Bias-motivated crime is not limited to a small number of communities. Its effects, however, are most often experienced by oppressed social groups – typically racial, ethnic, religious, and sexual minorities, as well as persons with disabilities and persons targeted because of their gender identity.

With the understanding that bias crime is a social problem that creates a cause for concern, importance lies in looking to theory to explain why bias crimes occur. Although it might be easy to blame hatred alone for the occurrence of bias crimes, hatred does not adequately explain why bias crimes are committed. Hatred can manifest itself in many forms, some of which actually include criminal offending; however, other forms of hatred such as hate speech are constitutionally protected (Gerstenfeld, 2004). Bigotry and intolerance are not strangers to the United States, and it is likely that most Americans hold biases to which they may or may not admit or of which they may not be aware. However, not all Americans choose to criminally victimize others based on bigotry, prejudice, or hatred. Predicting such criminal activity can be particularly difficult; thus, looking to theory for guidance can provide insight into complex issues such as bias crimes. Before discussing theoretical perspectives, however, this dissertation seeks to describe the current relative lack of empirical evidence on bias crime.

Celebrated Cases and Public Awareness of Bias Crime

Bias-motivated crimes have come to the American public's attention only in recent decades; however, the underlying bigotry and intolerance of such crimes are not novel phenomena in the United States. The recent attention to bias crime does not imply that bias crime did not exist previous to its identification and naming. In actuality, examples of bias crime are not only evident throughout American history, but world history as well. American slavery and the Holocaust are prime examples, yet these merely scratch the surface of the bias-based brutalities humans have inflicted upon one another in the past. However, not until the 1980s did the terms *hate crime and bias crime*[2] advance into public consciousness and discourse (Green, McFalls, & Smith, 2001). Since that time, there has been flurry of attention given by the media, the police, and various legislators to crimes motivated by the bigotry toward an individual based on their identification or their perceived identification with a certain social group. According to Chakraborti and Garland (2009), many victims of bias crime are chosen because of their group association related to race, religion, disability, or sexual orientation. In two well-known cases of bias crime offending, the brutal murders of James Byrd, an African American man, and Matthew Shepard, a gay college student, have made Americans painfully aware of the consequences that such bigotry and intolerance can have on society. Although bias crime can surface in many forms and include people of various subordinate social identities, the underlying factor found in all bias crime is always bigotry (Levin & McDevitt, 1993). A bigot is defined by Miriam-Webster (1991) as, "one obstinately or intolerantly devoted to his opinions and prejudices" (p.

[2] The term bias crime is used in this dissertation as opposed to the term hate crime. Although the term hate crime is often used in the literature, scholars have moved toward the use of bias crime as a more precise wording of the crime (McDevitt & Williamson, 2003). The FBI defines hate crimes as crimes motivated by the offender's bias based on the victim's race, sexual orientation, religion, ethnicity, national origin, and disability (Federal Bureau of Investigation, 2010).

149). Certainly, understanding bigotry can help to inform the discussion of bias crime occurrence.

Lack of Theory on Bias Crime Occurrence

Theoretical explanations of bias crime offending and victimization are largely underdeveloped in the social science literature. As suggested, bias-based crime is not new to the United States; rather, importance lies in understanding and appreciating such crimes through the conceptual lenses of the various social sciences. Social scientists have posited theoretical explanations for bias crime from the disciplines of criminology, psychology, sociology, and political science. Most importantly, the discipline of sociology is largely lacking a cogent explanation of the phenomenon.

Moreover, bias crime does vary contextually; each incident is differentially based on time, space, victim, and offender. It is important to consider who the victims are does indeed matter. After all, the basis for labeling a bias crime as such is due to its unique characteristic of having a victim targeted based on her or his larger subordinate social group affiliation – in short, who the victims are. Thus, it comes not as a surprise that bias crimes targeted toward a variety of subordinate social groups may have differential outcomes. Specifically, a goal of this dissertation is to contribute to the discussion of bias crimes occurrence in the United States at the county level. In accepting the realization that social science does not possess much in way of explaining bias crime, it is important to focus on various factors that may contribute to an enhanced understanding of the particular criminal event at the county level.

With the motivations of bias crime offenders in mind, it is difficult to identify with any certainty the underlying reasons why individuals choose to commit bias crimes. Although there are theories that attempt to explain bias crime offending, the scholarly literature is largely underdeveloped in this area. Therefore, after a review of existing theories presented in Chapter Two, this dissertation will examine the perspective of social disorganization theory with regard to the occurrence of bias crime at the county level.

Social disorganization theory is increasingly important to consider when conducting bias crime research as it provides a macro-level ecological perspective to a concept traditionally examined through the lens of micro-level theories. There is much value in understanding the numerous effects of bias crime; however, the way community groups affect bias crime occurrence – is largely unknown in the social science literature. With its ability to speak to macro-level effects of bias crime occurrence, social disorganization theory is optimal for examining county-level variation in bias crime occurrence.

Research Questions, Data, and Methodology

This dissertation seeks to address several research questions regarding bias crime occurrence at the county level of analysis. The following are research questions informed by traditional indicators of social disorganization theory. The research questions are as follows:

Question 1: What are the relationships between traditional indicators (low economic status, social heterogeneity, family disruption, residential mobility, and violent crime rate) of social disorganization concepts (as measured by US Census Data, ARDA, and *Congressional Quarterly*) and bias crime at the county level?

Question 2: What are the relationships between traditional indicators (low economic status, social heterogeneity, family disruption, residential mobility, and violent crime rate) of social disorganization concepts (as measured by US Census Data, ARDA, and *Congressional Quarterly*) and anti-race motivated bias crime at the county level?

Question 3: What are the relationships between traditional indicators (low economic status, social heterogeneity, family disruption, residential mobility, and violent crime rate) of social disorganization concepts (as measured by US Census Data, ARDA, and *Congressional Quarterly*) and anti-sexual orientation motivated bias crime at the county level?

Question 4: What are the relationships between traditional indicators (low economic status, social heterogeneity, family disruption, residential mobility, and violent crime rate) of social disorganization concepts (as measured by US Census Data, ARDA, and *Congressional Quarterly*) and anti-religion motivated bias crime at the county level?

Question 5: What are the differences between anti-race, anti-religion, and anti-sexual orientation bias crime occurrences at the county level?

The purpose of this dissertation is to examine the relationships between indicators of social disorganization theory and the incidence of bias crime occurrence at the county level of analysis. Four primary models will be introduced – one examining bias crime occurrence in the aggregate and three examining different types of bias crime motivation: anti-race, anti-religion, and anti-sexual orientation. Additionally, each motivation will be compared against the others in order to identify meaningful differences.

Given the lack of empirical evidence informing bias crime occurrence, especially at the county level, this dissertation will use quantitative methods to add to the discussion about bias criminality in the United States. The data used for this dissertation will be aggregated from existing data available from United States government agencies – namely, the FBI and the USCB. The primary data used to capture the dependent variables and some independent variables will be provided by the FBI's Uniform Crime Report. After the introduction of the Hate Crime Statistics Act of 1990, the FBI has been collecting reported bias crime data nationwide. In addition, relevant data from the USCB will be used to construct appropriate independent variables. These variables will be assembled using indicators of social disorganization theory.

Quantitative analyses will be performed to address the specific research questions asked in this dissertation. In addition to descriptive statistics, this dissertation will provide the appropriate bivariate analyses to determine existing relationships. Moreover, the research questions will be answered through multivariate analyses. Further details about the data and methodology will be provided in Chapter Three.

Lack of Research on Bias Crime with Counties as Units of Analysis

Given bias crime research is in its infancy, there is relatively little scholarship available for review. A significant contributor to this problem is the reality that it was not until the early 1990s that the United States began to collect data on bias-motivated crimes. In 1990, the United States Congress passed the Hate Crime Statistics Act. It was at this point, and for the first time, that the FBI began to collect data from local law enforcement agencies about the occurrence and frequency of bias crimes (McDevitt J. , Balboni, Bennett, Weiss, Orchowsky, & Walbolt, 2000).

Similar to other types of crime, there are numerous entities that measure bias crime. The most relevant is the United States Attorney General's Office which was required to collect data on the information surrounding hate crimes due to the passage of the Hate Crime Statistics Act of 1990 (Perry, 2001). This legislation was the first attempt of the United States government to collect accurate information about hate crimes. The accuracy of these statistics is often debated, however. Regardless, every year, law enforcement agencies around the country identify and report the occurrence of bias crime to the FBI (Nolan, Akiyama, & Berhanu, 2002). In response to the new support for bias crime data collection participation, the FBI realized a need to develop an additional data collection program supplemental to the Uniform Crime Report (UCR) and designed wholly for bias crime. Although the definition of bias crimes is rather narrow, the FBI reports that bias crime reports have increased since the beginning of data collection (Perry, 2001). Unfortunately, there is a large discrepancy between the bias crime incidents that the UCR captures as a result of the Hate Crime Statistics Act of 1990 and the incidents that other anti-violence agencies record. This suggests there are far more bias crime incidents that occur than are reported.

Even with the FBI's annual attempts to collect bias crime data, difficulty remains in obtaining an accurate picture of the scope of bias crime in the United States as local law enforcement agencies are not required to report (Green, McFalls, & Smith, 2001). McDevitt, Balboni, Bennett, Weiss, Orchowsky, and Walbolt (2000) report that though the number of reporting agencies grew substantially throughout the 1990s - from about 2,000 to approximately 12,000 – incident frequencies remained markedly constant. In 1992, the FBI reported 7,755 bias crimes as having occurred in the United States; by 1996, that number had risen only to 8,759. This is curious given the disproportionate increase in reporting agencies compared to reported bias crimes.

In addition to legislative and law enforcement efforts, the Anti-Defamation League (ADL) collects data on various anti-Semitic hate crimes. The data that are collected are generally self-reports from victims and can therefore provide much more qualitative data. This is an area in which the UCR is lacking as it traditionally collects quantitative data (Nolan, Akiyama, & Berhanu, 2002). The qualitative data that the ADL collect tend to be rich in detail and inclusive of a wide range of events including non-criminal incidents. For instance, incidents that range from anti-Semitic slurs to campus crimes are collected annually (Perry, 2001). An advantage of the ADL's data collection efforts is that it also provides a place for victims to report incidents where they are able to feel comfortable. Although anti-Semitic events are still likely underreported, perhaps the ADL provides a less bureaucratic environment that is more appealing to victims than a law enforcement agency.

The Southern Poverty Law Center (SPLC) has also been active in measuring bias crime for numerous years. Although there is an emphasis on tracking and recording hate motivated incidents by hate groups, the SPLC gathers significant information every year in its *Intelligence Report*. Unlike the ADL's specialization on anti-Semitic incidents, there is not a group that collects specifically race-related bias crime information (Perry, 2001). However, most of the bias-motivated incidents that the SPLC collects involve anti-racial and anti-LGB incidents (Perry, 2001). Like the ADL, the SPLC offers qualitative supplements to the data available in the UCR.

The National Gay and Lesbian Task Force (NGLTF) is another advocacy group that collects hate crime data. Each year, the NGLTF selects six or nine cities around the country in which to measure the occurrence of anti-LGB bias-based offending (Perry, 2001). The LGB population in these cities is then surveyed and reports of victimization are aggregated. Unfortunately, one drawback is that the surveys are conducted mainly through gay and lesbian publications – from newsletters to websites. Often, closeted gay, lesbian, or bisexual persons avoid these publications and consequently, the survey suffers from underreporting. However, every year the data from just a few cities outpace the reports to the UCR for anti-LGB bias crime (Perry, 2001). This illuminates the inconclusiveness of the UCR with regard to bias crime.

More recently created, the United States Extremist Crime Database (ECDB) identifies and follows the occurrence of ideologically motivated homicides (Gruenewald, 2011). The focus of this database is primarily on tracking far-right extremists; therefore, there is notable overlap between the homicidal actions of hate crime offenders and, for example, white supremacists and other far-right groups. This database is helpful in understanding the entire scope of homicide – especially as it related to extremist activity. Since 85% of bias crime consists of violent offenses (Freilich & Chermak, 2013), examining ideologically motivated homicides is particularly relevant to understanding bias criminality.

Additionally, there are various other advocacy groups and anti-violence proponents that anecdotally collect bias crime data. However, there seems to be a lack of cohesion between victims and the groups collecting the information. As such, whether it is data from the UCR, the ADL, the SPLC, the ECDB, or the NGLTF, there are likely many bias crimes that go undetected.

Given the limited sources for accurate bias crime data, there should be no surprise that quality scholarship is lacking. There are numerous scholarly accounts of the frequency of bias crime occurrence; however, the extant literature remains largely descriptive in nature (Green, McFalls, & Smith, 2001). As Green and colleagues (2001) suggest, bias crime data are largely available only from government agencies (such as the FBI) and watchdog groups that monitor anti-government, militia, and bias-motivated activities.

Although the descriptive analyses that result are valuable, the limitations are significant. Without detailed accounts of bias crime victims, offenders, and the context in which the crimes occur, it is difficult to conduct research able to answer directed questions. Moreover, collecting original bias crime data presents a problem for researchers. Bias crime incidents themselves are difficult to identify and observe, thereby leaving researchers to rely on unreliable records from the government and watchdog groups. Access to would-be offenders is not often available - especially given the easily identified hate groups are not responsible for the majority of bias crime. Moreover, discerning motive is difficult at best, providing little room for scholars to retrieve accurate data on bias offending. In addition, Green, McFalls, and Smith (2001) suggest more robust bias crime scholarship would result from access to reliable data sources such as surveys of victims, ethnographies, and official records.

Direction and Contribution of Research

Although there are likely to be several limitations to this study, a number of contributions to the bias crime discussion are expected to emerge. Since empirical studies about bias crime are relatively limited in the social science literature, this study will add to the general discussion of macro-level effects of bias crimes – more specifically, at the county level. Moreover, this dissertation will add to the literature with regard to social disorganization theory and its contribution to understanding the occurrence of bias crime at the county level. In addition, this dissertation will examine the unique characteristics of anti-LGB victimization as compared to those of other subordinate groups such as race and religion.

Counties as Units of Analysis

This dissertation seeks to uncover findings regarding traditional indicators of social disorganization theory and its connection with the occurrence of bias crimes at the county level of analysis. Although there are likely numerous factors that contribute to a certain county's prevalence of bias crime occurrence, this dissertation will provide insight into whether the differential opportunities available in a community to remain socially organized affect bias crime occurrence. This dissertation is unique due its contribution based on counties as the units of analysis. Although many social scientists have provided much insight into the nature of bias crime offending and victimization, there is a significant gap in the literature with regard to offending at the county level. Given that criminal occurrence at all levels requires government intervention, an understanding of county level factors that influence bias crime in the United States will be a beneficial contribution to the bias crime literature as it can ultimately aid in informing local governments – and the federal government - in bias crime prevention. Thus, this dissertation seeks to contribute toward a greater body of knowledge regarding the various social factors creating a climate ripe for the occurrence of bias crime in the United States.

Organization of Dissertation

This dissertation will be segmented into eight chapters. After the introductory chapter, Chapter Two will discuss the existing research on bias crime and Chapter Three will introduce theoretical contributions to the literature. Chapter Four will be composed of research questions, hypotheses, and a discussion about the proposed data and methodology for the dissertation. The results of descriptive analyses will be presented in Chapter Five. Chapter Six will present the findings from appropriate bivariate findings. The multivariate findings addressing the research questions will be presented in Chapter Seven. Chapter Eight will conclude the dissertation with relevant discussion about the findings of the analyses along with the policy implications and future research recommendations.

Summary

No single explanation is able to provide a framework for understanding the extent and nature of bias crime. However, scholars have posited various social science theories in an attempt to contribute to the explanation of the occurrence of bias crimes. Based on the existing literature, this dissertation will attempt to contribute to the knowledge of bias crime occurrence at the county level through the lens of social disorganization theory. The aim of this dissertation is to explore the extent to which the traditional indicators of social disorganization theory inform not only inform the occurrence of bias crime at the county level, but also aid in understanding the meaningful differences in frequency between oppressed social group victimizations.

CHAPTER 2: REVIEW OF BIAS CRIME RESEARCH

The extant bias crime literature is largely descriptive in nature. Given the scholarly exploration of bias crime offending and victimization largely dates back only to the 1980s, scholars are just beginning the journey toward an empirical understanding of the phenomenon. However, the existing literature is important nonetheless as it informs the current study and its attempt to uncover the factors that affect the prevalence of bias crime incidence. Not only will this literature review explain what is known about bias criminality in the United States, but is will also provide a foundation for this dissertation. The following literature review will include a discussion of what is known about bias crime including: bias crime victimization, bias crime offending, perspectives on bias crime incidence, policy perspectives, and strengths and weaknesses of the bias crime literature. Since there is not significant empirical evidence informing the literature regarding macro-level bias criminality, this literature review will provide insight into the phenomenon.

Bias Crime Victimization

Not surprisingly, victims of bias crimes find the experience to be quite traumatic. Although some controversy exists in the literature, it seems there is a possibility that bias crimes could be more traumatic than other crimes (Gerstenfeld, 2011). At the victim level, it is not uncommon for individuals to experience lowered self-esteem, marked fear, anger, and sadness (Barnes & Ephross, 1994). Furthermore, Barnes and Ephross (1994) suggest these emotional reactions to bias-motivated crime are not unlike the reactions to other criminal victimizations. Moreover, Jacobs and Potter (1998) note that all crime victims experience negative psychological and emotional effects, not just bias crime victims. Certainly, there is merit to the argument that criminal victimization is universally traumatic; nevertheless, this remains to be proven in the scholarship (Gerstenfeld, 2011). Given this, and as previously mentioned, bias crimes are considered by many scholars to be more hurtful than non-bias offending and thereby warrant legislative and policy attention (Iganski, 2001).

There are several studies finding bias crime victimization to be more harmful than other types of criminal victimization. Perhaps most convincingly, and echoing the cited effects of bias crime by of Barnes and Ephross (1994), in a study of lesbian, gay, and bisexual individuals, responses indicated that those who had been victims of bias crimes reported greater levels of anger, depression, and anxiety than those individuals reporting non-bias crime victimization (Herek, Cogan, & Gillis, 2002). Moreover, in a study of bias crime victimization in Boston, Massachusetts, bias crime victims reported more fear and a lower level of safety as opposed to non-bias crime victims (McDevitt J. , Balboni, Garcia, & Gu, 2001). The time it takes for a victim to recover is considered as well. Craig (2002) notes that victims of bias crimes often take five or more years to recover from the crimes; this is two times greater than the recovery period necessary for non-bias crime victims to recover from their incidents. Although the reality of the psychological and emotional effects bias crime victims face is still in need of further research, importance lies in looking at the significance of anecdotal instances of more severe physical injury resulting from bias crime victimization.

Injuries caused by bias crime offending often tend to be quite severe. According to Messner, McHugh, and Felson (2004), bias-based offenses tend to be more likely to result in injury than all other types of non-bias crime. Although this finding is not universal across victim groups, evidence seems to suggest such attacks do result in extreme brutality. This evidence of excessive physical trauma is reported by Levin and McDevitt (1993); however, the supporting data were from official police data in Boston, Massachusetts. Certainly, underreporting of bias crime victimization mitigates the relevance of this finding. However, anecdotally, it has long been observed that bias crime victims seem to experience extreme physical brutality in their attacks. It is not insignificant that anti-LGB attacks seem to be particularly extreme. In such cases, the minority of incidents involved a gun - a potential indication of the offender's intent to brutalize the victim (Lieberman, Arndt, Personius, & Cook, 2001). After all, the intense animus toward LGB persons could result in a particularly personal – and therefore, brutal - attack on the victim.

As previously discussed, bias crime is viewed as affecting more than simply the victim, but the larger social group of which the victim is a part as well. In effect, the bias-based offense is used to send a message of intolerance and terror to an entire community of persons (Tsesis, 2003; Boekmann & Turpin-Petrosino, 2002; Green, McFalls, & Smith, 2001; Iganski, 2001). These directed messages of hate can contribute to the occurrence of secondary victimization (Noelle, 2001). Often, secondary victimization comes in the form of psychological effects – effects that are reported to be more negative than those arising from non-bias attacks (Rose & Mechanic, 2002). Although reactions to bias crime victimization in a community can vary, there is certainly consistency in the effects of the violence on the general community.

In addition to community-level effects of bias-motivated crime, scholars suggest individuals affected by bias-motivated criminality are less likely to report the incidents due to the fear of potential retaliation by the offender (Cogan, 2001). This reality has led bias crime experts to have a skeptical view on the accuracy of bias crime statistics. After all, the "dark figure of crime" is applicable to bias-motivated crimes as well. Moreover, if the victim identifies as LGB, she or she may be less likely to report the crime given the particularly low level of lack of acceptance and tolerance for difference that exists in American society.

Anti-Race Bias Crime

Given that anti-race bias crime is the most frequently occurring bias-based type of crime in the United States, it is rather surprising to most that there is a relatively underdeveloped – and largely lacking – body of literature on anti-race victimization (Perry, 2003b). Although bias crime victimization is most certainly problematic for all racial groups not identified with the white community, bias crime has been especially apparent in its persistence and frequency in occurrence against the African American community. Although the data relied upon are official data – for which there are known inadequacies – African Americans are the most frequently targeted social group for bias crime victimization (Gerstenfeld, 2011). However, not all scholars agree, as Messner, McHugh, and Felson (2004) found that African Americans' risk for victimization is similar to other socially marginalized racial groups. Certainly, FBI data do not confirm these findings, as 61% of racially-motivated bias crimes were committed against African Americans in 1995 (Torres, 1999).

As previously mentioned, many scholars consider American enslavement of African Americans to be one of the earliest – and most egregious – bias crimes ever to occur in the United States, with the institution's roots beginning in the 1600s (Gerstenfeld, 2011). After Reconstruction, bias-based attacks against African Americans continued. For instance, lynching was used frequently in the South as a terroristic tool to prevent African American citizens from exercising their civil rights – including voting (Torres, 1999). According to Torres (1999), this method of terror was used 1,481 times between 1889 and 1918. The overwhelming majority of the victims were African American.

Moreover, the African American community has long been subject to intimidation in many forms across the United States. From cross burnings to church arson, bias-based offending against the African American community has been used to send messages of intolerance and bigotry. Torres (1999) explains that churches have long been important to the African American community as these are historically one of the first and only independent institutions.

Although the majority of anti-race motivated bias crimes are committed against African Americans in the United States, other racial groups are negatively affected by bias crime as well. For instance, Asian Americans have long been exposed to intolerance in the United States. Internment camps for Asian Americans during World War II are often considered to be one of the most prominent examples of institutionalized oppression and intolerance against persons of Asian descent. After the Pearl Harbor bombing in 1941, significant anti-Japanese sentiment existed in the United States (Chen, 2000). This resistance was extreme enough that the federal government created internment camps to isolate those Americans with Japanese ancestry during World War II. Although many defended this bigoted act as being necessary for national security, it is curious that German Americans were not interned – nor were Italian Americans (Chen, 2000).

More recently, and perhaps one of the most publicized accounts of anti-Asian American violence, was the murder of Vincent Chin in 1982. Chin was brutally murdered with a baseball bat by two white men in Detroit, Michigan who espoused anti-Asian sentiments – reportedly because of recent American automobile manufacturing layoffs (Chen, 2000). At the time, increased sensitivity to the decline of the American automobile industry – and the perceived "threat" of Japanese automobile manufacturers' rising market share – seemed to fuel much of the animus toward those who identified as Asian American.

Certainly, a long history of bias-based racial oppression and victimization exists in the United States. Given the nature of this dissertation and the tendencies of African Americans to be singled out for bias-based offending, concentration is placed on the African American community as opposed to extensive attention to various other racial and ethnics groups. For instance, in 2007, 36% of bias crimes were committed against African Americans versus 9.5% against whites, 3.2% against multiracial groups, 8.7% against Hispanics, 2.5% against Asians and Pacific Islanders, and 5.4% against other ethnicities (Federal Bureau of Investigation, 2007).

Anti-Religion Bias Crime

Second to anti-race based bias crime occurrence is anti-religion based bias crime. There are innumerable religious faiths in the United States; however, this project does not seek to identify and survey the experiences of each. Instead, focus will be placed on those of Jewish, Muslim, and Amish faiths.

With nearly 78.4% of Americans identifying with the Christian faith – whether Catholic or Protestant – Christians hold a clear majority (Pew Forum on Religion and Public Life, 2008). Given this, Christians enjoy the ability to control their surroundings to their interests; namely, this religious group possesses power. This renders others from differing faiths to be part of a subordinate status. Historically, in the United States, persons of the Jewish faith have been excluded and persecuted. As previously discussed, this should come as no surprise given Jewish individuals' struggle for acceptance and tolerance has been challenging across the world as well.

Anti-Semitism has been in existence for more than a millennium – making it one of the oldest examples of hatred and intolerance in human history (Gerstenfeld, 2011). Still, anti-Semitic bias crime research is limited; as mentioned, the majority of anti-Semitic bias crime data collection and research is conducted by the Anti-Defamation League (ADL) – a group that has been monitoring anti-Semitic incidents since 1979 (Anti-Defamation League, 2001). The ADL's efforts have largely captured incidents of anti-Jewish crime, bigotry, or intolerance. It should be noted, however, that the ADL's data do go further than government data in that they include non-criminal events as well as criminal events (Gerstenfeld, 2011).

Although the great majority of anti-religion bias is focused on anti-Semitism, since the September 11, 2001 terrorist attacks in New York, Pennsylvania, and Virginia, there has been increasing attention paid to anti-Muslim and anti-Arab bias crime (Gerstenfeld, 2011). As previously mentioned, there is unsubstantiated perception by some Americans that those of the Muslim faith – or those who appear to be of Arab descent, though not one in the same – pose a threat to the security of the United States.

Adding to this discussion is a study conducted by Disha, Cavendish, and King in 2011. This study examined the reported upsurge in anti-Muslim and anti-Arab violence in the United States since the terrorist attacks of September 11, 2001. Furthermore, Disha, Cavendish, and King (2011) were interested in exploring the "spaces of hate" and the "times of hate." Included in the discussion is the power differential hypothesis. Similar to its presentation earlier in this dissertation, this hypothesis suggests that members of a majority group are empowered, and thereby implicitly encouraged, to act out when minorities are present in low numbers (Levine & Campbell, 1972). Taking this into consideration, the authors found that temporal and spatial aspects of anti-Arab and anti-Muslim bias crime led to three salient findings. First, historical events such as September 11, 2001 can act as a catalyst that allows individuals – in this case, Americans – to identify a "new enemy" upon which to place acts of hatred (Disha, Cavendish, & King, 2011). Regardless of nationality, many Americans would be likely to have a perception that the new enemy is Arab or Muslim. Second, this study accentuates the importance of understanding that bias crime incidents might occur more frequently in areas where there is a larger population of a targeted group. For instance, in communities with high populations – or relatively high populations – of Muslim or Arab people, there is a greater likelihood of bias crime victimization. However, Disha, Cavendish, and King (2011) caution that in reality, the communities in which Arabs and Muslims were most at risk following September 11th were in places in which they were few in number. Essentially, the authors contend that there is greater risk because small oppressed social groups have high visibility and little protection. As they suggest, there is strength in numbers. This finding falls in line with Levine and Campbell's (1972) power-differential hypothesis.

Bias crime is also committed against smaller groups of religious minorities. Often, when one considers such crimes, anti-Semitic or anti-Muslim bias crime comes to mind. However, other religious groups – such as the Amish – are affected by bias crime as well. Byers and Cryder (2002) studied anti-Amish bias offending in the rural Midwest. In an act called "claping," the authors qualitatively examined the contributing factors toward the occurrence of such activity. The study exposed several types of "claping" – including acts such as forcing Amish buggies off streets with automobiles, turning over Amish outhouses facilities, and throwing flour at Amish buggies (Byers & Cryder, 2002). Given the authors' examination of routine activities theory, it comes as no surprise that offenders view the Amish as a vulnerable, and thereby suitable, target – especially given their relatively few numbers and differential dress and lifestyle characteristics. Moreover, in accordance with religious tenets, the Amish are reluctant to call the police when such crime happens; this is likely to mitigate the effects of capable guardianship. Motivation was found to be based not only on prejudice, but also on the notion that the Amish deserved the harm occurring from their victimization (Byers & Cryder, 2002). Although understanding aspects of anti-Amish bias crime does not explain all offending against religious minority groups, it does provide a qualitative perspective of offending through the theoretical lens of routine activities theory.

Anti-Sexual Orientation Bias Crime

According to the FBI, bias crime committed against individuals due to their actual or perceived sexual orientation is increasingly problematic. For instance, in 2008 the FBI reported 1,297 bias crimes committed against LGB individuals (Federal Bureau of Investigation, 2008). Historically, the figures reflecting anti-LGB bias crime place third in frequency – behind race and religion (Gerstenfeld, 2011). In addition, the figures released from the FBI are only reported crimes; certainly many anti-LGB bias crimes remain unreported to authorities. McDevitt and Williamson (2003) note that victims of LGB bias crimes are least likely of all bias crime victims to report the incidents. Although the exact reasons for this are not known, it is reasonable to acknowledge that bias against LGB persons is pervasive throughout American culture. Yang (1997) suggests that anti-LGB behaviors – such as bias crimes - are essentially actions taken with the support of values present in a community's culture. This differs from other types of bigotry as anti-LGB prejudice – and often violence - is frequently overlooked by many social, religious, and governmental institutions (Herek, 1989).

In perhaps one of the earliest and most salient studies of anti-LGB violence, Comstock (1991) provides an overview of both anti-LGB bias based victimization and offending. With regard to the gender of the anti-LGB victim, males do tend to be victimized more frequently – but not by much. This finding is similar for rape. In addition, persons of color are more frequently victimized than are those identified as white (Comstock, 1991). However, these conclusions only reflect physical effects of anti-LGB victimization – not the well-noted emotional damage that often occurs as well. Moreover, Comstock (1991) notes that LGB persons are far more likely – regardless of racial identity – to be victims of violent crimes than are citizens of the general population.

In addition, Comstock (1991) notes that the context of anti-LGB bias crime is important to consider. Essentially, Comstock (1991) suggests that – all things equal – the majority of anti-LGB bias crimes occurred near "LGB" spaces. For instance, 59% of victims reported that the bias crimes occurred near a public gay/lesbian area such as a bar or "bath house." It follows that LGB individuals more likely to be present in such areas, and therefore are vulnerable to attacks. In these settings, LGB people are both present and in many cases, identifiable (Comstock, 1991). However, caution should be taken when assuming all individuals in a "LGB space" identify as such, as the perception of having an LGB identity is enough to incite victimization.

In his 1991 bias crime survey, Comstock provided a foundation of knowledge upon which much understanding of anti-LGB bias crime offending is based. In comparing his survey data to national crime statistics, Comstock (1991) concluded that contextual perpetrator information if similar to other bias crime offending incidents. For instance, 94% of perpetrators of anti-LGB violence are male; this is slightly greater than the figure for violence against the general population. It is commonly known that males are engaged in the most criminal offending; in this case, males are the perpetrators in 78% of violent victimizations (Comstock, 1991). Additionally, Comstock (1991) notes that the majority of the anti-LGB perpetrators are white (67%), which is in contrast to 69% for all violent crimes. Moreover, Comstock (1991) reports that anti-LGB offenders are younger than offenders of general crimes. This differential is comparatively noticeable with 46% of anti-LGB offenders being under the age of 22. This figure is 29% for offenders in the general population (Comstock, 1991). Also noteworthy is the fact that the many anti-LGB violent crimes are committed in groups. These are not necessarily organized hate groups; rather, they typically are comprised of groups of young males. Comstock (1991) found that in the general population, only 27% of violent crimes are committed in groups; for anti-LGB violent crimes, that figure climbs to 48%.

Furthermore, in a sample of 290 LGB identified individuals, Rose and Mechanic (2002) report that 73% of the respondents had been victim in at least one homophobic event. The seriousness of the victimization varied considerably, from sexual assault to threats of violence or other acts. Given the purpose of the study was to determine the psychological effects of anti-LGB bias crime victimization, it is not surprising that homophobic sexual assaults had the highest incidence of psychological distress (Rose & Mechanic, 2002). In addition, Rose and Mechanic (2002) found that those victimized by anti-LGB sexual assault were more likely to report these offenses to the police than were other anti-LGB bias crime victims.

Superordinate Group Victimizations

In the discussion regarding bias crime victimization, many members of superordinate groups often inquire about their inclusion in bias crime victimization. According to some scholars (Jacobs & Potter, 1997) attention to bias crime is relegated to mere identity politics and ignores the victimization of majority groups.

Although it is certainly true that any individual can be targeted because of her or his identification with a social group, the problem of bias crime victimizations is most often a result of power differentials. For instance, Gerstenfeld (2004) suggests it is not usually the straight-identified individuals concerned about being targeted by LGB-identified individuals. Nonetheless, there have been instances in which super-ordinate group members have been victimized because of their larger social group identification. To accommodate these instances, most bias crime language is framed to be inclusive of all social groups of people. This includes majority groups such as Whites, Christians, and heterosexuals. Violence against any individual is certainly worthy of attention; however, this dissertation seeks to focus efforts on the victimization of marginalized social communities – specifically communities of color, religious minorities, and the LGB community.

Bias Crime Offending

In order to fully understand the scope of the bias crime problem in the United States, it is important to consider the context surrounding bias crime offenders as well as victims. Therefore, this dissertation offers a discussion of not only typical offenders, but the social context that surrounds these offenders. Hate and intolerance and their dissemination throughout American culture are certainly imperative to the understanding of bias crime occurrence. Individuals promulgating hateful and intolerant speech are considered as well. In addition, discussion of a major hate organization – the Ku Klux Klan – provides context as well.

Individuals and Intolerance

Given that bias crime research is a relatively new scholarly endeavor, understanding of bias crime offenders is limited in the scholarly literature. However, as mentioned in his ethnographic study of hate groups, Ezekiel (1995) notes that the majority of bias crimes are actually committed by individuals – not organized hate groups. Of course, as noted by (Comstock, 1991) many of these individuals act together as a group during the commission of bias crimes. This fact stands in opposition to what most common view of hate groups as the face of hatred in the United States. In actuality, the typical bias crime offender tends to be young and male – sometimes offending in small unaffiliated groups (Franklin, 2002). Moreover, from their study of bias-motivated assaults, Messner, McHugh, and Felson (2004) found that a large number of bias crime offenders were intoxicated at the time of the incident.

Although there has been some progress with the bias crime offender research, significance lies in examining the bigoted attitudes and speech that fuels the individual acts of bias-motivated crimes. Certainly, hate speech is protected by the First Amendment to the United States Constitution; however, the vitriol espoused by some may be linked to the encouragement of bias-motivated criminality (Tsesis, 2000).

Hate Groups

Bias, prejudice, and hate are not relegated to individuals. There are – and long have been – many hate groups in the United States. Perhaps the best known voice of hate, the Ku Klux Klan has had various periods of popularity nationwide. With origins dating back to Reconstruction Era Tennessee, the Ku Klux Klan has always stood for hate and intolerance disguised as an organization seeking "100% Americanism."

Although the Klan originated in Tennessee during Reconstruction, its ugly head has surfaced many times in American history – from 1965 to the present day. The second wave of Ku Klux Klan activity started in the early 1920s as a response to a changing racial and religious climate in the United States. Given this dissertation seeks to focus on counties, it is important acknowledge in depth the influence The Ku Klux Klan had over one particular community. As such, the Ku Klux Klan reared its ugly head in Detroit, infiltrating the political and social stage of the nation's fourth largest city at the time (Widick, 1972).

The Ku Klux Klan was founded on fundamentalist principles of Christianity and thereby its main purpose was to promote hate and intolerance toward those who were not White, Protestant, and heterosexual. In their own publication dating back to the early 1900s, the Ku Klux Klan defined many of their ideals, one of which was white supremacy. Americanism - a form of nationalism, and Protestantism were also promoted (Widick, 1972). Therefore, in

Detroit, a city with a growing number of European Catholics and Southern African Americans, the Ku Klux Klan found much inspiration for flourishing throughout much of the early 1900s through the 1950s (Widick, 1972).

According to Jackson (1967) the first Kleagle, or chapter of the Detroit Ku Klux Klan, was formed in 1921. Although the organization had a slow start, by 1925 there were over 100,000 Ku Klux Klan members in Detroit (Boyle, 2005). The membership consisted of mainly White, Protestant, and working class individuals from the Detroit area (Widick, 1972). There were other Kleagles in Michigan, but Detroit was the stronghold for the entire state (Jackson, 1967). Although the Ku Klux Klan had a significant membership in the early 1920s, it was not quite as socially unacceptable to be a member as would be today. Without a doubt, the Ku Klux Klan was considered a hateful group in the 1920s; however, the following was much stronger, perhaps empowering the unfortunate reality for which the organization stood. The Ku Klux Klan became so socially acceptable that even President Warren G. Harding (OH) was a member of the certified hate group (Boyle, 2005). Certainly, the President's association with the hate group indicates the level of national acceptance of the exclusion and oppression of certain social groups.

The Ku Klux Klan was fairly prevalent in Detroit's culture as well. It was not uncommon during the early 1920s to see Ku Klux Klan advertisements in *The Detroit Free Press* seeking more members or announcing rallies (Jackson, 1967). In addition, Jackson (1967) explains that there were smaller subgroups within the Detroit Ku Klux Klan for boys and for women called the Junior Klan and the Women of the Ku Klux Klan, respectively. Therefore, there was no getting around the fact that the Ku Klux Klan had a strong grip on Detroit. As the city kept changing demographically and socially, the Ku Klux Klan continued to grow in strength.

Although not always visible to Detroit residents, the Ku Klux Klan was alive and prosperous in the early 1920s. This led to the common occurrences of cross burnings and rallies in the Detroit area. The first major rally by Ku Klux Klan members was held in Royal Oak in April of 1923 (Jackson, 1967). Approximately eight thousand Ku Klux Klan members gathered to listen to the grand goblin discuss the superiority of the white race, both physically and mentally, in the Great Lakes region (Jackson, 1967). According to Jackson (1967), in an apparent attempt to prevent the Ku Klux Klan from holding future rallies, the State of Michigan passed the 1923 Burns Act which outlawed public meetings of masked men. However, this did not stop the Ku Klux Klan from rallying. Soon after the passing of the law, an unmasked group of 25,000 to 50,000 Klan members rallied in Dearborn, Michigan (Jackson, 1967; Boyle, 2005).

Boyle (2005) tells the story of one of the most infamous of Detroit's race-related events that occurred on a summer evening in 1925. Dr. Ossian Sweet, an African American doctor who had moved into a prominently white neighborhood, found himself subject to a crowd of jeering Whites surrounding his house in protest. Although there were 17 police officers posted for protection at Dr. Ossian Sweet's new house, the crowd of angry Whites overwhelmed Sweet and his family. Armed with rifles for protection, Dr. Sweet and his family spent the first night in the home without incident. The second night, violence broke out and two White men in the angry mob were shot from inside Sweet's house. One man was killed and another was only injured. The Sweet family was arrested and detained, but later acquitted of all charges. While the Ku Klux Klan was never officially involved in the incident, most believe that the organization had significant influence on the planned mob scene at Dr. Sweet's home. With the proliferation of

Ku Klux Klan members in Detroit at the time, it is highly likely that there was involvement of the Klan.

The Ku Klux Klan was influential to many aspects of Detroit in the 1920s, one of which was local politics. In one of the Klan's first attempts at politics, the organization proposed to outlaw parochial schools in Michigan (Widick, 1972). The proposal was defeated; however the political move by the Ku Klux Klan reflected the still deep hatred for Catholics in the Detroit area by Klan members.

In yet another political campaign in 1924, the Ku Klux Klan sponsored write-in mayoral candidate Charles Bowles who nearly won the election (Jackson, 1967). Bowles ended up losing the election by a narrow margin, although many in Detroit contended that he actually won. Claims were then made that the votes were tallied wrong in an attempt to prevent Bowles from taking the office of mayor of Detroit (Jackson, 1967). The winner of the election, Mayor John Smith, though not a Ku Klux Klan supporter, ended up appeasing their desires for hatred and intolerance. In a published letter, Smith told African Americans to stay in "their own neighborhoods" and not to move to White spaces of Detroit (Jackson, 1967). While this action had nothing to do with the Ku Klux Klan, Smith essentially pleased many of the hateful Whites in the Detroit area by writing the letter.

To many, the Ku Klux Klan was one of the most influential organizations that could be found in Detroit in the 1920s. Although it was not always visible, the Ku Klux Klan made every effort possible to recruit new members, integrate itself into the local press, and legitimize itself with White citizens based on its desire for the attainment of "100% Americanism." However, through its many cross burnings, rallies, sour political endeavors, and hateful protests, Detroit citizens became wise to the error of the Klan's ways. By 1934, the Ku Klux Klan became disorganized and died out in Detroit. The hatred that was the driving force of the Klan was not necessarily dead; however, an organized outlet no longer existed in the Detroit area (Jackson, 1967).

The Influence of Religion

Many scholars have associated religion to the promotion of bigotry in a variety of ways. For instance, Craig (2002) suggests that many religions have anti-LGB views that guide their interpretations of sacred doctrine. Moreover, it is no secret that organized religion has been exclusive of women throughout history. Although neither of these examples is universal – given there are numerous religious institutions supportive of social justice and acceptance of diversity – organized religion in the United States has provided a vehicle to mobilize those who are inclined to retain bias against certain communities.

Primarily, this is true of Christianity in the United States. For instance, interpretations of the Christian bible have been used to justify slavery, anti-Semitism, segregation, the oppression of women, and the persecution of the LGB community, among others. Unfortunately, this is not limited to history books; rather, the intolerance fueled by the religious community is still seen in the 21st century. To be equitable, there are many Christian organizations that pride themselves on their contribution to the advancement of human rights and social justice. Specifically, the United Church of Christ has been supportive of the LGB community for decades; more recently, the Episcopal Church has pronounced its support as well. Moreover, at times the Roman Catholic Church and varieties of Lutheran, Presbyterian, and United Methodist churches, have vowed to support a mission of social justice – albeit with a discriminatory notion of inclusion. As time progresses, it is likely that the number of parishes supporting social justice and acceptance of LGB populations will grow. Such has been the reality over the recent decades.

Theoretical Perspectives on Bias Crime Incidence

Given that consideration of bias crime is in its infancy, the volume of research surrounding bias crime offending remains largely underdeveloped (McDevitt, Levin, & Bennett, 2002). Nevertheless, various scholars have introduced limited theoretical perspectives useful for understanding bias crimes and the related policy implications. Green, McFalls, & Smith (2001) provide a framework of typologies in which bias crime theories can be organized, while considering that theoretical perspectives generally either consider an individual or societal unit of analysis. In order to provide a comprehensive overview and critique of current theoretical perspectives on bias crime, the following typologies are used: psychological; social-psychological; sociological; economic; and political (Green, McFalls, & Smith, 2001).

Psychological Perspectives

Bias crimes can be examined from a societal perspective or an individual perspective (Green, McFalls, & Smith, 2001). Psychological theories used to contribute to an understanding of bias crimes suggest an individual – or micro - unit of analysis. Given the difficulty of studying individuals involved in bias crimes, most theoretical accounts of bias crimes tend to consist of a societal unit of analysis (Green, McFalls, & Smith, 2001). However, there are psychological perspectives that can be useful in attempting to explain various components of bias crimes. It is common for bias crime scholars to acknowledge the influence of prejudice and the authoritarian personality in bias crime offending.

<u>Prejudice</u>

Although prejudice does not directly cause a person to commit a bias crime, it can undoubtedly become an integral part of an individual's personality and therefore an informant to their outward actions. It is commonly understood that prejudice is a learned behavior and not innate (Allport, 1954). Allport (1954) also suggests that the formation of prejudice begins early and occurs in several stages. First, children learn to take part in social categorization in various ways. For instance, a child might begin categorizing others by race, gender, and age (Allport, 1954). However, there are numerous ways that children and adults can categorize other individuals. Second, children begin to learn about in-groups and out-groups and therefore learn the concepts of and differences between "us" and "them" (Allport, 1954). Third, children learn about the various stereotypes affiliated with different social groups (Allport, 1954). Allport (1954) describes these stereotypes as exaggerated beliefs that are linked with certain social groups. These judgments about individuals that identify with certain groups can be positive or negative, but are generally always exaggerated and incorrect (Gerstenfeld, 2004). Moreover, Allport (1954) suggests that these stereotypes aid in the creation of prejudice which is defined as "an avertive or hostile attitude toward a person who belongs to a group, simply because he belongs to that group, and is therefore presumed to have the objectionable qualities ascribed to that group" (p. 7).

Prejudice can have various effects on individuals. No one is a neutral observer; however, there is a difference between those who perceive others with prejudice and those who do not (Gerstenfeld, 2004). Optimally, individuals find themselves without the need to prejudge others based on various characteristics. However, when an individual is influenced by prejudice, the outcome can be quite severe. In his ethnographic study of the American radical right, Ezekiel (1995) presents numerous examples of extreme prejudice. One such example involves Arthur, a member of the Ku Klux Klan, who prejudicially suggested that "Blacks don't make as much 'cause they are all out raping and robbing White people" (p. 21). Ezekiel (1995) also presents Arthur's anti-Semitic views that Jewish people engineered and invented abortion, and, "They crucified Christ! They crucified Christ. In my opinion, they did it" (p. 22). It is evident that not only was Arthur particularly misinformed, but he held very deep prejudices against at least two categorical groups. Although not all prejudices are as hateful and intolerant as those presented here, it is plausible that prejudicial attitudes, when coupled with affective disorders, can contribute toward acts of avoidance, discrimination, assaults, and even social extermination (Allport, 1954).

The effects of prejudicial attitudes can be quite disagreeable; however, research consistently shows that education is negatively related to prejudice (Wilson & Ruback, 2003). For instance, in their study of racial attitudes, Schuman, Steeh, Bobo, and Krysan (1997) found that the higher the education level of a Caucasian community, the greater acceptance of African American individuals in schools and homes. That education is negatively related to prejudice leads Wilson and Ruback (2003) to suggest that it is possible for more highly educated communities to have lower bias crime statistics – and less severe bias crimes – than less-educated communities. Undoubtedly, that education negatively affects prejudice is particularly helpful in efforts to understand bias crimes. However, how education affects prejudice can only be used to provide information about psychological traits that might influence bias crime offending.

<u>Authoritarianism</u>

The authoritarian personality was first introduced by Adorno, Frenkel-Brunswik, Levinson, and Sanford (1950) in their study examining right-wing extremism. The authors suggest that that authoritarian personality could be characterized by the following factors: a need for rigid and stereotyped views; a low tolerance for ambiguity; and an attraction to uncomplicated, authoritative, and conspiratorial ideologies (Adorno, Frenkel-Brunswik, Levinson, & Sanford, 1950). Given that prejudice can be learned, Adorno, Frenkel-Brunswik, Levinson, and Sanford (1950) introduce the idea that parents with an authoritarian personality are likely to raise children who view the world as hierarchical instead of equal and who view power and authority as the most important components in any relationship. Moreover, Adorno, Frenkel-Brunswik, Levinson, and Sanford (1950) suggest that these children have been taught to view internal impulses, such as disregard for rules, as evil and therefore have been encouraged to fight them. Children may project these impulses on others; consequently, this suggests they cannot be trusted (Adorno, Frenkel-Brunswik, Levinson, & Sanford, 1950). Additionally, the children of authoritarian parents fear showing aggressive behaviors to their parents and consequently transfer their aggression to other children, who in their view are vulnerable (Adorno, Frenkel-Brunswik, Levinson, & Sanford, 1950).

Authoritarianism can certainly provide some insight into the workings of the mind of some bias crime offenders. There seems to be some anecdotal truth to Adorno, Frenkel-Brunswik, Levinson, and Sanford's (1950) perspective; however, the perspective should be considered with caution. In Green, Adelson, and Garnett's (1999) study, attitudinal surveys were used to determine if there was a particular personality profile for bias crime offenders. From the authors' findings, it is apparent that there is no uniform psychological profile for bias crime offenders. There may be many people with authoritarian personalities; however, there are very few individuals who espouse the authoritarian personality and commit bias crimes (Green, Adelson, & Garnett, 1999).

From the perspectives presented, prejudice and authoritarianism are likely only to provide insight into an individual's personality. It is evident that neither psychological trait is likely to be causally related to bias crime offending. The two perspectives discussed do seem to contribute toward an understanding of bias crime offending; however, they also provide insight into less serious instances of intolerance. Therefore, the inconclusive psychological perspectives might lead scholars to examine broader, macro-level perspectives.

Sociological Perspectives

Unlike psychological and social-psychological perspectives which focus more on the individual involved in bias crime offending, sociological accounts provide a broader, more abstract explanation (Green, McFalls, & Smith, 2001). To begin, Blumer's group position perspective provides a sociological interpretation of prejudice.

Prejudice and Group Position

Bigotry or prejudice toward another group is always present in bias crime offending (Levin & McDevitt, 1993). Blumer (1958) suggests that racial prejudice exists in a form of group position as opposed to particular sentiments that one group has toward another. In other words, a group with power over another simply acts in a manner that opposes the subordinate group's desire for power and privilege (Sidanius & Pratto, 1999). Essentially, the dominant group functions to preserve its position, which is that of the dominant group (Blumer, 1958).

Blumer (1958) describes race prejudice as the result of four feelings that are always present in the dominant group. Although prejudice is not limited to dominant racial groups, it is no secret that dominant groups that generally express the majority of prejudicial- and therefore, oppressive - sentiments. In the United States, Caucasians tend to find themselves in dominant positions more frequently than other racial groups. For example, some whites often embrace the following four feelings toward African Americans and other oppressed racial groups: that they are superior, that the subordinate race is intrinsically alien or different, that they have a right to claim certain privileges and advantages, and that they often possess a fear or suspicion that the subordinate race has plans to overtake the interests of the dominant race (Blumer, 1958). Racial prejudices, then, can be seen as stemming from a perceived challenge to these feelings by subordinate groups.

Prejudiced members of dominant racial groups also maintain that they have a claim to certain privileges and advantages (Blumer, 1958). For instance, from informal observation, the "average" American is often described as a Caucasian man and not a member of any other racial, gender, or ethnic group. This implies, of course, that America is a "White man's country" and with that ownership comes privilege. With white privilege, a Caucasian person is "entitled" to certain advantages such as claims of property; the right to certain jobs; occupations and professions; access to the law; positions of control in the government; and the right to certain schools, clubs, and churches (Blumer, 1958). When these privileges are threatened, prejudice can appear as a result (Blumer, 1958); and as suggested, prejudice forms the perfect foundation for bias crime offending.

Additionally, Blumer (1958) explains racial prejudice through group function and adds a sociological bent to what is usually considered a psychological problem. While the group position perspective offered by Blumer (1958) can be quite helpful in understanding the underpinnings of bias crimes, it is not able to explain the phenomena in their entirety.

Social-Psychological Perspectives

Social-psychological explanations of bias crimes focus on the relationship between individual psychological characteristics and larger societal influence (Green, McFalls, & Smith, 2001). Given most theoretical development pertaining to bias crimes has occurred at the societal level, social-psychological perspectives are well suited to aid in the explanation of how social conditions affect individuals. Consequently, there is a perspective scholars have attempted to use to understand and explain bias criminality - social learning theory.

Social Learning Theory

Recently, social learning theory has been considered helpful in explaining bias crimes. Social learning theory is defined as a cognitive process in which an individual's personality and environment continuously interact (Beirne & Messerschmidt, 2000). Through a social learning perspective, there is some evidence that bias crime perpetrators are influenced by the various attitudes around them (Gerstenfeld, 2002). Whether affected by the attitudes of parents, friends, or the media, bias crime offenders have shown that they espouse many of the same bigoted views and fear of diversity as those who influence them (Gerstenfeld, 2002).

Two studies have supported social learning theory as an explanation for bias crime offending. One study conducted by Byers, Crider, and Biggers (1999) examined incidents of claping in the Midwest. Claping can be defined as anti-Amish bias crime. Findings suggest that participants in bias crimes against the Amish gained their belief and attitudes from their peers and families. Another study examined bias crime offenders who had committed anti-LGB bias crimes. Similar the Byers, Crider, and Biggers (1999) study, Franklin (2000) found that those who had committed an anti-LGB bias crime had friends who shared their anti-LGB ideologies.

Although it is clear that bias crime offenders must be learning their prejudices from those who surround them, social learning theory is relatively weak in explaining bias crimes. Social learning theory does help explain how certain individuals gain their prejudiced or bigoted beliefs, but the theory does little to help us understand why these particular individuals take part in bias crime offending.

Economic Perspectives

Examining bias crimes from a broader, societal perspective, economic theories of bias crime present closely aligned arguments. Like other typologies of bias crime theories, economic perspectives are still unable to fully explain bias crime offending. However, of the bias crime theories, those with an economic basis have historically been the most popular explanations of bias crime offending (Hamm, 1994). Consequently, there are numerous anecdotal examples of how economic conditions might affect bias crime offending.

<u>Realistic Group Conflict Theory</u>

Realistic group conflict theory suggests that inter-group hostility emerges from power differentials and conflict over scarce economic resources (Gerstenfeld, 2002; Campbell, 1965; Green, McFalls, & Smith, 2001). Inter-group hostility can arise from a number of situations. Early on, researchers suggested that group conflict theory could explain the negative relationship between the economic conditions of the South and the frequency of lynching of African Americans (Hovland & Sears, 1940). Essentially, Hovland and Sears (1940) found that as cotton prices lowered and the economy turned downward, the rate of lynching increased, implying Whites attacked African Americans when they believed that their privilege and access to scarce resources were threatened. Moreover, in a more recent study, Jacobs and Wood (1999) found cities that had greater economic competition between African Americans and Caucasians had greater white killings of African Americans.

Perhaps a reason for realistic group conflict theory's popularity is the apparent availability of related anecdotal stories. For instance, in 1982, Vincent Chin - a Chinese American man was murdered in Detroit, Michigan by laid off American automobile workers (Perry, 2001). Apparently Chin was mistaken for a Japanese American, a group that the automobile workers blamed for losing their jobs and viewed as taking over their privileged access to the American automobile market. Yet another example tells a story of the Ku Klux Klan terrorizing Vietnamese shrimpers in Texas in 1981. White shrimpers in Galveston Bay felt that newly immigrated Vietnamese shrimpers were competing unfairly and therefore called upon the Ku Klux Klan to intimidate immigrants into leaving the area (Levin & McDevitt, 1993). Months of terror ensued, resulting in property destruction, violence, and intimidation (Stanton, 1992). In both cases, Vincent Chin and the Vietnamese shrimpers, economics were at least part of the drive toward committing bias crimes. American Whites placed blame on another racial group for their economic losses, regardless of any merit to their claims that those groups were responsible for those losses. After all, a social construct such as race – at its sociological base - is unlikely to contribute to a prediction of economic downturn.

In a slightly different manner, some scholars suggest that strain theory contributes to bias crime offending. Rather than a discussion of group conflict, in this context, strain theory explains how individuals become economically and socially strained when there is a shortage of jobs and opportunity to engage in the socially accepted aspects of society. Potentially, would-be bias crime offenders reason that their situation would be brighter if it were not for members of other racial or socially oppressed groups taking “their” jobs. Mindsets such as this could therefore lead to a rise in bias crimes against people of different ethnicities and races (Anderson, Dyson, & Brooks, 2002).

Defended Neighborhoods Theory

Given the popularity of economic perspectives for explaining bias crimes, it would be rather easy to assume that scholars have arrived at a definitive understanding of the cause of bias crimes. Rather, recent research on economic conditions and bias crime offending has provided surprising results. Green, Strolovitch, and Wong (1998) provide evidence that economics do not in fact affect bias-motivated behavior. In their study, the researchers examined unemployment data in New York City between 1987 and 1995. They found no link between the city's monthly unemployment rate and bias crimes (Green, Strolovitch, & Wong, 1998). Instead, the findings of the study suggest that it was an influx of ethnically diverse people moving into formerly homogeneous neighborhoods that is linked to bias crime offending. Essentially, Green, Strolovitch, and Wong (1998) propose the perspective that residents of homogenous neighborhoods use bias crimes as a method of "defending" their neighborhood from new residents who may be different in some way. The defended neighborhoods thesis differs from the realistic group conflict theory in that the new in-migrants of a neighborhood are not creating new power differentials; rather, they are changing the collective identity of the neighborhood (Green, McFalls, & Smith, 2001). However, as residents of the neighborhood familiarize themselves with the newcomers, the hostility is likely to transform into indifference or even acceptance (Green, McFalls, & Smith, 2001).

Green and colleagues' (1998) findings were perhaps among the most important to the development of bias crime theory. In one study, the authors contested the long-held beliefs that downturns in the economy are likely to encourage an increase in bias crimes in a community and introduce a new perspective - defended neighborhoods. The defended neighborhoods perspective can certainly aid in the understanding on bias crimes in neighborhoods, and even at larger levels such as cities; however, the perspective should be considered with caution as it ignores various influences such as those of politics (Green, McFalls, & Smith, 2001).

Scapegoat Theory

Closely related to realistic group conflict theory and strain theory, scapegoat theory (Allport, 1954) suggests that when a downturn in the economy occurs, people lash out at convenient groups. It is important to emphasize that the out-groups are those that are convenient to blame even if there is little evidence of their involvement. However, the groups that are selected are generally the out-groups for which the offender maintains some level of frustration and anger (Gerstenfeld, 2004).

Perhaps the prime example of scapegoat theory is the representation of Middle Easterners as violent zealots and terrorists after events such as September 11, 2001 or the Oklahoma City bombing (Gerstenfeld, 2002). Although much of the scapegoating can be implied by the media, these sentiments can be initiated by politicians and other interest groups (Green, McFalls, & Smith, 2001). For instance, in an attempt to find groups to blame, or scapegoat, following the attacks of September 11, 2001 and the economic downturn that was a result, the Christian pastor Jerry Falwell blamed the attacks on so-called "abortionists, pagans, feminists, the LGBT community, and the American Civil Liberties Union" (Gerstenfeld, 2004; Green, McFalls, & Smith, 2001). Regardless of the facts, the usual lineup of out-groups is often blamed for events such as a September 11, 2001 and downturns of the economy.

Political Perspectives

As a societal-level approach to explaining bias crimes, political typologies have been used to understand, at least in part, why bias crime offending occurs. Many would even argue that bias crimes exist as a construction of use for political gain (Jacobs & Henry, 1996). However, most agree that bias crimes do indeed exist as a problem and require attention political attention. With that taken into consideration, the influence of cultural ideologies and social movement theory has been discussed in the literature.

Cultural Ideology Influence

The influence of cultural ideology speaks to the values, shared beliefs, and customs of a society (Herek & Berrill, 1992). Although bias crimes occur within an extremely broad cultural context, cultural ideologies do affect bias crime offending (Craig, 2002). One such ideology is that of violence. Craig (2002) suggests that violence is increasingly considered as an option when facing conflict; and at times, ethnic and racial oppressed social groups are used as scapegoats for these bias crimes.

In addition, if a political culture is sympathetic to intolerance, the result can be prejudice and bigotry – potential indicators of bias crime (Craig, 2002). For instance, during the Reagan era of the 1980s, progressive legislation aimed at civil rights for all people was attacked (Craig, 2002). Specifically, the Reagan administration opposed the previously passed Voting Rights Act of 1965 and the Equal Rights Amendment, which was defeated in 1983. This political culture created a climate of intolerance, leading some to believe that bigotry, prejudice, and bias crimes were acceptable (Pinkney, 1994).

Social Movement Theory

Social movement theory has been used to help explain bias crime in terms of a political perspective. Green and colleagues (2001) suggest that bias crime offenders are motivated to take action based on "political opportunity" structures. In addition to any bias these offenders may already have toward their victims, social movement theory suggests that various political factors may contribute to acting on one's bias. For instance, any political legitimization of biases may be likely to embolden a would-be offender and is considered a political opportunity (Karapin, 1996; Koopmans, 1996). In addition, the authors suggest the current likelihood of punishment based on bias offending is yet another political opportunity.

There are different ways to interpret the salience of the cultural ideologies and social movement perspectives. As Craig (2002) implies, political conservatism may very well provide the foundation for "culturally approved" intolerance. Moreover, lack of political action may leave the door open for bias-related crimes to be tolerated. For instance, in a radio interview following the September 11, 2001 attacks, U.S. Representative and Republican John Cooksey from Louisiana made the statement, "Someone who comes in that's got a diaper on his head and a fan belt wrapped around that diaper on his head, that guy needs to be pulled over" (Gerstenfeld, 2004). It is clear that Representative Cooksey was interested in transferring his bigoted views to the public. This politician's influence certainly affects the general cultural ideology in America; however, it is difficult to determine whether such accounts directly cause bias crimes to occur.

In contrast, given that bias crimes first attracted wide attention in the 1980s (Green, McFalls, & Smith, 2001), it is evident that attention was paid to the brutal outcomes of bigotry and prejudice – even during the ultra-conservative Reagan administration. The lack of credibility these perspectives are given in the criminological literature is likely due to the assumption that the cultural ideology and social movement claims are grounded in ideological bickering. After all, it was the socially conservative President George H.W. Bush who signed the Hate Crime Statistics Act of 1990 into law (Gerstenfeld, 2004) and several of the most publicized bias crimes occurred during President William J. Clinton's administration. As suggested, the influence of cultural ideology speaks to the values, shared beliefs, and customs of a society (Herek & Berrill, 1992) and it likely affects political social movements as well.

Perhaps more research is necessary in determining the affect politics can have on cultural ideologies and social movements as they pertain to bias crime.

There are very few empirical studies explaining the nature of bias criminality. The reason is likely due to the relatively short amount of time that bias crimes have come to the attention of the public and the controversy that seems to surround the topic. However, a few of the existing theories have made an impact on our understanding of bias crimes. Many scholars still find some truth to economic theories since studies have provided telling results. At the same time, Green and colleagues' (1998) defended neighborhoods thesis seems to move us away from economic theories and toward perspectives focused on demographic movement. Therefore, this dissertation seeks to explore the macro-level effects bias criminality has on American counties. As such, social disorganization theory is most appropriate for the current study examining the relationship between counties and bias crime occurrence.

Policy Perspectives on Bias Crime

Inevitably, when a social problem emerges as salient, it becomes part of a larger dialogue within the realm of public policy. Namely, once bias crime became an issue for which attention was paid, individuals and interest groups alike began to put pressure on the government to solve the problem through public policy. Although there have been a variety of ideas presented, the most frequent proposed solution to a social problem such as bias crime is legislation. As such, an overview of the legislative attention to bias crime incidence is warranted.

Bias Crime Legislation and Controversy

In the aggregate, there is relatively little controversy over the negative judgment assigned to the occurrence of bias crime. Most fair-minded individuals realize that no person should be victimized for any reason; however, the debate begins to expand when taking a victim's identity into account. Most social scientists proffer that in the name of equality, all victims should be treated the same under the law. Yet others take into account the disproportionate levels of social power afforded groups in society and the resultant direct harm placed on marginalized populations through various types of victimization. Regardless, this presents a situation where public figures must decipher a solution to the problem of bias crime victimization. Generally, this comes in the form of legislation. As expected – and with most topics handled by way of politics – there is great controversy over the nature of bias crime laws.

The advent of bias crime legislation took place in 1990 with the Hate Crime Statistics Act approved by the United States Congress. This legislation required the FBI to collect data about the frequency of bias crime offending. Essentially, this meant that for the first time in American history, the federal government would have an official overview of the frequency of bias crime offending as reported by each state. Nevertheless, even this law allowing the FBI to collect data on bias crime was met with controversy. In addition to resistance from conservative Republican politicians, many law enforcement officials were skeptical of bias crime data collection as well.

Bias Crime and Law Enforcement

Regardless of potential good will, law enforcement – both the police and prosecutors – have had difficulty navigating their reactions to bias crime offending and the related legislation. Perhaps the most salient reason for this difficulty is the ambiguity of bias crime incidence. As previously stated, bias crimes are often difficult to identify. Unlike all other crimes, for bias crime prosecution, the offender's motive must be proven (Franklin, 2002). Consequently, law enforcement officials often have difficulty determining this given an offender's motive is often unknown (Franklin, 2002). Law enforcement officials are tasked with not only protecting the public, but also identifying social problems for further public attention. As such, Steinberg, Brooks, and Remtulla (2003) have suggested a "but for" rule is of aid to the law enforcement community. In essence, the "but for" rule helps the police and prosecutors determine whether a certain criminal act was indeed a bias crime. For instance, using this rule, a law enforcement official would be able to state, "but for the hate motivation, the crime would never have been committed" (Steinberg, Brooks, & Remtulla, 2003). In addition, enforcement of bias crime is largely discretionary (Haider-Markel, 2002). Discretion is a significant aspect of law enforcement activity – whether when determining the type of crime that has occurred at the scene or when determining the proper charge for the defendant. After all, police officers have long been considered "street level bureaucrats" who are directly responsible for numerous public services – including the identification of bias crime occurrence (Lipsky, 1980). Although there had been an upsurge in training for law enforcement in the identification of bias crime, this activity has mainly been relegated to large cities (Haider-Markel, 2002).

Additionally, ideological influences have had an effect on attitudes regarding bias crime in the law enforcement community. Notably, the majority of prosecuting attorneys tend to be politically and socially conservative (McPhail & DiNitto, 2005). Given this, it is no surprise that prosecutors have been reluctant to pursue bias crime charges. Moreover, scholars and prosecutors alike acknowledge the evidentiary burden that bias crimes add to a case (McPhail & DiNitto, 2005). Since motivation is difficult to determine, and prosecuting attorneys tend to pursue cases they know they can win, bias crime charges tend to remain unpopular. After all, intent is generally the only requirement for prosecution for all other crimes – both violent and property-related. McPhail and DiNitto (2005) also note prosecutors face pressure from the public to prosecute crimes in accordance to community values. As such, the authors note that prosecutors tend to shy away from prosecuting anti-LGB bias crime in cities where there is a high proportion of its population adhering to religiosity and social conservatism.

Spatial Characteristics of Bias Crime

In a study of bias crime at the county level, Wilson and Ruback (2003) found that bias crime was most likely to occur in rural areas – as opposed to urban areas. Given that social disorganization theory is widely respected among criminologists, these findings come as a surprise. As such, urban areas often are characterized by ethnic and racial heterogeneity, dense populations, and at times – poverty (Wilson & Ruback, 2003). The authors suggest that bias crime may be more prevalent in rural areas as opposed to urban areas because urban areas have a higher level of interaction between people from different social groups than do rural areas. Alternatively, in an area with great homogeneity, the frequency of interaction with diverse populations will be relatively low. Perhaps, it is the case that rural areas provide an atmosphere where individuals have low levels of interaction with difference and perhaps may exhibit greater prejudice. Thus, rural residents are more accepting of bias-motivated behaviors (Wilson & Ruback, 2003).

It seems that areas with greater racial interactions – such as is the case in urban areas – there may have higher bias crime rates by virtue of their demographic make-up (Wilson & Ruback, 2003). Perhaps the more frequently one interacts with individuals with whom she or he differs the greater opportunity there is for bias-motivated crime to occur. However, Wilson and Ruback (2003) suggest this occurs due to a "threshold effect." In essence, citizens in urban areas may be less likely to report bias crime – or perceive one as such – and dismiss the incident based on a sentiment that nothing can or will be done to resolve the problem.

As mentioned, bias crime research largely has been lacking. It is important, however, to examine bias crime at the city level. After all, bias crime does more than affect subordinate groups; it affects entire communities. Importance lies in the pursuit of the understanding of how communities are affected by bias crime at the community level.

In perhaps one of the most salient articles regarding location and bias crime, McVeigh, Bjarnason, and Welch (2003) examined bias crime reporting at the county level. In this study, the authors found that there is relevance in examining the local contexts present in a county when observing the incidence of bias crime. For instance, the existence of various instruments of social movements at the local level – such as political and civil rights organizations - can be associated with higher rates of bias crime reporting. Certainly, relevance lies in understanding that even when bias crime social movements occur – official reporting or policy creation – it does not necessarily mean that policies will be enforced evenly across locations (McVeigh, Bjarnason, & Welch, 2003).

McVeigh, Bjarnason, and Welch (2003) mention that there is importance in using official data and provide argument against Kitsuse and Cicoural's (1963) contrasting claim. In effect, official data are known to lack reliability and should therefore be avoided (Kitsuse & Cicourel, 1963). Alternatively, McVeigh, Bjarnason, and Welch (2003) suggest it is due to this lack of reliability that there is value in analyzing official data. After all, it is by virtue of the unpredictability of results obtained from official data – differing in space and time – that allow social scientists to understand the ever-changing nature of crime and, in this case, bias crime. Moreover, by examining bias crime occurrence at the county level, McVeigh, Bjarnason, and Welch (2003) add rural areas to the discussion. When concentrating on standard Metropolitan Statistical Areas (MSAs), many of the bias crimes are overlooked (McVeigh, Bjarnason, &

Welch, 2003). Examining bias crime reporting at the county level allows for the inclusion of urban, suburban, and rural areas.

Strengths and Weaknesses of Prior Studies

Bias crime research has grown tremendously in volume in the past few decades. There is no doubt this is the result of increased attention paid to bias crime events. As late as the 1980s, bias crime research was still in its infancy (Gerstenfeld, 2011). Although it has expanded as a field of study, there is still much to be uncovered with regard to bias crime offending, victim experience, legislation, and public policy approaches. Certainly, this dissertation seeks to contribute toward that end – providing additional information about bias crime and the community. It is upon the numerous strengths of bias crime research that this dissertation builds.

Much of the early research focused on descriptive analyses of bias crime events. Essentially, this endeavor led to only a marginal understanding of the basic structural elements of a bias crime. Bias crime offenders were examined as were the victims. However, little was developed with regard to social science theory and the way such theories could explain the phenomenon of bias crime occurrence.

Moreover, from a victimology standpoint, the research has expanded to survey issues related to traditionally marginalized groups. Understanding that bias crime, unlike most interpersonal crime, is related to intergroup struggles for power, researchers moved into exploring systems of oppression. It is evident that the preservation of power is particularly related to the incidence of hate criminality. This dissertation takes that and applies it to social disorganization theory.

One of the strengths of the bias crime literature is its coverage of the spatial characteristics of bias crime events. Specifically, understanding the nature of and location of bias crime events helps to elucidate the factors associated with the risk of bias crime occurrence. Although scholars have posited various theoretical contributions to this end, there is somewhat of a consensus in the literature that those areas that are more rural in nature are more likely to experience bias crime offending. Perhaps this is curious given the previous discussion of the defended neighborhoods perspective – one which assumes a certain level of diversity in a larger community, such as a county. Conversely, rural areas – often encapsulated by the concept of a county - tend to be rather homogenous compared to larger cities. This fact can inform our understanding of the risk of bias criminality and its occurrence in United States counties.

Along with the numerous strengths, there are many weaknesses of bias crime research. Primarily, is it evident that bias crime research is greatly underdeveloped as there are relatively few academic studies that have been conducted informing social science about the nature of bias crime incidence. Not only is there a lack of empirical work to try to explain the nature of bias criminality, but also there are very few studies that explain the effect of bias crimes on American communities – whether at the state, city, or county level. Moreover, there is a lack of work comparing and contrasting the various types of bias crimes that affect the American public. Essentially, there is relatively little known about the differences between anti-religion, anti-race, and anti-sexual orientation bias crime events. This dissertation seeks to explore each of these significant gaps in the literature.

Summary

Bias crime is a phenomenon about which the social science literature is relatively silent. Over approximately the past 30 years, scholars have been able to provide many descriptors of bias crime victimization and offending. Through this endeavor, it has become clear that greater interdisciplinary exploratory and explanatory research is necessary. Based on the current and presented scholarly information, this dissertation seeks to add to the discussion surrounding bias crime. Through an exploratory approach, this research will add to the understanding of bias crime victimization at the county level. With a gained comprehension of this knowledge, perhaps various municipalities across the United States will be able to implement public policies to mitigate the occurrence – and the effects of – bias crime offending.

CHAPTER 3: SOCIAL DISORGANIZATION THEORY

This chapter examines the macro-level social disorganization theory and its application to bias criminality from the perspective of numerous social sciences. The majority of criminologists have attempted to explain crime through the lens of micro-level theories, thus focusing on individual characteristics or situations. Conversely, communities and crime scholars lean toward a macro-level approach, examining the various ways that communities both influence crime and are influenced by it. Specifically, social disorganization theory has been used to explain crime in American communities. Social disorganization theory suggests that a community which is unable to identify its common goals and effect appropriate social controls is more likely to suffer from crime (Sampson & Groves, 1989). Social disorganization theory posits that communities facing high residential mobility, a lack of social cohesion (collective efficacy), urbanism, low socioeconomic status of residents, unsupervised peer groups, and high rates of family disruption are more likely to experience criminal events. This theory has been tested quite thoroughly and the results of those studies are presented in this chapter.

Studies of bias crime have largely been descriptive in nature. Moreover, such studies focus on the perpetrators and, at times, the offenders. This dissertation seeks to examine American communities – in this case, counties. Given the unit of analysis for this dissertation is the county, a theoretical framework from the communities and crime perspective is most important. The purpose of this dissertation is to add to the knowledge of bias criminality and its effects on communities. Therefore, social disorganization theory – with its emphasis on communities and crime – presents a solid theoretical framework with which to examine bias criminality.

Social disorganization theory also informs the research design of this dissertation. Common indicators of social disorganization theory are considered and included as the basis for creation of independent variables for this dissertation. Additionally, in order to provide an appropriate explanation of bias crime occurrence at the county level, the historical development of social disorganization theory is presented and discussed. An historical presentation of the social disorganization literature provides insight into the development of the theory, from its genesis to the most recent contributions, thereby providing theoretical and methodological guidance for this dissertation.

Social Disorganization Theory

Social disorganization is one of the most popular theories in the study of communities and crime. The roots of social disorganization theory extend back to Robert Park (1952) and his theory of human ecology. The main concept was that each city had a certain *organic unity* and *natural areas* where various groups of people lived. In addition, Park theorized that these *natural areas* could change based on the ecological process of "invasion, dominance, and succession." Robert Park and Ernest Burgess (1925) contributed the notion of *concentric zones* in cities. Burgess suggested that at the city center was Zone I - or the business district. Zone II was typically the oldest section of the city and included frequent "invasion, dominance, and succession." Farther out in the city is Zone III, which was comprised of modest homes and apartments, occupied by residents who had escaped Zone II. Zone IV was occupied by residents who lived in single-family homes and expensive apartments. Zone V was the commuter zone. Park and Burgess (1925) suggested that the changes that occurred throughout the zones exemplified the "invasion, dominance, and succession" perspective in which residents moved in a radial fashion outward into a different zone.

Informed by the research of Park and Burgess (1925), Clifford R. Shaw and Henry D. McKay (1942) examined juvenile delinquency and its uneven dispersion in space and time across Chicago. The Chicago School researchers found that juvenile delinquency tended to be concentrated in areas of the city with low economic status. These particular neighborhoods where delinquency and crime were concentrated were also near areas of heavy industry or commerce, had declining populations, and had numerous abandoned buildings. In addition, Shaw and McKay found that these *disorganized neighborhoods* remained in such a manner regardless of the race, ethnicity, or national origin of its residents. Such findings were still new to criminology and positioned Shaw and McKay in the direction of examining communities for contributing factors to crime, rather than assuming individual culpability.

Ultimately, Shaw and McKay (1942) suggested that neighborhoods that were in transition tended to be the most socially disorganized. These neighborhoods often had particularly high rates of residential mobility compared to other areas of the city, had a high level of racial heterogeneity, and had low socioeconomic statuses. Given these unstable structural elements, socially disorganized neighborhoods were characterized as having low social control. Therefore, the institutions that might provide social control in more stable and organized neighborhoods were comparatively weak in socially disorganized neighborhoods. Essentially, the researchers implied that in the inner city families could be disrupted, institutions such as schools and churches would be poorly attended and in a state of disorder, and political groups would be ineffective (1942). Shaw and McKay (1942) then theorized that this community breakdown, as opposed to a delinquent's individual shortcomings, led to higher rates of juvenile delinquency and crime.

A criticism of social disorganization theory was that it emphasizes middle class values and is biased against differentially organized neighborhoods (Pratt & Cullen, 2005). There are numerous cultural and ethnic differences that are evident between any given neighborhoods in a city. To place judgment on "disorganized" neighborhoods does not necessarily make them *disorganized*; rather, it allows them to be seen as differentially organized. Consequently, numerous scholars viewed social disorganization theory as irrelevant and excluded it from modern criminology. Although researchers regarded social disorganization theory as relevant throughout the 1950s and 1960s, by the 1970s Shaw and McKay's theory had been marginalized and nearly abandoned by criminologists (Pratt & Cullen, 2005).

A Resurgence of Social Disorganization Theory

During the 1980s, criminologists found a renewed interest in Shaw and McKay's social disorganization theory. As crime and disorder seemed to creep back into the public's attention during the 1980s, there was a need to further examine macro-level issues related to crime and delinquency. Some scholars suggest the second wave of interest in social disorganization theory came as a result of the conservatism and social inequality present in Reagan Administration policies in the early 1980s (Cullen & Agnew, 2003). Whether the cause of the renewed interest was due to unequal policy or increasing crime rates, social disorganization theory was reignited to help explain the relationship between communities and the crime they experience on a day to day basis. In order to present the progression of social disorganization theory since the 1980s, the following sections provide discussion of significant contributions to the perspective.

<u>Blau and Blau (1982)</u>

In their 1982 study, Blau and Blau examined urban violence in 125 of the largest cities in the United States. The authors found that socioeconomic inequality between African American and Caucasian residents, in addition to socioeconomic conditions generally, increased violence. However, Blau and Blau (1982) reported that once economic inequalities were controlled, the rates of violent crimes were no longer influenced by poverty. Moreover, Southern location and the proportion of African Americans in a specific location had a minimal influence on violence. This suggests that if there is indeed a culture of violence, that particular culture is rooted in economic inequality and not in race.

From the results of the Blau and Blau (1982) study, there is further evidence that macro-level factors could influence crime rates. In this case, economic inequality, a major tenet of Shaw and McKay's social disorganization theory, positively affects the violent crime rate. Although Blau and Blau (1982) examine several theoretical perspectives, including labeling theory and Marxist theory, their study exemplifies the relevance of community-level factors and their effects on crime. Although the authors exposed a similarity with Shaw and McKay's theory in that poverty influences crime rates, Blau and Blau (1982) suggest that race and Southern location are not as influential in predicting criminality. Therefore, it is worth noting that even with slightly different variables, the Blau and Blau (1982) provide some indication that economic inequality and poverty seem to provide a better explanation of criminality.

Sampson (1986)

Sampson is one of the leading scholars that have advanced social disorganization theory. In 1986, Sampson proposed adding family disruption to the structural factors of poverty, urbanism, residential mobility, and racial/ethnic heterogeneity. The relevance of this addition to social disorganization theory is that if a neighborhood has a number of households with inadequate parents or single-parent households, and it has the original structural factors of the theory present, social disorganization is likely to result. It is important to note, however, that

Sampson (1986) explained that a neighborhood would need to have numerous households with family disruptions - not just an isolated case. The idea is that disrupted families would lead to a lack of social control. This, in turn, would contribute toward the inability of a neighborhood to control delinquent or criminal behavior.

Sampson's contribution was particularly useful due to his extension of social disorganization theory. Since the renewed interest began in the early 1980s, no scholars have posited extensions to Shaw and McKay's social disorganization theory. Although Sampson retained much of Shaw and McKay's original structural components of the theory, he included family disruption as well. Blau and Blau (1982) may have reintroduced discussion about social disorganization theory, but unlike Sampson, they did not add any structural components to the theory. Therefore, it is clear that Sampson began the trend of important extensions to social disorganization theory that would come for the next ten years.

Skogan (1986)

Yet another study that has informed social disorganization theory is Skogan's 1986 examination of the effect of fear of crime on neighborhood change. Skogan (1986) suggested that fear can cause dramatic impacts on communities such as the following: withdrawal from community life; a weakening of the informal social control process that is known to inhibit crime, delinquency, and disorder; a weakening of the organization in the community and its ability to mobilize to reach its goals; poor business conditions; the presence of crime and delinquency from outside the community and the growth of the same within the community; and changes in the population. According to Skogan (1986), even though fear of crime does not necessarily reflect the actual crime rate, it can affect the overall organization of the community.

Those communities that are gripped with the fear of crime can be excluded from social and economic benefits of the mainstream society.

Skogan's contribution to the development of social disorganization primarily concerns the effect of fear of crime in communities. This adds a new variable that is based on the overall feelings of the residents of the community and mediates the theorized outcome of crime. Being aware that only the fear of crime is enough to cause social disorganization is helpful in two ways. First, awareness of this theory could help some communities share facts about crime rates. After all, in some communities, there is always the real possibility that residents are overly concerned about the crime rate. Attenuating their fears might help to rebuild social cohesion and prevent crime and disorder caused by social disorganization. Second, even if a community is particularly troubled with a high crime rate, combating residents' fears could have an impact on their willingness to get involved in their communities, and ultimately lower social disorganization and crime.

Bursik (1988)

Perhaps some of the largest contributions to the development of social disorganization theory were Bursik's criticisms that he posited in 1988. The first criticism is that many dismiss social disorganization because it cannot address individual-level behaviors. Bursik (1988) argued that since the objective of the theory is to examine community-level factors that lead to disorganization, it is inappropriate to expect social disorganization theory to contribute to the social psychological literature. Bursik's (1988) second criticism lies in the fact that social disorganization theory assumes stable ecological structures. He suggested more emphasis should be placed on the dynamics of urban change in order to better assess social disorganization in any community. A third criticism is the ambiguity of the measurement of social disorganization.

Bursik (1988) suggests that Shaw and McKay (1942) did not properly differentiate between social disorganization and the phenomena it supposedly causes. For instance, is delinquency considered social disorganization or rather the outcome of social disorganization? Fourth, there are discrepancies in how crime and delinquency is measured. This may the result of differential handling by the criminal justice system on many levels. However, there is likely some variation in the records, whether they are self-report or official records. Last, there are differences in the definition of social disorganization that vary by location. If the definition is defined as the inability of a community to attain goals that are agreed upon by the community, then there is an assumption that the community agrees upon one definition of community goals. Bursik (1988) suggested that since communities differ, then so do definitions of social disorganization.

Also important to the development of the social disorganization perspective are Bursik's extensions of the theory. First, Bursik (1988) suggested the use of contextual analyses with the use of official data and self-report data. Although difficult to attain, the use of these two data types would significantly improve criminological knowledge of the contextual effects of social disorganization. Second, victimization data could be used to better understand issues surrounding social disorganization. Additionally, Bursik (1988) suggested that other theoretical perspectives, such as routine activities theory, can be used concurrently to social disorganization to aid in the understanding of neighborhood factors.

Bursik (1988) contributed to the development of social disorganization in numerous ways. Not only did he criticize the theory and analyze prior studies, but he provided suggestions for future research. This approach differed from much of the other research available on the topic of social disorganization in that it did not test the theory or any part of the theory.

However, the perspectives and theoretical development that Bursik proposed are useful in tracing the development of social disorganization over the years.

Sampson and Groves (1989)

Sampson and Groves's 1989 test of social disorganization theory was a first of its kind. To some, it is considered a classic in criminology (Lowencamp, Cullen, & Pratt, 2003). Up until that point, Shaw and McKay's social disorganization theory had never been tested by social scientists. The authors hypothesized that ethnic heterogeneity, low economic status, residential mobility, and family disruption would lead to social disorganization. Sampson and Groves (1989) also measured social disorganization with three factors: sparse local friendship networks, unsupervised teenage peer groups, and low organizational participation. As a consequence of social disorganization, crime rates were hypothesized to increase. The theory was first tested by administering a survey to 10,905 residents of Great Britain. The results from the survey supported social disorganization theory. In the same study, the researchers administered a replication and surveyed another 11,030 residents of Great Britain with the same results. Although Sampson and Groves suggested that there are a few limitations, most importantly that social disorganization was only measured with three variables, the overall results were theoretically consistent with Shaw and McKay's social disorganization theory.

To give more credit to Sampson and Groves's test of social disorganization theory, it is important to mention that Lowencamp, Cullen, and Pratt conducted a replication in 2003. These authors used data from the 1982 British Crime Survey and used similar models and measures to those that Sampson and Groves used. The authors' results suggested Sampson and Groves's results were not artifactual and are therefore consistent with social disorganization theory.

Sampson and Groves's (1989) testing of social disorganization theory was particularly influential in terms of criminological theory development. Not only was this the first test of the theory, but the results of both studies supported the theory. Another notable contribution of Sampson and Groves's study was the addition of "family disruption" to the theory. Although Sampson included this factor from his 1986 study, for the 1989 study, the authors extended the theory and tested it. Not only did Sampson and Groves discover there may be more merit to social disorganization theory than has previously been thought, but the addition of "family disruption" allowed a more thorough examination of the theory and it exemplified the importance of macro-level theories. To date, no other researchers had made such an impact on social disorganization theory since Shaw and McKay. Sampson and Groves's theory testing paved the way for replications and further development of social disorganization theory.

Sampson and Wilson (1990)

After numerous of extensions of social disorganization theory, Sampson and Wilson (1990) acknowledged that the meaning of *social disorganization* had become the inability of a community structure to realize the common values of its residents and maintain effective social controls. Therefore, the authors suggested that there are various macro-social forces (e.g. housing discrimination and segregation) that interact with community-level factors to hinder the formation of social organization. Moreover, Sampson and Wilson (1990) suggested cultural disorganization provided another way to examine crime and race. The authors discussed cognitive landscapes, or ecologically structured norms that help people know how to navigate the expectations of conduct. Also pertinent is the idea of social isolation. Essentially, this is the lack of contact with institutions or individuals from the mainstream society. The authors suggest that these factors are not necessarily present in the neighborhood context. Rather, they result from structural inequalities that many poor, urban communities routinely experience.

Sampson and Wilson (1990) contributed significantly to the discussion on social disorganization and communities and crime. Although their discussion of social disorganization is similar in many ways to previous studies, they proposed the idea of cultural disorganization. This concept provided a fresh view on issues such as race and crime and poverty and crime. By acknowledging that there are external factors that influence cognitive landscapes and social isolation of community residents, Sampson and Wilson set the stage for the later examination of cultural issues such as Elijah Anderson's (1999) study, *Code of the Street* and Warner's (2003) study of attenuated culture and social disorganization theory.

Bursik and Grasmick (1993)

Neighborhoods and Crime: The Dimensions of Effective Community Control was another influential contribution to social disorganization theory. Although the authors cover a lot of theoretical ground in their book, the systemic theory of neighborhood crime control emerged as the take away contribution. Bursik and Grasmick (1993) suggested that in the systemic model, there is a link between local crime control and the numerous public control systems present in any community. For instance, every neighborhood or community has a variety of economic and political institutions that control it. Using this systemic model, the authors examined various aspects of urban community life, such as fear of crime and gang involvement.

In past studies, scholars have added to social disorganization theory, tested it, and examination various factors that mediate a community's ability to prevent social disorganization. Bursik and Grasmick (1993) take social disorganization theory further by introducing the systemic model, therefore expanding the understanding of the theory. Although the authors broaden the understanding of social disorganization theory, they do not take into account the influence that culture has on social institutions and crime rates. They claim that crime can be explained without culture taken into account, therefore proposing that the structural perspective of social disorganization theory is sufficient. Although Bursik and Grasmick (1993) largely ignored culture, they made this apparent, and therefore prompted further studies based on cultural aspects of urban community life.

<u>Sampson, Raudenbush, and Earls (1997)</u>

One of the largest contributions to social disorganization theory came in the way of a concept that is nearly oppositional to disorganization. Sampson, Raudenbush, and Earls (1997) applied the term "collective efficacy" and used its presence to explain the lack of crime and disorder in public spaces. Collective efficacy is similar to the notion of social capital. Coleman (1988) explains social capital as a network between various individuals that helps people achieve common goals. The authors argued that when there is much social capital in a community, there is a lower amount of observable crime. Utilizing the theory of social capital, collective efficacy theory suggests that when there is "cohesion and mutual trust," residents are likely to take action to achieve community goals of public order (Sampson, Raudenbush, & Earls, 1997). This amounts to residents of a community getting together to organize a neighborhood watch group or making complaints about disorder to the police.

In a test of their theory of collective efficacy, Sampson, Raudenbush, and Earls (1997) videotaped both sides of the street in a large portion of Chicago, Illinois in order to observe instances of physical disorder (such as abandoned properties or automobiles). Additionally, the authors interviewed residents of the various communities about the apparent social disorder. The results of the study indicated that physical and social disorders were closely related to differential land use and poverty. Therefore, the authors were able to conclude that lessened collective efficacy and structural factors were instrumental in the explanation of crime.

Sampson, Raudenbush, and Earls's (1997) addition to social disorganization theory is perhaps among the most salient. Since the early 1980s, when social disorganization theory began to emerge back into favor, numerous scholars have attempted to examine factors associated with neighborhood disorder. However, these authors concentrated on the presence of organization (informal social control) as opposed to the lack of social cohesion, or social disorganization. The authors' efforts to examine this new perspective allow the examination of factors that can influence social *organization*. For instance, with collective efficacy theory, researchers can examine the reasons why individuals and communities do not have the ability to achieve common goals. They also can study why certain communities do have the ability to achieve varying levels of collective efficacy. However, the authors stated that because collective efficacy matters, that does not mean that various forms structural inequality should be ignored. Sampson, Raudenbush, and Earls contributed one of the most significant pieces of the social disorganization puzzle and provided insight on how collective efficacy fit together with residential mobility, socioeconomic status, urbanism, ethnic heterogeneity, family disruption, and unsupervised peer groups (Pratt & Cullen, 2005).

Morenoff, Sampson, and Raudenbush (2001)

More recently, efforts were made by Morenoff, Sampson, and Raudenbush (2001) to examine the linkage of concentrated disadvantage and collective efficacy and its effect on homicide. The results indicated that both factors independently predict increased homicide. The authors also found that spatial proximity to homicide is related to increased homicide rates.

Essentially, the authors used homicide to represent urban violence. The overall results suggested that spatial dynamics and neighborhood inequalities are important in explaining urban violence.

The findings from the Morenoff, Sampson, and Raudenbush (2001) study represent a different attempt to examine social disorganization theory. Rather than studying crime or delinquency in general, the authors chose to use homicide as an indicator of urban violence. This is an important contribution in that is exemplifies how social disorganization theory can be used to explain a specific type of crime as opposed to general references of crime, delinquency, or disorder. Certainly, this perspective allows a testing of social disorganization theory as it affects bias crime occurrence. Similar to other studies, however, the authors continued to use the construct of *collective efficacy* in order to examine social cohesion.

Warner (2003)

Most of the studies in the social disorganization literature discuss structural disorganization. Although there seems to be merit to this perspective, Warner (2003) examined the role of attenuated culture and its effect on communities. Using survey data, the author examined residents from 66 neighborhoods from a Southern community. Prior research has suggested that when cultural elements are reduced, it cannot provide for effective social control in the community (Kornhauser, 1978). Warner's results support that conclusion as she found that the level of social ties and concentrated disadvantage influence cultural strength. This, in turn, has a significant impact on social control.

Warner's recent study is an important contribution because it suggests the inclusion of culture into the social disorganization perspective. Sampson and Wilson (1990) suggested that cultural disorganization become included in social disorganization theory along with the structural perspective. Although there has previously been discussion about this in past studies, some scholars such as Bursik and Grasmick (1993) have dismissed culture in favor of a structural approach. Warner brought culture back into the discussion, and for some, has provided hope that further integration between structural and cultural factors will occur with social disorganization theory.

Sampson (2012)

More recently, Robert Sampson (2012) has reexamined communities and crime in Chicago. Perhaps the most salient contribution of this work is Sampson's offering of a general theoretical approach to understanding neighborhoods and crime in American cities. Given this is a significant contribution to the literature on communities and crime, there a several aspects of Sampson's work worth noting. For instance, Sampson (2012) suggests that with regard to racial segregation and concentrated disadvantage, neighborhoods replicate themselves. Given racial segregation and concentrated disadvantage are not new phenomena in American communities; they tend to continue from decade to decade with little change. Sampson (2012) refers to this as "stability of change." In addition, Sampson posits that racial segregation and concentrated disadvantage affect neighborhoods in that they influence collective efficacy, cynicism about the legal system, residents' reception of community disorder, and neighborhood stigmatization. Perhaps another important contribution of Sampson's (2012) work includes his assertion that communities are influenced by the context of larger community dynamics. It is therefore an ineffective approach to treat each community as if it were independent from its surroundings.

What is most important to recognize from Sampson's work on Chicago neighborhoods is that much of what affects a community's level of disorganization is continuous – even with the relative increase in placelessness. This is highly important to the current literature on communities and crime as it contributes the notion that macro level effects are often overlooked and should be included in future studies.

Testing and Applying Social Disorganization Theory

According to Sampson (2003), learning from macro-level social disorganization theory, it is apparent that there exists more of a need to change communities rather than to change people – and by virtue of that, their behavior. Therefore, implementing policy and directing community action toward affecting a community as a whole is particularly appropriate. Although social disorganization theory has not been used to examine bias crime offending at the county level, it has been approached in a variety of other settings. For instance, social disorganization theory can be and has been applied to communities in a variety of ways including Shaw and McKay's Chicago Area Projects (CAP) in Chicago, Project on Human Development in Chicago Neighborhoods (HDCN), urban renewal, community policing, disorganization and far-right extremist violence, and *Weed and Seed*. At times, these tests of the theory overlap; however, they are common implementations of social disorganization theory, regardless of their effectiveness. These applications of social disorganization theory are helpful in that they can inform public policies created to combat bias crime occurrence in American communities.

<u>Chicago Area Project (CAP)</u>

Perhaps most salient is a discussion of communities and crime policy with a summary of Shaw and McKay's application of their own social disorganization theory. CAP was a program put in place in Chicago, Illinois in 1932 to lower delinquency across the city. Several projects lasted through the 1960s and had a variety of goals. Shaw and McKay selected high crime neighborhoods in which to implement the CAP program. Of particular importance to the researchers and the Chicago Area Project was the mobilization of community groups to aid in the development of social organization and social control. Existing groups, such as labor unions and churches were targeted first, but the aim was to include as many law-abiding citizens as possible in hopes that their involvement would help create *community committees* (Vito, Maahs, & Holmes, 2006). In addition, Shaw and McKay set out to develop informal relationships with the delinquent youth, especially gangs, in crime ridden neighborhoods (Vito, Maahs, & Holmes, 2006). This allowed troubled youth to have access to recreational programming all the while providing exposure to "conventional" residents. Other work was initiated as well, such as efforts to clean up neighborhoods and rid them of garbage, graffiti, and other forms of physical decay (Vito, Maahs, & Holmes, 2006). All of these efforts exemplify social disorganization theory's proposition that disorganization is a problem of the community rather than the individual residents.

Unfortunately, there is no rigorous evaluation of the CAP program in Chicago. Given the length of time that CAP was in effect, there were various reports written throughout years. At best, CAP provided mixed results (Vito, Maahs, & Holmes, 2006). In some communities with strong community committees, there were reductions in juvenile delinquency. However, many neighborhoods reported no results or even an increased delinquency rate. Although the Chicago Area Project was unable to provide clear results related to social disorganization theory, the efforts likely set the stage for later applications of the theory.

<u>Project on Human Development in Chicago Neighborhoods</u>

In 1995, Sampson (2012) notes that a research program named Project on Human Development in Chicago Neighborhoods (PHDCN) was begun in order to study criminality in Chicago while accounting for the context of community. Essentially, the methodological basis for this study was a rather extensive survey of Chicago residents – amounting to approximately

8,782. In designing the survey, Sampson (2012) notes that two specific components were constructed to measure "informal social control" and "social cohesion" – certainly, two important indicators of social disorganization theory. The result of this was the creation of a collective efficacy scale used to measure the same in Chicago's neighborhoods. Additionally, this study aimed to inform the growing communities and crime literature.

Although PHDCN was rather extensive, several findings emerged from the endeavor. First, researchers found that collective efficacy in Chicago's neighborhoods varied widely, certainly by time and space. However, that collective efficacy that did exist at greater levels was associated with lower crime rates. Second, Morenoff et al. (2001) report that the density of neighborhood-based organizations and the higher participation by residents in volunteer programs predicts high levels of collective efficacy; in turn, creating controls for poverty and crime.

Urban Renewal

On the surface, it seems relatively easy to build a case for urban renewal – or gentrification. In continuing with social disorganization theory, urban renewal would add higher-income households to poverty-stricken neighborhoods. Some believe urban renewal functions as a balancing act and equalizes the neighborhood with social, political, and economic benefits (Vito, Maahs, & Holmes, 2006). However, certainly the gentrification of a neighborhood exacerbates the tensions - or strain - between various social classes. Gentrification has been associated with creating evidence of social dislocation. However, some scholars hope that the renewal of socially disorganized neighborhoods would improve social cohesion and lower crimes rates. In reality, and as suggested, this is a failed policy as urban renewal often forces poorer residents to leave the area (Vito, Maahs, & Holmes, 2006). As wealthier residents move into the area, property taxes increase and cause the neighborhood to be out of reach for its original residents, thereby worsening social cohesion. In many cases, this is an unintended and undesired effect of urban renewal. However, historically urban renewal has been a tool for furthering racial inequality.

A particularly troubling example of gentrification occurred in Detroit, Michigan during the 1950s. Detroit has a long and bitter history with racial inequality, though the urban renewal that occurred in the neighborhoods of the Lower East Side and in Paradise Valley was extremely difficult for African American residents of the city (Sugrue, 2005). This urban renewal, as it was called, was really a relocation of African Americans and an attempt by the city to "clean up." In the midst of a housing crisis, the city removed "slum" areas of the city in which many African American residents lived. Not only did this leave these disadvantaged residents without a home, but it overcrowded the unaffected African American neighborhoods of Detroit. In addition, the city of Detroit also was undergoing a massive highway project which further displaced numerous African American families. Detroit's urban renewal plan was nothing more than another example of structural inequality. There may be other examples of urban renewal programs that are well-intentioned. However, the problem with the application of social disorganization theory to urban renewal programs is that it may be implemented without regard to those who do not have the resources to continue living in the community.

Community Policing

Community policing is not itself a policy; rather it is a philosophy of policing. In addition, it can be considered a direct application of social disorganization theory. Skogan (2006) suggests community policing is a process of changing police culture and decision making processes. Essentially, it leaves many of the decisions of how to police neighborhoods up to the residents and the officers who patrol those neighborhoods (Skogan, 2006). There are three processes that are often considered to be part of community policing. Skogan (2006)suggests that decentralization, problem solving, and citizen involvement are instrumental to the practice of community policing. It is capable of tackling a wide range of community problems, not just crime. Therefore, community policing takes on many community problems and works with community member to solve them (Vito, Maahs, & Holmes, 2006). Therefore, it can be viewed more as a type of community action and it can involve various criminological theories such as social disorganization and broken windows.

The various practices of community policing can be seen as community action related to social disorganization theory. The policies and community actions that are often achieved under a community policing framework are thought to build collective efficacy and restore social control to neighborhoods. It should be noted, however, that Sampson, Raudenbush, and Earls (1997) discovered that community policing can build collective efficacy for neighborhoods that already have it. These neighborhoods are generally white and have numerous resources available to them. Conversely, the authors note that the philosophy of community policing has yet to provide evidence that it builds collective efficacy in neighborhoods that did not previously engender collective efficacy (Skogan, 2006).

It would seem inappropriate to discuss community policing and social disorganization theory without mention of broken windows theory. Although broken windows theory is an entirely different theory than social disorganization theory, community policing is so expansive that broken windows theory is often used to inform community policing policies and community actions. Broken windows theory refers to the theory that Wilson and Kelling developed in 1982 to explain that social disorder and physical decay undermined a community’s ability to defend itself against crime. Abandoned cars, graffiti, panhandling, street prostitution are all forms of disorder which Wilson and Kelling suggested a community has given up (Wilson & Kelling, 1982). Therefore, crime and disorder spiral out of control and unless there is significant intervention, crime pushes the community downhill. Community policing is often employed to develop policies and community actions that can reduce social disorder and physical decay. In many respects, the move toward community policing has allowed broken windows theory an opportunity to become a popular theory for the explanation of neighborhood crime and disorder. Using this perspective to inform social disorganization theory is rather salient in exposing the ways a community can continue to build collective efficacy.

Keeping in mind that community policing can appease both the social disorganization theorist and the broken windows proponent, there are numerous functions that a community policing department can have. For instance, many police departments take part in engaging with the community in various ways such as holding citizen police training academies, conducting surveys to gather information about community satisfaction, opening storefront police offices, walking door-to-door to identify problems, mailing out newsletters, conducting education classes on issues such as drugs, and working with municipalities to enforce health and safety rules (Skogan, 2006).

Perhaps the best example of community police in practice is the Chicago Alternative Policing Strategy (CAPS). Although CAPS was based on broken windows theory, from its community policing framework, numerous community building policies and community actions resulted. For instance, according to Skogan (Skogan, 2006), there were four central elements that were integral to community policing in Chicago: turf orientation, community involvement, problem solving, and interagency partnerships. First, turf orientation can be best described as the presence of community service officers or problems solvers whose job is to respond to the "problem of the week." Second, community involvement was a large component of CAPS. There were various forms of community involvement such as identifying local problems, helping police set priorities, taking individual actions and actions in conjunction with the police, and the usage of beat meetings to hold police officers accountable for their efforts. Third, problem solving involved numerous topics, not all of which were criminal matters. The stipulation was that something was defined as a problem only if it was an ongoing situation or a group of related events. Last, the police worked with other agencies to create partnerships. This allows the police to have abandoned automobiles towed quickly and to have vacant lots mowed. In other cases, police worked with agencies who would immediately paint over graffiti.

In conjunction with the community residents in Chicago, Illinois, the police were able to make some progress in the city (Skogan, 2006). Crime was down since the program was implemented, but nationwide trends indicated similar results. Skogan (2006) found that African Americans and Caucasians saw improvement due to CAPS, but the Latino community did not. All four of the CAPS community policing strategies discussed address pertinent theoretical issues relating to urban decay, crime, and disorganization. Given community policing is a broad concept in policing, it allows for various community activities and policies to be developed. Regardless of how and where community policing is practiced, the core idea is to leave many of the decisions of how to police neighborhoods up to the residents and the officers who patrol those neighborhoods.

Weed and Seed

Terence Dunworth and Gregory Mills (1999) describe *Weed and Seed* as an incubator for social change. Social change is brought about by strategies that mobilize and coordinate resources in targeted communities. Essentially, *Weed and Seed* is a policy directed at stabilizing conditions in high crime neighborhoods and promoting community restoration (Dunworth & Mills, 1999). As mentioned, policies do overlap in scope, and *Weed and Seed* is no exception. Although *Weed and Seed* brings many new ideas to the table to rebuild communities, there is some familiarity with the policy.

Weed and Seed policies generally have four essential components (Dunworth & Mills, 1999). First, communities engage in analysis and planning of the problems that need to be addressed in their communities. In addition, strategies are implemented to address these problems. Second, neighborhood weeding takes place. Weeding involves concentrated efforts of law enforcement in order to identify, apprehend, and prosecute various criminals. Third, community policing is implemented in order to bridge the gap between weeding and seeding. Fourth, the community begins to seed. This involves numerous human services including youth activities, adult literacy classes, and parental counseling.

In a nationwide evaluation of *Weed and Seed*, Dunworth and Mills (1999) found that the policy is a rather strong stimulant of community building. It aids in creating public and private partnerships to develop programs that benefit communities. In addition, *Weed and Seed* policies concentrated on building trust and on encouraging community participation in efforts to revitalize communities. It is evident that *Weed and Seed* displays the factors of social disorganization theory in that the goal is to involve the community and various agencies in attaining a social cohesion in order to lower crimes rates together.

<u>Community Disorganization and Racially Motivated Crime</u>

In his 2007 study, Lyons explores the relationship between community context and the various crimes motivated both by animus for black persons and white persons. Lyons used official data from the City of Chicago Police Department, U.S. Census data, and community survey data from Chicago. In doing so, he was able to discern the contextual factors that affected the creation of social organization – or collective efficacy. Lyons (2007) found that perhaps in opposition to general assumptions about bias or hate criminality, anti-black crime is actually most likely to occur in relatively organized communities with high levels of social control. On the other hand, anti-white crime tends to take place in rather disorganized neighborhoods – spaces known for residential instability. With these findings taken into account, Lyons (2007) certainly establishes a new perspective through which to view bias-based criminality. As mentioned, applications of social disorganization theory to bias crime are almost non-existent; therefore, any scholarly attention to community organization and residential instability is quite salient.

Disorganization and Far Right Violence

More recently, Freilich, Adamzcyk, Chermak, Boyd, and Parkin (2013) introduce a county-level test of social disorganization theory as applied to far-right extremist violence. Primarily, Freilich et al. (2013) approached the study with the intention of examining variations in the counties in which far-right extremists lived during the time of the criminal event. Social disorganization theory was used in order to help uncover some of the variations in the spatial aspect of the study – the county. Moreover, the authors examined the differences that American counties provided in understanding far-right extremist attacks. However, Freilich et al.'s (2013) study adds to the literature in a significant way in that it uses social disorganization theory to explain these variations. The results of the study indicate that perhaps social disorganization theory is helpful in this explanation as it provides details into the counties in which perpetrators resided at the time of the attack. This is then juxtaposed against the findings with regard to the location of the attack. In this way, the authors suggest that certain variables from social disorganization theory do work to explain “regular crime” and far-right extremist criminality alike. However, there are some differences in that not all attributes can explain both types of crime (Freilich, Adamczyk, Chermak, Boyd, & Parkin, 2013). It is certainly worth noting that this study is quite new in its usage of social disorganization theory to speak to far-right violence. Given this dissertation’s focus is on bias crime occurrence at the county level, Freilich et al.’s (2013) is particularly relevant.

In summary, various policies and community actions designed to lower crime rates can be informed by testing social disorganization theory. Shaw and McKay’s CAP program used their social disorganization theory and found mixed results. Urban renewal projects, such as those in Detroit, suggest that injecting social, economic, and political stability can build social cohesion, however they are usually met with failure. Community policing perspectives often use social disorganization theory and broken windows theory in order to create a different culture of policing, which in turn provides community actions that support community involvement and social cohesion. Chicago’s CAPS project found limited success in its white and African-American communities, but failed in the Latino community. The PHDCN primarily identified ways of understanding informal social control and social cohesion – all in an effort to examine collective efficacy. Researchers found *Weed and Seed* to be a strong stimulant of community building in a national evaluation. Freilich et al. (2013) found that social disorganization theory does help to explain some attributes of far-right extremist violence, but not other. The involvement of the community and the promotion of social cohesion and change reflect the basic implications of social disorganization theory.

Social Disorganization Theory and Bias Crime in the United States

From Shaw and McKay's (1942) original social disorganization theory to the 2010s, there has been significant theoretical development of this important communities and crime perspective. Social disorganization theory began as a macro-level theory to examine the differences in crime between neighborhoods. Shaw and McKay theorized that these neighborhoods often had particularly high rates of residential mobility compared to other areas of the city, had a high level of racial heterogeneity, and had low socioeconomic statuses. Although this theory went through a period of several years where it was considered irrelevant, it returned to life during the early 1980s. Since that time, there have been numerous contributions by various scholars. There have been tests of different variations of the theory over the years and nearly all studies have reported results supporting social disorganization theory's relevance. To date, the variables that are most often considered to be central to social disorganization are socioeconomic status, urbanism, racial heterogeneity, residential mobility, unsupervised peer groups, family disruption, and collective efficacy. These variables are used to inform this dissertation as it relates to bias crime. Moreover, there have been suggestions that social disorganization theory include structural and cultural variables. Although there is some debate about that issue, there is overall support for social disorganization theory as is currently exists (Pratt & Cullen, 2005).

The bias crime literature is largely underdeveloped with regard to theory – both at the micro and macro levels. The aim of this dissertation is to investigate whether traditional indicators of social disorganization theory inform the knowledge base on bias crime occurrence in United States counties. Therefore, the following discussion presents the necessary components of social disorganization upon which this dissertation is based. It is with regard to the indicators of social disorganization theory explored by other scholars in their studies of crime and violence, that this dissertation expands knowledge of bias criminality in the United States.

Although the aforementioned discussion of social disorganization theory is pertinent to understanding the perspective through which this dissertation is considered, of most relevance are the traditional indicators of social disorganization theory that will be used to measure its presence. Freilich, Adamczyk, Chermak, Boyd, and Parkin (2013) considered social disorganization theory and its relevance in explaining far-right terrorism occurrence in various contexts. Freilich et al. (2013) explore whether social disorganization theory can be used to account for county-variations in where far-right terrorists lived during the time of incidence. Additionally, the authors created a unique measure of social cohesion by which social disorganization theory could be tested. This was achieved by aggregating opinion data from the General Social Survey. The work of Freilich et al. (2013) informs this dissertation in that it identifies eight conceptual indicators of social disorganization theory that can be used to understand terrorism at the macro-level. Given the similarities between terrorism and bias crime, several of these indicators are useful in informing the construction of appropriate measures to test social disorganization theory and its ability to inform bias crime occurrence at the county level. The following indicators identified by Freilich et al. (2013) will be used to inform the measures social disorganization theory in this dissertation: 1) deprivation; 2) diversity; 3) disorganization; and 4) social cohesion.

Hypotheses

Given this dissertation seeks to explore the bias crime occurrence in American counties, several of Freilich, et al.'s (2013) indicators of social disorganization theory are used. Based on the authors' study, this dissertation will similarly measure social disorganization with the following indicators: low economic status, social heterogeneity, social cohesion, and residential mobility.

Low Economic Status

Deprivation can be measured in a variety of ways; however, this dissertation will consider deprivation as an economic indicator. In terms of economics, there is importance in identifying one's ability to engage in the larger economy. For instance, attaining and maintaining employment, the ability to purchase goods are two examples of ways economic participation can be measured. As such, the lack of presence of these indicators could indicate a specific economic deprivation. Lacking meaningful employment and the inability to have purchasing power are certainly worthy of consideration as they represent the inability of a person to take part in the larger economy. Therefore, this dissertation examines *whether higher percentages of unemployment in United States counties are more likely to experience bias crime occurrence (H1).*

Social Heterogeneity

Although social heterogeneity – or diversity - refers to a broad range of concepts, it is certainly relevant with regard to bias crime occurrence. Perhaps the very concept of bias crime is related to the notion of diversity – the presence of "difference" creating a sense of disorganization in a community. This can be measured in a variety of ways; however, the most feasible way is by examining the demographics of a given community. In the case of this dissertation, that means examining counties for various levels of diversity. This will be measured by accounting for the percentage of racial minorities living in the given counties. Moreover, diversity will be measured by accounting for the number of foreign born persons living in each county as well.

This dissertation examines whether higher levels of social heterogeneity in United States counties are related to greater bias crime occurrence. More specifically, diversity is measured by identifying the presence of specific racial, ethnic, and religious populations in United States counties. Therefore, this dissertation explores *whether higher percentages of non-white residents in United States counties is related to greater bias crime occurrence (H2).* As mentioned, diversity is also accounted for in this dissertation by recognizing the presence of religious minorities. As such, this dissertation examines *whether higher percentages of foreign born persons living in United States counties is related to bias crime occurrence (H3).*

Social Cohesion

In order to capture more traditional indicators of social disorganization theory, another aspect of the theory is measured. With relation to the notion of social cohesion, it is possible to examine the maintenance of marital family bonds in American counties. This will be accomplished by measuring the percentage of divorced persons residing in each county in the United States. Therefore, this dissertation examines *whether high percentages of divorce in United States counties affect the level of bias crime occurrence in the respective counties (H4).* Moreover, scholars note that a community's violent crime rate can be used to measure the level of social disorganization present in that community. After all, when citizens are organized in a manner that contributes to collective efficacy, it follows that crime is less likely to occur in that community. Additionally, the presence of violent crime in a county is used to measure the social cohesiveness of such communities. As such, this dissertation seeks to determine *whether a higher crime rate in a United States county affects the level of bias crime occurrence (H5).*

Residential Mobility

This dissertation also examines the impact of residential mobility on the likelihood of bias crime occurrence in United States counties. If residents are moving to and from specific neighborhoods – or counties – it is possible that these communities do not have the opportunity to organize and thereby prevent criminality. In addition, perhaps the more people in a community that rent their homes, the less likely a community is to be socially organized. With that lack of social organization, it is then possible that these neighborhoods may experience bias crime occurrence at a differential level from other neighborhoods. Therefore, this dissertation explores *whether a higher percentage of residential mobility impacts the level of bias crime occurrence in United States counties (H6).*

CHAPTER 4: DATA AND METHODOLOGY

Chapter Four presents the data and the methodological approach used for this dissertation. Researchers have studied the numerous reasons why bias crime offending might take place; however, the extant literature is relatively silent in its discussion of factors that potentially create a community climate that is rich for bias crime offending. By examining various characteristics of American counties, their populations, and the frequency of bias crime reporting in them, this dissertation strives to explore the potential predictors of bias crime using United States counties - or their equivalent - as the units of analysis. The aim is to be able to test social disorganization theory's ability to explain bias crime occurrence at the county level. Essentially, this dissertation seeks to examine macro-level communities as they affect the occurrence of bias crimes. As such, the essence of bias crime awareness and prevention may lie in understanding the factors of social disorganization theory and the links to bias crime victimization. Given this, Chapter Four includes a discussion of classifying bias crime events, using official data, a data collection strategy, the creation of variables for the study, and a discussion of relevant methodological techniques.

Classifying Bias Crime Events in Unites States Counties

One of the challenges scholars have faced with regard to studying bias crime is simply the defining of such crimes. As noted, bias crime is a relatively newly identified type of crime in the United States and the world, alike. Although bias crime has historically existed for many years, it is only recently that it has been explored in the academic literature. Whether in the psychological, sociological, or criminological literature, the scholarly attention is relatively recent. With this taken into consideration, it is important to acknowledge that the definition of bias crime differs by space and time as well. However, this dissertation uses the official definition of hate crime as introduced by the FBI. The FBI (2008) defines hate crimes as crimes motivated by the offender's bias based on the victim's race, sexual orientation, religion, ethnicity, national origin, and disability. Although there are numerous additional social groups that could be included – such as age, residential status, and political affiliation – this dissertation follows the direction of the FBI with regard to definition. Since the FBI is the only government entity that collects annual hate crime data that can be analyzed at the county level, those data are used to measure bias crime incidence in United States counties.

It is also important to consider how bias crime occurrences exist within the context of Unites States counties. Although there is little known about bias crime in general, there is even less known about the relationship between communities and bias crime events. Scholars have examined bias crime as it exists at the national, state, and even city levels. However, bias crime occurrence in Unites States counties has not been examined in the prior research. Certainly, it is plausible that a variety of factors may influence the rate of bias crime occurrence. For instance, by examining counties, this study may be able to uncover their differences between different sizes of communities and their effects of bias crime occurrence. It is likely that there is a meaningful difference between suburban, urban, and rural communities and their influence on bias crime occurrence. By utilizing counties as the unit of analysis, this dissertation is able to account for those differences by way of including all appropriate data.

Using Official Data

This dissertation seeks to add to the scholarly literature by way of analyzing official data collected at the national, or macro-level. By testing social disorganization theory and its efficacy in explaining bias crime occurrence, this study speaks to the effects that are known from official data. Although official data are used in this study, it is important to highlight the strengths and weaknesses this type of data possesses. The following paragraphs explain the importance of official crime data in criminological studies.

Advantages of Official Data

Official data are frequently used in criminological studies due to their availability and accessibility. In fact, most of the records used in criminological research tend to be arrest reports – official records collected by local police departments (Maxfield & Babbie, 2011). Considering this definition, it is essential to note that much of the official crime data in existence in the United States are collected and maintained by local, state, and federal government entities. Although this can be at the local, state, or federal level, governments have a vested interest in recording crimes – and working to combat those crimes based on crime trends extracted from the data.

In a seminal study of self-reporting and official data as they relate to delinquency, Hindelang, Hirschi, and Weiss (1979) present several influential findings. Primarily, the authors suggest that official crime data do in fact provide valid representations of the demographics of criminality in the United States. This is extremely salient as it substantiates the use of official crime data – especially when compared to the utilization of other data types, such as self-reports. In addition, most official crime data record serious crimes – as opposed to minor crimes (Kleck, 1982). This is important to consider in that the reported bias crimes in the United States tend to be more severe in nature than they are trivial. Moreover, when the findings of self-report studies were compared to those from official records, the findings were remarkably consistent – both in terms of reliability and validity (Hindelang, Hirschi, & Weis, 1979); (Maxfield, Weiler, & Widom, 2000).

Additionally, official crime data are a matter of public record, and are therefore accessible by researchers and citizens alike. Official data are certainly available in paper format in libraries and government agencies; however, the Internet allows for a more accessible approach. For instance, by navigating to the FBI's website – and the USCB's – researchers can have access to annual crime statistics and various demographic figures. Certainly, there are limitations to official data – as is discussed later in this chapter – however, there is a need to consider bias criminality at the county level. Given the breadth of this approach, using official data is not only one of the few feasible approaches to data, but also perhaps the most inclusive as well. After all, using official data allow this dissertation to explore bias criminality across the United States as a whole – as opposed to a mere selection of communities. The result could be perhaps a more thorough – if not generalizable – set of findings about bias crime occurrence in the United States.

Drawbacks to Using Official Data

Although there are several advantages of using official crime data, there are also several negatives to the data type as well. Primarily, official crime data have a reputation for being rather conservative by nature. Essentially, because of the voluntary nature of official crime data collection, researchers often note missing data. Generally, when considering the "dark figure of crime," we know that more crime occurs than is reported to the police in the United States. This is certainly the case for bias crime as well; in fact, underreporting may even be more pronounced here than with other crime.

In addition, Hindelang, Hirschi, and Weiss (1979) suggest that official crime records can be too stringent to uncover the intricacies of criminality. Moreover, the limited nature of official records might include the fact that variation is difficult to ascertain. It may be that official records will have more minor crimes reported than major crimes. For instance, it is likely that official crime data include most reported traffic offenses, but do not account for the same proportion of robberies, rapes, and arsons. It follows that bias crime may be reported in less serious situations more frequently than serious examples. With the exception of celebrated cases, which are most likely to be reported, it may be that the bias homicide does not get reported as a being related to bias. Whether this is due to the aforementioned lack of gravity with which some police departments treat bias crime or due to oversight, bias crime is often unrecorded. Certainly, this includes the phenomenon of underreporting as well.

Official crime records also reflect the biases that may be present in criminal justice actors. Due to the disproportionate representation of lower socio-economic status individuals, males, and African Americans in the criminal justice system (Piquero, MacIntosh, & Hickman, 2002), it is probable that a similar disproportionate representation exists in the official crime records. This would certainly skew the findings of any study with dependent variables constructed from official crime data. Certainly, this limitation is acknowledged as problematic; however, when considering bias crime occurrence – given the power structure and relations – it is also necessary to consider whether the entire reporting system for bias crime reflects reality. Given the victims of bias crime tend to be from social minority groups, such as African Americans, Jewish persons, and lesbian and gay citizens - and since the police are overwhelmingly white males, it is important to consider whose story is being captured in official crime records. If official crime records reflect the power structure present in the United States, it would presumably reflect the stories of those in power – in essence, those who are part of social majority groups. After all, those in power often dictate the nature of the local culture – whether it be related to sex, race, sexual orientation, or ability.

Data Collection Strategy

The data used for this dissertation are collected from two United States government agencies and two private entities. The primary data used to capture the dependent variables and certain independent variables were provided by the Federal Bureau of Investigation's Uniform Crime Report. After the introduction of the Hate Crime Statistics Act of 1990, the FBI has been collecting reported bias crime data nationwide. These data are reflected annually in the Uniform Crime Report.

In order to properly collect the relevant data to construct dependent variables representing bias crime occurrence in United States counties, the website of the Inter-University Consortium for Social and Political Research (ICPSR) at the University of Michigan was accessed. The ICPSR has archived a variety of hate crime data from the FBI – including data for the relevant years of 2000-2009 that are necessary for this study. Each file is archived by year; therefore, each of the ten appropriate years was downloaded for the purposes of this study. The files are quite large and do include appropriate information about the frequency of hate crime occurrence, motivation of offender, and location of criminal offense. Each data file was downloaded from ICPSR in *Microsoft Excel* format, reorganized, and exported to a master *SPSS* file.

The FBI's UCR data are organized by incident, thereby inhibiting analyses at the county-level unit of analysis. Given this dissertation is specifically aimed at understanding bias crime at the county level, the incident-level data from the FBI were aggregated in order to create a county-level measure. The data were rearranged in *Microsoft Excel* so that the unit of analysis was transformed from incident-level to county-level. The created measure allowed for the number of bias crimes that occurred in each county between 2000 and 2009 to be counted. The resultant data allow for the answering of the research questions posed in Chapter Three.

In addition, data from the United States Census Bureau are used to construct the independent variables. As mentioned, the 2000 census was used as a marker for the subsequent decade. These data were gathered by accessing the United States Census Bureau's website and using the *American FactFinder* tool. From this, data representing the appropriate measures of social disorganization as well as control variables were extracted from the database. Data were downloaded in *Microsoft Excel* format and were later reorganized and added to the master *SPSS* file.

Other county-level data were provided by various sources. Religious data are provided by the Association of Religious Data Archives (ARDA). Since the USCB is prevented by law from collecting information of Americans' religious affiliations and practices, accessing the ARDA's website proved fruitful in obtaining data related to religious congregants present in the United States. In order to remain consistent with United States Census Bureau data used to construct various independent variables, data for the year 2000 were accessed and downloaded to represent the following decade. Data were available for download in *SPSS* format.

In addition, data representing the political participation of United States citizens were obtained from *Congressional Quarterly* Voting and Elections Collection. The data are available in Microsoft Excel formal for the year 2000. This allows for the creation of the relevant independent variable representing voter participation to be created and used in analyses. Specifically, this dissertation uses the number of persons per county voting in the 2000 presidential election to measure political participation.

The dependent variables for this dissertation are based on the frequency of bias crime occurrence in United States counties. In addition to including the aggregate figure of bias crime occurrence, dependent variables based on the motivation of the offender are included as well.

Each of these presents the frequencies of bias crime occurrence in each county. Specifically, the three most commonly occurring motivations are examined: anti-race, anti-sexual orientation, and anti-religion. Many of the independent variables in this dissertation are based on the traditional indicators of social disorganization theory. This allows for analyses to be conducted that explore the relevance of social disorganization theory as applied to bias crime occurrence at the county level. In order to verify that the models are answering the research questions accurately, numerous control variables are included. Each of the datasets were downloaded and aggregated in an *SPSS* file. Moreover, the research conducted for this dissertation is classified as "exempt" by Michigan State University's Institutional Review Board[3] and is therefore cleared for analyses.

Counties as the Unit of Analysis

The unit of analysis for this study is counties – or each state's equivalent – in the United States. For instance, the state of Louisiana signifies their sub-state political units as parishes. In contrast, the rest of the United States uses the term county to represent its sub-state units. In the case of this dissertation, counties are used because they allow for a more precise level of measurement than larger political units such as states. In addition, using counties as the unit of analysis can help to control for variation between the states (Maltz & Targonski, 2002). In essence, using counties allows for a greater number of communities to be studied. Moreover, as observed in Porter, Rader, and Cossmann (2012), ecological data measured at the county level are appropriate for testing social disorganization and the relevant theory. Given social disorganization theory is a macro-level theoretical approach to understanding crime, measuring it at a larger political level, such as at the county level, is appropriate. The FBI does report bias crime data at the county level and the city level, but as mentioned - county level data provide

[3] IRB #x13-1200e, Exempt #i045116

greater precision (Maltz & Targonski, 2002). However, a limitation is the fact that the majority of counties do not, in fact, report having bias crimes occur.

In order to achieve a large enough sample size to work toward statistical conclusion validity, each county and parish in the United States is included in the study. Moreover, Washington, DC is included as well. However, counties and parishes that do not report bias crimes are only included in the main model. Table 2 presents basic characteristics of all 3,141 United States counties.

Table 4.1: Characteristics of United States Counties by State

State	*Number of Counties*	*Population (2000)*
Alabama	67	4,447,100
Alaska	27	626,932
Arizona	15	5,130,632
Arkansas	74	2,673,400
California	58	33,871,648
Colorado	64	4,301,261
Connecticut	8	3,405,565
Delaware	3	783,600
District of Columbia	1	572,059
Florida	67	15,982,378
Georgia	159	8,186,453
Hawaii	4	1,211,537
Idaho	44	1,293,953
Illinois	102	12,419,293
Indiana	92	6,080,485
Iowa	99	2,926,324
Kansas	105	2,688,418
Kentucky	120	4,041,769
Louisiana	64	4,468,976
Maine	16	1,274,923
Maryland	24	5,296,486
Massachusetts	14	6,349,097
Michigan	83	9,938,444
Minnesota	87	4,919,479
Mississippi	82	2,844,658
Missouri	115	5,595,211
Montana	56	902,195
Nebraska	93	1,711,263
Nevada	17	1,998,257
New Hampshire	10	1,235,786

Table 4.1 (Cont'd)

New Jersey	21	8,414,350
New Mexico	33	1,819,046
New York	62	18,976,457
North Carolina	100	8,049,313
North Dakota	53	642,200
Ohio	88	11,353,140
Oklahoma	77	3,450,654
Oregon	36	3,421,399
Pennsylvania	67	12,281,054
Rhode Island	5	1,048,319
South Carolina	46	4,012,012
South Dakota	66	754,844
Tennessee	95	5,689,283
Texas	254	20,851,820
Utah	29	2,233,169
Vermont	14	608,827
Virginia	136	7,078,515
Washington	39	5,894,121
West Virginia	55	1,808,344
Wisconsin	72	5,363,675
Wyoming	23	493,782
Total	**3,141**	**281,421,906**

As is evident from the Table 4.1, the majority of states have dozens of counties within their borders – some more than others. Containing 254 counties, Texas is the state with the highest number of counties; with three, Delaware has the fewest. The District of Columbia has one county, the County of Washington. California is the most populous state as it has 33,871,648 residents, as of 2000. Wyoming has a population of 493,782 individuals, making it the least populous state in the country. Nationwide, as of the 2000 Census, the United States had a total of 281,421,906 residents.

Given that so many counties do not report bias crime to the FBI, it is important to account for this fact in the primary model. This allows for a more inclusive analysis that can speak to all United States counties. In contrast, subsequent models include only counties in each state that reports bias criminality to the FBI. As such, counties and parishes that report zero bias crimes are included as well. The subanalyses that exclude non-reports allow greater precision in understanding the impacts of bias criminality. Essentially, given they only include the counties that do in fact report incidents as having occurred, the analyses are able to speak to actual bias crime occurrence without potentially being moderated by non-reports.

The total N is 3,141 - as this figure represents the total number of counties and parishes in the United States. However, the FBI data indicate that the majority of counties in the United States report zero hate crimes per year. For this dissertation, UCR Hate Crime data from 2000-2009 and U.S. Census data from 2000 are used. As mentioned, although U.S. Census data are available for a variety of years, relevant independent variables are constructed from the 2000 U.S. Census data as to provide indicators that speak to the years 2000-2009. In addition, ARDA data from 2000 are used for the creation of religion-related independent variables. Data from *Congressional Quarterly* are used to construct an independent variable representing political participation in 2000.

Operationalization of Dependent and Independent Variables

Numerous variables are used to analyze the posed research questions. Moreover, the operationalization of each variable is explained and the data source for each variable is identified and justified. Each variable is constructed in a manner so as to measure or support the measurement of traditional indicators of social disorganization theory. Control variables are also used to ensure the findings of the analyses speak directly to the specific research questions asked.

Operationalization of Dependent Variables

The goal of this dissertation is to determine the likelihood of bias crime occurrence in United States counties. Given this, the concept this dissertation seeks to measure is the presence of bias crimes across the United States. As previously discussed, bias crime is defined as a criminal act motivated by animus toward the victim's affiliation with an oppressed social group (Gerstenfeld, 2004). Considering this definition, the operationalization of this concept also requires understanding what is not considered a bias crime for the purposes of this study. More specifically, this dissertation uses the FBI's definition of a *hate crime* to operationalize the concept. The FBI uses the following definition to categorize hate crimes in the United States: "The Hate Crime Statistics Program of the FBI's Uniform Crime Reporting (UCR) program collects data regarding criminal offenses that are motivated, in whole or in part, by the offender's bias against a race, religion, sexual orientation, ethnicity/national origin, or disability and are committed against persons, property, or society" (Federal Bureau of Investigation, 2008). It is important to note that offender motivation is the primary difference between the FBI's designation of hate crimes and that of other index offenses. Certainly, motivation is difficult to determine, but the FBI relies on local police departments' designations of motive and the existence of bias criminality. This means that the data the FBI collects and maintains are only as valid and reliable as are the local police departments reporting the offenses. There are likely numerous bias crimes that go unreported each year. However, the FBI cannot possibly determine the existence of these crimes unless they are reported as such.

Bias crime is quantitatively measured by examining the reported figure of bias crimes by United States law enforcement agencies. This is indicated by considering the bias crimes known to the FBI. The dependent variables for this dissertation are constructed from the frequencies of bias crime offenses – as reported – to the FBI for each of the United States law enforcement jurisdictions. These data are available for the range of years 2000-2009 and are continuous in nature.

The FBI's Hate Crime data were accessed and downloaded from the Inter-University Consortium for Political and Social Research (ICPSR) at the University of Michigan. These data are publicly available and provided in datasets organized by year. UCR Hate Crime data are available for all years 2000-2009. These UCR files provide data for hate crime incident per motivation and quarter for each year. Moreover, they include the various states and agencies from which the hate crime report originated. This informs the creation of the dependent variables - essentially, the total number of bias crimes in each United States county by motivation type. It is also necessary to provides statistics for each state and agency that did not report data for the respective year. These data are used to consider the research questions posed in Chapter Two.

Creation of Dependent Variables

In order to determine the variation that may exist between different types of bias criminality, several dependent variables are used. First, all reported bias crime incidents are collected for each United States county or parish. Therefore, the total number of bias crimes that occur in each United States county are used to construct the dependent variables – which are continuous in nature. Even with a dependent variable that is continuous in nature, it is important to acknowledge the number of zeroes present in the data. Given this, appropriate analytical techniques are considered and utilized. Moreover, these data are available at the county level and are disaggregated to build three other dependent variables. These variables are constructed in a manner that allows this dissertation to examine the nature of anti-sexual orientation, anti-race, and anti-religion motivated bias crime. Moreover, this dissertation seeks to examine the differences between the various types of motivation that affect bias crime occurrence.

The following identify the type and source of data used to construct the dependent variables in this dissertation:

1) Bias crimes reported (by county)

- Data source: UCR (2000-2009)

2) Anti-sexual orientation bias crimes reported (by county)

- Data source: UCR (2000-2009)

3) Anti-race bias crimes reported (by county)

- Data source: UCR (2000-2009)

4) Anti-religion bias crimes reported (by county)

- Data source: UCR (2000-2009)

In order to understand the nature of bias crime occurrence in the United States, it is necessary to examine the frequencies of the three most commonly occurring bias crime. Given the data represent bias crime reported to the FBI for the years 2000-2009, importance lies in breaking the data down into useful segments. First, Table 4.2 presents the number of all bias crimes reported in the United States, organized by state and federal district. The data are presented for all years 2000-2009. Second, Table 4.3 displays the characteristics of bias crime identified by the following motivations: anti-race, anti-sexual orientation, and anti-religion. Although the unit of analysis for this dissertation is United States counties, descriptive data are organized by state as this organization is more amenable to presentation in table format. The 3,141 counties and parishes that exist in the United States are too numerous, and therefore too cumbersome, to present in a single table.

Table 4.2: Reported Bias Crime Totals by State

State	*2000*	*2001*	*2002*	*2003*	*2004*	*2005*	*2006*	*2007*	*2008*	*2009*	*Total*
AL	0	0	2	1	3	0	1	6	11	9	33
AK	0	0	0	0	0	0	0	0	0	0	0
AZ	248	395	244	253	197	152	161	167	194	226	2,237
AR	4	3	0	176	92	135	118	35	92	78	733
CA	1,988	2,250	1,651	1,476	1,164	1,427	1,376	1,532	1,507	1,119	15,490
CO	109	135	105	89	60	132	150	170	164	223	1,337
CT	169	181	135	152	119	111	143	128	156	192	1,486
DE	35	23	13	17	26	49	54	52	63	39	371
DC	5	11	14	31	49	48	57	41	42	37	335
FL	216	266	240	216	220	204	199	153	135	115	1,964
GA	35	39	31	28	17	17	13	13	10	11	214
HI	0	0	0	0	0	0	0	0	0	0	0
ID	49	35	44	21	33	33	23	42	30	35	345
IL	192	298	172	222	159	175	159	173	124	137	1,811
IN	111	79	79	49	50	54	40	41	61	55	619
IA	33	33	48	46	23	39	34	29	33	17	335
KS	43	72	58	50	40	78	113	118	118	130	820
KY	73	83	79	81	61	42	60	46	62	154	741
LA	12	10	16	7	21	20	23	33	75	17	234
ME	29	33	40	87	37	60	62	78	65	51	542
MD	210	227	199	234	216	188	205	141	97	96	1,813
MA	465	605	435	422	286	380	386	359	333	328	3,999
MI	439	456	420	439	500	663	666	639	582	327	5,131
MN	170	210	203	215	205	206	137	157	164	153	1,820
MS	2	3	3	1	2	0	0	0	4	2	17
MO	74	69	47	51	56	65	75	96	87	120	740
MT	21	14	14	5	53	69	27	22	25	29	279
NE	18	56	76	47	54	71	57	45	12	78	514
NV	97	101	63	99	72	77	127	63	97	48	844
NH	33	27	27	39	36	34	35	45	46	26	348
NJ	652	766	570	594	714	738	755	748	744	549	6,830

Table 4.2 (Cont'd)

NM	16	20	15	11	18	18	20	14	10	15	157
NY	209	399	413	313	261	251	250	199	311	356	2,962
NC	33	90	65	88	62	93	107	79	139	106	862
ND	5	17	18	19	9	12	16	14	18	14	142
OH	247	388	285	235	325	185	324	328	360	313	2,990
OK	83	51	49	43	51	42	54	33	51	66	523
OR	142	223	61	96	126	138	147	179	199	136	1,447
PA	147	138	94	122	89	120	99	89	70	38	1,006
RI	46	63	38	46	22	15	20	47	36	36	369
SC	34	42	72	56	91	104	113	132	159	114	917
SD	7	5	4	10	5	9	78	37	42	43	240
TN	222	337	126	134	118	127	175	234	264	170	1,907
TX	305	468	367	308	267	274	254	255	258	168	2,924
UT	81	71	58	64	57	50	39	59	41	50	570
VT	20	17	23	28	24	35	21	21	20	25	234
VA	98	177	105	112	129	146	174	175	145	67	1,328
WA	250	293	175	233	154	181	187	203	264	222	2,162
WV	69	41	46	33	28	49	34	45	46	28	419
WI	49	62	33	31	27	49	89	72	97	56	565
WY	9	10	5	12	4	3	5	21	7	8	84
Total	**7,604**	**9,392**	**7,080**	**7,142**	**6,432**	**7,168**	**7,462**	**7,408**	**7,670**	**6,432**	**73,790**

As is evident in Table 4.2, California reliably reports the highest number of bias crimes in the United States. In the ten year period from 2000-2009, California reported 15,490 bias crimes as having occurred within its boundaries. Of the ten years, 2001 had the highest number of reported bias crimes in California, with 2,250 incidents reported. The lowest number of bias crimes reported was in 2009, when the state had 1,119 incidents. In addition, the state that reports the lowest number of bias crimes is Mississippi, with 17 incidents reported between 2000 and 2009. The year of 2008 held the most reported bias crimes in Mississippi. That year, the state reported four bias crime incidents as having occurred.

Alaska and Hawaii are excluded from analyses in this dissertation. Although Alaska does report bias crime to the FBI, its political structure is divided into organized and unorganized boroughs instead of counties. In the available UCR Hate Crime data, Federal Information Processing Standard (FIPS) are absent. This precludes analyses due to the lack of availability of assigned codes. The District of Columbia suffers from the same issue; however, since the district falls into only one political unit, Washington, the data can be accurately utilized in this dissertation. Any data that may exist for Hawaii are unavailable from the UCR and therefore not included in the dataset.

Table 4.3 presents basic statistics surrounding the context of bias crime occurrence. Specifically, the total number of bias crimes in each state is presented. In addition, those reported crimes are presented by motivation type. The research questions of this dissertation address the differences between anti-race, anti-sexual orientation, and anti-religion motivated bias crime. Although other types do occur, they are excluded from analyses in this dissertation.

Table 4.3: Bias Crime Motivations (2000-2009)

State	***Total***	***Anti-race***	***%***	***Anti-sex. orient.***	***%***	***Anti-religion.***	***%***	***Other***	***%***
Alabama	33	25	75.76	5	15.15	3	9.09	0	0.00
Alaska	0	0	-	0	-	0		0	-
Arizona	2,237	1,446	64.64	318	14.22	377	16.85	96	4.29
Arkansas	733	590	80.49	79	10.78	32	4.37	32	4.37
California	15,490	9,718	62.74	2,798	18.06	2,362	15.25	612	3.95
Colorado	1,337	849	63.50	172	12.86	207	15.48	109	8.15
Connecticut	1,486	867	58.34	171	11.51	282	18.98	166	11.17
Delaware	371	232	62.53	53	14.29	55	14.82	31	8.36
District of Columbia	335	90	26.87	218	65.07	26	7.76	1	0.30
Florida	1,964	1,371	69.81	283	14.41	309	15.73	1	0.05
Georgia	214	134	62.62	58	27.10	16	7.48	6	2.80
Hawaii	0	0	-	0	-	0	-	0	-
Idaho	345	223	64.64	37	10.72	73	21.16	12	3.48
Illinois	1,811	1,174	64.83	288	15.90	250	13.80	99	5.47
Indiana	619	427	68.98	98	15.83	72	11.63	22	3.55
Iowa	335	223	66.57	50	14.93	35	10.45	27	8.06
Kansas	820	582	70.98	121	14.76	71	8.66	46	5.61
Kentucky	741	558	75.30	112	15.11	55	7.42	16	2.16
Louisiana	234	171	73.08	17	7.26	22	9.40	24	10.26
Maine	542	289	53.32	152	28.04	65	11.99	36	6.64
Maryland	1,813	1,251	69.00	120	6.62	431	23.77	11	0.61
Massachusetts	3,999	2,437	60.94	711	17.78	742	18.55	109	2.73
Michigan	5,131	3,876	75.54	526	10.25	541	10.54	188	3.66
Minnesota	1,820	1,335	73.35	265	14.56	204	11.21	16	0.88
Mississippi	17	15	88.24	0	0.00	2	11.76	0	0.00
Missouri	740	542	73.24	73	9.86	90	12.16	35	4.73
Montana	279	153	54.84	49	17.56	41	14.70	36	12.90
Nebraska	514	369	71.79	58	11.28	71	13.81	16	3.11
Nevada	844	556	65.88	123	14.57	134	15.88	31	3.67
New Hampshire	348	169	48.56	86	24.71	72	20.69	21	6.03
New Jersey	6,830	3,819	55.92	494	7.23	2,493	36.50	24	0.35
New Mexico	157	103	65.61	34	21.66	17	10.83	3	1.91
New York	2,962	1,391	46.96	275	9.28	1,265	42.71	31	1.05
North Carolina	862	647	75.06	84	9.74	70	8.12	61	7.08
North Dakota	142	113	79.58	15	10.56	10	7.04	4	2.82
Ohio	2,990	2,081	69.60	348	11.64	273	9.13	288	9.63
Oklahoma	523	381	72.85	41	7.84	65	12.43	36	6.88
Oregon	1,447	906	62.61	287	19.83	208	14.37	46	3.18
Pennsylvania	1,006	685	68.09	82	8.15	201	19.98	38	3.78

Table 4.3 (Cont'd)

Rhode Island	369	181	49.05	108	29.27	75	20.33	5	1.36
South Carolina	917	586	63.90	106	11.56	116	12.65	109	11.89
South Dakota	240	182	75.83	27	11.25	27	11.25	4	1.67
Tennessee	1,907	1,294	67.86	310	16.26	205	10.75	98	5.14
Texas	2,924	1,983	67.82	458	15.66	323	11.05	160	5.47
Utah	570	334	58.60	75	13.16	117	20.53	44	7.72
Vermont	234	113	48.29	66	28.21	39	16.67	16	6.84
Virginia	1,328	891	67.09	119	8.96	210	15.81	108	8.13
Washington	2,162	1,450	67.07	336	15.54	250	11.56	126	5.83
West Virginia	419	291	69.45	71	16.95	29	6.92	28	6.68
Wisconsin	565	374	66.19	107	18.94	59	10.44	25	4.42
Wyoming	84	48	57.14	16	19.05	19	22.62	1	1.19
Total	**73,790**	**47525**	**64.41**	**10,500**	**14.23**	**12,711**	**17.23**	**3,054**	**4.14**

Table 4.3 presents the breakdown of bias criminality by motivation for the years 2000 through 2009, combined. From this, it is evident that out of the 73,790 reported bias crimes occurring in the United States over the ten year period, 64.41% were motivated by animus toward the victim's race. Second to race as a motivation for bias crime offending is religion. It is anti-religion based animus that accounts for 17.23% of bias criminality. Bias crimes motivated by anti-sexual orientation based animus are the third most frequently occurring type of bias crime. From 2000-2009, 14.23% of bias crimes in the United States were motivated by anti-sexual orientation hostility.

Operationalization of Independent Variables

Social disorganization theory has long been discussed as a leading theoretical perspective explaining the incidence of crime in communities. As such, concepts that are used to test social disorganization theory are introduced in Chapter Three. The following section explains the operationalization of these concepts into feasible independent variables. This dissertation uses *American FactFinder* from the United States Census Bureau in order to construct appropriate independent variables – both those that capture traditional indicators of social disorganization theory and appropriate control variables. Sampson and Groves (1989) identified four traditional indicators of social disorganization theory. It is Sampson and Groves' (1989) study upon which the social disorganization indicators are based in this dissertation.

Low economic status, social heterogeneity, residential mobility, and social cohesion are commonly considered to represent factors of social disorganization theory and its ability to predict crime and violence in communities. Therefore, these four concepts are used to test social disorganization theory and the theory's ability to predict bias crime occurrence at the county level in the United States. Although Sampson and Groves's (1989) indicators are used, this dissertation adds numerous variables to measure and test social disorganization theory. The majority of these variables are informed by the more recent work of Freilich, Adamczyk, Chermak, Boyd, and Parkin (2013). It is from this study that various indicators of social disorganization theory as well as control variables are informed.

Low Economic Status

One traditional indicator of social disorganization theory is the concept of low economic status (Shaw & McKay, 1942). Kornhauser (1978) suggests that low economic status is perhaps the most salient indicator of social disorganization theory. Kornhauser (1978), in effect, suggests that communities with lower economic capabilities have fewer resources to discourage criminality. In order to operationalize this concept for the purposes of this dissertation, three concepts are considered: percent unemployed, percent living below the poverty line, and the percent of citizens without a college degree.

Based on Sampson and Groves' (1989) study, the occupational status of persons in each county is considered. Specifically, this includes examining the percentage of individuals employed. First, the percentage of unemployed persons in each United States county or parish is used to measure low economic status. These data are taken from the United States Census Bureau's *American FactFinder*. Second, the percentage of individuals living below the poverty line in each county is used to measure low economic status. Similar to percent unemployed, these figures are available from *American FactFinder* for each United States county or parish. Third, the percentage of individuals residing in each county without a college degree is used to measure low economic status. These data are available and are sourced from the *American FactFinder*. Each of these estimations of unemployment is available for all United States counties or parishes for 2000.

Social Heterogeneity

Social heterogeneity – which also can be defined as diversity - is yet another factor that is important when considering the social organization or disorganization of a community. The social heterogeneity of a county is likely an important factor in understanding the distribution of crime. Kornhauser (1978) also suggests that racial heterogeneity is an adequate measure of social disorganization theory as more diverse communities have greater difficulty organizing. Even Suttles in his (1972) study suggested that heterogeneity increases delinquency and weakens the various aspects of social organization. The identification of the following serve to operationalize social heterogeneity: percentage of non-white persons, percentage of foreign-born persons, percentage identifying as Jewish, and the percentage of citizens identifying as Muslim.

First, the percentage of non-white persons living in each United States county or parish is used to measure social heterogeneity. This is constructed by attaining available data from *American FactFinder*. Certainly, given the overwhelming number if white-identifying individuals in the United States, it is important to consider the experiences of individuals who are non-white. Second, social heterogeneity is operationalized by identifying the percentage of foreign-born persons present in each county. This indicator is used to represent the level of immigration each United States county experiences. Third, the diversity of religious population in each county is considered as well. In order to determine religious diversity, the percentage of individuals who are Jewish, Muslim, and Christian are identified. Specifically, because the overwhelming majority of individuals in the United States identify with Christianity in some manner, the percentage of Catholic citizens and the percentage of Protestant citizens are considered as a control variable. Although Christianity can be separated into numerous sects, only Catholicism and Protestant denominations in the aggregate are considered. Often this separation is into "Catholic" and "other Christian" given the nature of how Christianity has historically evolved. Therefore, "other Christian" includes the entire range of sects from mainline denominations to evangelical sects of Christianity. Each of these estimations of social heterogeneity is available for all United States counties or parishes for 2000.

Social Cohesion

As is appropriate when measuring aspects of social disorganization theory, considering a community's level of social cohesion is necessary. As scholars have noted, the level of disorganization (or lack of social cohesion) that a community experiences may be related to the level of criminality it experiences. Therefore, in the case of this dissertation, social cohesion is measured by examining each county's crime rate. Additionally, the divorce rate is another measure of social cohesion used in this dissertation.

The United States Census Bureau's *American FactFinder* is used to capture the percentage of divorced persons living in each American county or parish. Historically, Sampson (1987) has suggested that family disruption can lead to criminal activity. As such, the percentage of divorced persons residing in each county or parish is used to measure family disruption. Specifically, divorce is used to represent the concept of social disorganization given it represents the disintegration of families in American communities. Certainly, this definition operates under the assumption that a family is such because a married heterosexual couple heads the household. Although there are numerous ways a family can be identified and structured, this dissertation is limited by the available data. It was not until 2010 that President Barack Obama instructed the United States Census Bureau to collect information on households that may include same-sex couples. Therefore, even with its current and inherit inequality, the term marriage, as of 2000 - only included heterosexual couples. As such, only heterosexual couples are included in the definition of family in this dissertation.

Although bias criminality is certainly included in the FBI's overview of American crime, it is important to discern the relative level of violent criminality present in each county or parish. This allows this dissertation to measure social cohesion in yet another manner. For instance, if a county with numerous incidents of bias criminality also has a high rate of other violent crime, this fact could be significant. In the event that the county has a low rate of violent crime otherwise, but a relatively high rate of bias crime, this could be a finding worthy of attention. This variable is operationalized by identifying and using UCR data for each American county or parish. The frequency of violent crime occurrence is used to measure violent (index) crime in American counties and parishes. Each of these estimations of social cohesion is available for all United States counties or parishes for 2000. In addition, political participation data are provided by *Congressional Quarterly's* Voting and Elections Collection. Specifically, these data allow for county-level measurement of percentage voting in the 2000 presidential election. Each of these variables is available for all United States counties for the year 2000 and is measured in a continuous manner.

Residential Mobility

In order to capture the concept of residential mobility, the percentage of home-owners in each United States county or parish is used. This is constructed in order to accommodate Brooks-Gunn et al.'s (1997) assertion that there are correlations between residential instability and poverty – two clear indicators of social disorganization. Sampson (2002) also suggests that there is much stratification in the way that neighborhoods interact with criminality. Moreover, Kasarda and Janowitz (1974) purport that the integration of new residents in a neighborhood does not always result in extensive friendship networks; rather, it supports the residential mobility that is theoretically problematic. As such, the data for this dissertation are available from the United States Census Bureau's *American FactFinder* for each United States county. Given home owners are likely to be more permanent fixtures in their communities than are renters, the percentage of those who own homes in a county is used to measure residential mobility. Moreover, the percentage of unoccupied housing in each county or parish is considered as a measure of residential mobility. This measure is different from the percentage of citizens owning homes because it accounts for rented properties as well. When considering whether a community is social organized, it is necessary to understand the percentage of individuals actually living in the community. Each of these estimations of residential mobility is available for all United States counties or parishes for 2000.

Control Variables

In addition to the dependent variables and the social disorganization-related independent variables, this study employs several control variables. In order to determine whether a relationship exists between two or more variables, it is important to use control variables as a constant. This allows the researcher to know whether the study is actually measuring what it set out to measure. In the case of this dissertation, several attributes of American counties and parishes are examined in an effort to obtain a constant during multivariate analyses.

In addition, the population of each American county or parish is included as a control variable in this dissertation. It is important to be able to discern the effect a county's population has not only on bias criminality, but also each of the traditional indicators of social disorganization theory. The population of each American county or parish is available from the United States Census Bureau for 2000. The population for each county is constructed from 2000 Census data in order to maintain consistency with the other data used in the study. Each county's population is available from the United States Census Bureau's *American FactFinder*.

Other control variables used are taken from the *American Factfinder* provided by the United States Census Bureau. They are as follows: percentage of individuals in each county where the language spoken is other than English, median age of residents, percent of veterans residing in each county, and percent Christian (Catholic and Protestant).

Moreover, drawing from Lyons's (2007) study, anti-white bias crimes are included as controls as well. In this dissertation, bias crime committed against superordinate groups is not considered directly; however, with regard to race, anti-white bias crimes are considered as a control variable. The existence of hate crime legislation in each state in 2000 is used a control variable as well. This is structured as a dichotomous variable and taken adopted from a collection of hate crime laws compiled by the Southern Poverty Law Center. Additional related variables break down the hate crime laws by the existence of the following protections: race, religion, and ethnicity; sexual orientation; gender; gender identity; and disability. Each of these variables is coded in a dichotomous manner as well. Although not directly related to traditional indicators of social disorganization theory, the preceding control variables provide greater information about the relationships present in this study.

Codebooks

As is appropriate in any study, the codebooks for relevant variables used in this dissertation are presented. The codebooks include not only the dependent variables, but also the independent variables necessary for this dissertation's analyses. Both continuous and discrete variables are included. Codebook 1 provides the variables necessary for measuring United States counties. Codebook 2 presents the variables used to represent social disorganization theory. Codebook 3 displays the control variables relevant to this dissertation. As follows, Table 4.4 presents the variables as are appropriate for considering the analyses in this dissertation.

Table 4.4: Codebooks for County, Social Disorganization, and Control Variables

Codebook 1. County Variables (2000-2009)	***Codebook 2. Social Disorganization Theory Variables (2000)***	***Codebook 3. Control Variables (2000)***
County Population Bias Crime Total Motivation Anti-Race Anti-Sexual Orientation Anti-Religion Bias Crime Event No=0 Yes=1	*Low Economic Status* % Unemployed % below Poverty Line % without Bachelor's Degree *Social Heterogeneity* % Non-White % Muslim % Jewish % Foreign-born *Social Cohesion* % Divorced Crime Rate *Residential Mobility* % Owning Homes % Unoccupied Houses	Median Age of Residents % of Anti-White Hate Crime Rate Hate Crime Legislation No=0 Yes=1 Race, Religion, Ethnicity Legislation No=0 Yes=1 Sexual Orientation Legislation No=0 Yes=1 Gender Legislation No=0 Yes=1 Gender Identity Legislation No=0 Yes=1 Disability Legislation No=0 Yes=1 % Voting in 2000 Presidential Election % Christian % Veterans % Language Spoken – Not English

Data Analyses

In Chapter Five, univariate (descriptive) statistics for each of the dependent and independent variables are presented. This allows for an explanation of such statistics such as the frequency distributions, measures of central tendency, and measures of dispersion – as appropriate. These analyses allow the reader to understand the nature and range of each variable. Moreover, it is from these analyses that the proper multivariate statistical methods can be determined.

Additionally, appropriate bivariate analyses are conducted to examine the relationships between the independent and dependent variables. The statistical techniques are determined by the appropriate and respective level of measurement. An effort was made to attempt parametric analyses. As such, correlations analyses are considered in order to determine the nature of relationship between each dependent variable and each independent variable.

In order to determine the relationship between numerous independent variables and the dependent variable, appropriate multivariate statistical methods are used. This is primarily determined by the nature of the dependent variables and how they are measured. In the case of this dissertation, the primary model is analyzed using Poisson-based negative binomial regression due to the large number of zeroes present in the dataset. Given so many zeroes are present in the FBI's UCR Hate Crime data, it is necessary to be reflective – and be inclusive of - that fact in the main model. Therefore, negative binomial regression is used to analyze the relationship between the independent variables and the continuous dependent variable. Since so many counties register zero incidents of bias criminality throughout the years 2000-2009, it is most appropriate to account for the over-dispersion in the data. As such, this means that the dependent variable for the main model in this dissertation is created using a continuous measure.

Additionally, in order to measure the relationships between the counties that do, in fact, report hate crimes and the traditional indicators of social disorganization theory; several sub-analyses are performed using OLS regression. Given that the proposed dependent variables in the sub-analyses are continuous in nature (number of bias crimes in United States counties); multiple regression is an appropriate method for the analysis of the counties that do indeed report bias crime occurrence. Removing the zeroes allows for a more accurate analysis of the counties that actually do report bias crimes each year. Given the sample size of this study is 3,141; it is important to use a technique that operates well with large samples. Therefore, ordinary least squares (OLS) regression is used as the statistical method of analysis for the identified sub-analyses.

Primary Models

As mentioned, four models are included in this dissertation. First, this dissertation examines the ability of social disorganization theory to predict the likelihood (or risk) of bias criminality in United States counties. Given this, the following discussion of Poisson-based negative binomial regression is appropriate for understanding the analyses appropriate when numerous zeroes are present in the data. Three subanalyses are included as well as they speak to the counties that do in fact report bias criminality. As such, following discussions of OLS regression explain the methods used to explore the relationships between traditional indicators of social disorganization theory and the incidence of bias criminality in United States counties between 2000 and 2009.

<u>Negative Binomial Regression</u>

In an effort to predict bias criminality in United States counties, negative binomial regression can be a helpful tool with regard to choosing a multivariate analysis. According to

Osgood (2000), Poisson-based regression models are appropriate as they are based on assumptions about error distributions. This is consistent with the character of count data. Due to the high number of counties in the United States do not, in fact, report bias crime occurrence – the result is a significant number of zeroes present in the bias crime data.

From the current dataset, it is unknown whether the counties with zero recorded bias crimes are a result of failure to report such crimes or the actual lack of bias criminality occurring in each United States county. However, the lack of zeroes indicates the need for a multivariate model that can account for presence of this issue. Although logistic regression can be viewed as an appropriate method for evaluating the relationships present in the main model, logistic regression can reduce statistical power (Gardner, Mulvey, & Shaw, 1995). Given multiple bias crime incidents are compressed into one figure in logistic regression, the method may undercount the total number of bias crimes (Piza, 2012). In order to avoid lowering statistical power and thereby falsely accepting a null hypothesis, logistic regression is not used in this dissertation.

Poisson-based negative binomial regression is appropriate due the uneven distribution of the dependent variables (Agresti, 2002). Relevant data justifying the use of negative binomial regression are presented in Chapter Five. In the case of this dissertation, the overdispersion is apparent by the presence of numerous zeroes in the data. As such, this dissertation uses negative binomial regression as a multivariate method to account for the greater variability of the dependent variable. This allows the model to predict bias crime occurrence with only a few counts, in nonlinear models (Gardner, Mulvey, & Shaw, 1995). Moreover, negative binomial regression allows for the analysis of the relationships between the numerous independent variables and the binary dependent variable present in this study. Thus, it allows for an analysis of relationships between variables that could not otherwise be analyzed properly using logistic or

OLS regression. While logistic regression can undercount rare events, OLS regression assumes adequate variance in data and requires it to maintain validity (Gardner, Mulvey, & Shaw, 1995).

OLS Regression

In addition, sub-analyses are conducted using OLS regression given the more standard variability of the involved counties. In essence, given that the appropriate dependent variables are continuous in nature (number of bias crimes per county), linear regression is appropriate. For instance, multivariate subanalyses are conducted that include each law enforcement entity does indeed report bias crime events to the FBI for each respective county. Given this, these research questions are explored using OLS Regression as the statistical method, given the dependent variables are continuous in nature. Ordinary Least Squares regression is a frequently used statistical method for measuring the effects of several independent variables on a dependent variable concurrently (Schroeder, Sjoquist, & Stephan, 1986). Consequently, multiple regression is often noted as the dominant paradigm in social science research (Freedman, 1991).

The robust nature of multiple regression makes it a particularly useful and an advantageous methodological tool for social scientists (Allen, 1997). As noted, there are several assumptions of multiple regression; however, multiple regression is often used even when one or more of these assumptions is violated as well (Berry & Feldman, 1985). Moreover, there are numerous methods sometimes known as diagnostics which are used to detect and correct for the various violations of multiple regression assumptions. Therefore, the flexibility of multiple regression allows researchers to use the method in situations where assumptions are violated. For example, although an assumption of multiple regression is that all variables are interval/ratio, it is possible to use multiple regression even when one or more of the independent variables is categorical (Allen, 1997). This allows researchers a much more broad selection of independent variables from which to choose.

Multiple regression is also advantageous in that the analytical method allows researchers to accomplish more than with simple linear regression. In many cases, social science researchers are interested in examining the effect that multiple independent variables have on the dependent variable. By design, multiple regression allows researchers to disentangle the effects of two or more independent variables on a dependent variable (Allen, 1997). Additionally, multiple regression allows researchers to determine the accuracy of the relationship with two or more independent variables and compare it to the accuracy of the relationship with one independent variable (Allen, 1997).

Although there are many advantages to using multiple regression, there are a number of researchers that argue that the method has its disadvantages. For instance, Freedman (1991) suggests that regression models are not always the best way of determining causality since common violations of assumptions rely on knowledge that the researcher does not have. However, in the case of this dissertation, the assumptions of multiple regression are not violated. One concern in many social sciences studies is missing data. In particular, regression models could be more meaningful if greater attention was paid to an appropriate research question, links to theory, quality of the data, and the inclusion of appropriate variables (1991). In essence, it is not necessarily the method of multiple regression that is criticized; but rather the carelessness with which it is often utilized. Since multiple regression is generally viewed as an extremely robust and flexible statistical tool, researchers may become less rigorous in their research design. As a result, some researchers view multiple regression as a method with limited or no ability to provide causal inference (1991). After all, a researcher cannot correct a weak research design with strong data analysis (Berk, 1991).

Summary

This dissertation seeks to explore the relationship between community-level factors related to social disorganization theory and bias crime occurrence in American counties. The data used are provided by the FBI's Uniform Crime Report, the United States Census Bureau, *Congressional Quarterly's* Voting and Elections Collection, and the Association of Religious Data Archives. Given the relatively sparse literature on bias crime and American counties, this dissertation seeks to make a several contributions. Primarily, this study provides insight into the numerous indicators of social disorganization theory and its ability to inform bias crime occurrence in United States counties. Secondarily, this dissertation seeks to examine the differences between the various motivations of bias crime offending at the county level. The results of the analyses used to answer the research questions and to address the hypotheses are presented in Chapters Five and Six, and Seven.

CHAPTER 5: THE CONTEXT OF BIAS CRIME IN UNITED STATES COUNTIES

The purpose of Chapter Five is to examine the context of bias criminality in United States counties. In order to understand the full context of bias criminality and its effect on United States counties, Chapter Five considers the descriptive statistics for contextual factors associated with bias criminality occurring between 2000 and 2009. First, this chapter presents the descriptive findings appropriate for the study. The dependent and independent variables are described to assess normality and the nature of missing data. These analyses present the data necessary to understand the nature of bias crime occurrence in United States counties.

The Nature of Counties in the United States: Descriptive Findings

In order to understand the context surrounding the nature of bias criminality in American counties, it is important to consider descriptive findings. Table 5.1 presents the number of counties within each state that reports at least one bias crime for each year, 2000-2009. In addition, the number of counties that report zero bias crimes are presented as well. This figure does include the counties that do not report bias crimes – whether they occur or not - to the FBI.

Table 5.1: Bias Crime Reporting by State

State	*Number of Counties*	*Number of Counties Reporting at Least One Hate Crime*	*%*	*Number Reporting Zero Hate Crimes*	*%*
Alabama	67	14	20.90	53	79.10
Alaska	27	0	0.00	27	100.00
Arizona	15	13	86.67	2	13.33
Arkansas	74	67	90.54	7	9.46
California	58	56	96.55	2	3.45
Colorado	64	46	71.88	18	28.13
Connecticut	8	8	100.00	0	0.00
Delaware	3	3	100.00	0	0.00
District of Columbia	1	1	100.00	0	0.00
Florida	67	54	80.60	13	19.40
Georgia	159	24	15.09	135	84.91

Table 5.1 (Cont'd)

Hawaii	4	0	0.00	4	100.00
Idaho	44	31	70.45	13	29.55
Illinois	102	64	62.75	38	37.25
Indiana	92	41	44.57	51	55.43
Iowa	99	42	42.42	57	57.58
Kansas	105	67	63.81	38	36.19
Kentucky	120	75	62.50	45	37.50
Louisiana	64	32	50.00	32	50.00
Maine	16	16	100.00	0	0.00
Maryland	24	21	87.50	3	12.50
Massachusetts	14	14	100.00	0	0.00
Michigan	83	79	95.18	4	4.82
Minnesota	87	60	68.97	27	31.03
Mississippi	82	12	14.63	70	85.37
Missouri	115	63	54.78	52	45.22
Montana	56	30	53.57	26	46.43
Nebraska	93	34	36.56	59	63.44
Nevada	17	11	64.71	6	35.29
New Hampshire	10	10	100.00	0	0.00
New Jersey	21	21	100.00	0	0.00
New Mexico	33	11	33.33	22	66.67
New York	62	53	85.48	9	14.52
North Carolina	100	62	62.00	38	38.00
North Dakota	53	16	30.19	37	69.81
Ohio	88	71	80.68	17	19.32
Oklahoma	77	55	71.43	22	28.57
Oregon	36	24	66.67	12	33.33
Pennsylvania	67	51	76.12	16	23.88
Rhode Island	5	5	100.00	0	0.00
South Carolina	46	45	97.83	1	2.17
South Dakota	66	26	39.39	40	60.61
Tennessee	95	82	86.32	13	13.68
Texas	254	115	45.28	139	54.72
Utah	29	11	37.93	18	62.07
Vermont	14	13	92.86	1	7.14
Virginia	136	79	58.09	57	41.91
Washington	39	35	89.74	4	10.26
West Virginia	55	36	65.45	19	34.55
Wisconsin	72	49	68.06	23	31.94
Wyoming	23	14	60.87	9	39.13
Total	**3,141**	**1,862**	**59.28**	**1,279**	**40.72**

From Table 5.1, it is evident that 59.28% of United States counties do in fact report bias crimes as having occurred within their boundaries. Certainly, this does not mean that bias crimes have not occurred in the nearly 40 percent of other counties – it simply indicates that bias crimes were not reported, either to the police or later, to the FBI. There are numerous states that report bias crimes as having occurred in 100 percent of counties. Those states are as follows: Connecticut, Delaware, District of Columbia, Maine, Massachusetts, New Hampshire, New Jersey and Rhode Island. Other states with the high percentages of counties reporting one or more bias crimes are California (96.55%), Michigan (95.18%), South Carolina (97.83%), and Vermont (92.86%).

Of particular importance for this dissertation is the acknowledgement of the high number of counties that report zero bias crimes. This is relevant as this distribution affects the effectiveness of the multivariate methods used to assess relationships. As mentioned, numerous states have a low percentage of counties reporting bias crimes; however, the following states are worthy of noting due to their particularly low percentages: Alabama (20.90%), Mississippi (14.63%), North Dakota (30.19%), and New Mexico (33.33%). Taking each of these percentages into account, it is important to note that overall 40.72 percent of United States counties do not report any bias crimes as having occurred between 2000 and 2009.

Given there are 3,141 counties in the United States, providing descriptions of bias crime reporting of all counties is rather excessive. Table 5.2 provides a brief survey of the ten most and least populous counties in the United States. Loving County, Texas reports the smallest population of any United States county, with 67 persons residing there. Los Angeles County, California has the largest population, with 9,519,338 persons living in the county. Table 5.3 provides further descriptive statistics about United States counties in 2000.

Table 5.2: Survey of County Populations across the U.S.

County/State	***Population (2000)***
10 least populous counties*	
1. Loving County, Texas	67
2. King County, Texas	356
3. Kenedy County, Texas	414
4. Arthur County, Nebraska	444
5. Petroleum County, Montana	493
6. McPherson County, Nebraska	533
7. San Juan, County, Colorado	558
8. Blaine County, Nebraska	583
9. Loup County, Nebraska	712
10. Thomas County, Nebraska	729
10 most populous counties	
1. Los Angeles County, California	9,519,338
2. Cook County, Illinois	5,376,741
3. Harris County, Texas	3,400,578
4. Maricopa County, Arizona	3,072,149
5. Orange County, California	2,846,289
6. San Diego County, California	2,813,833
7. Kings County, New York	2,465,326
8. Miami-Dade County, Florida	2,253,362
9. Queens County, New York	2,229,379
10. Dallas County, Texas	2,218,899

*The USCB reports a population of zero for Broomfield County, CO and South Boston County, VA.

Table 5.3: Descriptive Statistics for U.S. County Population (2000)

	U.S. Counties
N (Counties)	3,141.00
Mean	89,593.29
Median	24,595.00
Mode*	10,155.00
SD	292,463.10
Range	9,519,338.00
Minimum	0.00
Maximum	9,519,338.00

*More than one mode; lowest listed.

As mentioned, there are 3,141 counties in the United States. Their populations vary drastically – with a range of 9,519,338 residents. The mean number of county residents is 89,593.29. Although there are numerous modes, the lowest is 10,155 and the standard deviation is 292,463.10. Certainly, there is great variation in United States counties' populations.

In order to present additional useful descriptive statistics with regard to bias crime occurrence in U.S. counties, Table 5.4 presents the counties with the highest percentages of bias crime reporting for each state. This allows the name of each county reporting highest percentages of bias criminality to be identified. Additionally, the number of bias crimes per capita in each of the 50 counties is presented in order to account for each the variation in each county's population.

Table 5.4: Characteristics of United States Counties (2000-2009)

State	*Number of Counties*	*County with Most Bias Crime*	*Number of Bias Crimes*	*Population (2000)*	*Bias Crimes Per Capita (100,000)*
Alabama	67	Jefferson	13	66,2047	1.96
Alaska*	27	--	--	--	--
Arizona	15	Maricopa	1,679	3,072,149	54.65
Arkansas	74	Pulaski	61	361,474	16.88
California	58	Los Angeles	5,936	9,519,338	62.36
Colorado	64	Arapahoe	208	487,967	42.63
Connecticut	8	Hartford	390	857,183	45.50
Delaware	3	New Castle	216	500,265	43.18
District of Columbia	1	Washington	335	572,059	58.56
Florida	67	Broward	314	1,623,018	19.35
Georgia	159	Fulton	114	816,006	13.97
Hawaii**	4	--	--	--	--
Idaho	44	Ada	95	300,904	31.57
Illinois	102	Cook	768	5,376,741	14.28
Indiana	92	Monroe	184	120,563	152.62
Iowa	99	Scott	57	158,668	35.92
Kansas	105	Sedgwick	301	452,869	66.47
Kentucky	120	Fayette	94	260,512	36.08
Louisiana	64	Evangeline	66	35,434	186.26
Maine	16	Cumberland	202	265,612	76.05
Maryland	24	Baltimore	519	754,292	68.81
Massachusetts	14	Suffolk	1,754	689,807	254.27
Michigan	83	Wayne	921	2,061,162	44.68
Minnesota	87	Hennepin	751	1,116,200	67.28
Mississippi	82	De Soto	4	107,199	3.73
Missouri	115	Jackson	225	654,880	34.36
Montana	56	Missoula	57	95,802	59.50
Nebraska	93	Lancaster	218	250,291	87.10
Nevada	17	Clark	714	1,375,765	51.90
New Hampshire	10	Rockingham	102	277,359	36.80
New Jersey	21	Monmouth	1,230	615,301	199.90
New Mexico	33	Bernalillo	112	55,6678	20.12
New York	62	Suffolk	997	1,419,369	70.24
North Carolina	100	Mecklenburg	111	695,454	15.96
North Dakota	53	Morton	40	25,303	158.08
Ohio	88	Franklin	845	1,068,978	79.05
Oklahoma	77	Oklahoma	113	660,448	17.11

Table 5.4 (Cont'd)

Oregon	36	Multnomah	581	660,486	88.00
Pennsylvania	67	Philadelphia	326	1,517,550	21.48
Rhode Island	5	Providence	277	621,602	44.56
South Carolina	46	Richland	69	320,677	21.52
South Dakota	66	Minnehaha	124	148,281	83.63
Tennessee	95	Shelby	397	897,472	44.24
Texas	254	Harris	633	3,400,578	18.61
Utah	29	Salt Lake	342	898,387	38.07
Vermont	14	Chittenden	102	146,571	69.59
Virginia	136	Fairfax	192	969,749	19.80
Washington	39	King	714	1,737,034	41.10
West Virginia	55	Cabell	106	96,784	109.52
Wisconsin	72	Milwaukee	163	940,164	17.34
Wyoming	23	Natrona	19	66,533	28.58
Total	**3,141**	**--**	**23,791**	**50,288,965**	**--**

*Alaska reports bias crime by borough; not compatible with county-based data.
**Hawaii does not report bias crime to the FBI.

In Table 5.4, several characteristics of United States counties are presented. Due to the fact that there are 3,141 counties across the country, this table lists the county and its population in each state with the greatest number of bias crimes occurring. The top five most populous counties with the greatest number of bias crimes occurring between 2000 and 2009 are as follows: Los Angeles County, California (9,519,338), Cook County, Illinois (5,376,741), Harris County, Texas (3,400,578), Maricopa County, Arizona (3,072,149), and Wayne County, Michigan (2,061,162). In addition, to account for variation in county population, the bias crimes per capita are listed as well. Taking population into consideration changes the counties with the highest rate of bias crimes occurring. The county with the highest incidences of bias criminality per capita is Suffolk, Massachusetts with 254.27 bias crimes occurring per 100,000 persons. The four other highest figures of bias criminality per capita are as follows: Evangeline County, Louisiana (186.26); Monmouth, New Jersey (199.90); Morton, North Dakota (158.08); and Monroe County, Indiana (152.62).

Description of Independent Variables

This dissertation presents the relevant descriptive statistics for each independent variable as well. Predictor variables used to measure social disorganization theory are grouped conceptually - by economic deprivation, social heterogeneity, social cohesion, and residential mobility. In addition, the relevant descriptive statistics for all control variables are presented.

Economic Deprivation

Appendix A presents descriptive statistics for two measures of economic deprivation. First, descriptions of the employment status of residents of U.S. states are displayed. In addition, this table includes figures for the population and the population for individuals age 16 and older. This is presented as it is necessary in order to calculate the percent of unemployed people in each county. Using the total population would provide misleading employment figures. Second, Appendix A also displays the number and percent of individuals living below the poverty line in each county. The United States Census Bureau measures poverty with a weighted threshold that, in 2000, ranged from $8,794 for one person household to $35,060 for a nine person household (USCB, 2000). Table 5.5 presents appropriate measures of central tendency and dispersion for percent unemployed and percent living below the poverty line.

Appendix A presents descriptive findings for economic measures of United States counties in 2000. With a total population of 281,412,514, the United States has a vast range of residents living in each state. Wyoming is the least populous state with a total population of 493,782. California has the greatest population in the United States. In 2000, 33,871,648 individuals were residing in the state. In 2000, the percentage of unemployed Americans was a rather low 3.6%. The following five states had the lowest percentages of unemployed persons: Iowa (2.85%), Kansas (2.84%), Nebraska (2.45%), New Hampshire (2.65%), and Virginia

(2.73%). The five states with the highest percentages of unemployed persons were Alaska (6.10%), the District of Columbia (6.79%), California (4.34%), Mississippi (4.34%), and New Mexico (4.41%).

Moreover, in 2000 nearly 34 million (33,898,201) individuals lived below the poverty line in the United States. This amounts to 12.05 percent of the country's population living in poverty. Of course, this is poverty only as defined by the government – so there are likely many others that live just above the U.S. Census Bureau's poverty line threshold. Five states with the lowest percentage of residents living below the poverty line are as follows: New Hampshire (6.35%), Minnesota (7.73%), Wisconsin (8.42%), New Jersey (8.32%), and Maryland (8.28%). In addition, the five states reporting the highest percentage of individuals living below the poverty line were: West Virginia (17.46%), New Mexico (18.08%), Mississippi (19.27%), Louisiana (19.04%), and the District of Columbia (19.14%).

Table 5.5: Descriptive Statistics for Measures of Economic Deprivation (2000)

	Number Unemployed	***Number Living below Poverty Line***
N (Counties)	3,139.00	3,139.00
Missing	2.00	2.00
Mean	2,531.71	10,799.04
Median	659.00	3,243.00
Mode*	23.00	713.00
SD	9,862.43	43,982.13
Range	354,347	1,674,599
Minimum	0.00	0.00
Maximum	354,347	1,674,599

*More than one mode; lowest listed

Table 5.5 describes the two independent variables representing economic deprivation: the number of unemployed persons in each county and the number of persons living below the poverty level. These data were available for 3,139 counties; they were missing for two. The values range from 0 to 357,347 and mean number of unemployed persons in each American county is 2,531.71. The median is 659 and the mode is 23. The standard deviation is 9,862.43, indicating that there is a significant level of dispersion from the mean. The mean of numbers of persons living below the poverty line is 10,799.04 for United States counties. The values range from 0 to 1,674,599 and the median is 3,243. The mode is 713 and the standard deviation is 43,982.13, indicating great variation from the mean.

Social Heterogeneity

Appendix B displays the descriptive characteristics for several measures of social heterogeneity, or diversity. In order to understand how social heterogeneity affects the occurrence of bias criminality, several measures are examined. First, the number of non-white residents in each county is considered for analysis. This variable allows for the representation of racial and ethnic diversity. Second, the number of naturalized and non-naturalized foreign-born persons residing in each United States county introduces yet another measurement of a community's heterogeneity. Third, as indicators of religious diversity, the number of Jewish and the number of Muslim persons residing in each county are included in the analyses of this dissertation.

Appendix B presents the descriptive statistics for all measures of social heterogeneity. Nearly 25 percent (24.86) of the United States is populated by non-white persons. The following states have the highest percentages of non-white residents: California (40.45%), the District of Columbia (69.22%), Louisiana (36.09%), Maryland (35.97%), and Mississippi (38.62%). The states with the lowest percentages of non-white residents are Iowa (6.07%), Maine (3.05%), New Hampshire (3.96%), Vermont (3.22%), and West Virginia (4.95%).

Approximately ten percent (9.91%) of United States residents identify as being foreign-born. This figure represents all foreign-born persons, both naturalized and non-naturalized. The five states with the highest percentages of foreign-born persons are: California (23.60%), Florida (15.28%), Hawaii (16.22%), New Jersey (15.94%), and New York (18.64%). In addition, the states that report the lowest percentages of foreign-born persons are as follows: Mississippi (1.26%), Montana (1.63%), North Dakota (1.60%), South Dakota (1.48%), and West Virginia (0.98%).

Across the United States, only 2.18% of residents are Jewish. The states with the highest populations of Jewish persons are all on the east coast and are the District of Columbia (4.46%), Maryland (4.08%), Massachusetts (4.33%), New Jersey (5.56%), and New York (8.72%). States with the lowest percentage of Jewish persons residing within their borders are: Arkansas (0.06%), Idaho (0.08%), Mississippi (0.05%), South Dakota (0.05%), and Montana and Wyoming (both with 0.09%).

With even fewer adherents in the United States than Judaism is Islam, comprising only 0.55% of the population. Certainly, worthy of discussion is the District of Columbia, which is an extreme outlier. Approximately ten percent (10.57%) of residents in the District of Columbia identify as Muslim. This percentage is far higher than the next states with the highest percentages of Muslims residing there. Those states are as follows: Illinois (1.01%), Maryland (1.00%), New Jersey (1.43%), and New York (1.18%). No extreme outliers exist with regard to states with the lowest percentages of Muslim residents. However, the following states report the lowest percentages of those practicing Islam in the United States: Hawaii (0.05%), Idaho (0.03%), South Dakota (0.01%), Vermont (0.02%), and Wyoming (0.05%). Table 5.6 presents additional descriptive statistics for measures of social heterogeneity.

Table 5.6: Descriptive Statistics for Measures of Social Heterogeneity (2000)

	Non-White Residents	***Foreign-Born Residents***	***Jewish Residents***	***Muslim Residents***
N (Counties)	3,139	3,138	3,138	3,138
Missing	2.00	3.00	3.00	3.00
Mean	22,287.59	8,891.47	1,957.08	496.91
Median	2,514.00	360.50	0.00	0.00
Mode*	19.00	23.00	0.00	0.00
SD	126,261.45	74,089.18	17,478.39	3,832.42
Range	4,882,274.00	3,140,052.00	564,700	95,623
Minimum	2.00	0.00	0.00	0.00
Maximum	4,882,276.00	3,140,052.00	564,700	95623

* More than one mode; lowest listed

Table 5.6 describes the four independent variables representing social heterogeneity: the number non-white, foreign-born, Jewish, and Muslim residents in each United States county. For the measure of non-white residents, these data were available for 3,139 counties and they were missing for two. The values range from 0 to 4,882,276 and the mean number of non-white persons in each American county is 22,287. The median is 2,514 and the mode is 19. The standard deviation is 126,261.45, indicating that there is a substantial level of dispersion from the mean. For the measure of foreign-born residents, the mean in United States counties is 8,891.47 and the values range from 0 to 3,140,052. Data are available for 3,138 counties; three counties have missing values. The median is 360.50 and the mode is 23. In addition, the standard deviation is 74,089.18, indicating great variation from the mean. Moreover, the independent variable representing the number of Jewish residents in each American county has a mean of 1,957.08. Data are available for all but three United States counties. The median and mode are both 0. The data have a range of 0 to 564,700 and a standard deviation of 17,478.39. Similarly, the mean number of Muslim residents in American counties is particularly low at 496.91. The data are available for 3,138 counties and the values range from 0 to 95,623. Similar to the measure of the Jewish population, the median and the mode are both 0. The standard deviation is 3,832.42.

Social Cohesion

Appendix C presents relevant descriptive statistics for the measures of social cohesion in United States counties. The number of divorced persons and the number of index offenses in each county are presented. In addition, this table includes the crime rate (based on the FBI's reporting of index offenses in 2000).

From the table in Appendix C, several findings emerged. First, the mean percentage of individuals who are divorced in the United States is 7.66 percent. The top five states with the highest percentages of divorced persons are as follows: Maine (9.25%), Wyoming (9.21%), Nevada (10.81%), Oregon (9.26%), and Florida (9.40%). The five states with the lowest percentages are New Jersey (5.95%), Utah (5.92%), North Dakota (6.20%), New York (6.18%), and Massachusetts (6.66%).

With regard to each states crime rate per capita, five states emerged as having the highest level of reported index crimes per capita. Interestingly, Montana had the highest crime rate per 100,000 persons, with a figure of 7,040.94. Other states with high rates of crime per capita are: New Mexico (6,262.68), Arizona (5,854.25), Florida (5,625.88), and South Carolina (5,823.29). In contrast, New Hampshire reported the lowest crime rate, with 1,473.34 index crimes occurring per 100,000 persons residing in the state. Additional states reporting low levels of crime per capita are: Kentucky (1,473.34), Rhode Island (1,956.47), Illinois (2,024.97), and Maine (2,290.88). Table 5.7 presents additional descriptive statistics appropriate for continuous independent variables.

Table 5.7: Descriptive Statistics for Measures of Social Cohesion (2000)

	Number of Divorced Persons	*Number of Index Offenses*
N (Counties)	3,139.00	3,141.00
Missing	2.00	0.00
Mean	6,868.28	3,471.96
Median	1,882.00	477.00
Mode*	958.00	00.00
SD	21,201.16	13,595.26
Range	613,661.00	383,722.00
Minimum	6.00	0.00
Maximum	613,667.00	383,722.00

* More than one mode; lowest listed

Table 5.7 displays descriptive statistics for two measures of social cohesion used in this dissertation. In terms of the divorced persons in each county, 3,139 of the counties were included in the analysis. Two counties had missing data. The mean number of divorced persons across the United States was 6,868.28. The median was 1,882 and the mode was 958. The data ranged from values of six to 613,667 and the standard deviation was 21,201.16. Additionally, the mean number of index offenses occurring in United States counties was 3,471.96. The median was 477 and the mode was zero. The values ranged from zero to 383,722 and had a standard deviation of 13,595.26, indicating great variation.

Residential Mobility

Appendix D provides descriptive statistics necessary for understanding the nature of residential mobility measures in 2000. In this dissertation, the number of owner occupied housing units is used to represent the number of homeowners in each county. Moreover, the number of unoccupied housing units represents abandoned houses. Both measures represent residential mobility in United States counties.

According to the preceding tables, as of 2000, there were 115,899,421 total housing units in the United States. Approximately 60% (60.24%) of those housing units were occupied by the homeowner. This figure varied slightly across the country, with the District of Columbia reporting the lowest total number of owner occupied housing units. As of 2000, only 36.83% of the housing units were occupied by the homeowner. Other states with low percentages of owner occupied housing units were as follows: Hawaii (49.50%), Nevada (55.26%), Rhode Island (55.74%), and Alaska (53.07%). The five states with the highest percentages of owner occupied housing units are: Minnesota (68.39%), Iowa (67.46%), Michigan (65.96%), Indiana (65.91%), and West Virginia (65.56%).

With regard to the percentage of unoccupied housing units in each state in 2000, the mean value was nearly 9% (8.99%). Maine reported the highest percentage of unoccupied housing, with 20.51% of total housing units remaining unoccupied. Several other states reported rather high percentages as well. Those states are: Vermont (18.26%), Alaska (15.09%), Wyoming (13.51%), and New Hampshire (13.24%). In contrast, California reports the lowest percentage of unoccupied housing units in 2000, with a figure of 5.83%. Four additional states with figures well below the mean are: Massachusetts (6.80%), Iowa (6.75%), Connecticut (6.08%), and Illinois (6.01%). Table 5.8 provides additional descriptive statistics for the measure of residential mobility.

Table 5.8: Descriptive Statistics for Measures of Residential Mobility (2000)

	Number of Owner Occupied Housing Units	***Number of Unoccupied Housing Units***
N (Counties)	3,141.00	3,141.00
Missing	0.00	0.00
Mean	22,226.24	3,318.44
Median	6,995.00	1,320.00
Mode*	948.00	690.00
SD	59,472.87	7,606.58
Range	1,499,744.00	137,135.00
Minimum	0.00	0.00
Maximum	1,499,744	137,135.00

* More than one mode; lowest listed

As presented in Table 5.8, several additional descriptive statistics for two measures of residential mobility are used in this dissertation. With regard to the number of owner occupied housing units in United States counties, the data included values for all 3,141 counties. There were no missing values. However, the mean value was 22,226.24, the median was 6,995, and the mode was 948. The figures ranged from zero to 1,499,744 and the standard deviation was 59,472.87. Similarly, data for all counties were available for the number of unoccupied housing units. For this independent variable, the mean was 3,318.44 and the median was 1,320. The mode was 690 and the values ranged from zero to 137,135. Showing marked variability, the standard deviation was 7,606.58.

Table 5.9: Context of Bias Crime Laws in the United States (2000)

State	***Any Law***	***Protects Race, Ethnicity, Religion (RRE)***	***Protects Sexual Orientation***	***Protects Gender***	***Protects Gender Identity***	***Protects Disability***
Alabama	Yes	Yes	No	No	No	Yes
Alaska	Yes	Yes	No	Yes	No	Yes
Arizona	Yes	Yes	Yes	Yes	No	Yes
Arkansas	No	No	No	No	No	No
California	Yes	Yes	Yes	Yes	Yes	Yes
Colorado	Yes	Yes	Yes	No	Yes	Yes
Connecticut	Yes	Yes	Yes	Yes	Yes	Yes
Delaware	Yes	Yes	No	No	No	Yes
District of Columbia	Yes	Yes	Yes	Yes	Yes	Yes
Florida	Yes	Yes	Yes	No	No	Yes
Georgia*	Yes	No	No	No	No	No
Hawaii	Yes	Yes	Yes	Yes	Yes	Yes
Idaho	Yes	Yes	No	No	No	No
Illinois	Yes	Yes	Yes	Yes	No	Yes
Indiana	No	No	No	No	No	No
Iowa	Yes	Yes	Yes	Yes	No	Yes
Kansas	Yes	Yes	Yes	No	No	Yes
Kentucky	Yes	Yes	Yes	No	No	Yes
Louisiana	Yes	Yes	Yes	Yes	No	Yes
Maine	Yes	Yes	Yes	Yes	No	Yes
Maryland	Yes	Yes	No	No	No	No

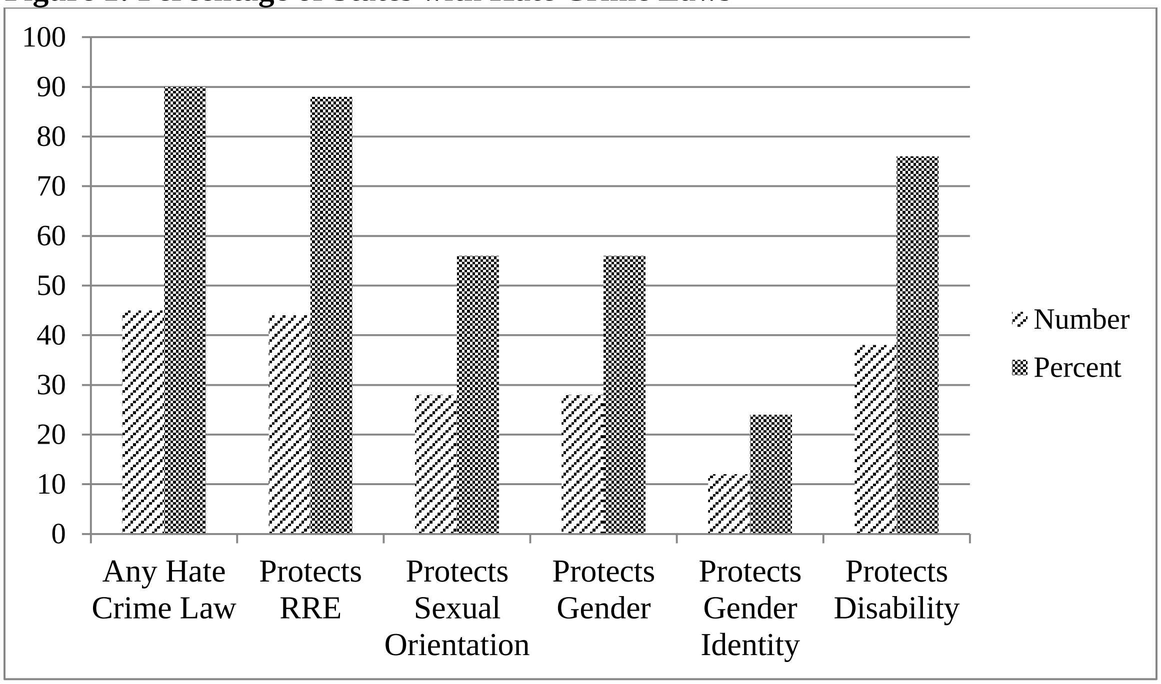
Table 5.9 (Cont'd)						
Massachusetts	Yes	Yes	Yes	Yes	No	Yes
Michigan	Yes	Yes	No	Yes	No	Yes
Minnesota	Yes	Yes	Yes	Yes	Yes	Yes
Mississippi	Yes	Yes	No	Yes	No	No
Missouri	Yes	Yes	Yes	Yes	Yes	Yes
Montana	Yes	Yes	No	No	No	No
Nebraska	Yes	Yes	Yes	Yes	No	Yes
Nevada	Yes	Yes	Yes	No	No	Yes
New Hampshire	Yes	Yes	Yes	Yes	No	Yes
New Jersey	Yes	Yes	Yes	Yes	Yes	Yes
New Mexico	Yes	Yes	Yes	Yes	Yes	Yes
New York	Yes	Yes	Yes	Yes	No	Yes
North Carolina	Yes	Yes	No	Yes	No	No
North Dakota	Yes	Yes	No	Yes	No	No
Ohio	Yes	Yes	No	No	No	No
Oklahoma	Yes	Yes	No	No	No	Yes
Oregon	Yes	Yes	Yes	No	Yes	No
Pennsylvania	Yes	Yes	No	No	No	No
Rhode Island	Yes	Yes	Yes	Yes	No	Yes
South Carolina	No	No	No	No	No	No
South Dakota	Yes	Yes	No	No	No	No
Tennessee	Yes	Yes	Yes	Yes	No	Yes
Texas	Yes	Yes	Yes	Yes	No	Yes
Utah	No	No	No	No	No	No
Vermont	Yes	Yes	Yes	Yes	Yes	Yes
Virginia	Yes	Yes	No	No	No	No
Washington	Yes	Yes	Yes	Yes	Yes	Yes
West Virginia	Yes	Yes	No	Yes	No	No
Wisconsin	Yes	Yes	Yes	No	No	Yes
Wyoming	No	No	No	No	No	No
Total 'Yes'	**45**	**44**	**28**	**28**	**12**	**38**

*Hate crime law struck down by U.S. Supreme Court

From Table 5.9, it is evident that the majority of states did, in fact, have hate crime laws in effect as of 2000. Only five states deemed such protections from bias criminality unnecessary. They are as follows: Wyoming, Arkansas, Indiana, South Carolina, and Utah. In contrast, Washington, Hawaii, Vermont, New Jersey, New Mexico, Missouri, Minnesota, the District of

Columbia, California, and Connecticut provide protection from bias criminality for all the identified categories. Georgia did pass a law protecting its citizens from bias crimes, only to have it struck down in 2000 by the United States Supreme Court on account of its vague nature and lack of specification for protected groups (Henry, 2009).

Figure 1: Percentage of States with Hate Crime Laws



As presented in Figure 1, 90% of states have a hate crime law of some variety. Although there is quite a bit of variation in the identities that are protected by state hate crime statutes, the majority (88%) do protect their citizens from bias crimes motivated by animus toward the victim's race, religion, and ethnicity. Bias crimes committed against persons with disabilities are also addressed by law in 76% of states. In addition, 56% of states protect victims based on gender and sexual orientation. Only a minority of states (24%) list statutory protections for those who are victimized based on their actual or perceived gender identity.

Control Variables

Appendix E and Table 5.10 present the descriptive statistics for the control variables used in this dissertation. The number of non-English speaking persons, the median age, the number of veterans, and the number of persons with a bachelor's degree are used to ensure the models are measuring the concepts of social disorganization theory properly. In addition, the number of Christians residing in each county and the number of persons participating in the 2000 presidential election are included. With the exception of median age, the overall number and percent are available for each control variable. Moreover, additional descriptive statistics such as measures of central tendency and measures of dispersion are analyzed and presented.

Table 5.10: Additional Descriptive Statistics for Control Variables (2000)

	Number Non-English Speaking	*Number of Veterans*	*Number with a Bachelor's Degree*	*Number of Christian Residents*	*Number Participating in 2000 Presidential Election*
N (Counties)	3,141.00	3,139.00	3,139.00	3,138.00	3,035.00
Missing	0.00	2.00	2.00	3.00	106.00
Mean	14,947.84	8,411.12	9,021.17	45,050.05	33,393.99
Median	1,094.00	2,460.00	1,432.00	12,432.50	9,307.00
Mode*	116.00*	919.00	315.00*	3,280.00*	1,519.00*
SD	111,340.62	21,706.02	33,045.30	158,426.51	97,515.46
Range	4,758,482.00	510,707	945,634.00	5,528,796.00	2,695,017.00
Minimum	0.00	5.00	0.00	18.00	137.00
Maximum	4,758,482.00	510,712.00	945,634.00	5,528,814.00	2,695,154.00

* More than one mode; lowest listed

Appendix E and Table 5.10 display appropriate descriptive statistics for relevant control variables used in this dissertation. For each of the control variables, the overwhelming majority of counties are represented. With regard to the number of persons voting in the 2000 presidential election, 3,035 counties are represented with data; 106 counties are missing.

For the number of Christian residents, data are missing for three counties. For the number of veterans and the number of residents with a bachelor's degree, only two counties each are missing. Data are available for all 3,141 counties with regard to the number of non-English speaking residents.

The mean number of non-English speaking residents in United States counties is 14,947.84. This accounts for the high range in values, ranging from zero to 4,758,482. The median figure for number of non-English speaking persons is 1,094 and the mode is 116. In addition, the standard deviation is 111,340.62.

The nature of the number of veterans ranges from five to 510,712. The mean for this control variable was 8,411.12 and the median was 2,460. The mode was 919 veterans per United States county in 2000. The standard deviation was rather large, with a value of 21,706. The range of persons holding bachelor's degrees across United States counties varies from zero to 945,634 with a mean of 9,021.17. In addition, the median figure for those having earned a bachelor's degree is 1,432 and the mode is 315. There is great variation across counties as the standard deviation is 33,045.30.

In terms of adherents to Christianity, the mean is 45,050.05. The median is 12,432 and the mode is 3,280. The figures range from 18 to 5,528,814 and the standard deviation is 158,426.51. With regard to political participation in the 2000 presidential election, the mean is 33,393. The median value is 9,307 and the mode is 1,519. The figures ranged from 137 persons voting in the election to 2,695,154 persons participating in the election. The standard deviation is 97,515.46.

In Appendix F, the number of anti-white bias crimes in United States counties is displayed. Although the main models examine differences between groups, it is important to examine and note the anti-white bias crimes that occurred in 2000. The results are located in Table 5.11. In the main models, anti-white bias crime incidents are excluded from the dependent variable named "anti-race bias crime." This is done because this dissertation seeks to examine bias criminality that has occurred against subordinate social groups – racial, religious, and sexual minorities. Although anti-white bias crimes are certainly worthy of investigation, they comprise 10.10% of all bias crimes and are not viewed as violent representations of oppression. After all, in order to oppress a social group must possess the power to maintain structural inequality – an advantage white Americans have and persons of color do not (Bell, 2013). The five states that report the highest number of anti-white bias crimes are as follows: Michigan (20.96%), Virginia (25.51%), South Carolina (29.41%), Tennessee (37.84%), and Florida (16.67%). The following tables provide additional descriptive statistics for anti-white bias crime.

Table 5.11: Descriptive Statistics for Measures of Anti-White Bias Occurrence (2000)

	Number of Anti-Race Bias Crimes	*Number of Anti-White Bias Crimes*
N (Counties)	737.00	738.00
Missing	2,401.00	2,403.00
Mean	1.04	6.67
Median	0.00	2.00
Mode	0.00	1.00
SD	3.35	24.10
Range	57.00	555.00
Minimum	0.00	0.00
Maximum	57.00	555.00

Table 5.11 compares the measures of central tendency and the measures of dispersion for both the dependent variable (number of anti-race bias crimes in 2000) and the control variable (number of anti-white bias crimes in 2000). Most important is the acknowledgement that only 738 counties in the United States reported a bias crime as having occurred in 2000. The overwhelming majority of counties (2,403) did not report any bias crimes as having happened within their borders. The mean is 6.67, the median is two, and the mode is one. Certainly, anti-white bias crimes are not the most frequently occurring bias crime. The range was zero to 555 anti-white bias crimes per county and the standard deviation was a 24.10.

Summary

The purpose of Chapter Five was to examine the nature and context of United States counties and the bias crimes that have occurred within them from 2000 to 2009. This allows for a description of that data prior to the answering of the research questions. As such, appropriate descriptive statistics were displayed for the dependent and independent variables used in this dissertation. More specifically, the descriptive statistics for the measures of social disorganization theory are presented. Chapter Six discusses the appropriate bivariate analyses for this dissertation.

CHAPTER 6: CONSIDERING BIAS CRIME OCCURRENCE IN UNITED STATES COUNTIES

The purpose of Chapter Six is to present the results of bivariate analyses used to support the investigation of the stated research questions in this dissertation. Numerous statistical methods are used to evaluate the existence of bivariate relationships; each is appropriate for the type of variables examined. These selection of these statistical techniques are informed by the nature of the dependent and independent variables. The bivariate analyses are organized and presented according to each of the main models in this dissertation. First, the nature of the relationships between the categorical dependent variable and each of the independent variables is presented and discussed. Second, the appropriate bivariate analyses for the subsequent models are presented and discussed.

Bivariate Analyses

Model One

Table 6.1 displays the results of chi-square tests for independence between the categorical dependent variable and the predictor variables for Model One. In this case, the dependent variable is a continuous measure (0 = no bias crimes occurring; 1 = at least one bias crime occurring) of bias criminality across United States counties. Chi-square analyses are used given the data are non-parametric.

Table 6.1: Model One Chi-Square Tests for Independence (Anti-race)

Predictor	***N***	***χ^2***	***p***	***ϕ***	***Cramer's V***	***df***
Population in 2000	3,141	664.394	.000	--	.460	2
Any hate crime law (HCL) in 2000	3,141	7.555*	.006	.050	--	1
HCL RRE**	3,141	26.356*	.000	-.093	--	1
HCL sexual orientation	3,141	27.249*	.000	-.094	--	1
HCL gender	3,141	.001*	.981	.001	--	1
HCL gender identity	3,141	28.567*	.000	-.096	--	1
HCL disability	3,141	25.335*	.000	-.090	--	1

*Yates's Continuity Correction
**Race, Religion, Ethnicity

From Table 6.1, numerous findings are apparent. A chi-square test for independence indicated a significant relationship between United States counties' populations and the occurrence of bias crime, χ^2 (2, N-3,141) = 664.294, *p*=.000. A Cramer's V value of .460 indicated a moderately strong association between the two measures. Additional chi-square tests for independence were conducted for each state's hate crime laws and their relationships to the occurrence of bias criminality in United States counties.

First, the relationship between the occurrence of bias criminality and the presence of any hate crime law in each state was explored. Since the tables were 2 by 2 for the remaining variables, Yates's correction for continuity was used to account for any overestimations in the chi-square analyses. As such, the Yates score was 7.555 and was significant at the .05 level (.006). In addition, the phi value was .050, indicating a weak association between the variables.

Second, the types of legislation were separated by the groups that were protected. The relationship between the occurrence of bias criminality and states that have laws protecting against racially, religiously, and ethnically motivated bias crime was significant (.000). The Yates's chi-square value was 26.356 and the phi was -.093, indicating a dependent, yet weak association. Similarly, the relationship between the occurrence of bias criminality and states that have laws protecting against anti-sexual orientation-motivated bias crime was also significant at the .05 level (.000). The Yates's chi-square was 27.249 with a phi of -.094. In contrast, the Yates's value for laws protecting gender was .001 and was not significant (.981). The phi was .001. Given these findings, it was evident that the occurrence of bias criminality in United States counties and the presence of hate crime laws protecting gender were independent of one another. Moreover, the Yates's score for laws protecting gender identity was 28.567 and was significant, with a value of .000. The reported phi was -.096. The relationship between the occurrence of bias crime and laws protecting disability had a Yates's score of 25.335 and was significant at the .05 level. The phi was -.090, which indicated a weak association between the two variables.

The following tables present the findings from several simple logistic regression analyses. Simple logistic regression was used as the data are non-parametric in nature. The tables are organized by traditional indicators of social disorganization theory. A separate table presents finding for simple logistic regression findings for the control variables. All analyses were bivariate in nature and conducted with the dependent variable used in Model One, a dichotomous indicator of bias crime occurrence in United States counties.

Table 6.2: Logistic Regression on Measures of Low Economic Status

Predictor	***β***	***Wald χ^2***	***p***	***Exp(B)****	***Cox & Snell R^2***	***Nagelkerke R^2***
Percent unemployed	.027	.797	.372	1.028	.000	.000
Percent below poverty line	-.081	161.172	.000	.922	.056	.075
Percent without a Bachelor's degree	-.166	145.677	.000	.847	.053	.072

*Confidence Interval (95.0%)

Table 6.2 displays the results of three simple logistic regression analyses. Each model included one independent variable and one dependent variable. Any relationship between the percentage of unemployed persons in United States counties and the presence of bias crime was not significant. However, the logistic regression analysis did indicate a significant relationship between the percentage of persons living below the poverty line in each county and bias crime occurrence. The model explained between 5.6% and 7.5% of the variance in the dependent variable. The B value is -.081, which indicated a negative relationship between the variables. The odds ratio for the percentage of persons living below the poverty line in United States counties was .992. This suggested that for each additional one unit increase in unemployment, United States counties was .922 times less likely to experience the occurrence of bias criminality. In addition, the relationship between the percentage of persons without a bachelor's degree residing in each county and the presence of bias criminality was significant at the .05 level. The model explained between 5.3 percent and 7.2 percent of the variance in the dependent variable. The B value was -.166. This indicated that for every one percent increase in persons without Bachelor's degrees residing in each county, bias criminality was .847% less likely to occur.

Table 6.3: Logistic Regression on Measures of Social Heterogeneity

Predictor	***β***	***Wald χ^2***	***p***	***Exp(B)****	***Cox & Snell R^2***	***Nagelkerke R^2***
Percent non-White residents	-.012	29.929	.000	.988	.010	.013
Percent foreign-born	.078	49.394	.000	1.082	.019	.026
Percent Jewish	.339	27.853	.000	1.404	.015	.021
Percent Muslim	1.041	31.07	.000	2.833	.015	.020

*Confidence Interval (95.0%)

In Table 6.3, the results for simple logistic regression analyses on four measures of social heterogeneity are presented. The logistic regression analysis did indicate a significant relationship between the percentage of non-White persons residing in a county and the existence of bias criminality. The model explained between 1.0% and 1.3% of the variance in the dependent variable. The B-value was -.012, indicating the presence of a negative relationship. Therefore, the odds ratio suggested that for every one percent increase in non-White residents, the likelihood of bias criminality occurring decreased by .988%.

In addition, the relationships between the remaining three measures of social heterogeneity were all significant and the .05 level. First, the percentage of foreign-born persons had a positive relationship the occurrence of bias criminality in United States counties, with a B value of .078. The model explained between 1.9% and 2.6% of the variance in the dependent variable. The odds ratio was 1.082, indicating that for every one percent increase in the population of foreign-born persons, the likelihood of bias criminality occurring increased by 1.082%. Second, the relationship between the percentage of Jewish residents and the occurrence of bias criminality was yet stronger, with a B value of .339. This model explained between 1.5% and 2.1% of the variance in the dependent variable. As such, for every one percentage increase in the Jewish population in United States counties, the likelihood of bias criminality occurring increased by 1.404%. Third, the strongest relationship existed with the percentage of Muslim residents in each county. The B value was 1.041, indicating a positive relationship. Additionally, the model explained 1.5% to 2.0% of the variance in the dependent variable. An odds ratio of 2.833 indicated that for every one percent increase in Muslim residents that existed in United States counties, the likelihood of bias crime occurring increased by 2.833%.

Table 6.4: Logistic Regression on Measures of Social Cohesion

Predictor	***β***	***Wald χ^2***	***p***	***Exp(B)****	***Cox & Snell R^2***	***Nagelkerke R^2***
Percent divorced	.207	75.618	.000	1.230	.025	.034
Crime rate	.000	10.531	.001	1.000	.006	.009
Percent voting in 2000 Presidential election	-.012	6.142	.013	.988	.002	.003

*Confidence Interval (95.0%)

Table 6.4 presents the findings of two simple logistic regression analyses representing measures of social cohesion. The percentage of divorced persons residing in United States counties had a positive relationship with the occurrence of bias criminality. The B value was .207. This model explained between 2.5% and 3.4% of variance in the dependent variable. The odds ratio was 1.230, indicating that with every 1% increase in divorced persons in United States counties, the likelihood of bias crimes occurring increased by 1.230%. In addition, the crime rate had a positive, yet weak, relationship with the occurrence of bias criminality in United States counties. The B value was .000 and the model explained between .6% and .9% of the variance in the dependent variable. The odds ratio indicated that as the crime rate increased by one unit in United States counties, the likelihood of the occurrence of bias criminality increased by 1.00%. The percentage of county residents voting in the 2000 Presidential election was statistically significant. With a B value of -.012, the relationship was negative and weak. However, the model did predict between .2% and .3% of the variance in the dependent variable. With every one percent increase in voter participation, the likelihood of bias criminality occurring was reduced by .988%.

Table 6.5: Logistic Regression on Residential Mobility

Predictor	*β*	*Wald* χ^2	*p*	*Exp(B)**	*Cox & Snell* R^2	*Nagelkerke* R^2
Percent owner-occupied housing units	.011	7.384	.007	1.011	.002	.003
Percent unoccupied housing units	-.041	104.198	.000	.959	.036	.048

*Confidence Interval (95.0%)

Table 6.5 presents findings from logistic regression analyses conducted on measures of residential mobility. Both models were statistically significant at the .05 level. The percentage of owner-occupied housing units had a positive relationship with bias crime occurrence in United States counties. The B value was .011 and the model explains between .2% and .3% of the variance in the dependent variable. Moreover, for each one percent increase in owner-occupied housing units in United States counties, the likelihood of the occurrence of bias criminality increased by 1.011%. In contrast, the percentage of unoccupied housing units present in United States counties had a negative relationship with bias crime occurrence, as is indicated by a B value of -.041. The model explained between 3.6% and 4.8% of the variance in the dependent variable. As such, the model suggested that for every one percent increase in unoccupied housing units, the counties were .959% less likely to experience bias criminality.

The results of simple logistic regression analyses conducted on the continuous control variables are found in the following table. All but the percentage of non-English speaking residents in United States counties had a statistically significant relationship with the occurrence of bias criminality.

Table 6.6: Logistic Regression on Control Variables

Predictor	***β***	***Wald χ^2***	***p***	***Exp(B)****	***Cox & Snell R^2***	***Nagelkerke R^2***
Percent Christian	-.017	74.979	.000	.983	.024	.033
Median Age	-.057	36.681	.000	.945	.012	.016
Percent non-English speaking	-.004	1.362	.243	.996		.0 01
Percent veterans	.084	25.897	.000	1.088	.008	.011

*Confidence Interval (95.0%)

Table 6.6 presents the results of five simple logistic regression analyses. Each one of the analyses was conducted with the dichotomous dependent variable. First, the relationship between the percentage of any denomination of Christians and the occurrence of bias crime was significant and negative. The B value was -.017. The model explains 2.4% to 3.3% of the variance in the dependent variable. The odds ratio suggested that for every one percent increase in Christian residents, bias crimes were .983% less likely to occur. Second, median age also had a negative, yet significant, relationship with bias crime occurrence. The B value was -.057. In addition, between 1.2% and 1.6% of the variance in the dependent variable was explained by this model. As such, as the median age increased by one unit, bias crime was .945% less likely to occur in United States counties. Third, the percentage of non-English speaking persons residing in each county was not statistically significant in its relationship with bias crime occurrence.

Fourth, the percentage of veterans residing in United States counties had a positive and significant relationship with the occurrence of bias criminality. The B value was .084, indicating the presence of a relationship that was rather weak. Between .8% and .11% of the variance in the dependent variable was explained by the model. Additionally, the odds ratio suggested that for every one percent increase in the veteran population in United States counties, the likelihood of bias criminality occurring increased by 1.088%.

Models Two, Three and Four

In order to determine the nature of relationships between the continuous dependent variables used in Models Two, Three and Four and the categorical independent variables, the Kruskal-Wallis Test was used. This test is a non-parametric alternative to ANOVA. Model Two represents the number of bias crimes that were motivated by animus toward race between 2000 and 2009 in United States counties. This is a continuous variable and it is used as the dependent variable for Model Two. Similarly, Model Three represents the number of anti-sexual orientation bias crimes that occurred during the same time period. Anti-religion bias crimes are represented in Model Four. Moreover Spearman rho analyses were conducted to measure the relationship between the continuous independent variables and the continuous dependent variables present in Models 1-4. Table 6.7 presents the findings from the Kruskal-Wallis tests, including the effect size. Table 6.8 displays the findings from Spearman rho analyses.

Table 6.7: Kruskal-Wallis Test for Models Two, Three, and Four

Model/Variable	χ^2	*df*	*p*	*ES*
Model 2 (Anti-Race)				
Population in 2000	1,222.030	2	.000	.389
Any hate crime law in 2000	11.715	1	.001	.004
HCL RRE	15.498	1	.000	.005
HCL Sexual Orientation	20.418	1	.000	.007
HCL Gender	1.858	1	.173	--
HCL Gender Identity	50.109	1	.000	.016
HCL Disability	20.459	1	.000	.007
Model 3 (Anti-Sexual Orientation)				
Population in 2000	992.960	2	.000	.316
Any hate crime law in 2000	.966	1	.326	--
HCL RRE	15.563	1	.000	.005
HCL Sexual Orientation	38.136	1	.000	.012
HCL Gender	14.277	1	.000	.005
HCL Gender Identity	58.488	1	.000	.019
HCL Disability	38.105	1	.000	.012
Model 4 (Anti-Religion)				
Population in 2000	999.951	2	.000	.318
Any hate crime law (HCL) in 2000	.046	1	.831	--
HCL RRE	18.387	1	.000	.006
HCL Sexual Orientation	16.247	1	.000	.005
HCL Gender	2.752	1	.097	--
HCL Gender Identity	39.165	1	.000	.012
HCL Disability	14.754	1	.000	.005

<u>Model Two</u>

A Kruskal-Wallis analysis of variance (ANOVA) revealed that county population varied significantly across counties that reported the occurrence of anti-race motivated bias crime, χ^2 (2) = 1,222.030, p = .000. In addition, the presence of any hate crime law in United States counties varied significantly across anti-race bias crimes in United States counties, χ^2 (1) = 11.715, p = .001. The following independent variables also had a statistically significant (p = .000) variation across anti-race bias crimes in United States counties: HCL RRE, χ^2 (1) = 15.498; HCL Sexual Orientation, χ^2 (1) = 20.418; HCL Gender Identity, χ^2 (1) = 50.109; and HCL Disability, χ^2 (1) = 20.459. These findings indicate that there was a significant difference in the dependent variable across each of these groups. Hate crime laws protecting gender did not have a statistically significant relationship with the number anti-race motivated bias crimes that occurred in United States counties.

Model Three

For the third model, a Kruskal-Wallis Test revealed several findings. The county populations varied significantly across the number of anti-sexual orientation bias crime events in United States counties, χ^2 (2) = 992.960, p = .000. Additionally, the following independent variables varied significantly (.000) across the dependent variable: HCL RRE, χ^2 (1) = 15.563; HCL Sexual Orientation, χ^2 (1) = 38.136; HCL Gender, χ^2 (1) = 14.277; HCL Gender Identity, χ^2 (1) = 58.488; and HCL Disability, χ^2 (1) = 38.105. The independent variable representing the dichotomous measure of the presence of hate crime law in the aggregate was not statistically significant.

Model Four

Kruskal-Wallis (ANOVA) analyses uncovered several results for Model Four. The county populations varied across number of anti-religion bias crimes that occurred in United States counties between 2000 and 2009. χ^2 (2) = 999.951, p = .000. Also significant at the .05 level were several other relationships. The following variables varied significantly across the dependent variable: HCL RRE, χ^2 (1) = 18.387; HCL Sexual Orientation, χ^2 (1) = 16.247, HCL Gender Identity, χ^2 (1) = 39.165; and HCL Disability, χ^2 (2) = 14.754. The independent variable representing the dichotomous measure of the presence of hate crime law in the aggregate was not statistically significant. Additionally, the independent measure (HCL Gender) was not significant.

Bivariate Analyses for Continuous Independent Variables

The following tables display the results of Spearman's rho correlation analyses conducted between the continuous dependent variables of Models Two, Three, and Four and the continuous independent variables. Each of the three tables is organized by specific model.

Table 6.8: Spearman's Rho Correlations for Model Two (Anti-Sexual Orient.)

Independent Variable	***N***	r_s	***P***
Low Economic Status			
Percent unemployed	3,139	.080*	.000
Percent below poverty line	3,139	-.259*	.000
Percent without bachelor's degree	3,139	-.340*	.000
Social Heterogeneity			
Percent non-white residents	3,139	.125*	.000
Percent foreign-born	3,138	.364*	.000
Percent Jewish	3,138	.468*	.000
Percent Muslim	3,138	.405*	.000
Social Cohesion			
Percent divorced	3,139	.171*	.000
Crime rate	3,139	-.137*	.000
Percent voting in 2000 presidential election	3,035	-.57*	.002
Residential Mobility			
Percent owner-occupied housing units	3,141	-.013	.480
Percent unoccupied housing units	3,141	-.372*	.000
Control			
Percent Christian	3,138	-.183*	.000
Median age	3,139	-.219*	.000
Percent non-English speaking	3,141	.234*	.000
Percent veterans	3,139	.026	.147
Percent of hate crimes that are anti-white	737	.368*	.000

*Significant at the .01 level

According to Table 6.8, there are numerous statistically significant findings for Model Two. For the measures of low economic status, each of the independent variables was significant at the .01 level. The Spearman's rho correlation between the percentage of persons who were unemployed in 2000 and the occurrence of anti-race bias crimes had a value of .080. This indicated a positive, though very small relationship. For the percentage of persons living below the poverty line in 2000, the Spearman's rho correlation indicated a value of -.259. This indicated a negative relationship, though it is of small strength. The percentage of persons holding a bachelor's degree, however, had a value of -.340 and is negative. This relationship with the occurrence of anti-race bias criminality was medium in strength.

The measures for social heterogeneity all proved to be statistically significant at the .001 level in their Spearman's rho correlations with the dependent variable. The percentage of non-White residents present in each United States county did have a positive relationship with the occurrence of anti-race bias criminality, though the strength of the relationship was small. The Spearman's rho correlation value was .125. The percentage of foreign-born persons in each county also had a positive relationship with the occurrence of anti-race bias criminality. The Spearman's rho value was .364, which indicated a medium strength in the relationship. Both the percentage of Jewish persons and the percentage of Muslim persons residing in each county had a positive and significant relationship to the occurrence of anti-race bias criminality. The Spearman's rho correlation for the percentage of Jewish residents was .468, suggesting a medium strength in the relationship. For the percentage of Muslim residents in each county, the Spearman's rho value was .405, providing evidence that a medium strength relationship existed between the variables.

Measures of social cohesion also exhibited statistically significant relationships at the .01 level with the dependent variable. The percentage of divorced persons residing in each county and the occurrence of anti-race bias criminality had a positive, yet small relationship. The Spearman's rho value was .171. In addition, the crime rate in 2000 had a negative and small relationship with the dependent variable. The Spearman's rho value was -.137. The percentage of persons voting in the 2000 presidential election was negatively correlated with the dependent variable. The Spearman's rho value was -.57, which was evidence of a small strength in the relationship.

The percentage of owner-occupied housing units in each county was not statistically significant in its relationship to the dependent variable. However, the percentage of unoccupied housing units present in each county was statistically significant at the .01 level in its relationship with the occurrence of anti-race bias criminality. The Spearman's rho value was -.57, indicating a negative, yet small strength in the relationship.

Numerous significant relationships were found in Spearman's rho correlation analyses between control variables and the dependent variable in Model Two. The percentage of Christian residents (any denomination) was negatively correlated with the occurrence of anti-race bias criminality in United States counties. The Spearman's rho value was -.183, indicating a small and weak relationship to the dependent variable. Median age also had a negative and small relationship to the dependent variable in Model Two. The Spearman's rho value was -.219. The percentage of non-English speaking individuals in each county was positively correlated with the occurrence of anti-race bias criminality. The Spearman's rho value was .234, which indicated a small strength of bivariate relationship. Moreover, the percentage of total bias crimes that were reported as anti-White was positively correlated to the occurrence of anti-race bias criminality. The dependent variable excludes anti-White bias crime incidents so as not to create an interaction effect. The Spearman's rho value was .368, indicating a medium strength in relationship with the dependent variable. The percentage of veterans residing in each county was not correlated to the occurrence of anti-race bias criminality.

Table 6.9: Spearman's Rho Correlations for Model Three (Anti-Religion)

Independent Variable	*N*	r_s	*P*
Low Economic Status			
Percent unemployed	3,139	.081*	.000
Percent below poverty line	3,139	-.215*	.000
Percent without bachelor's degree	3,139	-.367*	.000
Social Heterogeneity			
Percent non-white residents	3,139	.117*	.000
Percent foreign-born	3,138	.337*	.000
Percent Jewish	3,138	.518*	.000
Percent Muslim	3,138	.453*	.000
Social Cohesion			
Percent divorced	3,139	.145*	.000
Crime rate	3,139	-.132*	.000
Percent voting in 2000 presidential election	3,035	.012	.506
Residential Mobility			
Percent owner-occupied housing units	3,141	-.075*	.000
Percent unoccupied housing units	3,141	-.320*	.000
Control			
Percent Christian	3,138	-.155*	.000
Median age	3,139	-.203*	.000
Percent non-English speaking	3,141	.265*	.000
Percent veterans	3,139	-.021	.248
Percent of hate crimes that are anti-white	737	.285*	.000

*Significant at the .01 level

As is apparent in Table 6.9, numerous statistically significant findings emerged from the Spearman's rho correlation analyses. Several measures represented low economic status in the bivariate Spearman's rho correlations. Each was statistically significant at the .01 level. The percentage of unemployed persons in each United States county in 2000 was positively correlated with the occurrence of anti-sexual orientation bias criminality. However, this relationship was small in strength as its Spearman's rho value was .081. The percentage of persons living below the poverty line had a small, yet negative, relationship to the occurrence of anti-sexual orientation bias criminality. The Spearman's rho value was -.215. In addition, the percentage of residents without a bachelor's degree in 2000 was negatively related to the occurrence of bias criminality in United States counties. The Spearman's rho value was -.367, which indicated a medium strength of relationship.

Each of the measures representing social heterogeneity was statistically significant in its bivariate correlational analysis with the dependent variable. A Spearman's rho correlation analysis revealed that there was a small, yet positive relationship between the percentage of non-White residents in United States counties in 2000 and the occurrence of anti-sexual orientation bias criminality. The test statistic for this analysis was .117, indicating a small strength of relationship. The percentage of foreign-born persons residing in American counties was also positively correlated with the occurrence of anti-sexual orientation bias criminality. The spearman's rho value was .337, revealing a medium strength of relationship between the two variables. In addition, the percentage of Jewish residents in American counties was significantly correlated with the occurrence of anti-sexual orientation bias criminality, with a reported test statistic of .518. This indicated a positive and large strength of relationship between the two variables. The percentage of Muslim persons residing in United States counties had a Spearman's rho value of .453. This indicated a positive, yet medium strength in the relationship between the percentage of Muslim residents and the occurrence of anti-sexual orientation bias criminality.

Two of the three measures for social cohesion were statistically significant at the .01 level. First, the percentage of divorced persons residing in American counties was positively correlated with the occurrence of anti-sexual orientation bias criminality. The Spearman's rho test statistic was .145, indicating a small strength of relationship between the two variables. Second, the crime rate in 2000 had a negative relationship with the dependent variable. The Spearman's rho value was -.132. This relationship was small in strength. The percentage of persons in each county voting in the 2000 presidential election was not statistically significant in its relationship with the occurrence of anti-sexual orientation bias criminality.

Both measures of residential mobility had a statistically significant relationship with the dependent variable at the .01 level. First, the percentage of owner-occupied housing units had a Spearman's rho value of -.075. This indicated a very small strength of relationship that was negative in direction. Second, the percentage of unoccupied housing units in American counties in 2000 had a negative, yet medium strength, relationship with the occurrence of anti-sexual orientation bias criminality. The test statistic was -.320.

All but one control variable had a statistically significant relationship at the .01 level with the dependent variable for Model Three. The percentage of Christians (any denomination) residing in American counties was negatively correlated with the occurrence of anti-sexual orientation bias criminality. The Spearman's rho value was -.155, indicating that the strength of the relationship between the two variables was small. In addition, the median age of residents of American counties had a negative relationship with the dependent variable. The test statistic was -.203, suggesting that the relationship between the two variables was small as well. The percentage of non-English speaking residents was positively correlated to the occurrence of anti-sexual orientation bias criminality. The Spearman's rho value was .265, indicating the strength of the relationship was small. Moreover, the percentage of bias crimes that were anti-White in American counties had a statistically significant and positive relationship with the dependent variable. With a Spearman's rho value of .285, the relationship was also small in strength. The percentage of veterans residing in each American county had no statistically significant correlation with the occurrence of anti-sexual orientation bias criminality.

Table 6.10: Spearman's Rho Correlations for Model Four

Independent Variable	***N***	r_s	***p***
Low Economic Status			
Percent unemployed	3,139	.060*	.001
Percent below poverty line	3,139	-.238*	.000
Percent without bachelor's degree	3,139	-.385*	.000
Social Heterogeneity			
Percent non-white residents	3,139	.121*	.000
Percent foreign-born	3,138	.380*	.000
Percent Jewish	3,138	.537*	.000
Percent Muslim	3,138	.491*	.000
Social Cohesion			
Percent divorced	3,139	.105*	.000
Crime rate	3,139	-.117*	.000
Percent voting in 2000 presidential election	3,035	.007	.707
Residential Mobility			
Percent owner-occupied housing units	3,141	-.072*	.000
Percent unoccupied housing units	3,141	-.327*	.000
Control			
Percent Christian	3,138	-.157*	.000
Median age	3,139	-.209*	.000
Percent non-English speaking	3,141	.278*	.000
Percent veterans	3,139	-.031	.082
Percent of hate crimes that are anti-white	737	.290*	.000

*Significant at the .01 level

Table 6.10 presents the results of several bivariate Spearman's rho correlation analyses. Model Four represents the occurrence of anti-religion bias criminality as the dependent variable across all analyses. All three measures of low economic status were statistically significant at the .01 level for Model Four. Specifically, the percentage of unemployed persons residing in American counties had a positive, yet very small strength, relationship with the occurrence of anti-religion bias criminality. The Spearman's rho value was .060. Additionally, the percentage of persons living below the poverty line was negatively correlated with the dependent variable. The test statistic was -.238, indicating a small strength between the two variables. The percentage of person's without a bachelor's degree in 2000 was negatively correlated to the occurrence of anti-religion bias criminality. The Spearman's rho value was -.385. This figure suggested a medium strength relationship between the variables.

Each of the four measures of social heterogeneity and its relationship with the dependent variable was significant at the .01 level. First, the percentage of non-white residents in American counties was positively correlated with the occurrence of anti-religion bias criminality. The Spearman's rho value was .121, indicating the strength of the relationship was small. Second, the percentage of foreign-born persons was positively correlated with the dependent variable. However, the strength of the relationship was medium in nature, with -.380 reported as the test statistic. Third, the percentage of Jewish persons in United States counties was significantly and positively correlated with the incidence of anti-religion bias criminality. The Spearman's rho was .537, indicating a large strength in the relationship between the two variables. Fourth, the percentage of Muslims residing in American counties was positively correlated with the dependent variable. The Spearman's rho value was .491. This statistic suggests that there was a medium strength to the relationship between the two variables.

Two of the three measures of social cohesion had statistically significant relationships with the dependent variable. The percentage of divorced persons in American counties was positively correlated with the incidence of anti-religion bias criminality. The Spearman's rho statistic was .105, indicating that the strength of the relationship is small. In addition, the crime rate is negatively correlated with the dependent variable. With a test statistic of -.117, the size of this relationship was small as well. The percentage of persons voting in the 2000 presidential election did not have a statistically significant relationship with the dependent variable.

Two independent variables were used to represent residential mobility. Both were statistically significant at the .01 level in their relationships with the dependent variable. The percentage of owner-occupied housing units was negatively correlated with the occurrence of anti-religion bias criminality. The Spearman's rho value was -.072, indicating a negative, yet very small strength of relationship. The percentage of unoccupied housing units in American counties was also negatively correlated with the occurrence of anti-religion bias criminality. The Spearman's rho value was -.327. This figure suggested a medium strength relationship between the two variables.

All but one of the control variables had a statistically significant relationship with the dependent variable. First, the percentage of Christian (any denomination) residents in American counties was negatively correlated with the incidence of anti-religion bias criminality. The Spearman's rho value was -.157, indicating not only small strength, but also a negative relationship. The median age of United States county residents was also negatively correlated with the dependent variable. In this case, the test statistic was -.209. This suggested a relationship that is small in strength. In addition, the percentage of non-English speaking persons residing in American counties was positively correlated with the occurrence of anti-religion bias criminality. The Spearman's rho value was .278, indicating another small strength relationship. Similarly, the percentage of bias crimes that were anti-White by motivation was positively correlated with the dependent variable. The test statistic was .290, indicating small strength. The percentage of veterans residing in United States counties did not have a statistically significant relationship with the incidence of anti-religion bias criminality.

Key Findings

From the numerous bivariate analyses presented in this chapter, several notable findings emerged. For the main model (Model 1), it is apparent that several of the independent variables were good predictors of bias crime at the county level. The population of a county was significantly related to bias crime occurrence. This is relevant given the nature of both criminality and bias criminality in the United States. Although bias crimes do occur across the country, it is likely that they are not distributed uniformly. By considering this in the multivariate model, even more information will be apparent for bias crime occurrence in rural areas, urban clusters, and urbanized areas. Although several types of hate crime legislation had significant relationships with bias crime occurrence in American counties, the strength of the relationships were not particularly high. This indicates that there is not a strong relationship between hate crime laws and bias crime occurrence – one direction or another. Essentially, the existence of hate crime legislation (of any type) in a location is not a good predictor of bias crime occurrence.

Several measures of social disorganization theory are good predictors of bias criminality at the county level. The percentage of persons living below the poverty line was a useful measure of economic deprivation as it predicts the likelihood of bias crime occurrence. All measures of social heterogeneity were good predictors of bias criminality. Certainly, the percentage of Muslim residents in American counties was the strongest predictor of bias criminality. The measures of social cohesion did have a statistical significance in their relationships with bias crime occurrence; however, none of the relationships was particularly strong. Of the measures, the percent of divorced persons residing in each United States county was the strongest predictor of bias crime occurrence. It seems that the percentage of divorced persons residing in each county, although significant, is not a strong predictor of bias criminality. In addition, the measures of residential mobility were not good indicators of bias crime occurrence. Although the relationships were statistically significant, they were not strong enough to warrant the expectation of adequate prediction. Moreover, none of the control variables were good predictors of bias crime occurrence.

For Models 2, 3, and 4, there were several variables that seemed to be good predictors of bias criminality. The strongest predictors in Model 2 were those variables that measured social heterogeneity. Specifically, the percentage of persons who were foreign-born, the percentage of residents who were Jewish, and the percentage of persons who were Muslim were several of the strongest predictors of anti-race motivated bias criminality. However, the percentage of unoccupied housing units in each county, as a measure of residential mobility, was a good predictor of anti-race motivated bias crime occurrence. Models 3 and 4 indicated similar findings, with measures of social heterogeneity being the strongest predictors of anti-sexual orientation and anti-religion motivated bias crime occurrence.

Conclusion

The purpose of Chapter Six was to examine the bivariate relationships present between the dependent variables and the independent variables. This was accomplished by examining the variables used in each of the four models in order to inform their usage in the multivariate models. In Model 1, a chi square analysis and logistic regression were used to analyze non-parametric data. In Models 2, 3, and 4, the Kruskal-Wallis test and Spearman's rho correlations were conducted to analyze data that was non-parametric in nature. Chapter Seven presents the findings from the multivariate analyses.

CHAPTER 7: USING SOCIAL DISORGANIZATION THEORY TO PREDICT BIAS CRIME AT THE COUNTY LEVEL

The purpose of Chapter Seven is to present and discuss the findings from the multivariate analyses of the four main models. First, negative binomial regression is used to analyze the main model (Model 1). Given the large number of zeroes present in the data, and the resultant over-dispersion, this method allows for a more accurate examination of count data. Second, in Models 2, 3, and 4, Ordinary Least Squares regression (OLS) is used to determine the nature of the relationships between individual three motivations of bias criminality. In these models, only the counties that actually report bias criminality as having occurred are included in the analyses. These specific analyses allow for the exploration of the research questions. The research questions guide the order of presentation and the discussions address the relevance of the models to bias crime at the county level.

Question 1:

What are the relationships between traditional indicators (low economic status, social heterogeneity, family disruption, residential mobility, and violent crime rate) of social disorganization concepts (as measured by US Census Data, ARDA, and *Congressional Quarterly*) and bias crime at the county level?

Table 7.1 presents the findings from negative binomial regression analysis used on Model 1. Each of the continuous and dichotomous independent variables was loaded into the model. This model examines the relationship between the incidents of bias criminality during the decade spanning from 2000 to 2009. Traditional indicators of social disorganization theory comprise the majority of the variables, giving this model the ability to inform their predictive abilities on bias crime occurrence at the county level.

Table 7.1: Model 1 – Negative Binomial Regression

Predictor	***B***	***SE***	***P***	***VIF***
Constant[4]	8.589	1.974	.000	
Low Economic Status				
Percent unemployed	-.067	.069	.329	2.230
Percent below poverty line	-.025	.016	.117	3.087
Percent without bachelor's degree	-.037	.021	.081	3.414
Social Heterogeneity				
Percent non-white	.017**	.005	.000	2.129
Percent foreign-born	.065**	.022	.004	9.917
Percent Jewish	.190**	.036	.000	1.720
Percent Muslim	.361**	.124	.004	1.653
Social Cohesion				
Percent divorced	.158**	.038	.000	2.151
Crime rate	.000	.000	.266	1.057
Percent voting in 2000 presidential election	.012	.011	.302	3.541
Residential Mobility				
Percent owner-occupied housing units	-.013	.010	.181	4.418
Percent unoccupied housing units	-.018	.009	.055	4.964
Control				
Population in 2000[5]				1.800
1 = < 2,500 (Rural)	-1.652**	.162	.000	
2 = 2,500 – 49,999 (Urban cluster)	-.963**	.125	.000	
3 = > 50,000 (Urbanized area)	0	--	--	
Hate Crime Law (HCL) in 2000	1.380*	.582	.018	12.004
HCL – Race, religion, ethnicity	-1.375*	.568	.015	12.233
HCL – Sexual orientation	.521**	.139	.000	3.176
HCL – Gender	-.305**	.107	.004	1.712
HCL – Gender identity	-.321**	.117	.006	1.649
HCL –Disability	-.443	.157	.005	3.483
Percent Christian	-.002	.004	.599	1.630
Median age	-.046*	.022	.033	4.284
Percent non-English speaking	-.014	.011	.181	7.855
Percent veterans	-.007	.033	.837	3.274
Percent of bias crimes that are anti-white	.004*	.002	.017	1.061
Log Likelihood Chi-Square	1,283.11			
Probability > Chi-Square	.000			

$^{*}p \leq .05$, $^{**}p \leq .01$

Table 7.1 presents the findings from one negative binomial regression predicting the incidence of bias criminality at the county level. In order to assess the fit for Model 1, the

[4] In a comparative OLS regression model, only the percent of foreign-born persons (B=27.206) and the percent of non-English speaking persons (B=-6.123) had statistically significant results at the .01 level.
[5] Using population as a continuous variable, the negative binomial regression coefficient is .000 and is significant at the .01 level.

likelihood ratio test was conducted. The value was 1,283.11 with a 99% confidence interval. Therefore, it is evident that the model fits the data quite well.

With regard the independent variables related to measuring social disorganization theory, each of the indicators of social heterogeneity was statistically significant at the .01 level. Not one of the measures of low economic status was statistically significant. However, from Model 1, it is expected that bias crime occurrence would increase by 2% for each percentage increase in non-White persons residing in each county. Therefore, *Hypothesis 2* is supported. Similarly, the percent of foreign-born persons in each county was positively related to the occurrence of bias criminality from 2000-2009 in American counties. For each one percent increase in foreign-born persons residing in United States counties, it is expected that bias crime occurrence would increase by 7%. This finding supports *Hypothesis 3*. In addition, it is expected that bias criminality would increase by 19% for each one percent increase in Jewish persons residing in each county. Similarly, the percent of Muslim residents in American counties was positively related to the likelihood of bias crimes occurring. For each one percent increase in Muslim residents, it is expected that bias criminality would be 36% higher. One measure of social cohesion had a positive relationship with bias crime occurrence at the .01 significance level. It is expected that for each one percent increase in divorced persons residing in each American county that bias criminality would be 16% higher. Thus, *Hypothesis 4* is supported by this finding. The crime rate and the percent of persons voting in the 2000 Presidential election were not statistically significant. Moreover, neither measure of residential mobility was statistically significant in its relationship with bias criminality in American counties.

Also relevant are the relationships the control variables have with the dependent variable. From the negative binomial regression analysis, it appears that bias criminality and county population were negatively related. For each one percent decrease in population between > 50,000 and 49,999 (urbanized area to urban cluster), it is expected that bias crime occurrence would be decreased by 96.3%. Additionally, as the county population decreased one percent for all counties with a population under 50,000, (urban cluster to rural), bias criminality would be 165.2% less likely to occur. This finding suggests that that controlling for all other variables, the larger the population, the greater likely a bias crime is predicted to occur. Hypotheses 1, 5, and 6 are not supported by the findings of Model 1.

It is important to examine the interaction effects that might exist between the independent variables. Model 1 included collinearity diagnostics so as to test for the potential of multicollinearity being present in the model. The Variance Inflation Factor (VIF) for each independent variable indicates the potential for issues involving multicollinearity. All VIF values above 10 were identified. It appears that both HCL 2000 and HCL – RRE 2000 both had VIF values above 10, indicating caution should be used when including both variables in the model. The VIF score for the independent variable indicating the presence of any hate crime law in 2000 was 12.004. For hate crime laws that specifically protect race, religion, and ethnicity, the VIF score was 12.233. In Model 1, it is likely that the two independent variables were interacting. Given there is some intersection in the concept these variables attempt to measure, it would be reasonable to remove the second measure from any future analyses. Additionally, with VIF scores just below 10, the percent of foreign-born persons and the percent of non-English speaking persons residing in each American county were also likely interacting with one another. Although each variable is different in what it measures, it is entirely possible that a person who is foreign-born would also speak a language other than English. In future analyses, removing the control variable that measures the percent of persons speaking a language other than English would likely produce stronger results.

The impact of hate crime legislation on bias criminality was varied. Controlling for all other variables, the measure of hate crime legislation that includes any type of law had a positive relationship with bias crime occurrence. Specifically, for each one unit increase in counties with hate crime legislation, it is expected that there is a 138% increase in bias criminality. However, when the independent variables representing hate crime legislation are isolated by motivation type, the findings differ. The most common type of hate crime legislation protects its citizens from crimes committed based on animus toward their race, religion, or ethnicity. The aggregate measure of these three types of bias crime motives had a negative relationship with bias crime occurrence at the county level. For each one unit increase in counties with race, religion, and ethnicity protected by legislation, it is expected that bias crime will decrease by 137.5%. When the law protects citizens based on their sexual orientation, the variable had a positive relationship with the occurrence of bias criminality. Specifically, for each one unit increase in counties with sexual orientation-based laws, it is expected that the occurrence of bias criminality rises by 52.1%. This relationship was significant at the .01 level. Conversely, the independent variables gender and gender identity had negative relationships with the occurrence of bias crime occurrence. For each one unit increase in legislation at the county level, counties can expect 30.5% fewer gender-motivated bias crimes and 32.1% fewer gender identity-motivated bias crimes to occur. Each of these relationships was significant at the .01 level.

Two additional independent variables had statistically significant relationships with bias crime occurrence at the .05 level. First, median age had a negative relationship with the dependent variable in Model 1. For each one unit increase in median age in United States counties, it is expected that bias criminality will increase by 4.6%. Second, the percent of all bias crimes that were anti-White, by motivation, has a positive relationship with bias crime occurrence in United States counties. For each one percent increase in anti-White bias crime incidence, total bias crime levels can be expected to increase by .4%.

Question 2:

What are the relationships between traditional indicators (low economic status, social heterogeneity, family disruption, residential mobility, and violent crime rate) of social disorganization concepts (as measured by US Census Data, ARDA, and *Congressional Quarterly*) and anti-race motivated bias crime at the county level?

In order to explain differences between the three most frequently occurring motivation types, OLS regression is used for three separate models. Model 2 regresses the independent variables on anti-race motivated bias crime counts. Models 3 and 4 regress the independent variables on anti-sexual orientation motivation and anti-religion motivation, respectively. Table 7.2 presents the findings of an OLS regression analysis conducted for Model 2. The aim of this sub-analysis is to determine the predictive abilities of measures of social disorganization theory on the occurrence of anti-race motivated bias crime.

Table 7.2: Model 2 – OLS Regression Analysis (Anti-Race)

Predictor	***B***	***SE***	***β***	***VIF***
Constant				
Low Economic Status				
Percent unemployed	-12.824	10.156	-.062	2.230
Percent below poverty line	-.276	2.169	-.007	3.087
Percent without bachelor's degree	5.292	2.966	.109	3.414
Social Heterogeneity				
Percent non-white	1.482*	.692	.103	2.129
Percent foreign-born	16.561*	3.348	.513	9.917
Percent Jewish	6.548	3.732	.076	1.720
Percent Muslim	33.143*	15.612	.090	1.653
Social Cohesion				
Percent divorced	9.885	5.901	.081	2.151
Crime rate	.000	.000	-.029	1.057
Percent voting in 2000 presidential election	2.167	1.761	.076	3.541
Residential Mobility				
Percent owner-occupied housing units	-1.501	1.421	-.073	4.418
Percent unoccupied housing units	-1.004	1.407	-.052	4.964
Control				
Population in 2000	7.023	11.160	.028	1.800
Hate Crime Law (HCL) in 2000	-56.917	85.555	-.076	12.004
HCL – Race, religion, ethnicity	70.505	82.936	.098	12.233
HCL – Sexual orientation	-44.285*	22.018	-.118	3.176
HCL – Gender	21.047	15.711	.058	1.712
HCL – Gender Identity	26.612	17.819	.063	1.649
HCL – Disability	20.682	24.546	.052	3.483
Percent Christian	.697	.500	.059	1.630
Median age	-2.091	3.105	-.046	4.284
Percent non-English speaking	-3.711*	1.548	-.221	7.855
Percent veterans	-2.251	4.585	-.029	3.274
Percent of bias crimes that are anti-white	.058	.246	.008	1.061
F 9.495**				
R^2 .247				

*$p \leq .05$, **$p \leq .01$

Table 7.2 presents the findings from the OLS regression analysis conducted for Model 2. The R-square is .247, indicating that 24.7% of the variation in anti-race motivated bias crime was explained by all the independent variables considered together. In addition, the F value is 9.495 and is significant at the .01 level, indicating the model had a sample size large enough to hold predictive capabilities. With findings similar to Model 1, several indicators of social heterogeneity were significant at the .05 level.

Model 2 indicated that percent of non-White persons living in a county had a statistically significant relationship with the occurrence of anti-race motivated bias criminality. The estimated regression coefficient was 1.482. This figure suggests that as the percent of non-White persons residing in an American county increased by one unit, the likelihood of anti-race motivated bias criminality increased by 1.482 units. Moreover, the estimated regression coefficient was significant at the .05 level. The standardized beta coefficient similarly indicated that for every one standard deviation increase in percent non-White residents, anti-race motivated bias criminality increased by .103 standard deviations. The standard error was .692.

Model 2 also indicated that the percent of foreign-born persons residing in United States counties had a statistically relationship to the incidence of anti-race motivated bias crime. The regression coefficient was 16.561 and the standard error was 3.348. This figure suggests that for each percent increase in foreign-born persons living in American counties, the likelihood of anti-race bias criminality increased by 16.561 units. The standardized coefficient suggests that for every one standard deviation increase in foreign-born persons residing in American counties, anti-race motivated bias crime occurrence increased by .513 standard deviations.

The percent of Muslim residents was also statistically significant in its relationship with the likelihood of anti-race motivated bias criminality at the county level. Model 2 indicated that regression coefficient was 33.143, which was quite larger than the relationships the dependent variables had with both percent foreign-born and the percent non-White. The B value suggested that for each one percent increase in Muslim residents per American county, the likelihood of anti-race bias crime occurrence increased by 33.143 units. Essentially, as the standardized coefficient suggests, for every one standard deviation increase in Muslim residents, American counties were likely to experience a .090 standard deviation increase in anti-race motivated bias criminality. The standard error was 15.612.

In total, two control variables had statistically significant relationships with the dependent variable in Model 2. First, counties that had hate crime legislation protecting sexual orientation had a statistically significant relationship with the occurrence of anti-race motivated bias crimes. The unstandardized regression coefficient was -44.285. This value indicated that for each additional county that provides hate crime legislation protecting sexual orientation, the likelihood of anti-race motivated bias criminality decreased by 44.285 units. The standard error was 22.018. The standardized coefficient was -.118, indicating a .118 standard deviation decrease in bias criminality for every one standard deviation increase in sexual orientation hate crime laws in American counties. Second, the percent of non-English speaking individuals residing in each county had a statistically significant relationship with the occurrence of anti-race motivated bias crime. For every one percent increase in non-English speaking persons in American counties, the likelihood of anti-race motivated bias crime decreased by 3.711 units. The standardized coefficient was -.221, indicating that for each one standard deviation increase in non-English speaking persons residing in each United States county, there was a .221 standard deviation decrease in anti-race motivated bias crime occurrence. The standard deviation was 1.548.

Importance lies in examining the interaction effects that exist between the independent variables. Model 2 included collinearity diagnostics in order to test for the possibility of multicollinearity in the model. The Variance Inflation Factor (VIF) for each independent variable indicates the potential for problems with multicollinearity. For the purposes of this dissertation, any VIF values above 10 were identified. It appears that both HCL 2000 and HCL

– RRE 2000 both had VIF values above 10, warranting caution in their inclusion in the model. The VIF score for the independent variable indicating the presence of any hate crime law in 2000 was 12.004. For hate crime laws that specifically protect race, religion, and ethnicity, the VIF score was 12.233. It is likely that the two independent variables were interacting in this model. Given there is some overlapping in the concept these variables measure, it would be reasonable to remove the second measure from any future analyses. In addition, with VIF scores just below 10, the percent of foreign-born persons and the percent of non-English speaking persons residing in each American county were likely interacting. Although different in what they measure, it is probably that a person who identifies as foreign-born would also speak a language other than English. In future analyses, removing the control variable that measures the percent of persons speaking a language other than English would likely produce stronger results.

In summary, Model 2 suggests statistically significant relationships between three theoretically important variables. It seems that the more diverse a county becomes, the greater likelihood it will have anti-race motivated bias crime occurrence. The strongest relationships occurred when considering the percent of foreign-born persons and the percent of Muslim persons residing in each American county. Traditional indicators of low economic status, social cohesion, and residential mobility did not have statistically significant relationships with the occurrence of anti-race motivated bias crime.

Question 3:

What are the relationships between traditional indicators (low economic status, social heterogeneity, family disruption, residential mobility, and violent crime rate) of social disorganization concepts (as measured by US Census Data, ARDA, and *Congressional Quarterly*) and anti-sexual orientation motivated bias crime at the county level?

Model 3 involves an OLS regression analysis with anti-sexual orientation motivated bias crime occurrence. Each of the theoretically relevant variables and control variables from Models 1 and 2 are included in this analysis as well. The findings are presented in Table 7.3. Discussion of the findings and their relevance to the third research question follows the table. The aim of this sub-analysis is to determine whether traditional indicators of social disorganization theory have predictive abilities for the occurrence of anti-sexual orientation motivated bias crime.

Table 7.3: Model 3 – OLS Regression Analysis (Anti-Sexual Orientation)

Predictor	***B***	***SE***	***β***	***VIF***
Constant				
Low Economic Status				
Percent unemployed	-3.635	2.417	-.073	2.230
Percent below poverty line	.087	.516	.010	3.087
Percent without bachelor's degree	1.316	.706	.113	3.414
Social Heterogeneity				
Percent non-white	.221	.165	.064	2.129
Percent foreign-born	4.326**	.797	.559	9.917
Percent Jewish	.471	.888	.023	1.720
Percent Muslim	5.888	3.715	.067	1.653
Social Cohesion				
Percent divorced	2.626	1.404	.090	2.151
Crime rate	.000	.000	-.022	1.057
Percent voting in 2000 presidential election	.717	.419	.105	3.541
Residential Mobility				
Percent owner-occupied housing units	-.947**	.338	-.193	4.418
Percent unoccupied housing units	-.652	.335	-.142	4.964
Control				
Population in 2000	-.329	2.656	-.005	1.800
Hate Crime Law (HCL) in 2000	-5.408	20.358	-.030	12.004
HCL – Race, religion, ethnicity	4.160	19.735	.024	12.233
HCL – Sexual orientation	-5.595	5.239	-.062	3.176
HCL – Gender	5.834	3.739	.067	1.712
HCL – Gender Identity	2.344	4.240	.023	1.649
HCL – Disability	1.847	5.841	.019	3.483
Percent Christian	.138	.119	.049	1.630
Median age	-.165	.739	-.015	4.284
Percent non-English speaking	-.861*	.368	-.214	7.855
Percent veterans	-.730	1.091	-.040	3.274
Percent of bias crimes that are anti-white	.007	.059	.004	1.061
F 10.048**				
R^2 .258				

*p ≤ .05, **p ≤ .01

Table 7.3 presents the findings from the OLS regression conducted for Model 3. This sub-analysis is aimed at determining the predictive abilities of social disorganization theory for anti-sexual orientation motivated bias crime occurrence at the county level in the United States. The dependent variable for this analysis is continuous in nature and includes anti-LGB bias crime offenses that were reported as having occurred during the decade of 2000-2009.

The R-square was .258, indicating that nearly 26% of the variance in anti-sexual orientation bias crime at the county level was explained by the independent variables together. The F value was 10.048 and was significant at the .01 level. This indicates that the sample size was large enough for the model to hold predictive capabilities.

Compared to Model 2, Model 3 had fewer statistically significant findings. However, like the other models, social heterogeneity did have one significant relationship between the dependent variable and one of its measures. The percent of foreign-born persons residing in United States counties had a statistically significant relationship with the occurrence of anti-sexual orientation motivated bias crimes. The unstandardized regression coefficient for the relationship between percent foreign-born and anti-sexual orientation motivated bias crime occurrence was 4.326. This was a positive relationship indicating that for every one percent increase in foreign-born persons that reside in American counties, the likelihood of anti-sexual orientation motivated bias criminality increased by 4.326 units. The standard error was .797. The standardized regression coefficient indicated that for standard deviation increase in percent of foreign-born persons residing in American counties, there was a .559 standard deviation increase in anti-sexual orientation motivated bias crime occurrence.

In addition, one measure of residential mobility had a statistically significant relationship with the dependent variable. The percent of owner-occupied housing units in American counties had a negative relationship with the occurrence of anti-sexual orientation motivated bias crimes. The regression coefficient was -.947, indicating that for every one percent increase in owner-occupied housing units in United States counties, there was a .947 unit decrease in anti-sexual orientation motivated bias crimes. By examining the standardized coefficient, it is apparent that for every one standard deviation increase in owner-occupied housing units present in American counties, the likelihood of anti-sexual orientation bias criminality decreased by .193 standard deviations. The standard error was .338.

Only one control variable had a statistically significant relationship with the dependent variable in Model 3. This relationship was significant at the .05 level. The relationship between the percent of non-English speaking individuals and the occurrence of anti-sexual orientation motivated bias criminality had a B value of -.861. This figure indicated that for every one percent increase in the control variable, there was a .861 unit decrease in anti-sexual orientation bias crime occurrence. The standardized regression score was -.214 and the standard error was .368. The standardized score indicated that as the percent of non-English speaking persons residing in each American county increased by one standard deviation, the likelihood of anti-sexual orientation motivated bias crime occurrence decreased by .214 standard deviations.

Model 3 experienced similar interaction effects that exist between the independent variables as Model 2. Both HCL 2000 and HCL – RRE 2000 both had VIF values above 10, warranting caution when using these variables in the model. It is likely that the two independent variables were interacting in this model. Given there was some overlapping in the concept these variables measure, it would be reasonable to remove the second measure from any future analyses. In addition, with VIF scores just below 10, the percent of foreign-born persons and the percent of non-English speaking persons residing in each American county were likely interacting. Although still different in what they measure, it is likely that a person who identifies as foreign-born would also speak a language other than English. In future analyses, removing the control variable that measures the percent of persons speaking a language other than English would likely produce stronger results.

In summary, Model 3 explored the relationships between traditional indicators of social disorganization theory and anti-sexual orientation motivated bias crime occurrence in American counties. Only three independent variables had significant relationships with the outcome variable. Similar to Models 1 and 2, social heterogeneity had one indicator, percent foreign-born, that was related to the occurrence of anti-sexual orientation bias criminality. In addition, one predictor measuring residential mobility had a significant relationship as well. The percent of owner-occupied housing units in United States counties had a relationship with the outcome variable. The percent of non-English speaking persons residing in American counties was also significantly related to the likelihood of anti-sexual orientation motivated bias crime events. The indicators of social cohesion and low economic status were not significantly related to the dependent variable in Model 3.

Question 4:

What are the relationships between traditional indicators (low economic status, social heterogeneity, family disruption, residential mobility, and violent crime rate) of social disorganization concepts (as measured by US Census Data, ARDA, and *Congressional Quarterly*) and anti-religion motivated bias crime at the county level?

The purpose of Model 4 is to examine the relationships between the independent variables measuring traditional indicators of social disorganization theory and anti-religion motivated bias crime occurrence in American counties from 2000-2009. The control variables used in Model 4 are identical to those used in previous models. Table 7.4 presents the findings from an OLS regression analysis. The dependent variable is continuous in nature and consists of reported anti-religion motivated bias crime incidents.

Table 7.4: Model 4 – OLS Regression Analysis (Anti-Religion)

Predictor	***B***	***SE***	***Β***	***VIF***
Constant				
Low Economic Status				
Percent unemployed	-2.024	3.049	-.030	2.230
Percent below poverty line	-.158	.651	-.013	3.087
Percent without bachelor's degree	1.162	.890	.074	3.414
Social Heterogeneity				
Percent non-white	.161	.208	.035	2.129
Percent foreign-born	5.164**	1.005	.495	9.917
Percent Jewish	8.214**	1.120	.294	1.720
Percent Muslim	13.623**	4.686	.114	1.653
Social Cohesion				
Percent divorced	-.951	1.771	-.024	2.151
Crime rate	.000	.000	-.031	1.057
Percent voting in 2000 presidential election	-.103	.529	-.011	3.541
Residential Mobility				
Percent owner-occupied housing units	.266	.427	.040	4.418
Percent unoccupied housing units	.403	.422	.065	4.964
Control				
Population in 2000	1.127	3.350	.014	1.800
Hate Crime Law (HCL) in 2000	-35.204	25.681	-.145	12.004
HCL – Race, religion, ethnicity	35.636	24.895	.153	12.233
HCL – Sexual orientation	-3.772	6.609	-.031	3.176
HCL – Gender	6.741	4.716	.057	1.712
HCL – Gender Identity	10.710*	5.349	.079	1.649
HCL – Disability	.393	7.368	.003	3.483
Percent Christian	.283	.150	.074	1.630
Median age	-.297	.932	-.020	4.284
Percent non-English speaking	-1.376**	.465	-.254	7.855
Percent veterans	-.055	1.376	-.002	3.274
Percent of bias crimes that are anti-white	.002	.074	.001	1.061
F 15.627**				
R^2 .351				

*p ≤ .05, **p ≤ .01

According to Table 7.4, the R-square was .351, indicating that nearly 35% of the variance in anti-religion bias crime at the county level was explained by Model 4. The F value was 15.627 and was significant at the .01 level. This indicates that the sample size was large enough for the model to hold predictive capabilities.

It is evident from an OLS sub-analysis that there were several statistically significant findings. First, similar to the previous models, measures of social heterogeneity had statistically significant results. The percent of foreign-born persons residing in each American county had a regression coefficient of 5.164. This figure was statistically significant at the .01 level and was positive. This finding indicates that a one percent increase in foreign-born persons residing in American counties was related to a 5.164 unit increase in anti-religion motivated bias crime occurrence. The standard error was 1.005 and the standardized regression coefficient was .495. Using the standardized beta value to evaluate the relationship, it is evident that for each one standard deviation increase in the percent of foreign-born residents, the dependent variable increased by .495 standard deviations.

With an even stronger relationship to anti-religion based bias criminality, the percent of Jewish persons living in counties had a statistically significant relationship with the dependent variable in Model 4. The regression coefficient was 8.214 and the standard error was 1.120. For each one percent increase in Jewish residents, bias crime was expected to increase by 8.214 units. In order to compare across independent variables, however, it is important to examine the standardized coefficient as well. This value was .294, which indicates that for a one standard deviation increase in the independent variable, there was a .294 standard deviation increase in anti-religion motivated bias crime events.

The percent of residents that were Muslim was also statistically significantly related to the dependent variable at the .05 level. The B value was 13.623 and the standard error was 4.686. This regression coefficient indicated that each one percent increase in Muslim residents in American counties resulted in bias criminality increasing by 13.623 units. The standardized score was .114, indicating that for each one standard deviation increase in Muslim residents, there was a .114 standard deviation increase in bias crime occurrence in American counties from 2000-2009.

In addition, Model 4 indicated statistically significant relationships between two control variables and the dependent variable. First, in counties that report having hate crime legislation protecting gender identity, there was a significant relationship present with anti-religion bias crime events. This relationship was significant at the .05 level. The regression coefficient was 10.710 and the standard error was 5.349. This value indicated that for every additional county that includes gender identity laws, anti-religion bias crimes increased by 10.710 units. The standardized coefficient was .079. Therefore, it is evident that for every one standard deviation increase in hate crime laws that include gender identity, there was a .079 standard deviation increase in anti-religion motivated bias criminality. Second, the percent of non-English speaking persons residing in American counties had a statistically significant (at the .01 level) relationship with the dependent variable. This relationship was also negative as the B value was -1.376. For each one percent increase in non-English speaking persons residing in American counties, it can be expected that anti-religion motivated bias crime will decrease by 1.376 units. The standard error was .465. The standardized regression coefficient indicated that for every one standard deviation increase in the independent variable, there was a .254 standard deviation decrease in anti-religion motivated bias criminality in United States counties.

Model 4 resulted in similar findings for multicollinearity. It is evident that both HCL 2000 and HCL – RRE 2000 both had VIF scores above 10, creating question about the appropriateness of their inclusion in the model. It is probable that the two independent variables are interacting in Model 4. Given there is some overlapping in the concept these variables measure, it would be reasonable to remove the second measure from any future analyses. In addition, with VIF scores just below 10, the percent of foreign-born persons and the percent of non-English speaking persons residing in each American county were likely interacting with one another. Although categorically different in what they measure, it is probably the case that a person who identifies as foreign-born would also speak a language other than English. In future analyses, removing the control variable that measures the percent of persons speaking a language other than English would likely produce stronger results for the entire model.

To summarize Model 4, there were five statistically significant findings. The percent of foreign-born persons, the percent of Jewish residents, and the percent of Muslim residents in each county represented significant findings for measures of social heterogeneity. In addition, two control variables were statistically significant – the presence of hate crime laws protecting gender identity and the percent of non-English speakers present in each county. Similar to the preceding models, Model 4 provides insight into how the social heterogeneity aspect of social disorganization theory affects bias criminality at the county level. The traditional indicators of low economic status, social cohesion, and residential mobility did not have statistically significant relationships with anti-religion motivated bias crime from 2000-2009.

Question 5:

What are the differences between anti-race, anti-religion, and anti-sexual orientation bias crime occurrences at the county level?

Table 7.5 presents a summary of multivariate findings in this dissertation. Each of the independent variables is listed in the first column. Each of the statistically significant findings from Models 1, 2, 3, and 4 are presented together. For Model 1, negative binomial regression was used for the analysis. In Models 2, 3, and 4, OLS regression is used for the sub-analyses. The unstandardized and standardized regression coefficients are presented in order to allow comparisons of the independent variables effects on the dependent variables through different models.

Table 7.5: Summary of Multivariate Findings/Regression Coefficients (Standardized)

	Model 1	***Model 2***	***Model 3***	***Model 4***
Low Economic Status				
Percent unemployed				
Percent below poverty line				
Percent without bachelor's degree				
Social Heterogeneity				
Percent non-white	.017** (1.018)	1.482* (.103)		
Percent foreign-born	.065** (1.067)	16.561* (.513)	4.326** (.559)	5.164** (.495)
Percent Jewish	.190** (1.209)			8.214** (.294)
Percent Muslim	.361** (1.434)	33.143* (.090)		13.623** (.114)
Social Cohesion				
Percent divorced	.158** (1.171)			
Crime rate				
Percent voting in 2000 presidential election				
Residential Mobility				
Percent owner-occupied housing units			-.947** (-.193)	
Percent unoccupied housing units				

Table 7.5 (Cont'd)

Control				
Population in 2000				
Rural	-1.652** (.192)			
Urban cluster	-.963** (.382)			
Urbanized area				
Hate Crime Law (HCL) in 2000	1.380* (3.976)			
HCL – Race, religion, ethnicity	-1.375* (.253)			
HCL – Sexual orientation	.521** (1.684)	-44.285* (-.118)		
HCL – Gender	-.305** (.737)			
HCL – Gender identity	-.321** (.726)			10.710* (.079)
HCL – Disability				
Percent Christian				
Median age	-.046* (.955)			
Percent non-English speaking		-3.711* (-.221)	-.861* (-.214)	-1.376** (-.254)
Percent veterans				
Percent of bias crimes that are anti-white	.004* (1.004)			

$^*p \leq .05$, $^{**}p \leq .01$

Social Heterogeneity

Table 7.5 presents the summary of the multivariate findings from Models 1, 2, 3, and 4. It is clear that across all four models, the measures of social heterogeneity had the most consistent findings. In the main negative binomial regression model, all four indicators of social heterogeneity produced significant findings. This is the most indicators of social disorganization theory to have significant findings in the model. Specifically, the percent of persons that were foreign-born in each county seemed to have the greatest effect on the likelihood of bias criminality occurring. This was consistent across Models 2, 3, and 4 as well. Model 2 did report the strongest relationship between the variables, with a regression coefficient of 16.561. Other measures of social heterogeneity did not exceed 5.164 across all models. Therefore, of all findings, the percent of foreign-born persons residing in each county was the strongest predictor of bias criminality in the aggregate, and bias criminality when motivated by anti-race, anti-sexual orientation, and anti-religion animus.

Social Cohesion

The only measure of social cohesion that had any relationship with bias criminality at the county level was the percent of divorced persons residing in each county. This variable was only statistically significant in the main model – Model 1. The regression coefficient was .158 and was significant at the .01 level. However, this measure of social cohesion lost its statistical significance when regressed upon the three specific motivation types.

Residential Mobility

Similar to social cohesion, only one measure of residential mobility had a statistically significant relationship with the dependent variable. However, in this case, the relationship was negative and rather weak in Model 3. The regression coefficient was -.947 and was significant at the .01 level. This indicates that as the percent of owner-occupied housing units increases, the likelihood of anti-sexual orientation bias crimes goes down. This relationship is only significant in Model 3.

Population

County population also had a statistically significant relationship with bias criminality in Model 1. The findings here indicate negative, yet weak relationships. According to Model 1, it seems that as the population decreases in a county, the likelihood of bias criminality decreased as well. This was consistent across each of the three U.S. Census-defined cut points: rural, urban cluster, and urbanized area. The regression coefficient for urban cluster was -.963 and was significant at the .01 level. Even stronger, the regression coefficient for urbanized area was -.1.652. This figure was also statistically significant at the .01 level. However, these relationships disappeared for Models 2, 3, and 4.

Hate Crime Legislation

Overall, the presence of hate crime legislation had mixed results in its ability to predict bias crime occurrence in American counties. For Model 1, the measure of a county having any hate crime law in existence as of 2000 had a positive and statistically significant relationship with bias crime occurrence. The regression coefficient value was 1.380. This indicated that the presence of hate crime legislation resulted in the increase of bias crime offenses in American counties. Models 2, 3, and 4 did not produce statistically significant results for this variable. However, when examined by specific type of law, the results changed direction in several cases.

For instance, hate crime laws protecting for race, religion, and ethnicity in 2000 had a negative relationship with bias criminality. The regression coefficient was -.1.375. This indicated that the presence of hate crime legislation protecting for race, religion, and ethnicity does in fact decrease the likelihood of bias criminality. Only Model 1 produced a statistically significant relationship between these variables.

However, hate crime laws that protect its citizens based on sexual orientation produced statistically significant results in Models 1 and 2. In Model 1, the regression coefficient was .521 and was significant at the .01 level. This indicates, that overall, the presence of hate crime laws results in an increase of anti-sexual orientation motivated bias crime. That result changed, however, when examined in Model 2. Here, there was a rather strong, negative relationship between the presence of hate crime legislation protecting for sexual orientation and the occurrence of anti-race motivated bias criminality. The regression coefficient for this analysis was -44.285.

Both types of laws, protecting for gender and for gender identity, also had negative and statistically significant relationships with the dependent variable in Model 1. This indicates that with the added presence of these laws, bias crime occurrence decreases in American counties. The regression coefficient for gender was -.305 and for gender identity, the coefficient was -.321. Both relationships are statistically significant at the .01 level. In addition to Model 1, laws protecting for gender identity had a stronger effect on anti-religion motivated bias crime occurrence in Model 3. Here, there regression coefficient was 10.710 and was statistically significant at the .05 level. This finding indicates that as counties gain laws protecting its residents from bias crimes motivated by anti-gender identity animus, anti-religion motivated bias criminality increased.

Additional Control Variables

First, in Model 2, median age had a statistically significant relationship with the occurrence of bias crime occurrence from 2000-2009. The regression coefficient was -.046, indicating a weak relationship. However, it seems from Model 1 that as the median age in a county rises, the likelihood of bias criminality falls.

Second, in Models 2, 3, and 4, the percent of non-English speaking persons residing in American counties had negative and statistically significant relationships with the dependent variables. These findings are considered with caution given the multicollinearity findings discussed in earlier in the chapter. It is likely that the percent of non-English speaking persons residing in each county interacts with the percent of foreign-born persons living in each American county. However, the regression coefficients indicate that as the percent of non-

English speak persons increase in each county, the risk of bias crime occurrence decreases. The direction of the relationship is different than the relationship percent foreign-born has on the dependent variable. In Model 2, the regression coefficient was -3.711. Models 3 and 4 reported relationships with coefficients of -.861 and -1.376, respectively.

Third, the percent of bias crimes that are anti-White does seem to have a small, yet positive relationship with bias crime occurrence in Model 1. The regression coefficient was .004 and it was statistically significant at the .05 level. This indicates that as the percent of anti-White bias crimes increase in American counties, the likelihood of bias crime minimally increases overall.

Summary

The purpose of Chapter Seven was to present and discuss the findings from several multivariate analyses. Negative binomial regression was used for Model 1 – the main model. Since bias crimes are rare events, and numerous counties have zero reported bias crime incidents, negative binomial regression was chosen to account for the over-dispersed nature of the dependent variable. Theoretically relevant independent variables representing social disorganization theory were regressed on the dependent variable, which was the total recorded number of bias crime events per each United States county. Models 2, 3, and 4 used Ordinary Least Squares regression to analyze the effects of social disorganization theory driven variables on bias crime occurrence by motivation. Moreover, this chapter presented diagnostic statistics to assess the presence of multicollinearity. Chapter Eight includes a summary of the dissertation and a discussion of policy implications. Additionally limitations of the research are discussed as well as the future direction of bias crime research.

CHAPTER 8: DISCUSSION AND CONCLUSION

The purpose of Chapter Eight is to provide an overview and discussion of this dissertation. Much information has been assembled during the course of this study. Therefore, Chapter Eight includes a review of the dissertation and its relevant findings. In addition, attention is paid to the many limitations to this dissertation and to bias crime research in general. In sociology and criminal justice, direct applications to theory testing are often important in order to inform public policy. Since bias crime is generally addressed by the public sector (i.e. the criminal justice system), several implications for public policy are presented and discussed. Moreover, adding to the knowledge base in the social sciences is imperative to solving questions involving human behavior. As such, this dissertation presents and discusses several avenues for future research. There is much to do in terms of social science research on bias crime occurrence. Although this study certainly contributes to the discussion of bias criminality, additional research is needed to uncover the factors present when considering the context of bias-motivated crimes.

A Review of the Dissertation and Notable Findings

Chapter One provided an overview of bias criminality and the problems the phenomenon creates. In addition, the chapter introduced the notion that bias crime research is lacking overall, and in need of further investigation. Chapter Two provided a detailed discussed about what is known about bias criminality in the social science research. This chapter introduced descriptive information about bias crime occurrence by motivation type, as well as how society has responded to these specific crimes. Additionally, Chapter Two provided an overview of the social science theoretical perspectives most frequently considered when examining bias crime research. Chapter Three introduced social disorganization theory as the theory to be tested by the research questions and data in this dissertation. An overview of social disorganization theory was presented, including an explanation of the historical development of the perspective since its inception in the Chicago School. Chapter Four introduced the data and the methods used for the analyses. This chapter also presented each of the dependent and independent variables, and explained the theoretical relevance of each. Chapter Five presented the context of bias criminality as found in the data. This resulted in the display of descriptive findings for both bias crimes as they occurred in American counties and descriptive findings for each of the motivation types. Chapter Six included the various bivariate analyses and the resultant findings. These analyses examined the relationships between each of the dependent variables and each of the independent variables. Numerous statistical methods were used as were appropriate for each variable's level of measurement. Chapter Seven presented the main models for the dissertation. Model 1 used negative binomial regression to analyze the relationships between measures of social disorganization and bias crime occurrence in United States counties. Models 2, 3, and 4 used OLS regression to analyze the relationships between indicators of social disorganization theory and bias crime occurrence by motivation type.

Notable Findings

<u>Measures of Social Disorganization Theory</u>

From the four multivariate models, several notable findings emerged. The aim of this dissertation was to examine the traditional indicators of social disorganization theory and their effect on the likelihood of bias crime occurrence at the county level. Overall, each of the models provided indication that measures of social heterogeneity were helpful in predicting bias crime occurrence. In Model 1, all four measures of social heterogeneity had importance in predicting bias criminality at the county level. The percentage of non-White residents in American counties and the percentage of foreign-born residents both were notable in their ability to aid in the predictive ability of the regression model. In addition, the percentage of religious minorities that lived in American counties contributed to the model's predictive ability. However, the strongest finding involved the percentage of persons living in American counties who identified as Muslim. For Model 1, these measures of social heterogeneity seemed to be predictive of bias crime occurrence at the county level from 2000 – 2009. This is not particularly surprising as the increase in diversity of a community also represents the increased opportunity for interaction, perhaps strained, with people who are part of marginalized populations. Essentially, this refers to the situation where a white, American, Christian person encounters someone who is viewed as "the other." This seemed most likely when the member of a superordinate group interacted negatively with a Muslim resident. However, interactions with non-White persons and Jewish persons were also statistically significant. Model 1 suggested that this "exposure" to diversity was predictive of bias crime occurrence in United States counties.

Across Models 2, 3, and 4, findings were similar. In each of these subanalyses, the percentage of foreign-born persons residing in American counties contributed toward the prediction of bias crime occurrence. This is the only statistically significant finding that was consistent across all four models. Models 2, 3, and 4 have different dependent variables which are based on the specific motivation type. Therefore, it is evident that the percentage of foreign-born persons is predictive of the occurrence of bias criminality. In addition, the percentage of foreign-born persons residing in American counties also aids in the prediction of anti-race, anti-sexual orientation, and anti-religion motivated crimes. Certainly, there are different ways to view this finding. However, it should be noted that it is highly unlikely that the minority group is responsible for the commission of the bias crimes. In this case, foreign-born persons do not have the social standing (power) to be able to maintain a hegemonic type of violence. It is more likely that in counties that have a higher percentage of foreign-born persons, the members of superordinate groups might feel threatened and are acting accordingly.

Although measures of social heterogeneity were the prominent findings related to social disorganization theory, two other measures are important as well. First, in Model 1, examining the percentage of persons divorced aids in the predictive ability of the model. This is not a particularly strong relationship, but it is statistically significant at the .01 level. This is a cautious indication that the decrease of social cohesion is worth noting in understanding the predictors of bias criminality. This finding only surfaced in Model 1 and was rather weak. Second, one measure of residential mobility was statistically significant in Model 3. Specifically, this indicates that the percentage of owner-occupied housing units that exist in American counties is indeed predictive of bias crime occurrence. Essentially, as more residents purchase their homes and are considered to be permanent fixtures, the likelihood of bias criminality decreases. This is a weak relationship, but it is statistically significant at the .01 level.

The findings of this dissertation are evidence that the use of social disorganization theory, a macro-level theory - to explain bias crime is helpful. Traditional indicators of diversity, social cohesion and residential mobility had varying influence on Model 1's ability to predict bias criminality in American counties. However, measures of economic deprivation did not lend significant findings. This is an area that should be explored in future research.

Additional Variables

The population of American counties was relevant in the understanding of bias crime occurrence in this dissertation. From Model 1, it is evident that as the population decreases, so does the likelihood of bias criminality. In essence, as established in the literature, bias criminality can be expected to occur in greater frequency in urban areas. When considering the characteristics of the three U.S. Census defined population areas, this finding is expected. In many situations, urban areas have greater social diversity. With this diversity, as explained, comes the likelihood of bias crime occurrence. As the population decreases to urban clusters, the likelihood of bias criminality decreases as well. In rural areas, where the communities are rather homogenous, the likelihood of bias crime occurrence decreased yet again. Population is a relevant predictor of bias crime occurrence only in Model 1.

In addition, hate crime legislation had a rather inconsistent influence on the likelihood of bias crime occurrence in American counties. In Model 1, it seems as though the presence of hate crime legislation in general actually increases the chance of bias criminality. This is likely due to increased attention, and therefore better reporting that is the result of new laws. However, there is a difference that is worth nothing when the laws are broken down into specific protection types. For instance, when laws protecting race, religion, and ethnicity are present, bias criminality actually decreased. Again, this is likely because of increased attention, but there also may be a deterrence factor involved. In Model 1, this finding applies to laws protecting gender and gender identity as well. However, when the law protects sexual orientation, it seems that the occurrence of bias criminality increases across American counties. Although this finding is not strong enough to suggest that the laws are problematic in that they increased anti-sexual orientation bias criminality, it should be noted that the direction of this relationship is different from the other types of laws in Model 1. It very well may be that there is backlash toward the LGB community when counties do in fact have laws on the books protecting anti-sexual orientation bias criminality. However, Model 2 suggests yet another type of relationship is present. In Model 2, laws protecting race, religion, and sexual orientation are strongly associated with the decrease in anti-sexual orientation bias criminality. The cause of this is unknown; however, it would be worthy of examination in future studies.

Like sexual orientation, laws protecting a person's gender identity also had different findings in Models 1 and 4. In the main model, it seems that there is a relatively weak predictive ability of laws protecting for gender identity to affect the likelihood of bias criminality. This relationship was negative in Model 1, but was positive in Model 4. This suggests a presence of laws protecting gender identity actually increased the likelihood that an anti-religion based bias crime would occur. This finding is curious as gender identity and religion are seemingly unlinked. However, it is worth examining the specific motivation for anti-religion based bias crimes.

Limitations

Unfortunately, there are numerous limitations to this study. Each of the current limitations to this dissertation is discussed; however, there are certainly limitations to bias crime research that are beyond the scope of this small section in a dissertation. These limitations inform the future research implications presented toward the end of the chapter. Bias criminality is certainly an important and complex issue social scientists need to continue exploring.

Perhaps one of the major limitations of this study – and much of empirical research on bias criminality – is the reliance on official data. Given that so many counties, cities, and states do not report bias crimes to the FBI, any research from data that do exist should be viewed with caution. Certainly, each piece of research that investigates bias crime occurrence is worthwhile; however, the data that do exist are limited in nature. In addition, the reliance on using counties as the unit of analysis is a limitation as well. Given some communities spread across numerous counties, it would be appropriate to measure these communities collectively – or as cities.

However, due to the limited availability of county-level data, an exhaustive analysis is not possible.

A major limitation to this dissertation is political ideology and its effect on the quality of data. There are many ideological barriers to proper investigation of the context of bias criminality. First, many individuals see bias crime to be an example of identity politics (Jacobs & Potter, 1998). Generally, conservatives oppose an overreaching government. Perhaps this informs the reason many local governments are unwilling to report bias crime occurrence to the FBI. Of course, this is a matter of perspective, as there are many options for how crimes are classified in different locales. A bias crime that occurs in New York might be identified and labeled as a bias crime, but the same crime in Mississippi it is labeled as an assault. Certainly, this results in differential reporting. In addition, many conservatives may support having greater police presence in communities in the name of crime control; however, when the United States government attempts to enforce laws or collect information about bias criminality, this is considered by the same people as government intrusion.

The lack of cooperation by some conservatives at the national and local level is a serious impediment to a greater understanding of the problem. Since bias crime disproportionately affects minority communities, it comes as no surprise that some conservatives would oppose the identification and labeling of bias crimes as such. To do so would acknowledge the relationships that may occur between superordinate and subordinate communities, power, and hegemonic forms of oppression. The result of this lack of political cooperation is that it creates a situation where researchers are required to examine areas that are already known.

Another limitation relates to using the county as the unit of analysis. As collected and reported by the FBI, some bias crime incidents are reported as having occurred in multiple counties. Because the data are collected by city and state, there is not always an opportunity to accurately identify the county in which the crime occurred. For instance, some agencies exist within two or more counties. Therefore, when a bias crime is reported, two or more county names are associated with it. In the case of this dissertation, this leads to the exclusion of bias crime events that occur in many large cities. In the future, a similar analysis could be conducted using cities as the units of analysis. That would account for this limitation.

In addition, this dissertation is solely a quantitative effort. In future studies, qualitative inquiries could be included to enrich the understanding and depth of the research questions. Perhaps by talking with the gatekeepers of the criminal justice system – the police – additional findings would be uncovered. The detail gained by such analyses could shed light on the nature of the communities that most experience bias crimes, and perhaps explain effects of social disorganization theory from a different perspective.

Implications for Policy

There are numerous policy implications of this dissertation. First, this dissertation adds to the scholarly discussion on bias criminality as it affects the United States – particularly at the local level. This can be used to promote increased awareness for police officers, the government official most likely to interact with the effects bias crimes have on society. However, this information is pertinent across the criminal justice system and into the political arena as well. As laws and policies are debated and enacted, knowing what works and what does not if an effective way of informing policy. Better bias crime policy will allow researchers to add benefit to society by uncovering the “dark figure of crime” as it relates specifically to bias crime.

As mentioned in the discussion of limitations, much of the resistance to bias crime policy change comes from conservative ideology and the notion of bias crimes being reduced to mere identity politics. However, part of this debate may center on notions of federalism. The FBI is a federal agency, and therefore its existence is antithetical to many conservatives' positions on the proper role of government. Given conservatives favor local control, perhaps scholars and progressive politicians who recognize the importance of bias crime policy could make inroads by appealing to notions of local control.

Aside from the macro-level issues associated with bias crime occurrence, there are also policy implications for individuals in American communities. This aligns well with the major findings in this dissertation – the relationship between social heterogeneity and bias crime occurrence. Although it is not a new concept, increased diversity trainings – or sensitivity trainings – for criminal justice systems actors might be beneficial in creating a local government culture that is informed and equipped to tackle the specific issues many minority communities face with regard to bias criminality. Certainly, this can exist by way of inclusion into more police academy curricula and department trainings. In addition, the increased concentration on the recruitment of minority police officers could certainly allow police departments to service communities in a more complete fashion. After all, given police departments have historically been comprised of white, heterosexual males, there is room for most departments to diversify its force.

Implications for Future Research

There is much room for additional research related to bias crime, its effects on society, and the relevant governmental policy. This dissertation examined disorganization theory and its relationship to bias crime at the local level. Although findings were somewhat inconclusive, it would be appropriate to test other sociological theoretical perspectives as they relate to bias crime in the United States. Given this dissertation's main results were related to aspects of social heterogeneity – or diversity – theoretical perspectives that speak to social difference in communities might be enlightening. For instance Green's (1998) defended neighborhoods perspective may be appropriate in order to understand bias criminality as it exists related to the in-migration of minority groups in various spaces. Moreover, examining the masculinity literature and applying Messerschmidt's structured action theory may produce findings that explain how "doing gender" affect the occurrence of bias criminality across the United States.

Continuing to study social disorganization theory as it relates to bias crime still has much relevance in the social sciences. Examining the effect the same independent variables have on a dependent variable built from different data could be useful. Although the data on bias crime occurrence in the United States is indeed limited, many social advocacy groups collect and maintain records of officially reported and unreported bias-based incidents. The Anti-Defamation League, the Southern Poverty Law Center, and the Human Rights Campaign are just a few organizations that could be contacted in order to gain access to the rich data that are available.

Moreover, continuing to study social disorganization theory and its effect on bias criminality is possible by identifying and collecting data to create different measures of traditional indicators of the theory. This dissertation primarily used United States Census data; however, other measures were created from ARDA and *Congressional Quarterly* data.

Given this dissertation identified social heterogeneity as a major factor associated with bias crime occurrence, further studies on diversity-related policy could prove to be quite useful. An examination of the literature related to diversity programming in both the public and private sectors would add a layer of detail that could be of particular importance when considering how policy informs practice.

Overall, researchers are largely unable to make conclusive statements about the predictors of bias criminality. Currently, most of the extant research is descriptive in nature. This prevents researchers from knowing great detail about bias criminality both at the macro and micro levels. Given there is little empirical research in existence, any study that adds to the discussion and understanding of bias crime is worthwhile.

Conclusion

This goal of this dissertation was to identify predictors of bias criminality at the county level in the United States. This was accomplished through the lens of social disorganization theory. Although the findings are not resoundingly supportive of the application of social disorganization theory to the understanding of bias criminality, there are remarkable conclusions nonetheless. First, measures of social heterogeneity – or diversity – seem to yield the most conclusive evidence toward predicting the risk of bias crime occurrence. Certainly, these findings from various measures of social heterogeneity must be met with caution – as the data should not be used to promote or sustain socially oppressive structures. Second, the influence of hate crime legislation must be considered in depth. Although views on hate crime laws are highly politically polarized to date, this dissertation presents evidence that additional exploration as to their efficacy is necessary. The increased exposure to social difference and attention to hate crime legislation would, perhaps, promote a depoliticized atmosphere in which policy makers could consider the problem of bias criminality more accurately – and work toward mitigating bias-based offending in the United States. This dissertation is a contribution toward that end.

APPENDICES

APPENDIX A

Table A.1: Characteristics of Economic Deprivation (2000)

State	*Population*	*Population 16+*	*Number Unemployment*	*%*	*Poverty line Number*	*%*
Alabama	4,447,100	3,450,542	126,911	3.68	698,097	15.70
Alaska	626,932	458,054	27,953	6.10	57,602	9.19
Arizona	5,130,632	3,907,229	133,368	3.41	698,669	13.62
Arkansas	2,664,155	2,064,753	75,894	3.68	410,225	15.40
California	33,871,648	25,596,144	1,110,274	4.34	4,706,130	13.89
Colorado	4,301,261	3,325,197	99,260	2.99	388,952	9.04
Connecticut	3,405,565	2,652,316	92,668	3.49	259,514	7.62
Delaware	783,600	610,289	20,549	3.37	69,901	8.92
District of Columbia	572,059	469,041	31,844	6.79	109,500	19.14
Florida	15,982,378	12,744,825	412,411	3.24	1,952,629	12.22
Georgia	8,186,453	6,250,687	223,052	3.57	1,033,793	12.63
Hawaii	1,211,390	949,908	35,886	3.78	126,095	10.41
Idaho	1,293,953	969,872	36,784	3.79	148,732	11.49
Illinois	12,419,293	9,530,946	375,412	3.94	1,291,958	10.40
Indiana	6,080,485	4,683,717	152,723	3.26	559,484	9.20
Iowa	2,926,324	2,281,274	64,906	2.85	258,008	8.82
Kansas	2,688,418	2,059,160	58,415	2.84	257,829	9.59
Kentucky	4,041,769	3,161,542	109,350	3.46	621,096	15.37
Louisiana	4,468,976	3,394,546	146,218	4.31	851,113	19.04
Maine	1,274,923	1,010,318	31,165	3.08	135,501	10.63
Maryland	5,296,486	4,085,942	128,902	3.15	438,676	8.28
Massachusetts	6,349,097	5,010,241	150,952	3.01	573,421	9.03
Michigan	9,938,444	7,630,645	284,992	3.73	1,021,605	10.28
Minnesota	4,919,479	3,781,756	109,069	2.88	380,476	7.73
Mississippi	2,844,658	2,158,941	93,778	4.34	548,079	19.27
Missouri	5,595,211	4,331,369	148,794	3.44	637,891	11.40
Montana	902,195	701,168	28,710	4.09	128,355	14.23
Nebraska	1,711,263	1,315,715	32,287	2.45	161,269	9.42
Nevada	1,998,257	1,538,516	61,920	4.02	205,685	10.29
New Hampshire	1,235,786	960,498	25,500	2.65	78,530	6.35
New Jersey	8,414,350	6,546,155	243,116	3.71	699,668	8.32
New Mexico	1,819,046	1,369,176	60,324	4.41	328,933	18.08
New York	18,976,457	14,805,912	640,108	4.32	2,692,202	14.19
North Carolina	8,049,313	6,290,618	214,991	3.42	958,667	11.91
North Dakota	642,200	502,306	15,257	3.04	73,457	11.44
Ohio	11,353,140	8,788,494	282,615	3.22	1,170,698	10.31

Table A.1 (Cont'd)

Oklahoma	3,450,654	2,666,724	86,832	3.26	491,235	14.24
Oregon	3,421,399	2,673,782	112,529	4.21	388,740	11.36
Pennsylvania	12,281,054	9,693,040	339,386	3.50	1,304,117	10.62
Rhode Island	1,048,319	827,797	29,859	3.61	120,548	11.50
South Carolina	4,012,012	3,114,016	113,495	3.64	547,869	13.66
South Dakota	754,844	577,129	17,221	2.98	95,900	12.70
Tennessee	5,689,283	4,445,909	153,596	3.45	746,789	13.13
Texas	20,851,820	15,617,373	596,187	3.82	3,117,609	14.95
Utah	2,233,169	1,600,279	54,561	3.41	206,328	9.24
Vermont	608,827	479,140	13,997	2.92	55,506	9.12
Virginia	7,078,515	5,529,980	151,125	2.73	656,641	9.28
Washington	5,894,121	4,553,591	186,102	4.09	612,370	10.39
West Virginia	1,808,344	1,455,101	58,021	3.99	315,794	17.46
Wisconsin	5,363,675	4,157,030	134,311	3.23	451,538	8.42
Wyoming	493,782	381,912	13,453	3.52	54,777	11.09
Total	**281,412,514**	**217,160,615**	**7,947,033**	**3.66**	**33,898,201**	**12.05**

APPENDIX B

Table B.1: Characteristics of Social Heterogeneity (2000)

State	***Population***	***Number of Non-White Persons***	***%***	***Number of Foreign-Born Persons***	***%***	***Number of Jewish Persons***	***%***	***Number of Muslim Persons***	***%***
Alabama	4,447,100	1,284,292	28.88	77,478	1.74	9,100	0.20	7,670	0.17
Alaska	626,932	192,398	30.69	32,905	5.25	3,525	0.56	1,381	0.22
Arizona	5,130,632	1,257,021	24.50	564,906	11.01	81,675	1.59	11,857	0.23
Arkansas	2,664,155	534,379	20.06	63,030	2.37	1,600	0.06	2,044	0.08
California	33,871,648	13,701,589	40.45	7,993,001	23.60	994,000	2.93	259,762	0.77
Colorado	4,301,261	741,256	17.23	319,974	7.44	72,000	1.67	14,855	0.35
Connecticut	3,405,565	625,210	18.36	336,357	9.88	108,280	3.18	29,647	0.87
Delaware	783,600	198,827	25.37	39,935	5.10	13,500	1.72	3,691	0.47
District of Columbia	572,059	395,958	69.22	67,693	11.83	25,500	4.46	60,479	10.57
Florida	15,982,378	3,517,349	22.01	2,441,330	15.28	628,485	3.93	31,661	0.20
Georgia	8,186,453	2,859,172	34.93	504,287	6.16	93,500	1.14	38,882	0.47
Hawaii	1,211,390	917,326	75.73	196,430	16.22	7,000	0.58	609	0.05
Idaho	1,293,953	116,649	9.01	54,290	4.20	1,050	0.08	363	0.03
Illinois	12,419,293	3,293,822	26.52	1,372,426	11.05	270,000	2.17	125,203	1.01
Indiana	6,080,485	760,463	12.51	165,285	2.72	18,000	0.30	11,002	0.18
Iowa	2,926,324	177,684	6.07	77,047	2.63	6,400	0.22	4,717	0.16
Kansas	2,688,418	374,474	13.93	115,892	4.31	14,500	0.54	3,470	0.13
Kentucky	4,041,769	400,880	9.92	70,072	1.73	11,350	0.28	4,696	0.12
Louisiana	4,468,976	1,612,815	36.09	106,749	2.39	16,500	0.37	13,050	0.29
Maine	1,274,923	38,909	3.05	33,501	2.63	8,290	0.65	809	0.06
Maryland	5,296,486	1,905,178	35.97	467,016	8.82	216,000	4.08	52,867	1.00
Massachusetts	6,349,097	981,811	15.46	706,096	11.12	275,000	4.33	41,497	0.65
Michigan	9,938,444	1,972,391	19.85	464,429	4.67	110,000	1.11	80,515	0.81
Minnesota	4,919,479	519,197	10.55	215,941	4.39	42,000	0.85	12,305	0.25

Table B.1 (Cont'd)

Mississippi	2,844,658	1,098,559	38.62	35,724	1.26	1,400	0.05	3,919	0.14
Missouri	5,595,211	847,128	15.14	132,099	2.36	62,315	1.11	19,359	0.35
Montana	902,195	84,966	9.42	14,699	1.63	850	0.09	614	0.07
Nebraska	1,711,263	178,002	10.40	63,221	3.69	7,100	0.41	3,115	0.18
Nevada	1,998,257	496,371	24.84	281,775	14.10	77,100	3.86	2,291	0.11
New Hampshire	1,235,786	48,935	3.96	48,767	3.95	10,020	0.81	3,782	0.31
New Jersey	8,414,350	2,309,645	27.45	1,340,911	15.94	468,000	5.56	120,724	1.43
New Mexico	1,819,046	604,793	33.25	130,259	7.16	10,500	0.58	2,604	0.14
New York	18,976,457	6,082,768	32.05	3,538,160	18.64	1,653,870	8.72	223,968	1.18
North Carolina	8,049,313	2,244,657	27.89	373,156	4.64	25,545	0.32	20,137	0.25
North Dakota	642,200	49,019	7.63	10,297	1.60	730	0.11	902	0.14
Ohio	11,353,140	1,707,687	15.04	307,295	2.71	142,255	1.25	41,281	0.36
Oklahoma	3,450,654	822,220	23.83	115,420	3.34	5,050	0.15	6,145	0.18
Oregon	3,421,399	459,776	13.44	252,418	7.38	31,625	0.92	5,224	0.15
Pennsylvania	12,281,054	1,796,851	14.63	457,661	3.73	283,000	2.30	71,190	0.58
Rhode Island	1,048,319	157,128	14.99	108,202	10.32	16,100	1.54	1,827	0.17
South Carolina	4,012,012	1,316,452	32.81	104,013	2.59	11,000	0.27	5,761	0.14
South Dakota	754,844	85,440	11.32	11,172	1.48	350	0.05	50	0.01
Tennessee	5,689,283	1,125,973	19.79	139,100	2.44	18,250	0.32	18,464	0.32
Texas	20,851,820	6,052,315	29.03	2,549,836	12.23	128,000	0.61	114,999	0.55
Utah	2,233,169	240,194	10.76	135,441	6.06	4,500	0.20	3,645	0.16
Vermont	608,827	19,619	3.22	20,689	3.40	5,810	0.95	100	0.02
Virginia	7,078,515	1,958,405	27.67	512,409	7.24	76,140	1.08	51,021	0.72
Washington	5,894,121	1,072,298	18.19	538,423	9.13	43,500	0.74	15,553	0.26
West Virginia	1,808,344	89,567	4.95	17,774	0.98	2,400	0.13	1,528	0.08
Wisconsin	5,363,675	593,818	11.07	166,309	3.10	28,230	0.53	7,796	0.15
Wyoming	493,782	39,112	7.92	10,134	2.05	430	0.09	263	0.05
Total	**281,412,514**	**69,960,748**	**24.86**	**27,901,434**	**9.91**	**6,141,325**	**2.18**	**1,559,294**	**0.55**

APPENDIX C

Table C.1: Characteristics of Social Cohesion in States (2000)

State	***Number of Divorced Persons***	***%***	***Number of Index Offenses****	***Crime Rate (100,000)***
Alabama	371,218	8.35	169,728	3,816.60
Alaska	54,650	8.72	24,474	3,903.77
Arizona	440,890	8.59	300,360	5,854.25
Arkansas	232,296	8.72	110,134	4,133.92
California	2,474,567	7.31	1,277,054	3,770.27
Colorado	373,606	8.69	166,199	3,863.96
Connecticut	249,707	7.33	103,131	3,028.31
Delaware	60,943	7.78	37,516	4,787.65
District of Columbia	46,044	8.05	5,403	944.48
Florida	1,502,561	9.40	899,149	5,625.88
Georgia	656,777	8.02	382,028	4,666.59
Hawaii	87,188	7.20	56,033	4,625.51
Idaho	105,546	8.16	48,685	3,762.50
Illinois	867,414	6.98	251,487	2,024.97
Indiana	518,243	8.52	194,076	3,191.78
Iowa	210,767	7.20	92,667	3,166.67
Kansas	211,653	7.87	95,969	3,569.72
Kentucky	353,637	8.75	59,549	1,473.34
Louisiana	354,047	7.92	231,832	5,187.59
Maine	117,936	9.25	29,207	2,290.88
Maryland	366,483	6.92	195,198	3,685.42
Massachusetts	422,950	6.66	240,118	3,781.92
Michigan	799,643	8.05	424,952	4,275.84
Minnesota	336,648	6.84	174,228	3,541.59
Mississippi	221,798	7.80	97,663	3,433.21
Missouri	475,341	8.50	188,719	3,372.87
Montana	78,079	8.65	63,523	7,040.94
Nebraska	121,224	7.08	75,707	4,424.04
Nevada	216,097	10.81	84,250	4,216.17
New Hampshire	102,723	8.31	17,112	1,384.71
New Jersey	500,848	5.95	247,448	2,940.79
New Mexico	162,589	8.94	113,921	6,262.68
New York	1,173,090	6.18	515,531	2,716.69
North Carolina	576,718	7.16	407,771	5,065.91
North Dakota	39,836	6.20	17,475	2,721.11
Ohio	951,705	8.38	373,875	3,293.14

Table C.1 (Cont'd)

Oklahoma	315,452	9.14	160,668	4,656.16
Oregon	316,981	9.26	150,490	4,398.49
Pennsylvania	799,339	6.51	356,555	2,903.29
Rhode Island	79,251	7.56	20,510	1,956.47
South Carolina	290,037	7.23	233,631	5,823.29
South Dakota	51,773	6.86	25,709	3,405.87
Tennessee	511,189	8.99	274,200	4,819.59
Texas	1,559,049	7.48	1,046,189	5,017.26
Utah	132,270	5.92	89,520	4,008.65
Vermont	51,570	8.47	24,991	4,104.78
Virginia	504,369	7.13	198,432	2,803.30
Washington	529,708	8.99	296,674	5,033.39
West Virginia	154,363	8.54	67,497	3,732.53
Wisconsin	383,233	7.14	165,751	3,090.25
Wyoming	45,481	9.21	22,443	4,545.12
Total	**21,559,527**	**7.66**	**10,905,432**	**3,875.25**

*As defined by the FBI, index offenses include: murder and non-negligent manslaughter, forcible rape, robbery, aggravated assault, arson, burglary, larceny, and motor vehicle theft (FBI, 2010).

APPENDIX D

Table D.1: Characteristics of Residential Mobility in States (2000)

State	***Total Housing Units***	***Number of Owner Occupied Housing Units***	***%***	***Number of Unoccupied Housing Units***	***%***
Alabama	1,963,711	1,258,705	64.10	226,631	11.54
Alaska	260,978	138,509	53.07	39,378	15.09
Arizona	2,189,189	1,293,556	59.09	287,862	13.15
Arkansas	1,167,995	720,399	61.68	129,084	11.05
California	12,214,549	6,546,334	53.59	711,679	5.83
Colorado	1,808,037	1,116,137	61.73	149,799	8.29
Connecticut	1,385,975	869,729	62.75	84,305	6.08
Delaware	343,072	216,038	62.97	44,336	12.92
District of Columbia	274,845	101,214	36.83	26,507	9.64
Florida	7,302,947	4,441,799	60.82	965,018	13.21
Georgia	3,281,737	2,029,154	61.83	275,368	8.39
Hawaii	460,370	227,888	49.50	57,245	12.43
Idaho	527,824	339,960	64.41	58,179	11.02
Illinois	4,885,615	3,088,884	63.22	293,836	6.01
Indiana	2,532,319	1,669,162	65.91	196,013	7.74
Iowa	1,232,511	831,419	67.46	83,235	6.75
Kansas	1,131,200	718,703	63.53	93,309	8.25
Kentucky	1,750,927	1,125,397	64.27	160,280	9.15
Louisiana	1,847,181	1,125,135	60.91	191,128	10.35
Maine	651,901	370,905	56.90	133,701	20.51
Maryland	2,145,283	1,341,751	62.54	164,424	7.66
Massachusetts	2,621,989	1,508,052	57.52	178,409	6.80
Michigan	4,234,279	2,793,124	65.96	448,618	10.59
Minnesota	2,065,946	1,412,865	68.39	170,819	8.27
Mississippi	1,161,953	756,967	65.15	115,519	9.94
Missouri	2,442,017	1,542,149	63.15	247,423	10.13
Montana	412,633	247,723	60.03	53,966	13.08
Nebraska	722,668	449,317	62.17	56,484	7.82
Nevada	827,457	457,247	55.26	76,292	9.22
New Hampshire	547,024	330,700	60.45	72,418	13.24
New Jersey	3,310,275	2,011,473	60.76	245,630	7.42
New Mexico	780,579	474,445	60.78	102,608	13.15
New York	7,679,307	3,739,166	48.69	622,447	8.11
North Carolina	3,523,944	2,172,355	61.65	391,931	11.12
North Dakota	289,677	171,299	59.13	32,525	11.23
Ohio	4,783,051	3,072,522	64.24	337,278	7.05

Table D.1 (Cont'd)

Oklahoma	1,514,400	918,259	60.64	172,107	11.36
Oregon	1,452,709	856,951	58.99	118,986	8.19
Pennsylvania	5,249,750	3,406,337	64.89	472,747	9.01
Rhode Island	439,837	245,156	55.74	31,413	7.14
South Carolina	1,753,670	1,107,617	63.16	219,816	12.53
South Dakota	323,208	197,940	61.24	32,963	10.20
Tennessee	2,439,443	1,561,363	64.00	206,538	8.47
Texas	8,157,575	4,716,959	57.82	764,221	9.37
Utah	768,594	501,547	65.26	67,313	8.76
Vermont	294,382	169,784	57.67	53,748	18.26
Virginia	2,904,192	1,837,939	63.29	205,019	7.06
Washington	2,451,075	1,467,009	59.85	179,677	7.33
West Virginia	844,623	553,699	65.56	108,142	12.80
Wisconsin	2,321,144	1,426,361	61.45	236,600	10.19
Wyoming	223,854	135,514	60.54	30,246	13.51
Total	**115,899,421**	**69,812,617**	**60.24**	**10,423,220**	**8.99**

APPENDIX E

Table E.1: Descriptive Statistics for Control Variables

State	*Number Non-English Speaking*	*%*	*Median Age*	*Number of Veterans*	*%*	*Number with a Bachelor's Degree*	*%*	*Number of Christian Residents*	*%*	*Number Partic. in 2000 Presidential Election*	*%*
AL	162,483	3.65	35.80	447,397	10.06	351,772	7.91	2,435,373	54.76	1,621,897	36.47
AK	82,758	13.20	32.40	71,552	11.41	61,196	9.76	215,223	34.33	--	--
AZ	1,229,237	23.96	34.20	562,916	10.97	493,419	9.62	2,048,023	39.92	1,532,016	29.86
AR	123,399	4.63	36.00	280,510	10.53	190,090	7.14	1,522,072	57.13	909,546	34.14
CA	12,401,756	36.61	33.30	2,569,340	7.59	3,640,157	10.75	15,614,071	46.10	10,965,856	32.37
CO	604,019	14.04	34.30	446,385	10.38	599,028	13.93	1,697,259	39.46	1,741,368	40.49
CT	583,913	17.15	37.40	310,069	9.10	416,751	12.24	1,971,102	57.88	1,459,525	42.86
DE	69,533	8.87	36.00	84,289	10.76	80,376	10.26	318,122	40.60	327,622	41.81
DC	90,417	15.81	34.60	44,484	7.78	69,496	12.15	418,543	73.16	201,894	35.29
FL	3,473,864	21.74	38.70	1,875,597	11.74	1,573,121	9.84	6,576,205	41.15	5,814,074	36.38
GA	751,438	9.18	33.40	768,675	9.39	829,873	10.14	3,665,550	44.78	2,376,665	29.03
HI	302,066	24.94	36.20	120,587	9.95	142,478	11.76	438,675	36.21	367,871	30.37
ID	111,879	8.65	33.20	136,584	10.56	116,901	9.03	627,262	48.48	501,621	38.77
IL	2,220,719	17.88	34.70	1,003,572	8.08	1,317,182	10.61	6,867,625	55.30	4,601,446	37.05
IN	362,082	5.95	35.20	590,476	9.71	475,247	7.82	2,608,882	42.91	2,088,046	34.34
IA	160,022	5.47	36.60	292,020	9.98	278,350	9.51	1,711,426	58.48	1,308,519	44.72
KS	218,655	8.13	35.20	267,452	9.95	290,271	10.80	1,327,235	49.37	1,072,218	39.88
KY	148,473	3.67	35.90	380,618	9.42	271,418	6.72	2,159,541	53.43	1,544,187	38.21
LA	382,364	8.56	34.00	392,486	8.78	339,711	7.60	2,627,028	58.78	1,521,377	34.04
ME	93,966	7.37	38.60	154,590	12.13	129,992	10.20	463,541	36.36	651,817	51.13
MD	622,714	11.76	36.00	524,230	9.90	629,304	11.88	2,291,896	43.27	1,686,895	31.85
MA	1,115,570	17.57	36.50	558,933	8.80	834,554	13.14	4,069,606	64.10	2,702,984	42.57
MI	781,381	7.86	35.50	913,573	9.19	878,680	8.84	4,158,134	41.84	4,142,171	41.68
MN	389,988	7.93	35.40	464,968	9.45	605,210	12.30	3,035,510	61.70	2,331,221	47.39

Table E.1 (Cont'd)

MS	95,522	3.36	33.80	249,431	8.77	194,325	6.83	1,554,483	54.65	994,184	34.95
MO	264,281	4.72	36.10	592,271	10.59	507,892	9.08	2,893,159	51.71	1,588,679	28.39
MT	44,331	4.91	37.50	108,476	12.02	100,758	11.17	403,492	44.72	410,997	45.56
NE	125,654	7.34	35.30	173,189	10.12	179,181	10.47	1,006,860	58.84	697,019	40.73
NV	427,972	21.42	35.00	238,128	11.92	158,078	7.91	685,119	34.29	608,970	30.48
NH	96,088	7.78	37.10	139,038	11.25	153,874	12.45	589,022	47.66	569,081	46.05
NJ	2,001,690	23.79	36.70	672,217	7.99	1,063,665	12.64	4,858,756	57.74	3,187,226	37.88
NM	616,964	33.92	34.60	190,718	10.48	154,372	8.49	1,057,828	58.15	598,605	32.91
NY	4,962,921	26.15	35.90	1,361,164	7.17	1,954,242	10.30	11,461,411	60.40	6,782,220	35.74
NC	603,517	7.50	35.30	792,646	9.85	808,070	10.04	3,651,416	45.36	2,911,262	36.17
ND	37,976	5.91	36.20	61,365	9.56	67,551	10.52	470,112	73.20	285,788	44.50
OH	648,493	5.71	36.20	1,144,007	10.08	1,016,256	8.95	5,102,269	44.94	4,701,998	41.42
OK	238,532	6.91	35.50	376,062	10.90	297,082	8.61	2,096,476	60.76	1,234,229	35.77
OR	388,669	11.36	36.30	388,990	11.37	369,252	10.79	1,071,287	31.31	1,533,968	44.83
PA	972,484	7.92	38.00	1,280,788	10.43	1,153,383	9.39	7,116,698	57.95	4,912,185	40.00
RI	196,624	18.76	36.70	102,494	9.78	110,175	10.51	665,170	63.45	408,783	38.99
SC	196,429	4.90	35.40	420,971	10.49	351,526	8.76	1,908,638	47.57	1,127,003	28.09
SD	45,575	6.04	35.60	79,370	10.51	73,563	9.75	511,886	67.81	316,269	41.90
TN	256,516	4.51	35.90	560,141	9.85	478,463	8.41	2,905,619	51.07	2,076,181	36.49
TX	6,010,753	28.83	32.30	1,754,809	8.42	1,996,250	9.57	11,573,549	55.50	6,407,637	30.73
UT	253,249	11.34	27.10	161,351	7.23	213,959	9.58	1,668,851	74.73	770,754	34.51
VT	34,075	5.60	37.70	62,809	10.32	74,124	12.17	238,251	39.13	294,308	48.34
VA	735,191	10.39	35.70	786,359	11.11	835,011	11.80	2,943,551	41.58	1,540,003	21.76
WA	770,886	13.08	35.30	670,628	11.38	704,826	11.96	1,942,850	32.96	2,487,433	42.20
WV	45,895	2.54	38.90	201,701	11.15	109,651	6.06	650,016	35.95	648,124	35.84
WI	368,712	6.87	36.00	514,213	9.59	530,268	9.89	3,241,659	60.44	2,568,653	47.89
WY	29,485	5.97	36.20	57,860	11.72	47,066	9.53	230,725	46.73	218,351	44.22
Total	**46,951,180**	**16.68**	**--**	**26,402,499**	**9.38**	**28,317,440**	**10.06**	**141,367,057**	**50.23**	**101,350,746**	**36.02**

APPENDIX F

Table F.1: Controlling for Anti-White Bias Crime (2000)

State	*Total Bias crime*	*Number of Anti-Race*	*Number of Anti-White*	*Percent Anti-White*	*Percent of Total*
Alabama	0	0	0	0.00	0.00
Alaska	0	0	0	0.00	0.00
Arizona	248	165	11	6.67	4.44
Arkansas	4	3	0	0.00	0.00
California	1,988	1234	145	11.75	7.29
Colorado	109	74	6	8.11	5.50
Connecticut	169	104	14	13.46	8.28
Delaware	35	18	2	11.11	5.71
District of Columbia	5	3	0	0.00	0.00
Florida	216	149	36	24.16	16.67
Georgia	35	23	1	4.35	2.86
Hawaii	0	0		0.00	0.00
Idaho	49	28	4	14.29	8.16
Illinois	192	121	15	12.40	7.81
Indiana	111	76	12	15.79	10.81
Iowa	33	25	1	4.00	3.03
Kansas	43	32	4	12.50	9.30
Kentucky	73	62	12	19.35	16.44
Louisiana	12	8	1	12.50	8.33
Maine	29	12	0	0.00	0.00
Maryland	210	150	22	14.67	10.48
Massachusetts	465	282	44	15.60	9.46
Michigan	439	327	92	28.13	20.96
Minnesota	170	122	24	19.67	14.12
Mississippi	2	2	0	0.00	0.00
Missouri	74	61	14	22.95	18.92
Montana	21	9	0	0.00	0.00
Nebraska	18	12	1	8.33	5.56
Nevada	97	48	7	14.58	7.22
New Hampshire	33	11	1	9.09	3.03
New Jersey	652	401	36	8.98	5.52
New Mexico	16	5	1	20.00	6.25
New York	209	83	12	14.46	5.74
North Carolina	33	28	4	14.29	12.12
North Dakota	5	5	0	0.00	0.00
Ohio	247	181	36	19.89	14.57
Oklahoma	83	55	9	16.36	10.84

Table F.1 (Cont'd)

Oregon	142	93	5	5.38	3.52
Pennsylvania	147	109	19	17.43	12.93
Rhode Island	46	24	0	0.00	0.00
South Carolina	34	33	10	30.30	29.41
South Dakota	7	5	1	20.00	14.29
Tennessee	222	168	84	50.00	37.84
Texas	305	189	24	12.70	7.87
Utah	81	46	5	10.87	6.17
Vermont	20	7	1	14.29	5.00
Virginia	98	75	25	33.33	25.51
Washington	250	191	16	8.38	6.40
West Virginia	69	37	9	24.32	13.04
Wisconsin	49	23	2	8.70	4.08
Wyoming	9	7	0	0.00	0.00
Total	**7,604**	**4,926**	**768**	**15.59**	**10.10**

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