



GRADUATE SCHOOL
EAST TENNESSEE STATE UNIVERSITY

East Tennessee State University
Digital Commons @ East
Tennessee State University

Electronic Theses and Dissertations


Student Works

12-2018

Political Competition and Predictors of Hate Crime: A County-level Analysis

Eaven Holder
East Tennessee State University

Follow this and additional works at: <https://dc.etsu.edu/etd>

 Part of the [Criminology Commons](#), [Criminology and Criminal Justice Commons](#), [Politics and Social Change Commons](#), [Rural Sociology Commons](#), and the [Social Control, Law, Crime, and Deviance Commons](#)

Recommended Citation

Holder, Eaven, "Political Competition and Predictors of Hate Crime: A County-level Analysis" (2018). *Electronic Theses and Dissertations*. Paper 3491. <https://dc.etsu.edu/etd/3491>

This Thesis - unrestricted is brought to you for free and open access by the Student Works at Digital Commons @ East Tennessee State University. It has been accepted for inclusion in Electronic Theses and Dissertations by an authorized administrator of Digital Commons @ East Tennessee State University. For more information, please contact digilib@etsu.edu.

Political Competition and Predictors of Hate Crime: A County-level Analysis

A thesis

presented to

the faculty of the Department of Criminal Justice and Criminology

East Tennessee State University

In partial fulfillment

of the requirements for the degree

Master of Arts in Criminal Justice and Criminology

by

Eaven Holder

December 2018

Dustin Osborne, Ph.D., Chair

Bradley Edwards, Ed.D.

Jennifer Pealer, Ph.D.

Keywords: Hate Crime, Bias Motivated Offending, Multilevel Modeling

ABSTRACT

Political Competition and Predictors of Hate Crime: A County-level Analysis

by

Eaven Holder

Research on hate crime has tended to utilize sociological frameworks to best explain the incidence of such offending, but little research has been conducted to determine whether political factors may play a role. Although Olzak (1990) touched upon the relationship between racial violence and third-party politics during the American Progressive era (1882-1914), the research did not fully articulate how political competition may influence the commission of hate crime. The current study seeks to fill this gap, while also extending concepts associated with social disorganization theory and the defended communities perspective. It does so by utilizing a longitudinal research design to assess the impact of theoretical predictors and political competition measures on hate crime prevalence in counties across three states (Tennessee, Virginia & West Virginia) over a seven-year span (2010-2016).

ACKNOWLEDGEMENTS

I would have never been able to complete this project if not for the support of my family, friends, and faculty at ETSU. First, I cannot recognize enough the love and support that my family has given me over the past two years as a graduate student but especially my sister, Dr. Nicole Holder Lewis, in inspiring me to keep pursuing higher education as well opening her home to me as it were my own. Of course, I also have my wonderful parents to thank, each of which has always reminded me that I am loved and blessed beyond comparison.

I would like to also thank the chair of my thesis committee, Dr. Osborne, for his contributions to my work and pursuit of higher learning. The caliber of this work would certainly not be at its current standard if not for your sincere time and effort in which I am truly grateful. I hope that I can find another professor who can “talk baseball” just as well as you do. To Dr. Pealer, working as your graduate assistant has been one of the most fulfilling and fun times I can remember over the past two years and you have always strived to make me a better student and teacher. To Dr. Edwards, thank you for advice and for your willingness to be a part of this committee and for also showing me what ETSU is all about. Finally, to Tassi Dalton, thank you for taking interest in my research and for also making sure to always “tell me how it is.” Undoubtedly, I am grateful to all of the faculty in the department, each of which has played an integral part in the success of my graduate work. It goes without mention that I owe everything to Queen of the Office, Christine Ketelaar, who sent me that fateful tuition scholar email in which I now consider one of the happiest days in my life.

Finally, I want to recognize several of my peers and fellow graduate students, all of whom have created the best work environment a person could ask for. To the “old guard,” Coffey and Paul, thank you for making me feel welcome and included and for some of the best days of my life. And to the “new guard,” Andrew, Faith, and Hannah, you three have been the

best friends a person could ask for and I will truly miss spending days in the office with all of you. And last, but certainly not least, I want to thank Josie Klepper for always tolerating my random Earth, Wind, and Fire kicks and James Brown interpretations.

TABLE OF CONTENTS

	Page
ABSTRACT.....	2
ACKNOWLEDGEMENTS.....	3
CHAPTER 1: INTRODUCTION.....	10
Hate Crime in the United States.....	10
Defining Hate Crime.....	11
Hate Crime Policy.....	17
Hate Crime Law Categorization.....	18
Sentence Enhancements.....	18
Substantive Offenses.....	18
Civil Rights Statutes.....	18
Reporting Statutes.....	19
Reporting and Prevalence.....	23
Hate Crime Reporting.....	23
Victimization.....	24
Chapter Summary.....	27
CHAPTER 2: REVIEW OF LITERATURE.....	29
Individual Explanations.....	29
Theoretical Frameworks.....	32
Economic Explanations.....	32

Demographic Explanations	39
Social Disorganization & Collective Efficacy	39
Defended Communities Perspective	44
Competing Theories	46
Political Culture	47
Political Competition	48
Crime & Political Competition	49
Purpose of the Current Study	52
Chapter Summary	55
CHAPTER 3: DATA AND METHODOLOGY	57
Data Sources	57
Hate Crime Data	57
Socio-Demographic Data.....	58
Election Data.....	59
Sample Selection.....	59
Variables	61
Dependent Variable	61
Independent Variables	61
Social Diorganization.....	62
Population Density.....	62
Racial Heterogeneity.....	62

Disadvantage.....	63
Mobility.....	63
Defended Communities Perspective.....	63
White Population	63
Ethnic/Racial Minority Change	64
Unemployment.....	64
Interaction Effects.....	64
Political Competition	65
Control Variables	66
Plan of Analysis	67
Research Design.....	67
Hypotheses	67
Statistical Analysis.....	69
Univariate Statistics	69
Bivariate Statistics	70
Multivariate Statistics	70
Summary.....	73
CHAPTER 4: RESULTS.....	74
Descriptive Statistics.....	74
Bivariate Correlations	76
Multivariate Statistics	79

Unconditional Growth Model	79
Level-One Models	80
Model 2	80
Model 3	82
Model 4	83
Model 5	84
Level-Two Model	85
Summary	88
CHAPTER 5: DISCUSSION.....	91
Social Disorganization	91
Defended Communities Perspective	94
Political Competition	97
Limitations	99
Theoretical Implications	101
Future Research and Conclusion	102
REFERENCES	104
VITA.....	118

LIST OF TABLES

	Page
Table 1: ACS Years & Estimate Groupings	59
Table 2: List of Variables	68
Table 3: Level-One Descriptive Statistics	75
Table 4: Level-Two Descriptive Statistics.....	76
Table 5: Bivariate Correlations.....	78
Table 6: Model 1 (Unconditional Growth Model) Logistic Regression Output.....	80
Table 7: Model 2 (Defended Communities Perspective) Logistic Regression Output.....	82
Table 8: Model 3 (Political Competition) Logistic Regression Output.....	82
Table 9: Model 4 (Defended Communities & Political Competition) Logistic Regression Output	83
Table 10: Model 5 (Level-One Combined Model) Logistic Regression Output	84
Table 11: Model 6 (Level-Two Full Contextual Model) Logistic Regression Output.....	87

CHAPTER 1

INTRODUCTION

Hate Crime in the United States

The passage of the Hate Crime Statistics Act of 1990 has facilitated the growth of empirical analysis concerning hate crimes and the factors that serve to influence their characteristics and prevalence. Specifically, the tracking of hate motivated crimes in both the Uniform Crime Reporting System (UCR) and the National Incident-Based Reporting System (NIBRS) has allowed researchers to analyze data on hate crimes at the local, state, and national level (Nolan, Turley, Stump, & LaValle, 2015). As such, the knowledge of these crimes has been able to flourish in recent years. Much of the research literature has used socioeconomic and demographic factors to theoretically explain crime of bias (Green, Strolovitch, & Wong, 1998a; Hovland & Sears, 1940; Walters, 2010). However, very little research has focused on the political motivations of hate crime.

The purpose of the current research is to establish connections between various political variables and the prevalence of hate crime at the county level in the states of Tennessee, Virginia, and West Virginia, while controlling for other more established factors over a seven-year span (2006-2012). Hate crime prevalence will be analyzed within established criminological scopes of offending but will also be analyzed with state and national-level election results, specifically focusing on presidential, gubernatorial, and U.S. legislative elections (House and Senate). However, before doing so, it is necessary and beneficial to understand how hate crime is identified and defined, in addition to the available research on this type of offending.

The review of relevant research and literature follows a path towards the connection of hate crime and politics. The first chapter serves as a discussion of the importance of

understanding the nature of hate crimes, along with the legal definitions of relevant offenses. As hate crimes are a relatively new addition to legal codes, providing definitions are necessary to establishing a baseline understanding of bias-type crimes. Further, hate crime policy will be discussed. This includes policy narrowly tailored towards defining and addressing hate crime along with civil rights and protected status issues. The next chapter will be structured around the synthesis of research conducted on hate crime. Chapter three focuses on the methodology of the research, while chapter four details the results of the analysis. The final chapter concludes with a discussion of the findings as well as limitations and directions for future research.

Defining Hate Crime

Specific to the United States, it is necessary to analyze the development of not only hate crime definitions, but also hate crime policy. The terminology of “hate crime” or crimes committed with bias towards a certain group, was not derived until the mid-1980s (Jacobs & Potter, 1998). “Hate crime” was not developed within a vacuum but was instead derived as a culmination of preceding societal changes in America, such as the Civil Rights movement, the increased awareness of sexual orientation differences in the U.S., and the growth of a multicultural environment; as such, hate crime should not analyzed in isolation, but instead as a product of a constantly evolving society (Jacobs & Potter, 1998). Historically, the development of hate crime definitions and policy has been developing since the conclusion of the American Civil War (Jacobs & Potter, 1998).

Indeed, minority groups have historically and continuously been targeted due to their perceived differences, which is evident in past events such as religious persecutions, slavery, the development of Black codes, and the era of the Jim Crow South. To begin, the English Protestants who travelled to America to escape religious hardships did not dispose of their own customary prejudices (Streissguth, 2009). Instead, from the 17th to the 18th century, colonists

used formal and informal processes to restrict basic rights and liberties based on religion. For example, the colony of Maryland, founded by Catholics, passed the Act of Toleration in 1649, which only extended religious freedom to other Catholics. On the other hand, many other state constitutions did not originally allow citizenship to non-Protestants (Streissguth, 2009). Often, non-believers or non-Christians were subject to arrest, imprisonment, and even execution. However, the history of anti-religious incidents does not cease at examples of bias towards different sects and denominations of Christianity. Violence and vandalism has also been directed towards Jews and, more recently, Muslims (Cheng, Ickes, & Kentworthy, 2013; Levin & McDevitt, 2002). For example, the FBI has estimated that more hate crimes were directed towards Muslims in the thirty days after events of 9/11 than in a five-year span from 1997 to 2001 (Levin & McDevitt, 2002).

In terms of racial and the ethnic violence, the U.S. is historically ripe with examples that extend up to the passage of the Hate Crime Statistics Act of 1990 (Jacobs & Potter, 1998; Petrosino, 1999; Streissguth, 2009). In the past, many White Americans based their perceptions of African people through a Eurocentric perspective that characterized Africans as “uncivilized heathens” and non-Christians, which made it easier for colonists to devalue them and their culture (Fredrickson, 1991; Jordan, 1968; Petrosino, 1999). In addition, the advent of slavery in the United States helped maintain a rigid class structure in which wealthy, slave-owning Whites assumed the natural condition of Blacks was slavery. Africans were considered as inferior and not worthy of legal protections, much less Constitutional rights, and were often *infantilized* by the color of their skin (Levin & McDevitt, 2002; Streissguth, 2009). With the passage of the *Reconstruction Amendments* (13th, 14th, and 15th), Blacks were perceived to pose a threat to the reigning societal standards. As a result, violence was used against Blacks and newly-freed slaves

to maintain class boundaries. For example, after the Civil War ended in 1865, the Ku Klux Klan (KKK) was founded in an attempt to terrorize southern Blacks through the process of lynching's and lynch mobs (Jacobs & Potter, 1998). Lynching involved executing an accused individual without procedural due process of law in which Blacks were disproportionately victimized and were lynched in the southern states at a rate 350% greater than Whites (Cutler, 1969; Dennis, 1984; Wells-Barnett, 1969). From 1882 to 1968, nearly 5,000 people were lynched in the U.S., with most of the victims being Black.

However, the predominant violence against ethnic and racial minority groups did not end at the turn of the 20th century. The 1950s and 1960s saw the rise of the Civil Rights era, but also the rise of violence against Blacks and Jews across the South, especially with the introduction of homemade bombs (Jacobs & Potter, 1998). During the 1950s and 60s, bombing occurred almost bi-weekly and at least 200 Mississippi black churches were burned or bombed (Greene, 1996). Although America was experiencing the end of racial segregation in 1954, per the Supreme Court decision in *Brown v. Board of Education*, racial violence still escalated (Streissguth, 2009). In 1955, the famed murder of Emmitt Till, age 14, was carried out. In 1963, a predominately Black Baptist church was firebombed in Birmingham, Alabama, resulting in the death of four young girls. On April 4, 1968 Martin Luther King was assassinated in Memphis on the eve of a civil rights protest. It should be noted, however, that racial violence was also committed against other minority racial groups such as Native Americans, Hispanics, Asians, and also Whites. However, it is beyond the scope of this chapter to provide an exact and comprehensive history of all racial and ethnic violence. As such, this portion has focused on anti-Black incidents during this period, but that is not to detract from other anti-racial incidents.

Further, surges of nationalism and American nativism also increased rates of violence against immigrants. Starting primarily in the 1820s and extending into the 20th century, mainstream political platforms were often based on anti-immigrant stances, such as anti-Catholicism, Anti-Semitism, and anti-European immigration (Jacobs & Potter, 1998). Parties such as the “Know-Nothing Party” in the 19th century used economic strife and poor labor conditions to scapegoat new immigrants in the U.S, and the result was increased violence used against Catholics and Irish, especially during times of extreme economic distress (Jacobs & Potter, 1998; Streissguth, 2009). For example, mob violence in Philadelphia during the 1840s involved citizens invading Irish Catholic neighborhoods to kill residents, loot homes, and burn several Catholic churches (Jacobs & Potter, 1998; Streissguth, 2009). In addition, federal legislation was often passed to limit or stop immigration, such as the Exclusion Acts during the 1880s, which suspended Chinese immigration for 10 years, but was not repealed until 1943 (Streissguth, 2009).

Literature detailing the history of bias crimes based upon sexual orientation is sparse, however it is beneficial to understand the high-profile case of Matthew Shepard. In 1998, Matthew Shepard, a gay University of Wyoming student, was brutally tortured and murdered by two men. Shepard, lured by the two perpetrators who were pretending to be gay, was driven to an area in the desert where he was repeatedly beat and then tied to a fence where he was left to die. The two men’s attorney argued that his clients acted in such a manner because of Shepard’s homosexual tendencies, which prompted a violent response. This defense became known as the “gay panic” defense, which was disallowed by the judge (Levin & McDevitt, 2002; Streissguth, 2009). Combined with several other anti-gay incidents in the following years, Congress was spurred to

create new legislation to redefine hate crime offenses to include bias based upon sexual orientation (Streissguth, 2009).

As such, hate crimes are not a modern phenomenon, nor has the United States experienced a *hate crime epidemic*, as was widely believed in the 1980s (Jacobs & Potter, 1998; Petrosino, 1999). Indeed, the primary factor that is common throughout these historical and modern examples of hate crime is *bias* and *prejudice*. Although bias may often be an obvious indicator, it can be subtle and difficult to detect in all cases. (Levin & McDevitt, 2002).

Essentially, hate crimes are targeted attacks based on bias towards a group holding some type of protected status (Gladfelter, Lantz, & Ruback, 2017; Kesteren, 2016). Taken at face value, it would seem there is no clear distinction between hate crime and crime itself. For example, if two individuals commit two different offenses, it is important to note how one crime would qualify as biased. To begin, one should look at the status of victim, as they can be either symbolic or actuarial (Berk, 1990; Gladfelter et al., 2017). If the leading motivation of a crime is the symbolic value of the victim, such as the victim's race or gender, the crime can be categorized as a "hate crime." Although other mitigating factors may follow pursuant to the crime itself, they impose no significance upon the labeling of "hate crime" if they cannot significantly detract from the leading motivation of the victim's status. (Jacobs & Potter, 1998; Levin & McDevitt, 1993, 2002). However, the victimization of hate crime in and of itself is different from ordinary crime (Boeckmann & Petrosino, 2002; Green et al., 2001; Levin & McDevitt, 2002; Petrosino, 1999).

Research of Levin and McDevitt (2002) found the victimization of hate crime to be unique for several reasons. First, the primary victim of hate crime is the *larger society*. Hate crimes are not intended to target one primary victim, but instead the group the victim is perceived to belonging to. Or, as Levin and McDevitt (2002) put forth, hate crimes are meant to

victimize everyone “perceived as different,” which erodes societal bonds (p. 6). In addition, the researchers found that hate crimes tend to be excessively brutal, tend to be carried out by groups, and are perpetrated on total strangers. Further, hate crime offenders may see their victims as *interchangeable* in that the individual characteristics or past actions of the victim are somewhat irrelevant. Instead, victims are irrationally and randomly selected according to their group status. As a result, victims of hate crime are often not able to identify their assailant, nor can they develop a rationale for their victimization. As a result, hate crime victims are at heightened risk of physical and psychological distress and are sometimes motivated to retaliate (Levin & McDevitt, 2002).

This is not to say, however, that every criminal who is found to have some type of prejudice is culpable of a hate crime (Jacobs & Potter, 1998). Prejudice and bias is difficult and complex to determine. Every individual has the capacity of being prejudiced against certain individual or groups in which their prejudice is often rooted in culture, experiences, or irrationality. Some criminals may hold unconscious prejudices towards different economic classes or towards those are thought of to be more successful than them, but there is no “political salience” to such statuses (Jacobs & Potter, 1998). Instead, when criminals act upon “next generation” or “officially designated prejudices” that are denounced by laws, such as race, gender, or religious affiliation, the offender then becomes a suspect of hate crime (Jacobs & Potter, 1998, p. 16). As McDevitt et al. (2002) have stated, “The basic underlying factor found throughout all the hate offender groups is bigotry” (p. 306). Still, in the midst of hate crime complexities, it is essential to understand the role of law and policy in hate crime definitions.

Law serves as a representation of the official recognition of differences between common motivations of criminal behavior and those evolving from hate and/or bias (Jacobs & Potter,

1998). Federal definitions of hate crime were created by the FBI, who defined as crimes that “manifest evidence of prejudice based on race, religion, sexual orientation, or ethnicity” (28 U.S.C. § 534). The definition has recently been expanded to include both physical and mental disabilities and gender (McDevitt, Levin, & Bennett, 2002). Political definitions of hate crimes can differ by state. Although the definition is narrowly tailored, it is also broad enough to cover individuals considered to fall within the range of protected status in the United States (Boeckmann & Turpin-Petrosino, 2002). In a sense, official hate crime definitions are dialectic in that they are both specific and general at the same time.

Although hate crimes are perhaps easier to identify today than in past eras, it has been shown that this is not the case historically. Law is often written with the express and implicit interest of the groups who craft it. Simply put, law, and the criminal justice system, is frequently created to maintain classic power structures (Mann, 1993; Walker, Spohn, and DeLone, 1996). It is for this reason, among others, specific hate crime legislation did not arrive until the late 20th century and the 21st century. However, it is now beneficial to understand the policies and legislation that has criminalized hate crime and bias-motivated offenses, as the next section will serve to outline.

Hate Crime Policy

Policy has continuously evolved in order to formalize definitions of hate crime and impose specific punishments for offenders charged with commission of them (Jacobs & Potter, 1998). It should be noted that biased offenders are not simply charged with hate crime. For example, an individual who is charged with homicide and was found to have committed the act out of bias (against an individual with protected status) will also be charged under the relevant hate crime statute. Thus, the punishment for committing a hate crime is more severe than a crime

that was not motivated by prejudice or bias. However, state and federal policy vary in their definition and punishment of offenses considered as hate crime (Jacobs & Potter, 1998).

Hate Crime Law Categorization

Jacobs and Potter (1998) categorized hate crime laws into four distinct categories: (1) sentence enhancement; (2) substantive crimes; (3) civil rights statutes; and (4) reporting statutes. The following taxonomy of hate crime was developed as part of their research and is a broad outline of various policy and regulation of hate crime.

Sentence Enhancements. For the most part, hate crimes laws fall beneath the sentence enhancement category. These enhancements serve to create a harsher punishment for crime when the offender is found to have been motivated by bias. Although states vary in the size of the penalty enhancement, the Violent Crime Control and Law Enforcement Act of 1994 mandated a sentence enhancement of no less than three “offense levels” above the base offense level for the biased offense (Jacobs & Potter, 1998).

Substantive Offenses. Although most states impose sentence enhancements, other states have imposed new substantive offenses for hate crimes. These statutes take the form of new offenses such as “intimidation” or “institutional vandalism,” which recriminalizes vandalism into another substantive offense (Jacobs & Potter, 1998). Though most states do not use substantive hate crime law, groups such as the Anti-Defamation League (ADL) strongly recommend separate statutes for institutional vandalism, which is the destruction of property based on bias. Connecticut and New York serve as prominent examples of states that use substantive hate crime statutes to prosecute bias crime incidents (Jacobs & Potter, 1998).

Civil Rights Statutes. Crime motivated by bias or prejudice has been outlawed by multiple federal civil rights acts. However, it should be noted that civil rights statutes have not criminalized hate crime, but instead have criminalized *right-interferences* that have historically

affected minority subpopulations (Jacobs & Potters, 1998). In addition, civil rights laws were passed to provide enforcement for the Thirteenth and Fourteenth Amendment. For example, the Civil Rights Act of 1870 criminalized the conspiracy against the right of any citizen to vote (Streissguth, 2009). The subsequent Civil Rights Act of 1875 prohibited discrimination in public areas and allowed for federal prosecution of civil rights violations (Jacobs & Potter, 1998; Streissguth, 2009).

Narrowly-tailored to racial bias and prejudice, the Civil Rights Act of 1871, commonly known as the Ku Klux Klan (KKK) Act, allowed the federal government to suspend writs of habeas corpus to combat KKK members who had been federally prosecuted for violence towards newly-freed Black slaves. Following this, the Civil Rights Act of 1968 made it illegal to use force, intimidation, or any type of interference against specific types of activities such as civil rights protests, due to race, religion, or national origin (Streissguth, 2009). This can be considered the first piece of legislation to set the stage for the future creation of specific hate crime legislation in that it designated specific offenses, protected classes, and specific punishments for the violation of sec. 245 of the Act (Jacobs & Potters, 1998).

Reporting Statutes. One of the most significant policy decisions to date has been the passage of the Hate Crime Statistics Act of 1990 (HCSA). As stated previously, the term “hate crime” was not used in mainstream political speech until the mid-1980s and was not formulated in legislative terms until the 1990s (Nolan, Akiyama, & Brehanu, 2002). The popularity of movements supporting gay rights, civil rights, and women’s rights helped usher in an era of increased awareness of thriving prejudice in the 1970s and 80s, creating enough momentum to motivate the creation of the HCSA.

The HCSA requires the attorney general to gather statistics and other related information for the commission of hate crimes within the United States. This includes the formation of guidelines in the collection of hate crime data and the designation of the FBI as the official clearinghouse for this data. The HCSA also provides for the formalized definition of hate crime as crimes that “manifest evidence of prejudice based on race, religion, sexual orientation, or ethnicity” (Nolan et al., 2002, p.137). In addition, it provides specific offenses that can be sanctioned as hate crimes such as crimes of “murder, non-negligent manslaughter, manslaughter, rape, aggravated assault” or any type of destruction of property (p. 137). Lastly, the Act led to creation of the National Hate Crime Data Collection Program, which was implemented by the FBI. Proponents of the HCSA supported it for various reasons, which included the possibility of research and program development, future support of new hate crime legislation, providing law enforcement with better information to combat crime, victim support, and finally the aspect of raising public awareness to the extent of hate crimes (McVeigh, Welch, & Bjnarnas, 2003).

Although additional legislation (at the state and federal levels) followed the enactment of the HCSA, perhaps the most salient product was the creation of the Hate Crime Data Collection Program, which served as an adjunct data base to the Uniformed Crime Reporting (UCR) (Nolan et al. 2002). The UCR is a nationally-implemented data collection program in which participating law enforcement agencies submit information to the FBI for analysis and synthetization. There are two programs within the UCR: Summary UCR and the National Incident-Based Reporting System (NIBRS), which collects detailed information for *each* criminal incident reported to the FBI. The Summary UCR only provides aggregates of certain offenses, not including hate crime. Hate crimes are submitted and analyzed through NIBRS (Nolan et al., 2002; Nolan et al., 2015).

Though beneficial, one significant limitation with HCSA is that law enforcement agencies are not mandated to submit data. This has contributed to the growth of a “dark figure of hate crime” that calls into question the validity of national estimates (Nolan et al., 2015). Only eighteen states mandate the collection of hate crime statistics, leaving agencies in other states with the choice of reporting hate crime statistics outside of any mandate. (Jacobs & Potter, 1998). In addition, law enforcement officers may not have adequate training necessary to enforce hate crime law despite FBI recommendations of increased training and the implementation of specialized units to investigate hate crimes (Bell 2002; Nelson, Wooditch, Martin, Hummer, & Gabbidon, 2015). Also, reporting issues may be attributed to ambiguity of jurisdictional guidelines of investigating hate crime and whether departments encourage their officers to respond to biased incidents (Martin, 1995).

In spite of this limitation, the importance of the HCSA should not be understated, as it both mandates the federal collection of hate crime statistics and serves to develop a formal definition of this type of offending. Further, it developed distinct categories of bias and motivation, and serves as the first formal attempt to craft legislation to address the concern of criminal acts motivated by bias (Jacobs & Potter, 1998). Subsequent state and federal hate crime legislation has built upon the foundation that the HCSA developed.

As previously stated, many states vary in their implementation of hate crime statutes. Still, only forty-five states have specific legislation that targets hate crime, with some statutes being broader than others (Trout, 2015). Of those who have hate crime statutes, all protect individuals from racial, ethnic, or religious-motivated crimes. However, beyond the scope of race and religion, there is less unanimity among other protected classes. Thirty states protect

disability, thirty cover sexual orientation, twenty-seven cover gender, fifteen cover gender identity, thirteen protect age, and only five cover political affiliation (Trout, 2015).

Also, the Hate Crime Prevention Act (HCPA) has been on the forefront of hate crime legislation since the early 1990s. The first HCPA was developed to address growing fears of hate crime resulting from increased portrayal by the news media (Streissguth, 2009). Although the HCSA called for the collection of hate crime data, it did not state explicit punishment measures for hate crime offender. Initial attempts to pass the HCPA in 1997 were unsuccessful, leading to an amended version known as the Local Law Enforcement Enhancement Act approved by Congress in 1998. The Law Enforcement Act allowed for the increased role of the federal government to prosecute hate crimes. It also authorized the attorney general to monetarily award law enforcement agencies that implemented hate crime training and increased their hate crime investigations (Streissguth, 2009; Trout, 2015).

In 2009, Congress passed the Shepard-Byrd Act, which served as the most up-to-date version of the HCPA. The purpose the bill was to further broaden the federal scope of criminalizing and prosecuting hate crimes. Specifically, the bill was meant to “authorize Federal investigations and prosecutions of hate crimes described to the fullest extent permitted by the Constitution” (Trout, 2015, p. 137). To do this, the 2009 HCPA expanded the federal government’s jurisdiction over the investigation and prosecution of hate crimes as well increase federal funding to local programs wishing to further investigate hate crimes in their area. In addition, the HCPA also amended federal legislation to include gender, gender identity, juveniles, and persons with disabilities (Cheng et al., 2013).

In summation, the creation of hate crime legislation has been a long and slow process. Although California was the first state to create hate crime statutes in 1978, other states and the

federal government have been creating new policy in incremental fashion (Streissguth, 2009). Though the United States has seen federal policies implemented to curb violence against minority groups, official legislation defining the issue of “hate crime” did not arrive until 1990 with implementation of the HCSA; other legislation soon followed. Having discussed definitions and relevant policy to hate crime, it also necessary to synthesize the growing information on hate crime prevalence, trends, and how this type of offending is reported.

Reporting and Prevalence

This research will utilize the hate crime statistics published by the Federal Bureau of Investigation (FBI). In 2016, the FBI reported a total of 6,121 hate crime incidents, in which the majority (57.5%) were motivated by race, ethnicity, or ancestry. A further 21% were motivated by religious bias and 17.7% were motivated by bias toward sexual orientation (FBI, 2016). More often these crimes were committed near residences or roadways, but also at a variety of other areas including schools, churches, restaurants, or even hospitals. Overall, the FBI reported a slight increase of hate crimes from 2015 to 2016 (nearly 5%). Still, other research has found that certain groups are more likely to be victims of hate crime than others (Cheng et al., 2013; Masucci & Langton, 2017). Again, how bias motivated offenses are defined by law are important to bear in mind when understanding reporting and prevalence statistics.

Hate Crime Reporting

Hate crimes reports are synthesized through two primary national databases: Uniformed Crime Reporting (UCR)/National Incident-Based Reporting System (NIBRS) and the National Crime Victimization Survey (NCVS) (Nolan et al., 2015; Ruback et al., 2015). First, the NCVS is nationally-represented sample of households in the United States collected annually (BJS, 2016). This survey is advantageous in that it includes crime data that has *not* been reported to the police, and information regarding why the victims did not report their victimization to the

police (Ruback, Gladfelter, & Lantz, 2015). On the other hand, the Hate Crime Statistics Act of 1990 mandated the FBI collect official hate crime reports through the UCR/NIBRS. Hate crime statistics reported through the UCR are compiled through official police reports.

Past research by Nolan et al. (2015) assessed the accuracy of UCR data and found hate crimes were undercounted by police agencies by 67%. This is compounded by the fact that from 2011 to 2015, nearly 54% of hate crime victimizations were not reported to the police (Masucci & Langton, 2017). On the other hand, it should be noted that hate crime data collected from the NCVS is based on victims' perceptions that a crime was motivated by bias. Therefore, the two programs can be used a complimentary to despite the differences and shortcomings.

Victimization

Although hate crime victimization may be complex, the FBI has indicated victims of hate crime may be an individual, an institution, a government entity, a religious organization, or society. In addition, the FBI has created six categories of bias motivations by victim: (1) Race/ethnicity/ancestry, (2) religion, (3) sexual orientation, (4) disability, (5) gender, and (6) gender identity. Within each category are several bias motivations such as anti-Black, anti-Jewish, anti-gay, anti-mental disability, anti-female, or anti-transgender. If the victim of a hate crime incident qualifies for more than one group, then the incident is categorized as a "multiple-bias incident" (FBI, 2016).

In a trend analysis from 2004 to 2015 using the NCVS, Masucci and Langton (2017) found that the United States experienced an average of 250,000 hate crime victimizations each year. Overall, hate crime accounted for 4% of all violent victimizations in the U.S. However, there were no significant changes in the rate of violent hate crime from 2004 to 2015. Specifically, the researchers found different points of prevalence. From 2011 to 2015, anti-race bias was the most common motivate of hate crime victimization with 48% of respondents

believing their race was the primary factor. In addition, the data revealed that Hispanics were the primary target. Most NCVS-respondents (90%) reported some type of violence in their victimization, with over half of those respondents (61.6%) reporting simple assault. There were no statistically significant differences in NCVS *confirmed* hate crimes and the UCR reports for the 2004-2015-time period. In addition, the summarized findings of Masucci and Langton (2017) nearly mirror the only published BJS reports that relied solely upon NIBRS incidents, which covered incidents from 1997 to 1999. However, Strom (2001) found that, among anti-religion incidents, Jewish victims were the most often targeted (41%).

Cheng et al. (2013) conducted a 13-year analysis of UCR hate crime statistics from 1996 to 2008 focusing upon developing an understanding of possible trends. Primarily, they found that Blacks experienced hate crime at a disproportionate rate than other races. On the other hand, anti-White hate crimes were significantly lower for any other race. Further, Whites were found to have committed a larger portion of anti-race hate crimes than other races. They were further found to have committed more acts against Blacks than against any other racial group. Compared with inter-group conflict, Asians and AIANS (American Indian and Alaska Natives) had higher tendencies to commit anti-racial hate crimes against members of their own group. Overall, however, the researchers found that anti-racial hate crimes decreased from 1998 to 2006 (Cheng et al., 2013).

Besides anti-racial hate crimes, Cheng et al. (2013) found other areas of prevalence of bias-motivated offenses. Among anti-sexual orientation hate crime, the researchers found homosexuals were more likely to become victims of than other groups, such as heterosexuals or transsexuals. Further, anti-gay hate crimes were more prevalent than anti-lesbian hate crime. When analyzing anti-religious hate crime, Jews were consistently victimized more than other

religious groups. However, Muslims have experienced increased victimization since the events of September 11th, 2001. Although most anti-religious hate crimes were categorized as crimes against property, Muslims experienced slightly higher crimes against persons (65% against person and 35% against property). Cheng et al. (2013) hypothesized that bias-motivated offenders attempted to harm Muslims at a higher rate as form of “protection” against perceived threats of possible terrorism.

Finally, Ruback et al. (2015) conducted descriptive hate crime research using a county-level approach in Pennsylvania. The researchers did not restrict themselves to one data source, but rather combined information from the NCVS, UCR, the Southern Poverty Law Center (SPLC), and other local Pennsylvania data sources. In their analysis, they found that the majority of hate crime incidents occurred in urban areas. However the majority of hate crimes defined as “criminal” occurred in rural counties. The victim characteristics found by Ruback et al. (2015) are consistent with previous research. For the most part, Blacks, Jews, and Males experienced the bulk of hate crime victimization in Pennsylvania. Many of the identified offenders were White individuals. However, a sizeable portion of the offenders were categorized as White groups of individuals. In summary, the findings of Ruback et al. (2015) coincide with the past hate crime demographic analysis. Black, male, gay, or Jewish individuals are at the highest risk of hate crime victimization, especially those residing within an urban environment.

Lastly, this discussion will feature the most up-to-date findings on hate crime prevalence in the U.S. by using the 2016 FBI *Hate Crime Statistics*. First, over 15,000 law enforcement agencies participated in hate crime reporting, which was at about 2% increase from the previous year. There were over 6,000 single-bias incidents were reported, while only 58 multiple-bias incidents were reported (FBI, 2016). Of the 7,509 victims of 2016, the majority (58.9) were

targeted due to their race/ethnicity/ancestry in which half of those victims were Black. Among anti-race crimes, the most significant change was anti-White crimes, which featured a 2% increase from 2015. Further, slightly over a 20% of hate crime victims were targeted due to religion and over 15% of the victims were targeted because of sexual orientation. Among anti-religious crimes, Jews were the predominant target, but anti-Islamic bias rose by three percent. Overall, the FBI accounted for nearly a 5% percent increase in hate crime from 2015 to 2016 (FBI, 2016).

Chapter Summary

This chapter served to provide a basic understanding of hate crime within the United States by defining the offense, synthesizing the legalities and policies of hate crime, and discussing the relative trends and prevalence of hate crime. As defined by the 1990 Hate Crime Statistics Act, hate crime are offenses that are manifested by prejudice towards certain groups (FBI, 1999). However, definitions of hate crime vary across jurisdictions, as states may or may not include certain protected statuses included in other states (Jacobs & Potter, 1998; Petrosino, 1999; Trout, 2015). Further, many states vary in their punishment of hate crime such as sentence enhancements or by having specific statutes that punish hate crime separately. Still, formalized hate crime definitions should not understate the issue that bias-motivated offenses are historically rooted in the United States (Jacobs & Potter, 1998; Levin & McDevitt, 2002; Petrosino, 1999).

The following chapter will discuss the relevant literature in accordance to offending and biased offending. Included in the discussion are the multiple theoretical frameworks that have been used to explain hate crime to date, with a primary focus on economic and demographic explanations. Chapter three will detail the methodology employed in this research, including a discussion data sources, variables employed, and the statistical analyses that will be performed. Chapter four serves as the summarization of the performed analysis. The final chapter will offer

a discussion of the findings and is inclusive limitations, policy implications, and guidance for future research.

CHAPTER 2

REVIEW OF LITERATURE

This chapter serves as a comprehensive review of research that has attempted to explain or predict hate crime. It will not only cover micro-level predictors of hate crime but will also review various criminological theories commonly used to understand this type of offending at the macro level. In addition, the political science literature will be reviewed to provide a better understanding of political competition measures and their correlating effects. Finally, the chapter will cover the hypotheses that will be tested in this research.

Individual Explanations

Before delving into a macro-level analysis of hate crime offending, it is necessary to identify hate crime offenders and the various typologies that have been developed to understand them. Foundational research on hate crime offenders was established by Levin and McDevitt (1993, 2002), who suggested that these perpetrators can be placed into three specific categories: (1) Offenders motivated by thrill or excitement; (2) Offenders who saw themselves as defending their turf; and (3) offenders who wished to rid the world of groups deemed inferior or evil. These findings were based on a review of over 150 hate crime reports from the Boston Police Department. First, the majority of hate crime offenders (66%) were placed within the category of *thrill seeker*. These offenders were usually young, sporadic, and traveled in groups often led by one or two leaders. However, the authors posited that these offenders were not primarily motivated by “hate,” but instead picked their victims out of opportunity and convenience to attain their “rush.” Often, victims of these offenders were gay men considered to be easy targets because of their perceived status of being “weak.” Still, thrill-seeking offenders used socially-constructed differences to select their targets.

The next two groups advanced by Levin and McDevitt (1993, 2002) were the *defensive offenders* (25%), or those who pursued hate crimes to “defend their turf” and the *mission offenders* (<1%), or those who saw it as their “mission” to rid the world of differences they perceived as evil. Defensive offenders acted on what they believed to be their “territory” in which minorities, or simply those with differences, posed a threat to their property or way of life. However, these offenders were more often characterized as those dealing with inter-personal conflict or socio-economic instability and who used minority groups as a scapegoat for their own faults (Gadd, Dixon, & Jefferson, 2005; Ray & Smith, 2002). Like the *thrill-seekers*, defensive offenders were typically young and traveled in groups. However, these offenders usually had history of intergroup conflict or intimidation (McDevitt et al., 2002). Finally, the authors designated hate crimes offenders who proactively victimized as a method of “ridding the world of evil” as *mission offenders*. These offenders were totally committed to bigotry and made it their primary focus in life to terrorize any group deemed as different (Levin & McDevitt, 1993). These offenders usually joined organized hate group, but some operated alone (Levin & McDevitt, 1993, 2002; McDevitt et al., 2002).

However, McDevitt et al. (2002) reconsidered their typologies in later research, stating that additional factors presented to them by criminal investigators indicated the presence of other salient factors when analyzing hate crimes. This led to the creation of a fourth typology: those who were retaliatory in nature. Offenders within the *retaliatory* group commit their crimes as a follow-up attack based on an original incident; whether the incident occurred or not is often irrelevant. Although this group is similar to *defensive offenders*, those in the retaliatory group do not offend as a response to the presence a different group, but as a reaction to an initial incident. These offenders are usually young adults who work alone and use violence as a means of

retaliation. Only a small portion (8%) of hate crime offenders were found to be retaliatory (McDevitt et al., 2002).

It should be noted that Anderson et al. (2002) have cautioned against the profiling of hate crime offenders, as doing so may result in stereotypes and negative generalizations, tactics that hate crime offenders often use. Particular to the research of Levin and McDevitt (1993, 2000), Anderson et al. (2002) showed hesitance to identify hate crime offenders by demographic characteristics, specifically by race and gender. Instead, Anderson et al. (2002) characterized hate crime offenders as socially isolated, having low self-esteem, having the desire to belong, or being an individual who is viewed to be as “not welcome.” As a result, hate crime offenders will be strictly abide to their group’s philosophies and values to gain elevation. Often, intergroup values involve conflict and hate-based aggression, culminating in hate crime.

Messner, McHugh, and Felson (2004) conducted an empirical analysis of NIBRS hate crime data to construct descriptions of hate crime offenders and to also compare the similarities and differences among assaults motivated by bias and other types of assaults. Specifically, the researchers explored substance abuse. The team created two theoretical models to explain hate crime: Specialization and Versatility. Offenders that fit within the category of “specialization” were more prone to commit hate crimes due to their predisposed bias towards a group, not because of their propensity to commit crime in general. “Specialization” offenders were more calculating and future-oriented and tended to garner support from social groups (Levin & McDevitt, 2002; Messner et al., 2004). However, offenders who fit within category of “versatility” were more motivated to commit crimes of bias due to criminal propensities and not prejudice. These offenders have many criminogenic goals and may select a victim not for their

symbolic value, but instead as another part within their ritual of offending. However, the end result is still the same: hate crime (Messner et al., 2004; Wang, 1999).

Overall, the authors found differences among general offenders and hate crime offenders in that, first, hate crime offenders are more likely to be substance abusers. Offenders with suspected drug use were four times more likely to commit a hate crime and the majority of hate crime offenders were found to have been under the influence during the crime; the authors found a significant relationship between alcohol use and racial violence. In addition, bias offenses typically involve strangers, indicating that offenders probably do not pre-select victims. Messner et al. (2004) concluded that the bulk of hate crime offenders fit within the category of “versatility” in that symbolic victims are primarily selected out of opportunity and may come as a result of increased substance abuse or the propensity to commit harm or crime.

Theoretical Frameworks

This section serves as a discussion to the prominent theoretical explanations of hate crime. Although many of these theories, namely the criminological theories, were developed to explain criminality *in general*, some researchers have extended these theories to explain biased offending. This section differs from the former (Individual Explanations) in that it uses explanatory research to test theory instead of description alone. The relevant literature primarily fits within two categories: economic and demographic explanations. The literature reviewed in this segment was categorized in its respective sections based on theories it attempted to test. In addition, other theoretical frameworks outside the scope of economics and demographics were analyzed.

Economic Explanations

Many criminological theories are built upon economic models for explaining crime (Iwama, 2016). However, only a handful of these have been used to explain hate crimes. To start,

Merton (1968) first developed strain theory as a deviation from Chicago school criminology in that he believed the roots of crime did not derive from urbanicity but instead from the societal emphasis on conforming to conventional cultural values. For Merton (1968), the inherent disjunction between American culture goals and the legitimate means of attaining said goals induces *strain* in individuals, which increases the likelihood of using deviant or criminal behavior to obtain said goals or reduce their personal strain. However, not every individual who is strained turns to deviance. Instead, Merton (1968) created five different modes of adaptation to strain: Conformity, innovation, ritualism, retreatism, and rebellion. Individuals who fall within the “innovation” category are more likely to use criminal behavior to achieve economic success, whereas those who “conform” are the least likely to commit criminal acts. Those in the other groups are not as likely to commit deviant acts (Merton, 1968).

Empirical analysis of Merton’s theory has yielded mixed results. Often, researchers have had difficulty in conceptualizing “strain” as either a function at the individual or societal level (Baumer, 2007; Burton & Cullen, 1992). In addition, Merton’s theory of strain and anomie did not receive much attention until the late 1950s and early 1960s, as seen in Cohen’s (1955) *Delinquent Boys* and Cloward and Ohlin’s (1960) *Delinquency and Opportunity*. Cohen (1955) proposed that while delinquent subcultures may arise in highly-urban areas, they are often formed as a reaction to disadvantage and the lack of conventional institutions, which, in turn, may develop *strain*. Cloward and Ohlin (1960) further extended strain theory by the incorporation of *opportunity* by which strain is developed as a response to the lack of opportunity (Merton’s “legitimate means”) to find success and status. As such, deviance may also be explained by the opportunity to find *illegitimate means* by which crime in deviant subcultures are shaped by limited opportunity and the access to illegitimate means. Individuals

who reside in more organized criminogenic areas may produce more organized offenders who train juveniles in the performance of crime. Likewise, less organized areas who lack the opportunity of criminal learning may instead form violent subcultures based on conflict and social status (Cloward & Ohlin, 1960).

Still, Mertonian strain theory has endured empirical critique by which researchers have struggled with the most optimal method to operationalize the theory. Burton and Cullen (1992), in their evaluation of the empirical status of strain theory, stated many researchers have encountered issues with testing it via as a micro- or macro-level analysis. In addition, much of the empirical analysis of strain differed in the approach of measuring strain as result of aspirations exceeding expectations (see Hirschi, 1969) *or* strain because of blocked opportunities. Research within the former category has tended not to support the theory, but research in the latter group has more often led to support. Baumer (2007) has suggested a novel approach to strain theory by using a multilevel theoretical framework in which strain is best explained by four sequences: (1) differences across social collectivities; (2) the assimilation of cultural values; (3) differential causes of deviance; and (4) relationships between crime and the cultural structure of the individuals. Strain, then, is a combination of both individual-level and societal-level factors.

On the other hand, Agnew's (1992) general strain theory places less emphasis on economic strain, but the ties are certainly evident. Agnew (1992) instead stressed the importance of goal attainment outside the realm of material possession, but did not completely disregard the goal of material possession. This differs from Merton's (1968) assertion that material possession is not the *only* attainable goal emphasized in society. Instead, Agnew (2011) stated that strain was a product of an individual's' environment and nature, such a losing a family member or

suffering physical abuse as a child. Therefore, individual strain is not limited to economic goals but is a result of the blockage of *any* positively valued goal.

To further explain, Agnew (1992) stated that there are three primary forms of strain: Strain as a failure to achieve positively valued goals; strain as the removal of positively valued stimuli; and strain as the presentation of negative stimuli. However, it is not certain that every individual will use criminal behavior to alleviate strain. In addition, Agnew (2006a) identified a distinct set of strain situations that would most likely to lead to crime which were when (1) the strain is seen as unjust; (2) the strain is high in magnitude; (3) the strain is associated with low self-control; and (4) the strain creates a pressure or incentive to engage in criminal behavior as a coping mechanism. Each of these types are amplified by unstable negative emotions, but predominately anger (Agnew, 2006a). Agnew (2013) has further nuanced his general strain theory by detailing the criminal coping of strain in four stages: First, the experience of strain; second, the evaluation or appraisal of the strain; third, a negative emotion reaction to the strain; and fourth, coping with the strain.

General strain theory has received a modest amount of empirical attention (Lilly, Cullen, & Ball, 2015). Agnew (2006a, 2006b, 2013) himself found consistent evidence that exposure to strain increases the odds of criminality. However, individuals may experience multiple variations of strain that cannot be accounted for empirically. Thus, it may be difficult to identify when criminality stems from strain itself or is a byproduct of other factors. Among these other factors, some scholarly studies have identified casual links between strain, anger, and criminality. Yet, it is not clear whether strain causes anger, thus resulting in criminality, or if angry individuals are simply more likely to use criminality as a coping mechanism to strain (Mazerolle & Maahs, 2000; Mazerolle & Piquero, 1997).

Besides the combination of negative emotions and strain, other research has tended to focus on how strain *conditions* the effects on criminality. For example, positive social support groups or the *lack* of such groups may condition the effects on strain and offending in either a positive or negative manner (Cullen, Wright, & Blevins, 2006). Research by Hagan and McCarthy (1997) involved an exploration of delinquent youths living on the streets in the United Kingdom. They found youths living on the streets experienced unemployment, hunger, and the lack of shelter, and used criminogenic coping techniques to deal with the strain of being homeless. In addition, the authors found youths raised in more strenuous households (e.g. sexual or physical abuse), were more likely to leave home, but only to create new strain associated with living on the streets.

Both conceptions of strain theory can be used to explain the prevalence of hate crime (Walters, 2010). However, strain theory does not predict offenders of *hating* minorities due to the minority status, but as a threat to their own socio-economic status and goal attainment. Offenders may perceive minorities as a threat to their economic security and social status, in which minorities act as a blockage to their positively valued goals (Green et al. 1998a; Levin and McDevitt, 2002; Ray & Smith, 2002; Walters, 2010). As a result, offenders are more *strained* by the perceived influx of minorities in their physical and social environments. Thus, many minority groups become victims of bias motivated crimes carried out by the indigenous members of society (Young, 1999; Walters, 2010). In a sense, hate crime can also be understood as “violent backlash” based on increasing competition for scarce resources (Levin & McDevitt, 2002).

Hovland and Sears (1940) are credited with one of the first attempts to connect crimes of bias to economic factors through their research on the relationship between cotton prices and the incidence of lynching by utilizing a “frustration-aggression” paradigm of thought. Specifically,

Hovland and Sears stated, “The strength of instigation to aggression varies directly with the amount of interference with the frustrated good-response” (p. 301). As such, a positive correlation was found between cotton prices and the prevalence of lynching (of African Americans) from 1882 to 1920, leading the researchers to conclude that White frustration tied to economic incentives often transformed into aggression towards people of color.

The conclusions reached by Hovland and Sears (1940) have continuously been challenged, most notably by Mintz (1946), Hepworth and West (1988) and Green et al. (1998a), who readjusted the models developed by Hovland and Sears (1940) to improve accuracy and to also modernize their research. First, Mintz (1946), and later Hepworth and West (1988), reanalyzed Hovland and Sears (1940) in two ways: by extending the analysis from 1882 to 1930 (covering the Great Depression) and by using autoregressive moving average (ARMA) models to control for spuriousness. The researchers found somewhat consistent results with the research of Hovland and Sears (1940) in that Black lynchings strongly correlated with the Ayres index (national economic performance measure) post-1920, but Black lynchings did *not* strongly correlate with cotton prices.

However, Green et al. (1998a) found contrary results to both Hovland and Sears (1940) and Hepworth and West (1998). First, Green et al. used an alternative measure of national economic performance: percent changes in gross national product (GNP) and by using exponentiation of the dependent variable (Black lynching). By utilizing this different methodology, the researchers found no relationship between economic performances and Black lynchings. Further, the researchers conducted a modernized analysis by comparing hate crime in New York to a distributed lag model of unemployment for a seven-year period. In their analysis,

the researchers reached a conclusion that there was no substantial relationship between hate crime (specifically focusing on anti-gay and lesbian hate crime) and unemployment rates.

Some of the few contemporary studies that affirmed the results of Hovland and Sears (1940) were that of Beck and Tolnay (1990) and Tolnay and Beck (1995), each of which used several different techniques to retest former models of Hovland and Sears (1940). In doing so, they used more precise and up-to-date lynching data, adjusted cotton prices to inflation, differentiated between cotton prices and cotton productivity, and readjusted the statistical analysis used by Hovland and Sears (1940). Their findings coincided with Hovland and Sears (1940) in that adjusted cotton prices had an inverse relationship with Black lynchings. On the other hand, increased cotton productivity resulted in fewer Black lynchings (Beck & Tolnay, 1990).

Overall, the empirical analysis of economic explanation of hate crime has not offered conclusive evidence that economic status is the key predictor of bias motivated offenses. Although there is ample information to support the frustration-aggression thesis, which provides that bias motivated crime is a result of poor economic security and performance, it is important to understand the prevailing counter evidence, which states economic deprivation has little to no bearing on hate crime (Green et al., 1998a; Espiritu, 2004). Still, that is not to say economic explanations are *not* definitive. Indeed, Pinderhughes (1993) posited that bleak economic conditions lay the “foundation for racial conflict” by leaving individuals with uncertain futures, which can lead to increased group anxiety. As a result, Pinderhughes (1993) found this economic-based anxiety led to growth of intergroup violence among youth peer groups in New York. However, additional research has sought to go beyond simple economic explanations of hate crime by introducing economics as a function of sociological and political processes, such

as the research by Olzak (1990), who sought to establish a relationship between anti-Black violence, wage competition, and political competition; this research will be expounded upon in a later section of this literature review.

Demographic Explanations

Other researchers have proposed that demographic variables, such as intergroup composition or neighborhood racial makeup, to explain hate crime prevalence (Freilich, Adamczyk Chermak, Body, & Parkin, 2014; Lyons, 2007). Comparable to economic theories of hate crime, some demographic explanations coincide with the class conflict perspective. On the other hand, demographic explanations do not tend to explain the role of material possession and wealth to explain hate crimes, but instead focus on community configuration (Lyons, 2007). Particularly, research explaining this theoretical framework of hate crime has relied on social disorganization theory and other minor criminogenic theories (Iwama, 2016).

Social Disorganization & Collective Efficacy. Shaw and McKay (1942) first developed social disorganization theory as a response to increased urbanization in the early 20th century and the resulting social issues that had emerged because of it. They argued that crime was a product weak social organization, characterized by economic disparity, increased residential mobility, and racial and ethnic heterogeneity. Essentially, the researchers posited that a lack of organization led to informal social controls being relaxed and crime being more apt to flourish. Crime, therefore, is viewed as being regulated by the nature of the neighborhood, not by the nature of the individual.

Social disorganization theory has been empirically employed for general explanations of crime, primarily with the research conducted by Sampson and Groves (1989) and Pratt and Cullen (2005). First, Sampson and Groves (1989) used 1982 British crime survey data from more than 10,000 respondents that included measures of socioeconomic status, heterogeneity,

mobility, and other common social disorganization variables. However, the authors also included structural variables such as involvement in peer networks and participation in community institutions. In their research, they found structural factors affected social disorganization which, in turn, affected crime rates. It was found that more disorganized areas had higher levels of crime. However, a meta-analysis by Pratt and Cullen (2005) revealed that former social disorganization scholarship measured structural *causes* of social disorganization, such as poverty or ethnic heterogeneity, but did not measure social disorganization *itself*. Therefore, the authors affirmed that the concepts developed by Shaw and McKay (1942) had a relationship with crime, but it was not as strong as past researchers had put forth nor had previous research appropriately measured the concept.

In addition, when analyzing community-level factors, it is necessary to understand Sampson's (1986) collective efficacy theory as a revitalization of social disorganization. Neighborhoods are characterized by systemic relationships and interactions in which informal social controls are established through community networks (Lyons, 2007). Such neighborhoods are characterized by two primary constructs: (1) social cohesion and (2) a shared expectation of informal control in relation to public safety and crime prevention (Sampson, Raudenbush, & Earls, 1997). Communities that exhibit common factors of social disorganization tend to have weak collective efficacy.

Although collective efficacy was not developed to specifically explain crime, it was oriented towards crime in general. It follows that neighborhoods with high collective efficacy should informally prevent or control hate crime (Lyons, 2007). Therefore, social disorganization and collective efficacy, in this line of research, should be thought of cohesively to predict hate crimes. Social disorganization theory predicts greater rates of hate crime in economically

disadvantaged and unstable, mixed communities. However, neighborhood with strong social cohesion and informal social control should predict less hate crime (Lyons, 2007). Also, applying social disorganization to hate crime is an assumption that the contributing factors to hate crime are similar to other types of crime. Therefore, economic deprivation, racial heterogeneity, and high rates of residential mobility should too explain hate crime (Lyons, 2007). Socially disorganized communities may also experience higher rates of hate crime because they are less able to invest in social programs or have less experienced police trained to identify and respond to hate crime (Lyons, 2007; van Dyke & Widom, 2001).

Lyons (2007) is credited with one of the most noteworthy attempts to apply social disorganization, collective efficacy, and the defended community perspective (which will be covered later in this section) to crimes of bias, as his research examined the relationship between community structural conditions and racially motivated crimes. In his work, Lyons found results contrary to the social disorganization thesis. In fact, communities that exhibited forms of social cohesion and informal control (high social capital) were increasingly associated with anti-Black crimes, especially in neighborhoods characterized by racial homogeneity. The two primary constructs of social disorganization, economic disadvantages and residential mobility, did not account for hate crimes. Measures of social cohesion and informal social control were developed by results from the Project on Human Development in Chicago Neighborhoods (PHDCN) that asked over 8,000 Chicago residents about the state of their neighborhoods. Questioned included topics of trust and witnessed incidents of deviance (e.g. disrespectful youths, fights, graffiti, etc.) which were both scaled from one to five with lower scores indicated lower social cohesion/control.

Grattet (2009) also examined community demographics and its relationship with biased offending in Sacramento, California. The author found mixed support for the social disorganization theory in predicting bias crimes in that concentrated economic disadvantage and high rates of residential mobility were strongly correlated with increased rates of offending. However, there was no substantial correlation between ethnic heterogeneity and hate crime. Grattet also controlled for the influx of non-White residents in predominantly White neighborhoods and found a strong, positive relationship between hate crime and the increased mobility of non-White residents moving into a White area. On the other hand, the author found a negative relationship between hate crime and the movement of non-White individuals into non-White neighborhoods in that when White individuals move into a minority area, they are less likely to experience a hate crime. When comparing social disorganization variables with defended community's variables, Grattet concluded that the defended community variables had a much stronger relationship with hate crime prevalence. Because of this, Grattet concluded that bias crime is more than likely the result of more large-scale processes that dictate intergroup conflicts and resolutions, and not simply the result of neighborhood demographics.

Bell (2013) later compounded the research of Lyons (2007) and Grattet (2009) by examining violence that had been used against Blacks moving into White neighborhoods. Referred to as "move-in violence," the author found violence against "moved-in" Blacks dates back to the 1890s in which White residents viewed Blacks as a threat to property values and the quality of the neighborhood. New Black residents, then, were not necessarily perceived as a physical threat but a threat to the White idea that "their neighborhoods" were exclusive to those at the top of the racial hierarchy (Bell, 2013, p. 52).

Gladfelter et al. (2017) also conducted an analysis of the structural factors that predict hate crime. The authors did not restrict their research to aggregate counts of hate crime and did not use uniform victimization records, but instead analyzed social disorganization across “contexts.” To do this, the authors questioned whether the causes and correlates unique to hate crime were related to the causes and correlates of non-criminal bias activity. Also, Gladfelter et al. tested whether these relationships were consistent across different types of bias motivation, specifically focusing on anti-White, anti-Black, and anti-Hispanic crimes/non-criminal activities.¹ The author found results contrary to social disorganization in that social disorganization variables (particularly racial heterogeneity) did *not* predict high levels of hate crime. Instead, predominately disadvantaged white communities were more likely to foster anti-racial hate crimes than other, more racially diverse areas. These findings were significant in relation with anti-Black and Hispanic hate crimes.

Finally, Freilich et al. (2014) applied social disorganization theory to bias-motivated terrorism and the development of far-right hate groups. Although hate crimes and terrorism are not inextricably linked, the two have the possibility to overlap. Freilich et al. hypothesized that counties that are poorer, have higher levels of racial and ethnic diversity, have Jewish or Muslim congregations, have high rates of residential mobility, or have lower proportions of Protestant and Catholic adherents are neighborhoods that fall under the socially disorganized category and will have more far-right perpetrators residing there. Because social disorganization refers to the inability of a community to establish common goals and values of their residents to solve problems far-right bias will go unchecked (Bursick, 1988). The findings were mixed in that only counties with large Jewish congregations, high levels of residential mobility, and increased

¹ Hate crimes and non-criminal bias activity will be referred as to “hate crime incidents” for the purpose of discussing the research of Gladfelter et al. (2017)

Protestant presence were significantly more likely to feature far-right perpetrators. It would seem, then, that social disorganization only explain a fair amount variation in hate crime prevalence while other theories, such as collective efficacy and the defended communities perspective, are more apt to explain hate crime.

Defended Communities Perspective. Besides social disorganization and collective efficacy, other demographic theories have focused on interactions of the group and not the neighborhood. One social psychology theory, realistic group conflict theory, focuses on intergroup hostility that is derived from the conflicting goals of social groups (Iwama, 2016). The only way to mitigate intergroup hostility is to maintain common and attainable goals that require intergroup cooperation (Iwama, 2016; Jackson, 1993). This group conflict is more heavily amplified when groups are involved in racially-motivated resource competition (Lyons, 2007; Olzak, 1990; Soule and van Dyke, 1999; van Dyke et al., 2001).

A related theory, the defended communities perspective, was developed by Suttles (1972) in an attempt to explain violent crime as a result of spurious minority growth in racially homogenous communities. Race, as noted in his ethnographic research in Chicago, is a “common identity” in which groups become “defended neighborhoods” where members may use violent tactics to defend their community from perceived outsiders (Iwama, 2016; Lyons, 2007; Suttles, 1972). Therefore, hate crime is viewed as not as a result of social disorganization in communities, but is instead a product of responding to perceived external threats to normality (Heitgard & Bursik, 1987; Lyons, 2007). It follows, then, that hate crime should be more prevalent in areas of racial homogeneity and strong collective efficacy, in which informal social control and cohesion allows for the greater capacity for communal defense (Lyons, 2007; Portes,

1998; Waldinger, 1995). To reiterate, the concepts were solidified in the findings of Lyons (2007), Grattet (2009), and Gladfelter et al. (2017).

Green, Strolovitch, and Wong (1998b) applied these theories to their research of racially motivated crimes. While other demographic research has focused on static counts of racial proportions in communities, these authors used racial changes over time in relation to hate crime offenses. In doing so, they analyzed realistic group conflict theory, the power-threat hypothesis, and the defended community perspective. While the defended community perspective predicts hate crime in predominantly white areas, the power-threat hypothesis predicts less hate crime in White neighborhoods, since their “power” is not threatened in areas of White homogeneity (resulting in less violence to obtain power) (Blalock, 1957; Bobo, 1988; Levine & Campbell, 1972; Suttles, 1972; Tolnay, Beck, & Massey, 1989). The authors also controlled for economic conditions. By evaluating specific New York neighborhoods, Green et al. found results consistent with the defended neighborhoods perspective in that higher occurrences of racially motivated crime were found in predominantly White neighborhoods, but also in neighborhoods with high rates of minority in-migration over time especially in areas that, for several years before the in-migration, had been mostly White. These findings held true for anti-Black, Hispanic, and Asian crimes. Further, the predictive models also suggested that the in-migration of one particular racial or ethnic group primarily predicted hate crimes against that group, which mitigates possible spuriousness. The authors found very weak relationships between racial hate crime and economic conditions. Returning to the social disorganization research, these results are further compounded by the findings of Lyons (2007), who found the variables of the defended community perspective to be strongly correlated with racially-motivated hate crime. Still, although the developments of social disorganization, and the other related net factors, are

comprehensive and thorough in explaining hate crime, it is also important to elaborate on other hate crime research that does not fit within the two preceding categories.

Competing Theories

Included in the prominent hate crime literature are empirical works that do not fit within research that has utilized economic and demographic frameworks to explain biased offending. Instead, these other works have used theoretical concepts outside the scope of traditional criminology, or they have used criminological theories uncommon to hate crime research. These theories include feminist and gendered perspectives, control theory concepts, and factors from the field of psychology. Although these competing theories are not tested in this research, it is nonetheless beneficial to briefly detail them.

To begin, some researchers have identified that hate crime may be explained using feminist and conflict theories (Alden & Parker, 2005; Glaser et al., 2002; Walters, 2010). To do this, many of the authors have relied on Messerschmidt's (1993) theory of "doing gender" which posits that crime is a result of a dominant culture of masculinity that conditions how males approach their goal attainment. Hate crime, being an extreme form of discrimination, plays off this relationship by causing offenders to "do difference," as put forth by Perry (2001). Because of this, hate crime has been used to marginalize and discriminate against a group or individual deemed as "different." Empirical analysis has suggested that this relationship exists in that hate crime is more often committed by men to preserve "hegemonic masculinity" (Giddens, 1989; Messerschmidt, 1999; Bufkin, 1999). The results of several studies support this conclusion by which hate crime is *more* prevalent in areas with high levels of gender equality (Alden & Parker, 2005; Bufkin, 1999).

Outside of the scope of feminist criminology, Walters (2010) has proposed that hate crime may be best explained at the intersection of strain theory, Perry's (2001) "doing

difference,” and Gottfredson and Hirschi’s (1990) self-control theory. Consistent with the notion that offenders are those with low *self-control*, some have argued that the same logic can be applied to hate crime offenders since they too tend to be impulsive, insensitive, and short-sighted. In harmony with the research of Levin and McDevitt (2002), many hate crime offenders are those who seem to offend “for the thrill” or are those who offend as a biased defense mechanism. In addition, hate crime offenders have been characterized as those who are unemployed (or have low-skilled jobs) and who have low academic success, which is in accordance with the prominent self-control literature (Gottfredson & Hirschi, 1990; Levin & McDevitt, 2002; Ray & Smith, 2002; Sibbit, 1997; Walters, 2010).

Finally, some authors have noted that the psychological processes of hate crime offenders are important to include when analyzing this type of offending (Green, Glaser, & Rich, 2001). As such, this literature has examined the individual and group-level cognitive processes of hate crime offenders and as to why they develop their hostility, choose their victim, and commit a biased crime. Some have contended that hate crime may be a result of mental deficiencies such as anti-social disorder, paranoia, extreme frustration, or authoritarianism. Or, at the social level, groups such as the KKK require strict conformity as a result of extreme social pressure, which can induce various psycho-social processes such as the traditional steps of contagion, conformism, and the extreme display of group attitudes and norms (Bohnsich & Winter, 1993; Erb, 1993; Green et al., 2001; Hamm, 1994; Kleg, 1993; Rieker, 1997; Wahl, 1997; Watts, 1996; Willems, Wurtz, & Eckert, 1993).

Political Culture

Literature in other fields has shown that a relationship may exist between violence, voting, and the efficacy of government (Hobolt & Klemmensen, 2008; Olzak, 1990; Pacheco,

2008) As such, it is important to consider these factors when attempting to explain prevalence of bias-motivated crime.

Political Competition

Perhaps one of the most salient factors on social interactions is the role of political competition. Two pieces of literature, Hobolt and Klemmensen (2008) and Pacheco (2008), analyzed the role that political competition plays in the realm of political science. While Pacheco (2008) focused on how political competition can affect youth voting rates, Hobolt and Klemmensen (2008) took a unique perspective by analyzing how such competition can result in drastic policy changes.

To achieve his objective, Pacheco (2008) conducted a multivariate political competition analysis on the impact on youth voter turnout. Past research on political competition and political efficacy revealed high correlations between increased political competition and political interest, discussion, knowledge, and the intention to vote in upcoming elections (Gimpel & Schuknecht, 2003). Pacheco (2008) formulated that political competitions play more of a vital role at the state and local level in differing “political contexts.” Individuals, according to Pacheco (2008), live in multiple contexts simultaneously by which political competition exists at every location of social interaction, such as the house, the school, or the community. Thus, Pacheco (2008) correlated political competition at multiple levels with youth voting. He found that increased political competition has a positive relationship with youth voter turnout and that home resources and political discussion at the family level were the largest predictors of voting.

Hobolt and Klemmensen (2008) analyzed the role of political competition and contestation on government responsiveness, in that higher levels of political competition should theoretically yield more policies and more executive action. To measure this association, Hobolt

and Klemmensen operationalized two concepts of government responsiveness: *rhetorical responsiveness* and *effective responsiveness*. Government responses that were rhetorical emphasized speeches and publicity motives, and any response of formal policy was categorized as effective. Political competition was measured by differences in public preferences and issue opinions. They concluded that their hypotheses of political competition generally held true in the United States. American politicians had a moderate rhetorical response to political competition and had higher effective responses to political competition. Together, the research of Pacheco (2008) and Hobolt and Klemmensen (2008) concluded political competition can have sizeable ramifications at both the micro and macro level of analysis.

Crime and Political Competition. While there exists nuanced political science literature outlining the effects that political competition has on social processes (primarily in the realm of politics), there appears to be a dearth of research that has operationalized election results to predict crime (biased offending included). Instead, many scholars have utilized measures of political competition (or *partisanship* in other studies) to account for legal differences in hate crime such as issues related to law enforcement discretion or the timespan in which states have enacted new hate crime legislation.

To begin, research by Olzak (1990) constituted one of the first attempts to analyze the “political context of competition” in relation to racially-motivated violence. Olzak gauged the connection of racial violence and lynching from 1882 to 1914 to political changes, the cotton economy, and the increased migration of Blacks to urban communities. In a sense, this research expounds upon the analysis conducted by Hovland and Sears (1940). The political notion developed by Olzak was that increased political competition generated by the Southern Populism movement, a political movement that challenged White supremacy in the Democratic Party,

resulted in an increase of racial violence. Olzak (1990) used three indicators of political competition: Populist electoral contests, Presidential election year, and percentage of votes for third party candidates. All three indicators of political competition were significant in that each had positive correlations with lynching and racial violence. Primarily, she concluded that the Populist challenge, of all the indicators, appeared to have spurred increased lynching's the most. In addition, this research is also consistent with other historical analyses of racial violence in that racial violence fluctuated in concordance with wages of low-skilled laborers and with increased migration in Southern states.

Other research has implemented political competition to understand the discrepancies in hate crime enforcement and compliance. For the most part, this body of research is very similar to Blalock's (1957) racial threat theory, which originally included a discussion of the competition over political and economic resources. Thus, in this case, minority group size may "threaten" the majority's hold on political power, which may result in state sanctions to alleviate the perceived threats; this is perhaps best exemplified in the enforcement (or lack thereof) of criminal law (Liska, 1992). For instance, the size of Black populations has been positively associated with arrest rates, police force size and expenditures, and the use of capital punishment, among other forms of social control (Jacobs & Carmichael, 2002; Jackson & Carroll, 1987; Kent & Jacobs, 2005; Liska, Chamlin, & Reed, 1985). According to scholars such as King (2007), hate crime enforcement is no different.

Soule and Earl (2001) explored this topic by providing a comprehensive analysis of the intrastate and interstate factors that affect enactment of hate crime legislation. According to the authors, state hate crime laws are susceptible to internal political characteristics as well as external ones. While authors such as Grattet, Jenness, and Curry (1998) have narrowly examined

the *interstate characteristics* that alter hate crime legislation (also known as *institutional theory*), Soule and Earl contended that both sets of predictors are of equal importance. In relation to political competition, Soule and Earl included a measure of whether Democrats dominated the state legislature, hypothesizing that states with Democrat-controlled legislatures should have higher rates of hate crime adoption; they also created a dummy variable for whether the governor of the state was of the same political party as the majority of the states' legislators, arguing that states with drastic party differences between the governor and the legislature will have greater difficulty passing hate crime legislation. For the most part, their findings supported the general notion that less politically competitive states (in favor of Democrats) significantly affected the rate at which hate crime legislation was passed while the partisan difference between the executive and legislative branch had no significant impact on the outcome.

McVeigh et al. (2003) further applied the notion of political competition and hate crime law by examining political and community characteristics that affect hate crime *enforcement* via law enforcement reporting. As stated previously, hate crime legislation did not develop instantaneously, but instead was derived as a multi-decade culmination of various social movements and historical events. To McVeigh et al., hate crime legislation is not itself a successful "social movement" unless it is adequately reported by law enforcement agencies, each of which experience unique political incentives to strictly enforce, or not enforce, established laws. Motivated by *political mediation theory*, which focuses on the political context of institutional structures (such as law enforcement agencies), McVeigh et al. hypothesized that hate crime reporting can only flourish when political conditions surrounding law enforcement agencies are positively associated with enforcing hate crime law. These "conditions," according to the authors, are best represented by the existence of various factors including the presence of

civil rights organizations, the percentage of elections won by Democrats, and party competitiveness (similar to Pacheco's (2008) measurement of political competition). However, their results did not indicate that party competitiveness, nor Democratic voting, had any significant effect on hate crime reporting by law enforcement. Only when they were analyzed *in interaction* with the presence of civil rights organizations were they positively associated with hate crime reporting.

Overall, criminological research of hate crimes has often ignored the implementation of political measures to explain biased offending. While previous research has established a somewhat causal relationship between biased offending and certain events (such as 9/11 or the O.J. Simpson trial), contemporary research has been unable truly discern whether the political climate or large-scale political events, like elections, are associated with increased levels of hate crime occurrence (Iwama, 2018; King & Sutton, 2013). Therefore, this study seeks to provide a more comprehensive assessment of biased offending by including measures of political competition to predict the occurrence of hate crime.

Purpose of the Current Study

As established in the preceding review of the literature, a variety of differing theoretical explanations of offending can be utilized to explain hate crime. Further, relevant literature from the political science field details the importance of political competition in societal processes such as voting and governmental actions. For example, the research of Olzak (1990) touched upon the role of political competition on racially-motivated incidents during the late 19th century. The findings of this work are salient to the current research. However, that research was oriented towards explaining the political aspect of competition in terms of resource conflict and economic structures, and not necessarily the role of *political competition*.

The question thus remains: *Does political competition influence the prevalence of hate crime?* This research intends to build upon the previous literature by not only attempting to answer that question but also extend the theoretical bodies that have already been analyzed. Specifically, this research will test various hypothesis in relation to social disorganization theory and the defended community perspective. As the previous literature has shown, crime may occur in areas that are marked by social disorganization (Sampson & Groves, 1989; Pratt & Cullen, 2005). Hate crime, if similar, should mirror the effects of social disorganization and should occur in areas with high levels of concentrated poverty, high levels of residential transience, and high levels of racial and ethnic heterogeneity. Therefore, the social disorganization hypothesis is as follows:

Hypothesis 1: Hate crime is more prevalent in socially disorganized counties characterized by concentrated disadvantage, high levels of residential mobility, high levels of ethnic and racial heterogeneity, and high levels of population density.

Included in this research is the focus on previous literature that analyzed the defended community perspective and hate crime. Based on the findings of prior research, it should hold that hate crime will flourish in predominately white areas, especially those which are marked with concentrated disadvantage, as they will most likely perceived minority groups as possible threats (Green et al., 1998b; Lyons, 2007). Suttles (1972) identified communities in his ethnographic research who often aligned themselves on cultural values, which included race. It is necessary, in the line of hate crime research, to further extend the defend community perspective.

In this analysis, it will be applied through a *county-level* approach, in line with the research by Freilich et al. (2014). The hypotheses will be as follows:

Hypothesis 2: Hate crime is more prevalent in predominately white counties characterized by concentrated disadvantage.

Hypothesis 3: Hate crime is more prevalent in predominantly white counties that experience an in-migration of racial and ethnic minority groups.

Lastly, this review of literature focused on the concept of *political competition*. In doing so, a shortcoming in the hate crime literature was discovered as it is limited in its discussion of the role of politics in such offending. However, political science research has offered findings that measure the impact of political competition, especially within the realm of government actions and civics, such as with voting behavior (Hobolt & Klemmensen, 2008; Pacheco, 2008). In addition, the research of Olzak (1990) was instrumental to the foundation of this research in its analysis of racially-motivated violence and voting percentages in the late 19th century. Thus, this research will use established definitions of political competition, as set out by Olzak (1990) and Pacheco (2008), to better understand occurrence of hate crime at the county level. The hypotheses are as follows:

Hypothesis 4: Hate crime is more prevalent in counties with higher levels of average political competition as measured through presidential elections, gubernatorial elections, U.S. congressional elections, and federal-level special elections

Hypothesis 5: Hate crime is more prevalent in counties with higher voting percentages for third-party candidates

Chapter Summary

In terms of hate crime explanations, much of the relevant research falls into two primary encampments: economic explanations and demographic explanations. Still, other hate crime research has been dedicated to constructing hate crime offender typologies to better explain *who* these perpetrators might be and decipher their background characteristics (Anderson et al., 2002; Levin & McDevitt, 1993, 2000; McDevitt et al., 2002; Messner et al., 2004). However, the predominant predictors of hate crime have been explained using various macro-level theories of offending. Within the field of economic frameworks, the work of Hovland and Sears (1940) is heavily cited as cornerstone research connecting hate crime to economic indicators of frustration and aggression. However, research following the work of Hovland and Sears (1940) has mixed findings in support of economic indicators of hate crime (Beck & Tolnay, 1990; Green et al., 1998a; Hepworth & West, 1988; Mintz, 1946; Tolnay & Beck, 1995).

The other leading explanations of hate crime are best described as demographic-based. Primarily, these explanations are rooted in two distinct theories: Social disorganization and 'defended communities' in which crime is best predicted by neighborhood demographics such as residential mobility or concentrated disadvantage (Shaw & McKay, 1942). Unlike economic explanations, the demographic theories of hate crime are more consistent in terms of empirical support. Key research by Lyons (2007) analyzed the role of social disorganization, collective efficacy, and the defended community perspective and found that associated indicators were more accurate in predicting hate crime. Later research fused these findings to further support demographic explanations of hate crime (Bell, 2013; Gladfelter, 2017; Grattet, 2009).

Although there are other theories used to explain hate crime, this research will only focus on the most prevalent: social disorganization and defend communities. In addition, this research intends to fill a current gap in the literature by incorporating the role of political competition in understanding the problem. The primary question under assessment is whether political competition increases the likelihood of hate crime offenses. The following chapter will outline the methodological approach utilized to study the possible relationship between social disorganization, the defended community perspective and political competition with hate crime.

CHAPTER 3

DATA AND METHODOLOGY

This chapter begins by describing the data sources that are utilized for the current research. Next, it details the various measures that will be employed to analyze the dependent (hate crime) and independent measures (social disorganization theory, the defended community perspective, and political competition). Finally, it serves to introduce the method of statistical analysis and discuss the various models that will be employed to test the established hypotheses.

Data Sources

Hate Crime Data

There are two primary sources of official hate crime data in the United States: the Uniform Crime Reports (UCR) and the National Incident-Based Reporting System (NIBRS). Although both data bases are maintained by the FBI, incidents published through the UCR are not suitable for the current research due to reporting limitations. NIBRS makes county-level analyses more efficient, as each reported incident is matched with a Federal Information Processing Standard (FIPS) code instead of simply the name of the reporting agency. Determining the location of hate crimes reported by state-level agencies would be virtually impossible via the UCR, as the researcher could not determine the county in which its officers were operating at the time. This limitation is not present within the NIBRS dataset, increasing confidence in the validity of county-level counts of hate crime.

NIBRS data is disseminated by the Inter-university Consortium for Political and Social research in four linkable extract files: Incident, victim, offender, and arrestee (FBI, 2017). This research relies solely upon data available within the incident-level files. *Incidents* are defined as “one or more offenses committed by the same offender, or group of offenders acting in concert, at the same time and place” (FBI, 2017, p.10). Offenses that make up incidents can either be

categorized in Group A or Group B offenses, with the former typically being more serious in nature, such as assaults. Hate crime is considered as Group A substantive offense under data element 8A (Bias Motivation).

Socio-Demographic Data

As discussed, this study attempts to extend the research on predicting hate crime via the social disorganization and defended community perspectives. In order to do so, it draws upon the socio-demographic information contained within the U.S. Census Bureau's American Community Survey (ACS). The ACS is a nationwide survey that provides demographic, social, economic, and housing data that can be specified at the county level (U.S. Census Bureau, 2008). To achieve this, the ACS creates single and multiyear estimates based on sample data collected monthly. Thus, single-year estimates are collected over a 12-month period, 3-year estimates over a 36-month period, and 5-year estimates over a 60-month period (U.S. Census Bureau, 2008). Although there is a tradeoff between using longer-year estimates as opposed to shorter-year estimates, this research utilized five-year estimates for each time period for the purposes of consistency and accuracy (as longer timespans are considered to be more accurate (U.S. Census Bureau, 2008)). An overview of the ACS data can be viewed in *Table 1*.

Estimates are based on community and state populations and only communities with at least 65,000 residents are provided with single-year estimates (U.S. Census Bureau, 2008). As such, it is typically advantageous to use multiyear estimates to promote validity and reliability, especially when looking at data for less-populated areas (such as rural counties). Relevant to this research, the ACS provides a means by which to measure demographics at the county level.²

² Poverty data was gathered using models produced by Small Area Income and Poverty Estimates (SAIPE) program that utilizes demographic information disseminated by the ACS. This program has analyzed ACS data since 2005 (Bell et al., 2007).

Table 1: *ACS Years & Estimate Groupings*

Year	Dataset
2010	2010 ACS 5-Year Estimates
2011	2011 ACS 5-Year Estimates
2012	2012 ACS 5-Year Estimates
2013	2013 ACS 5-Year Estimates
2014	2014 ACS 5-Year Estimates
2015	2015 ACS 5-Year Estimates
2016	2016 ACS 5-Year Estimates

Election Data

To test political competition, this research utilized election results from presidential, gubernatorial, and (federal-level) congressional elections. It also considers results of any federal special elections held within the three states during the timespan under analysis. Although there are multiple sources of election data, the current study relied upon official results published through the websites of Tennessee’s Secretary of State, the Virginia Department of Elections, and the West Virginia Secretary of State. Within each year, results are categorized by election type. The years 2010 to 2016 were chosen for two primary reasons: availability of data and occurrence of elections of relevance to this research (U.S. Presidential & Congressional and state executive). Voting results were obtained at the county-level and then averaged in order to simplify the statistical models (to be discussed). Put differently, both political competition and third-party voting percentages are the average values across all elections for each county per year.

Sample Selection

Counties in Tennessee, Virginia, and West Virginia were selected for two primary reasons: (1) NIBRS certification status and (2) a geographical justification. First, and of most

importance, the counties in these states were selected due to the fact that all contained agencies feature 100% NIBRS certification. Agencies are only considered to be NIBRS certified if they have a compatible reporting system, demonstrate the ability to update submissions and meet deadlines, minimize error rates, and submit statistically reasonable reports (FBI, 2012); Tennessee, Virginia, and West Virginia are three of fifteen states (currently) that submit *all* of their crime data via NIBRS. As such, the counties within them should present the potential for an accurate estimate of hate crime incidence. In addition, these states share geographic similarities, in that they are considered to be within the Appalachian Region (as defined by the Appalachian Regional Commission, a federal-state partnership) (40 U.S.C § 14301). Therefore, any results may be generalizable to the Appalachian region.

Treating counties as the unit of analysis is beneficial for other reasons in that it allows for a unique perspective of hate crime prevalence as well as produces results that have the potential to extend to more rural communities (this study utilizes both metropolitan and nonmetropolitan counties). Though social disorganization and the defended communities perspective were written as community-level theories rooted in urban areas, research over the past decade has been able to expand traditional denotations of the community from urban areas to rural locales, especially with the seminal work of Osgood and Chamber (2000), whose findings revealed that social disorganization measures (residential instability, ethnic heterogeneity, and concentrated disadvantage) also share a relationship with rural offending. In the time since, several empirical studies have further suggested that social disorganization (and perhaps other urban-level theories) may be generalizable to a rural setting (Kaylen & Pridmore, 2011).

Variables

Dependent Variable

The dependent variable assessed in the current research was *hate crime incidence*, which was operationalized as the total number of hate crimes reported in a given county for each year under analysis. Hate crime reports were gathered from NIBRS and aggregated as simple counts per county via use of the previously discussed FIPS code. Because this research only used raw counts of hate crimes, it does not differentiate between bias motivations or bias types. As such, hate crime counts are inclusive of all motivations and bias types and are broken down into annual aggregated counts for the seven-year span of 2010 to 2016. Exploratory analysis of the data suggests that hate crime incidence is a relatively rare event, with many counties reporting zero for most years and others featuring only one or two incidents. As such, *hate crime incidence* was transformed into a binary variable where one (1) equates to the occurrence of at least one hate crime in a county for the respective year and zero (0) indicates no reported hate crimes. This mandates the utilization of a logistic analysis technique to model *hate crime incidence*, which will be discussed later in the chapter.

Independent Variables

In accordance with past research, this study utilized data from the ACS and official election results to operationalize variables related to social disorganization, defended communities perspective, and political competition. As stated previously, social disorganization and the defended communities perspective measures were drawn from the ACS, whereas political competition measures were drawn from official election results available through state agencies.

Social Disorganization.

Population Density. Past research has suggested that hate crime tends to be more prevalent in areas of dense population (Rubeck et al., 2015). The current study includes a measure of *population density* to further explore this relationship. The measure was constructed by dividing the total population of each county by the total square miles of land contained within its boundary.

Racial Heterogeneity. Shaw and McKay (1942) argued that areas with prominent levels of racial and ethnic heterogeneity would experience higher levels of crime. According to the literature on collective efficacy, this relationship might exist because of the inability of residents to communicate and form strong bonds to prevent crime and disorder (Kornhauser, 1978). To date, heterogeneity has not been consistently found to share a significant relationship with hate crime incidence (Freilich et al., 2014; Gladfelter et al., 2017; Grattet, 2009; Lyons, 2007).

Still, when testing social disorganization theory, it is necessary to be exhaustive in considering all relevant variables. Thus, this study utilized a measure of racial heterogeneity well-rooted in previous research (as used by Sampson, 1985; Sampson & Groves, 1989) and designed to measure population diversity in a given area across four primary groups (non-Hispanic Whites, non-Hispanic Blacks, Hispanics/Latinos, and an “Other” category). This index was calculated using the following formula:

$$(1 - \sum p_i^2)$$

In this formula, p_i^2 represents the fraction of the county population for a given racial or ethnic group (Sampson & Groves, 1989) whereby scores closer to one (1) represent more heterogeneous counties and scores closer to zero (0) indicate more homogenous areas (with consideration to the relative size of other groups in the population).

Disadvantage. Although the literature on hate crime features mixed conclusions as to the effects of economic conditions (see Green et al., 1998a) it is still beneficial (as was the case with heterogeneity) to assess it in the current study. In addition, some researchers have proposed that while poor economic conditions do not solely predict hate crime, predominately White areas characterized by concentrated disadvantage tend to foster bias-motivated offenses (Gladfelter et al., 2017; Grattet, 2009; Green et al., 1998b). To measure the effects of socioeconomic disadvantage within each county, two measures were employed: *single-parent households* and *poverty*. *Single-parent households* is the measure of the percentage of households within each county featuring a single parent and children under the age of eighteen (18), while *poverty* measures the percentage of all persons within a given county living under the federally-defined poverty line.

Mobility. The final component of testing social disorganization is a measure of *residential mobility*. As discussed within the literature on this perspective, increased rates of residential mobility may inhibit the likelihood that individuals in a neighborhood create bonds to deter possible criminal activities (Shaw & McKay, 1942, 1969). Per Shaw and McKay (1942), areas with high levels of residential stability (low mobility) will feature low levels of criminal activity. The measurement of *residential mobility* for the current project is in line with the research literature (Iwama, 2016; Morenoff et al., 2001; Sampson, Morenoff, & Raudenbush, 2005; Stowell, 2007), and involves taking the percentages of all individuals (within each county) ages five (5) and over who have moved within the past year.

Defended Communities Perspective.

White Population. The key variable in testing the defended communities perspective is *White population*, as its influence is well-documented in the hate crime literature (Gladfelter et al., 2017; Grattet, 2009; Lyons, 2007). Although increased prevalence of hate crime is typically

found within the intersection of predominately White areas and other relevant measures (e.g., poverty), it is first essential to establish a base count. Thus, *White population* was measured as the total proportion of Whites in a given county, as derived from the ACS.

Ethnic/Racial Minority Change. Previous research on hate crimes has highlighted the finding that anti-racial hate crime is more common in areas that are both predominantly white and feature higher levels of minority in-migration (see Grattet, 2009), often referred to as “move-in” violence (Bell, 2013). Although ethnic and racial minority change is not a central tenet to the work of Shaw and McKay (1942), is it more relevant to the defended communities perspective (Lyons, 2007). *Minority change* was calculated as the percent change in ethnic/racial minority population composition over a one-year span. For example, *minority change* for 2010 was computed as the percent change in minority composition from 2009 to 2010.

Unemployment. Although research that has revitalized the work of Hovland and Sears (1940) through the use of unemployment measures has featured predominately non-significant findings, it is still useful to extend, and possibly expound upon this relationship. Research by Pinderhughes (1993) supports the notion that increased frustration and aggression as a result of bleak economic conditions *may* lead to intergroup hostilities. In addition, the work of Grattet (2009) and Gladfelter et al. (2017) has established a relationship between hate crime and White, disadvantaged areas. To capture this possible influence, the current project includes a measure of *unemployment*, which was operationalized as a percentage of all persons over the age of 16 within a given county who are unemployed.

Interaction Effects. The potential for the defended communities’ measures to work together to influence incidence of hate crime requires the exploration of potential interactions between the measures. Including interaction terms allows for an understanding of the unique

impact of each variable in addition to any cumulative effect it may have in combination with other factors. Interaction terms are created by first mean-centering each measure, and then multiplying the resulting values (Jaccard & Turrisi, 2003). The interaction terms utilized in the current study assess the intersection between *White population*, *minority change*, and *unemployment*, as these relationships are rooted in past hate crime research (e.g. Green et al., 1998b; Glafelter et al., 2017). Interactions are represented by the following formulas:

$$[White\ population\ (Mean-Centered)] \times [Minority\ change\ (Mean-Centered)]$$

$$[White\ population\ (Mean-Centered)] \times [Unemployment\ (Mean-Centered)]$$

Political Competition. The final independent variables included in the study are *political competition* and *third-party voting percentage*, which serve as the keystone of the research. Although the work also extends the literature on social disorganization and defended communities perspective, the primary purpose is to gauge the impact of political competition on hate crime prevalence while accounting for predictors associated with these other theories.

Operationalizing political competition relies upon on three previous studies: Olzak (1990), McVeigh et al. (2003), and Pacheco (2008). Olzak's (1990) measures included status as a Presidential election year and the percentage of third-party votes cast in the election being analyzed. These findings are meaningful in that each indicator of political competition had a significant relationship with lynchings in the United States. The current analysis expands on the work of Olzak (1990) by focusing on all forms of hate crime (and not just lynchings).

To partially capture *political competition*, the current study used a measure developed by Pacheco (2008), who analyzed the relationship between state and local political competition with long-term turnout by youth voters. It is operationally defined as:

$$Political\ Competition = 100 - |(\% Democratic\ Vote - 50)|$$

Where low values represent little to no competition and high values represent counties that have high levels of competition. These values were calculated over a seven-year span (2010-2016) as to encompass the necessary elections relevant to this research. Because including separate *political competition measures* for the results of each election (within a given county and for a given year) as a separate measure may lead to over-specification of the models employed, an average was taken. Each county's score for the *political competition variable* is thus based upon the combined results of all elections for the given year, with scores closer to 1 suggesting higher levels of political competition within a county.

Third-party vote constitutes the second measure (in line with the work of Olzak, 1990) of political competition. *Third-party vote* was operationalized as the proportion of votes cast for candidates of any party outside of the mainstream political landscape (defined as the Democratic and Republican Parties). Much as the case with *political competition*, *third-party vote* was averaged across all elections for each given county and year. Both measures were collected for each corresponding year and then were averaged over the seven-year span (for each year) to produce one central measure of *political competition* and one central measure of *third-party votes*.

Control Variables

This research controlled for *total violent crime* in a given county in order to account for the possibility of overlaps between hate crime and other forms of violent offending. The measure is simply a reflection of the overall violent crime rate (per 100,000 residents) for each county and was collected via the UCR county-level detailed arrest and offense data (excluding juvenile offenders), as disseminated by ICPSR. A detailed summary of the variables and tested theories can be found in *Table 2*.

Plan of Analysis

Research Design

As discussed, the current study takes a county-level approach to better understand the relationship between hate crime and predictors associated with the various theoretical frameworks being tested. Rubeck et al. (2015) demonstrated that hate crime could be analyzed at the county level in their study of offending in Pennsylvania from 1999 to 2011. However, their research design was descriptive in nature and did not test any potential theoretical explanations. This research, on the other hand, used a longitudinal, non-experimental design to analyze the prevalence of hate crime over a seven-year span from 2010 to 2016.

Hypotheses

Although the research hypotheses were discussed in Chapter 2, it is beneficial to briefly reiterate them here in order to more fully understand their connection to the broad research purpose, measures utilized, and methodology.

H₁: Hate crime is more prevalent in socially disorganized counties characterized by concentrated disadvantage, high levels of residential mobility, high levels of ethnic and racial heterogeneity, and high levels of population density.

This hypothesis serves to address the generalizability of social disorganization theory to the problem at hand and utilizes the following variables: *Population density*, *ethnic heterogeneity*, *poverty*, *single-parent households*, and *mobility*. The hypothesis was tested in Model 6.

Table 2: *List of Variables*

Measure	Variables	Description
Social Disorganization	<i>Population density</i>	<i>Total population</i> divided by total square miles in county
	<i>Racial heterogeneity</i>	Index of the relative size of each racial group in a given county
	<i>Poverty</i>	Percentage of all persons below the poverty line
	<i>Single-parent households</i>	Percentage of single-parent households with children under 18
	<i>Mobility</i>	Percentage of population (age ≥ 5) who moved in the past year
Defended Communities	<i>White Population</i>	Total proportion of Whites in the population
	<i>Minority change</i>	Percent change of ethnic/racial minority change
	<i>Unemployment</i>	Percentage of civilian labor force (age ≥ 16) who are unemployed
Political Competition	<i>Political Competition</i>	Election competition between Republican and Democrat officials
	<i>Third-party votes</i>	Percent of total third-party votes
Control Variables	<i>Violent crime</i>	Violent crime rate in a given county

H₂: Hate crime is more prevalent in predominately white counties characterized by disadvantage.

H₃: Hate crime is more prevalent in predominantly white counties that experience an immigration of racial and ethnic minority groups.

These hypotheses test the defended communities perspective and make use of the following variables: *White population*, *ethnic/racial minority change*, and *unemployment*, as well as the created interaction terms. These propositions were tested in models 2, 4, 5, and 6.

H₄: Hate crime is more prevalent in counties with higher levels of average political competition as measured by results of presidential elections, gubernatorial elections, U.S. congressional elections, and federal-level special elections.

H₅: Hate crime is more prevalent in counties with higher voting percentages for third-party candidates.

These hypotheses test the political competition model of hate crime and use the following variables: *Political Competition* and *Third-party percentages*. They were tested in models 3, 4, 5, and 6.

Statistical Analysis

Univariate Statistics. Statistical analysis for this study proceeded in a series of three stages. First, descriptive statistics were calculated in order to identify the characteristics of counties included within the sample. Included in these calculations were measures of central tendency and dispersion for both the dependent and independent variables. In addition, calculating the descriptive statistics served to provide direction regarding the method of analysis to be employed, as selection of the appropriate form of regression is dependent upon the distribution of the dependent measure (*hate crime incidence*). As discussed, exploratory analysis revealed that the incidence of hate crime is not normally distributed, with the majority of

counties featuring either (0) or (1) hate crimes in a given year. As such, *hate crime incidence* was recoded as a binary variable (0= no hate crimes reported; 1= at least one hate crime reported). This decision, and its impact on the methods chosen, is expounded upon in the “multivariate analysis” section of this chapter.

Bivariate Statistics. Bivariate correlations were computed to examine the relationships between the independent variables in order to check for issues of multicollinearity. Although some models are contingent upon independent measures *not* having a linear relationship, highly correlated independent measures also make it more difficult to discern “true relationships” in a multivariate analysis (Kennedy, 1985). As such, this is a necessary step to ensuring the estimation procedure in this research is reliable.

Multivariate Analysis. The third and final stage involved the presentation of the regression models used to determine the impact of the independent measures on hate crime incidence. A total of six logistic regression models will be presented. These models did not maintain a traditional linear modeling structure; instead, they were examined via use of a longitudinal hierarchical linear modeling methodology (HLM). In many areas of social science research, data is often “clustered” or “nested” inside of naturally occurring hierarchies such as students within a school or workers inside of an organization (Raudenbush, Bryk, Cheon, Congdon, & du Toit, 2004; McCoach, 2010). As such, these types of observations are not independent from each other and require an approach that controls for the non-independence of observations. A similar structure is present in the current work, as the impact of each independent measure is assessed longitudinally (over the course of seven years), with years being nested within each of the 284 counties. Here, a two-level model was employed to assess changes

in *hate crime incidence* within counties and between counties while controlling for other salient factors.

This modeling technique, as developed by Bryk and Raudenbush (1987), uses a two-stage conceptualization by which models that measure within-subject trajectories (level-one) become the dependent measure for the between-subject trajectories (level-two). Particular to this assessment, “individual” growth was transformed into a within-county model that measured the effect of time (years) and predictors associated with the defended communities’ and political competition frameworks on the dependent variable of *hate crime incidence*. Level two, then, measured the variation of the dependent measure (time and hate crime) between counties and additionally tests for the influence of the social disorganization measures. HLM is not unfamiliar to the field of criminology and criminal justice and has been employed on many occasions to control for natural clusters within data (e.g. Sampson, Raudenbush, & Earls, 1997; Papachristos, Meares & Fagan, 2007).

The construction of the multilevel models followed sequential steps common to HLM analyses (McCoach, 2010). The initial model is an *unconditional growth model* that only accounted for time as the predictor of the dependent measure of hate crime (Model 1). This model is necessary not only to understanding how time may affect hate crime prevalence, but also for estimating variance components that can later be compared for prediction purposes (McCoach, 2010).

Similar to the initial unconditional model, the level-one growth models maintain the predictor of time (years), but also include the independent measures being tested. This research utilized four separate growth models to assess the effects of independent measures and time on hate crime prevalence. Model 2 analyzed *hate crime incidence* within the scope of the provided

defended communities' measures of *White population*, *minority change*, *unemployment*, and the two interaction terms. Model 3 investigated the role of political climate, which was operationalized via *political competition* and *third-party percentages*. The fourth model is a combined growth model that included all measures associated with the defended communities perspective and political competition. Model 5 is identical to Model 4 except that it also included the control measure for *violent crime*.

All variables in each of the level-one models were grand-mean centered, excluding *White population* and *minority change*, which were previously mean-centered before the creation of the associated interaction terms. The choice of grand-mean centering, as opposed to group-mean centering, is based on the necessity to render intercept terms that are more meaningful and, for the purposes of this study, to examine the relationship between hate crime and predictor variables as it varies between the counties (Kreft, Leeuw, & Aiken, 1995; Hoffman & Gavin, 1998). While these two methods of scaling are different in terms of computation, they also produce findings that conceptually differ from each other in that group-mean centering allows for the researcher (in this case) to interpret the coefficients as an individual-level effect (here, within the county) as opposed to an estimator that assesses variation across counties, which is more ideal in this scenario (Ulmer & Johnson, 2004).

The level-two model is a *full contextual model* that contains both level-one and level-two predictors of *hate crime incidence*. Level-two models allow for a determination of the effects of each independent predictor while accounting for any county-level characteristics (in this case measures associated with the social disorganization perspective) that are not allowed to vary from year to year, meaning that the model measures the between-county effect of social disorganization as well as within-county effects of the level-one models *simultaneously*. The

level-two contextual model was employed in models six. Again, all variables (except *White population* and *minority change*) were grand-mean centered before running the analysis.

Summary

This chapter served to provide an outline of the research methodology for the current study. In sum, this research is best considered as a non-experimental, longitudinal study that examines the relationship between hate crime and variables associated with social disorganization theory, the defend communities perspective, and political competition. Data used in construction of these variables were gathered from secondary sources, including NIBRS, the ACS, and state voting databases. Statistical analysis (the results of which are to be discussed in the subsequent chapter) proceeded in three stages. First, descriptive statistics (univariate analysis) were calculated to provide a more in-depth understanding of variable distribution. Next, correlations (bivariate analysis) were calculated between the independent measures to test for multicollinearity. Finally, this study employs the use of an HLM technique to account for the nested nature of the data and answer each of the established research questions.

CHAPTER 4

RESULTS

This chapter will highlight and summarize the various statistical analyses that were conducted for the current study, which include descriptive, bivariate, and multivariate statistics. First, descriptive statistics were assessed in order to provide an overview of the data and created measures. Next, bivariate statistics were calculated in order to assess correlations between the independent and dependent measures and test for potential multicollinearity issues. Finally, a multilevel modeling technique (using a form of logistic regression) was utilized to test the study hypotheses.

Descriptive Statistics

The first step in this analysis involved the calculation of descriptive statistics. Because a multilevel model was used, the descriptive data was reported in accordance to the level in the model from which it came. As such, a summary of the findings can be found in two separate tables; Table 3 outlines the data for all level-one variables while Table 4 contains information pertaining to the level-two variables.

Analysis of the data indicated that the majority of counties did not report at least one hate crime in the given time span ($\bar{x} = 0.31$). Instead, agencies within these counties (including both county-level and local agencies) were most likely to report zero hate crimes, as the mean (0.31) indicates that only 31% reported at least one hate crime for a given year.

In relation to the level-one independent variables, counties tended to be predominantly White ($\bar{x} = 0.85$) and experienced a mean minority growth rate of roughly three percent each year. As for the measure of political competition, counties tended to be less politically

competitive, as the mean of *political competition* ($\bar{x} = 0.83$; $s = 0.09$) was closer to one (1) than to 0.50.

Table 3: *Level-One Descriptive Statistics*

Variable	Mean	SD	Minimum	Maximum
Hate crime	0.31	0.46	0.00	1.00
Unemployment	8.53	2.87	0.60	20.10
White population	0.85	0.14	0.36	0.99
Minority change	2.67	3.51	-8.71	38.78
Political competition	0.83	0.09	0.58	1.00
Third-party votes	3.84	2.56	0.03	28.55
Violent crime rate*	255.53	292.49	0.00	4296.64

*per 100,000 citizens

On average, third-party candidates received nearly four percent of the total vote in a given year, averaged across presidential, congressional, and gubernatorial elections. These counties also experienced an average violent crime rate of nearly 255 violent crimes per 100,000 residents. However, *violent crime* was quite dispersed, ranging from zero (only a few counties failed to report any violent crimes) to nearly 4,300 violent crimes per 100,000 citizens.

The level-two descriptive statistics (Table 4) detail the measures associated with the social disorganization perspective. The typical county featured a *population density* of approximately 182 persons per square mile, with slightly over 17% of its residents living in *poverty*, and nearly 12% having moved within the previous year (*residential mobility*). Six percent (6%) of households featured children under the age of 18 residing with a single parent (*single-parent households*). Finally, the typical county was relatively homogenous in terms of racial composition, with the measure for *racial heterogeneity* featuring a mean value of 0.23. This is similar to the distribution for *minority change*, which indicates that the two measures may

explore a similar concept and calls for an assessment of potential multicollinearity issues prior to running the multivariate models.

Table 4: *Level-Two Descriptive Statistics*

Variable	Mean	SD	Minimum	Maximum
Population density	182.51	609.09	5.41	8561.60
Racial heterogeneity	0.23	0.16	0.04	0.59
Poverty	17.25	5.66	3.80	42.23
Mobility	11.59	3.37	4.94	27.76
Single-parent households	5.85	1.57	1.85	12.17

Bivariate Correlations

Bivariate correlations provide an initial understanding of the relationships that may exist between the independent predictors and hate crime within a given county. In addition, they aid in exploring potential issues with multicollinearity, which exists when independent measures are too highly correlated with one other. Past research has suggested that a correlation of 0.80 or above between two independent variables may reveal multicollinearity (Marsh, Dowson, Pietsch, & Walker, 2004). A summary of the findings can be found in Table 4.

Mobility ($r = .467$; $p < .01$) shared the strongest relationship with *hate crime incidence* among the independent variables, followed by the interaction term of *White population x minority change* ($r = -.318$; $p < .05$), which shared a negative relationship with the dependent measure. It is necessary to note that every measure of social disorganization was significantly correlated with *hate crime incidence* and in the direction that was expected under Hypothesis 1, except for *poverty* ($r = -.262$; $p < .01$), which had a moderately-weak and negative correlation with hate crime. The defended communities perspective, on the other hand, received mixed support from the bivariate analysis in that all measures of the perspective were significant excluding

minority change and *White population x unemployment*. Similar to social disorganization, there were significant correlations between *hate crime incidence* and the defended communities perspective that operated contrary to the research hypotheses. For instance, *White population* ($r = -.207$; $p < .01$) and *White population x minority change* ($r = -.318$; $p < .01$) were both negatively correlated with hate crime, contrary to Suttle's (1972) original analysis that found racial violence was *higher* in predominately White communities with minority in-migration. Both measures of political competition did not significantly correlate with *hate crime incidence*.

Analysis of the bivariate correlations revealed that *racial heterogeneity* and *White population* ($r = -.962$; $p < .01$) were strongly correlated and above the 0.80 threshold for multicollinearity. This is problematic because these two variables, if included together in the same model, run the risk of obscuring any unique relationship that may exist between the racial composition of a county and the variation in hate crime. Essentially, *racial heterogeneity* and *White population* are measuring the same concept. For this reason, *racial heterogeneity* was omitted from the final level-two model (Model 6) to avoid any potential issues related to multicollinearity. *Poverty* and *unemployment* ($r = .641$; $p < .01$) as well as *minority change* and *racial heterogeneity* ($r = -.602$; $p < .01$) also shared moderately strong correlations, but not enough to mandate further action.

Other interesting correlations to note are ones that crossed theoretical boundaries. For example, *political competition* was moderately correlated with *White population* in a negative direction ($r = -.477$; $p < .01$), signifying that more racially homogenous counties also tended to be less politically competitive (as measured by voting percent differences between Democratic and Republican candidates).

Table 5: *Bivariate Correlations*

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Hate crime incidence	—													
2. White population	-.21**	—												
3. Minority change	-.13	.57**	—											
4. White population x Minority change	-.32**	.34**	.16*	—										
5. Unemployment	-.16*	.08	-.00	.16*	—									
6. White population x Unemployment	.02	.13	.17**	-.24**	.25**	—								
7. Political competition	-.02	-.45**	-.17**	.28**	-.17**	-.18	—							
8. Third-party votes	.10	.30**	.21**	-.21**	-.04	-.00	-.23**	—						
9. Population density	.34**	-.22**	.00	-.10	-.20**	.21**	.08	.02	—					
10. Racial heterogeneity	.28**	-.96**	-.60**	.18**	-.13*	-.09	.41**	-.24**	.22**	—				
11. Poverty	-.26**	.18**	-.00	.27**	.64**	.02	-.04	.00	-.22**	-.28**	—			
12. Mobility	.47**	-.14*	-.05	-.25**	.09	.01	-.06	.26**	.27**	.20**	.06	—		
13. Household instability	.26**	-.51**	-.35**	.12	.37**	-.10	.14*	-.18**	-.02	.50**	.24**	.34**	—	
14. Violent crime	.29**	-.04	-.08	-.06	.37**	-.00	-.07	.06	.02	.03	.24**	.11	.27**	—

**p<.01; *p<.05

This relationship is bolstered by the fact that *political competition* was significantly correlated with *minority change* ($r = -.447$; $p < .01$) as well *racial heterogeneity* ($r = -.243$; $p < .01$) in the negative direction, revealing that counties with higher rates of racial heterogeneity and minority in-migration become more politically competitive.

Multivariate Statistics

In this stage of the analysis, logistic regression was utilized to model the log likelihood of a county experiencing at least one hate crime in a given year, and the impact that the various level-one and level-two measures had in influencing this outcome. As previously discussed, using this technique allows for accurate estimates of nested data (observations nested within counties) and an assessment of *hate crime incidence* both within- and between-counties simultaneously. The coefficients in these models can be interpreted as the measure of the change in the natural log odds of the likelihood of *hate crime incidence* associated with any changes in the respective predictor variable(s) (King, 2007; Vèlez, 2001). All variables included in these models were grand-mean centered, excluding those utilized in the created interaction terms, which were mean-centered prior to their inclusion. Furthermore, all predictors were treated as fixed effects, as preliminary analysis indicated that none were statistically-significant when included as potential random effects.

Unconditional Growth Model

The initial multivariate model was classified as an *unconditional growth model*, which included only time as a predictor of the dependent measure. While unconditional growth models usually contain no predictors (see McCoach, 2010), this study utilizes a longitudinal design that spans over seven years, necessitating the inclusion of time as a predictor variable. Doing so serves two primary roles in that it provides estimates of variance components that can later be modeled with additional level-one and level-two predictors and allows for a determination of

whether *hate crime incidence* significantly changes over time (which is necessary when deciding to maintain time as fixed or random effect in the subsequent models). A summary of the findings can be found in Table 6. Here, time failed to operate as a significant predictor of *hate crime incidence*, meaning that the log-odds of at least one hate crime being committed within counties did not vary by year. As such, time, as well as all other variables, were modeled as fixed effects in subsequent models.

Table 6: *Model 1 (Unconditional Growth Model) Logistic Regression Output*

Variable	Coefficient	Standard error	t-ratio	Odds-ratio
Time	-0.005	0.02	-0.235	0.995
Constant	-0.77			
Log likelihood	-2,297.37			

Level-One Models

Model 2. The level-one contextual models maintained time as a predictor of *hate crime incidence*, while adding measures associated with the defended communities perspective and political competition. The first (Model 2) was designed to test the hypotheses associated with the defended communities perspective. A complete summary of the results can be found in Table 7. The results suggested that most of the variables associated with the perspective were significantly related to the log-odds of at least one hate crime occurring in a given county; however, they operated in a manner that offers mixed support for the defended communities perspective. *White population* ($t= -4.57$; $p<0.001$) was a significant predictor of the incidence of hate crime within a given county in that any one-unit increase in *White population* reduced the odds of at least one reported hate crime by nearly 98 percent. This is contradictory to Suttle’s (1972) initial assertion of racial violence, which posits that racial violence is most likely in areas

characterized by the interaction of minorities moving into predominately racially homogenous areas. It is important to bear in mind, however, that *White population* was grand-mean centered prior to being entered into the model and that a one-unit change in the variable is not meant to be interpreted as an absolute percentage of Whites residing in a given county. Instead, any one-unit changes in the independent measures are micro-unit changes *above* the original grand-mean in a given year.

This is especially noteworthy when analyzing the relationship between *hate crime incidence* and the interaction term between White population and minority change, which showed that when predominately White counties experienced an influx of racial and ethnic minorities, those same counties also experienced a reduced log-odds of at least one hate crime occurring. In fact, when this interaction occurred in the positive direction, the odds of at least one hate crime within a county were reduced by approximately 63%; this too is contrary to the defended communities perspective. With that said, *minority change* was a positive (while rather weak) indicator of the occurrence of at least one hate crime by which the influx of minorities in a county (not controlling for the predominant race) resulted in a marginal increase in the log-odds of *hate crime incidence*. Nonetheless, the findings in this model, while mostly significant, lend little support to the defended communities perspective as originally conceptualized.

Table 7: *Model 2 (Defended Communities Perspective) Logistic Regression Output*

Variable	Coefficient	Standard error	t-ratio	Odds-ratio
Time	-0.017	0.027	-0.636	0.983
White population	-3.837*	0.840	-4.570	0.022
Minority change	0.115*	0.033	3.459	1.122
White population x Minority change	-1.010*	0.237	-4.236	0.366
Unemployment	-0.027	0.030	-0.917	0.973
White population x Unemployment	-0.066	0.936	-0.336	0.936
Constant	-0.700			
Log likelihood	-2,311.770			

*p<.01

Model 3. The third model assessed possible relationships between *hate crime incidence* and measures associated with the theory of political competition; a summary of the findings can be viewed in Table 8. Neither of the measures were significantly related to *hate crime incidence* within counties. However, the measures did perform in the expected direction in that increases in either *political competition* or *third-party votes* did slightly increase the odds of the dependent measure occurring by nearly 23% and 5% respectively.

Table 8: *Model 3 (Political Competition) Logistic Regression Output*

Variable	Coefficient	Standard error	t-ratio	Odds-ratio
Time	-0.002	0.035	-0.05	0.998
Political competition	0.257	1.110	0.252	1.293
Third-party votes	0.041	0.029	1.427	1.042
Constant	-0.790			
Log likelihood	-1,389.510			

Model 4. The fourth model combined the measures included in the two previous level-one models (defended communities perspective and political competition theory) in order to assess predictor influence while controlling for those associated with the other theory. As evidenced by Table 9, this model largely reaffirmed the findings from the two previous models. *White population*, *minority change*, and the interaction term between the two measures were each significantly related to *hate crime incidence*. *White population* ($t= -4.524$; $p<.01$) and the interaction term, *White population x minority change* ($t= -1.416$; $p<.01$) again operated in a manner contrary to the defended communities perspective; *minority change* ($t= 0.129$; $p<.01$) maintained a negative relationship with the dependent measure.

Table 9: *Model 4 (Defended Communities & Political Competition) Logistic Regression Output*

Variable	Coefficient	Standard error	t-ratio	Odds-ratio
Time	-0.031	0.036	-0.845	0.970
White population	-4.524*	0.947	-4.775	0.011
Minority change	0.129*	0.041	3.131	1.138
White population x Minority change	-1.416*	0.287	-4.931	0.243
Unemployment	-0.022	0.033	-0.650	0.979
White population x Unemployment	0.001	0.226	0.005	1.001
Political competition	-0.732	1.087	-0.674	0.481
Third-party votes	0.050	0.029	1.714	1.052
Constant	-0.630			
Log Likelihood	-1,397.170			

* $p<.01$

What is also interesting to note from this model was the shift in *political competition* from a positive predictor of hate crime to a variable that predicts reduced log-odds of hate crimes in a

given county. Controlling for a county's racial composition and unemployment resulted in an output that predicts lower levels of *hate crime incidence* when a county is more politically competitive.

Model 5. Model 5 included all of the measures utilized in the previous model, with the addition of the control for *violent crime*. Alone, *violent crime* ($t= 5.36$; $p<0.001$) performed as a significant predictor of *hate crime incidence* in that a one-unit change translated to a three percent increase in the odds of at least one hate crime occurring within a county. In addition, controlling for *violent crime* allowed for two additional variables that were previously nonsignificant to emerge as significant predictors: *unemployment* and *third-party votes*. Table 10 offers a summary of these findings.

Table 10: *Model 5 (Level-One Combined Model) Logistic Regression Output*

Variable	Coefficient	Standard error	t-ratio	Odds-ratio
Time	-0.033	0.037	-0.876	0.968
White population	-4.415**	0.938	-4.705	0.012
Minority change	0.130**	0.042	3.121	1.139
White population x				
Minority change	-1.444**	0.291	-4.954	0.236
Unemployment	-0.098**	0.035	-2.753	0.907
White population x				
Unemployment	0.118	0.231	0.510	1.125
Political competition	-0.284	1.080	-0.263	0.752
Third-party votes	0.062*	0.030	2.069	1.064
Violent crime	0.003**	0.001	5.360	1.003
Constant	-0.660			
Log likelihood	-1,411.840			

* $p<.05$; ** $p<.01$

In this model, controlling for *violent crime* induced *unemployment* ($t = -0.098$; $p < .01$) as a significant predictor of *hate crime incidence* in which a one-unit change in the unemployment rate was associated with a nearly ten percent reduction ($e^{0.907}$) in the odds of at least one hate crime. While *unemployment* did operate as a rather weak predictor of hate crimes within the defended communities perspective, it did so in a direction that was unexpected. Similar to the relationship between *White population* and *political competition*, this particular finding may be due to the fact that the counties in this study (which were predominately White) also tended to have higher rates of unemployment. Indeed, from the bivariate correlations in Table 5, there is a significant, albeit weak, positive relationship between *White population* and *unemployment*, but it was only able to operate as significant when *violent crimes* was present in the model. This hypothetical relationship will be more accurately assessed in the level-two full-contextual model.

As for the political competition variables, controlling for *violent crimes* also allowed for *third-party votes* ($t = 0.062$; $p < .05$) to perform as a significant predictor of *hate crime incidence* in the direction that was expected under the research hypotheses in which counties that had higher rates of voting for third-party candidates in a qualifying election (presidential, congressional, and gubernatorial) were associated with a nearly 7% percent increase in the odds of at least one hate crime, suggesting that the inclusion of *violent crime* helped clarify the role of the independent predictors on hate crime.

Level-Two Model

The final model used in this analysis was the *level-two full contextual model*, which featured all measures utilized in Model 4 (defended communities, political competition, and the control measure) as well as the variables associated with social disorganization theory. This allows for a better understanding of the county-level characteristics that may affect hate crime likelihood and helps to clarify which competing theory is more precise in predicting biased

offending. Furthermore, by using a multi-level modeling technique, the level-two model provides a more accurate assessment of *hate crime incidence* in that it controls for differences for within-county effects (defended communities and political competition) as well as between-county effects (social disorganization) simultaneously within the same model. To achieve this, all measures of social disorganization were averaged over the years being assessed (2010-2016), and then included in the full contextual model (juxtaposed with the yearly measures of the previous models). *Racial heterogeneity* was excluded from the model due to multicollinearity. Instead, *White population* was retained to serve as a measure of a county's racial composition. The results of Model 6 are summarized in Table 11 on the following page.

First, the most notable result from this model was that all social disorganization variables excluding *household instability* operated as significant predictors of *hate crime incidence*. In addition, all of the variables, except for *poverty*, functioned in the expected direction under the first hypothesis in that any increase in *population density* ($t= 2.965$; $p<.01$) or *mobility* ($t= 0.15$; $p<.01$) resulted in a significant increase in the odds of the dependent variable. The relationship between the dependent measure and *household instability* ($t= 0.169$; $p= .059$), while nonsignificant, also operated in the expected direction. *Poverty* ($t= -0.089$; $p<.01$), on the other hand, performed in a manner contrary to the social disorganization interpretation of hate crime in that poorer counties tended to feature a reduced likelihood of experiencing at least one hate crime; in particular, any one unit change in the poverty rate resulted in nearly a 10 percent reduction ($e^{0.914}$) in the odds of at least one hate crime occurring in a given county.

The second finding to be taken from this model is that the introduction of social disorganization measures in the full contextual model rendered all other measures (excluding *violent crime*) as nonsignificant. While these findings will be covered and analyzed in greater

detail in the following chapter, the results of this model do not necessarily provide substantial support for the notion that social disorganization variables are better at predicting *hate crime incidence* overall, but instead that the social disorganization theory is more appropriately applied at the county level. Indeed, previous research has consistently found the defended communities perspective to be a more salient theory in predicting hate crime at the census tract and block-group level; while, on the other hand, social disorganization theory is more suited to explaining variation in crime at both smaller and larger levels of analysis. For the most part, however, social disorganization received a modest amount of support from this model.

Table 11: *Model 6 (Level-Two Full Contextual Model) Logistic Regression Output*

Variable	Coefficient	Standard error	<i>t</i> -ratio	Odds-ratio
Time	-0.005	0.040	-0.136	0.995
Population density	0.002*	0.000	2.965	1.002
Poverty	-0.089*	0.024	-3.743	0.914
Mobility	0.150*	0.034	4.375	1.162
Household instability	0.169	0.089	1.901	1.184
White population	1.068	1.296	0.825	2.911
Minority change	-0.042	0.048	-0.875	0.958
White population x Minority change	-0.124	0.342	-0.364	0.883
Unemployment	-0.055	0.042	-1.306	0.947
White population x Unemployment	0.046	0.251	0.185	1.047
Political competition	0.054	1.103	0.049	1.056
Third-party votes	0.047	0.031	1.494	1.048
Violent crime	0.002*	0.001	4.741	1.002
Constant	-0.910			
Log likelihood	-1,423.770			

*p<.01

Summary

This chapter was dedicated to providing an overview of the distribution of the explored measures, the correlations that existed between them and the results of the various multilevel models designed to test the established hypotheses. The multilevel framework allowed for an assessment of within-county trajectories while also controlling for the impact of between county measures. Utilization of a logistic modeling strategy allowed for a determination of the influence that each explored measure had on the likelihood that a given county would experience at least one hate crime incident in a given year.

The various models revealed a number of significant relationships between the dependent measure, *hate crime incidence*, and the independent measures. The unconditional growth model, which included time as the only predictor, suggested that there was no significant relationship between time and hate crime incidence. While this model had no theoretical implications attached to it, unconditional growth models act as a formative element to multilevel analyses in that they provide variance components that may be essential later in the study and act as a valuable tool in the decision-making process of allowing variables in future models to vary as fixed or random effects (McCoach, 2010). Due the fact that time did not operate as a significant predictor of hate crime, it was treated as a fixed effect in all models.

All level-one contextual models (models 2, 3, 4, and 5) were used to analyze the role of the defended communities perspective and political competition on *hate crime incidence*. Results suggested that the variables associated with the defended communities perspective (*White population, minority change, unemployment*, and the interaction terms) were significant predictors of hate crime, even when controlling for county-level politics and *violent crime*. However, these relationships were not in the direction that was expected under Suttle's (1972) original work, which theorized that predominately White, disadvantaged areas would experience

higher levels of racial violence in tandem with increased minority in-migration. In all respective level-one models, this was not the case as there was a significant, negative relationship between *hate crime incidence* and the interaction term *White population x minority change*, meaning that the log-odds of at least one hate crime was significantly reduced when counties had higher proportions of Whites *and* increased minority in-migration. *Third-party votes* was the only political competition measure that operated as significant, but only in the level-one combined model (Model 5) by which counties that had higher percentage votes for third-party candidates also had increased log-odds of *hate crime incidence*.

The level-two full contextual model (Model 6) included all the measures from the final level-one model (Model 5) as well as the variables associated with social disorganization theory. While the application of the results of this model may be disputable, the overall findings support social disorganization as a theory that is better suited to explaining *hate crime incidence* variation at the county level. This is mostly due the fact that all variables associated with social disorganization, excluding *household instability*, operated as significant predictors of the dependent measure. In addition, these same variables also acted in a manner that was expected under the central tenets of Shaw and McKay's (1942) work except for *poverty*, in which higher poverty rates significantly *reduced* the odds of at least one hate crime occurring within counties. The second notable result from this model was that the presence of the social disorganization predictors also rendered the measures associated with the defended communities perspective and political competition as nonsignificant, perhaps highlighting the fact that social disorganization is appropriate at multiple levels of analysis while the defended communities perspective is more applicable to smaller settings such as blocks or tracts.

Having a provided an overview of the statistical analyses that were computed in this portion of the research, the following chapter will provide a more detailed explanation for the findings that include both implications for theory and policy initiatives. In addition, it will cover the limitations of the study and propose guidelines for future research on the topic.

CHAPTER 5

DISCUSSION

This study sought to explore hate crime incidence by assessing its relationship with predictors derived from three theoretical frameworks. These frameworks included two prominent sociological theories of crime, social disorganization and the defended communities perspective, in addition to a conceptualization of political competition derived from the political science literature. To assess the various hypotheses being tested in the study, hate crime data was gathered from the National Incident-Based Reporting System (NIBRS) and correlated with community-level data from the American Community Survey (ACS) and voting data from official state sources. This chapter will offer a more nuanced explanation of the results detailed in the previous chapter. In addition, it will provide a discussion of the limitations of the work and outline theoretical implications as well as offer guidance for future research on hate crime.

Social Disorganization

Originally conceptualized by Shaw and McKay (1942), social disorganization theory was developed to explain the spatial distribution of crime in urban communities. Their work revealed that high-crime communities tended to be heterogeneous in terms of racial and ethnic makeup, had high levels of residential mobility, and were economically disadvantaged. These findings were later expounded upon by the work of Sampson (1986), who suggested that the structural variables that defined social disorganization were not sufficient to explain variation in criminality, as collective efficacy served as the mediating mechanism between characteristics and prevalence of offending. This extension of social disorganization posited that when neighborhoods are socially disorganized the members of the community cannot establish meaningful bonds with each other (i.e. collective efficacy), which, in the long-run, affects the ability of a neighborhood to informally control crime. Put differently, it is not necessarily

structural characteristics that foster crime, but instead that these characteristics serve to reduce cohesion and the ability of residents to work together.

While social disorganization and collective efficacy have received a modest amount of support in explaining crime (see Pratt & Cullen, 2005), this support has not always extended to the hate crime literature. When utilizing the theory to explore hate crime, scholars have often operated on the assumption that hate crime is no different than “regular” crime and that the same factors that explain general criminality also apply to biased offending. However, previous analyses have not offered conclusive evidence that this is the case (Grattet, 2009; Lyons, 2007). The current study sought to assist in better addressing this possibility. In addition, it took a unique approach by assessing whether structural characteristics associated with the theory influenced hate crime at the county level, an extension not yet explored within the literature.

For the most part, the findings were supportive of the application of social disorganization to explain hate crime at the county level. The relevant hypothesis (Hypothesis 1) stated that counties characterized by social disorganization would experience increased likelihood of hate crime. Here, social disorganization was measured using ACS data to capture structural conditions including racial heterogeneity, concentrated disadvantage, household instability, and residential mobility. Counties considered to be “socially disorganized” were found to be significantly more likely to experience at least one hate crime in a given year. All measures, except for poverty and racial heterogeneity (proxied as *White population* as opposed to the more traditional measure developed by Sampson (1986)), operated in the direction that was expected under the research hypothesis. Conceptually, these findings imply that hate crime is no different than “general” crime and that the ecological factors that contribute to crime also apply to biased offending.

The only variable that performed contrary to what was expected was *poverty*, which featured an inverse relationship with *hate crime incidence*. While this relationship is not necessarily implied in the hate crime literature, researchers using a county-level approach to explore the generalizability of the theory to rural areas have often found that poverty may work differently within them (as compared to their urban counterparts) (Bouffard & Muftic, 2006; Osgood & Chambers, 2000). Typically, in urban criminology, poverty is not considered as the sole predictor of crime. Instead, it is viewed as a significant formative element by which low economic status leads to greater residential instability and ethnic heterogeneity. This then results in social disorganization, which is conducive to higher rates of crime.

Poverty has been hypothesized to work differently in rural communities because of differences in underlying structural mechanisms that regulate social life within them (Bouffard & Muftic, 2006; Lee, Maume, & Ousey, 2003). For instance, many empirical assessments of social disorganization have placed emphasis on the principle of *social isolation*, in which socially disorganized communities are also socially isolated from middle class values and norms. They are therefore said to have limited access to mainstream institutions. For rural communities, social isolation may also take the form of *geographical isolation*, which has the ability to combat the negative effects of social disorganization since poverty would inherently limit the ability of poorer citizens to move from one community to another (Bouffard & Muftic, 2006). As such, homogeneity in any form, whether it be racial or economic, may operate as a reinforcement mechanism to instill greater levels of social cohesion and shared values (Lee et al., 2003; Websdale, 1995).

It is important to note that this research utilized a sample of counties that on the whole featured heightened economic struggles. For example, the mean poverty rate of the counties

under analysis was two percent higher than the national average of 15.15 percent.³ Additionally, these counties were also characterized by a high number of White citizens in proportion to other races (\bar{x} = 0.85) and had a corresponding lack of *racial heterogeneity* (\bar{x} = 0.23). *Poverty* in this research may have acted in accordance to the findings of previous studies by operating as a factor of stability, thereby decreasing hate crime as a side effect of crime reduction. As seen in Table 5, it is evident that the intercorrelations between the social disorganization measures are more in-line with the work of Osgood and Chambers (2000) in that *poverty* shared a negative correlation with racial heterogeneity (r = -.279) and relatively weak correlation with *mobility* (r = .062) and *household instability* (r = .242). This contradicts the classical pattern of correlations found by Park and Burgess (1924). With that said, the first research hypothesis received a modest amount of support in that most measures performed in line with predictions.

Defended Communities Perspective

The defended communities perspective was treated as a competing theory (with social disorganization) that may also explain county-level variation in hate crime. The theory was first developed through the ethnographic research of Suttles (1972), who conducted field studies to understand the nature of urban racial violence in the 1970s. Unlike the work of Shaw and McKay (1942), which emphasized the role of internal community-level processes and dynamics, Suttles (1972) suggested that offending was more influenced by “external threats” than internal structural factors. Racial violence, then, is used as a defense mechanism to the influx of unwanted racial in-migration to predominantly racially homogenous neighborhoods. This theory was tested by analyzing the racial and economic composition of counties in addition to patterns

³ The national poverty rate average was calculated using ACS national-level poverty data for each year in examination (2010-2016) and then averaged over the seven-year time span.

of migration. Because the theory suggests that interactions exist among these measures, interaction terms were developed and included in the various models.

The first defended communities hypothesis (Hypothesis 2) predicted that hate crime would be more prevalent in economically disadvantaged counties that were also predominately White. None of the models that included the defended communities measures were supportive of this hypothesis, as the interaction term (*White population x Unemployment*) did not emerge as a significant predictor of *hate crime incidence*. While *unemployment* (as a standalone variable) did operate as a significant predictor of hate crime in Model 5 (the level-one combined model), its direction was not consistent with the defended communities perspective.; this finding may be best understood by referencing the discussion of *poverty* above, as the two measures were strongly correlated ($r = .641$). In addition, the findings are somewhat consistent with previous hate crime scholarship, which has not offered conclusive support for the role of unemployment in influencing biased offenses. In fact, some scholars (see Lyons, 2007) have suggested that biased offending will be *more* prominent in economically stable communities.

The second defended communities hypothesis (Hypothesis 3) predicted that hate crime would increase in predominately White counties experiencing higher levels of minority immigration. However, the results of each of the level-one models do not support this hypothesis at the county level. Separately, *White population* and *minority change* operated as significant predictors of *hate crime incidence* in a direction that is not expected under the defended communities perspective. Specifically, when the proportion of Whites in given county increased, the odds of at least one hate crime decreased. A similar pattern was witnessed between *minority change* and *hate crime incidence*. Perhaps most important is the observed relationship between *hate crime incidence* and the interaction between *White population* and *minority change*

due to the fact that the defended communities perspective does not simply predict crime on the basis of a community's racial composition, but instead on the *interaction* between a community's racial composition *and* its respective rate of minority in-migration (Bell, 2013; Green et al., 1998b; Lyons, 2007).

Findings are contrary to the crux of Suttle's (1972) initial assertion that racially homogenous areas (usually predominantly White areas) use violence as a reactive approach to any perceived external forces that threaten a community's sense of cohesion, which is usually formed on the basis of race. If true, predominately White counties with high levels of ethnic and racial minority in-migration should experience greater rates of biased offending as a reactive process to change. All models in this research offered a different finding. The interaction term actually operated as a significant predictor for the *reduction* of biased offending by almost 44 percent ($e^{-1.44}$) in each model in which it was included, meaning that predominately White counties where the minority population increased saw the odds at least one hate crime decreased by almost half.

These findings are not without an applicable theoretical framework, however. The measures of *White population* and *minority change*, when understood separately, are more in line with Blalock's (1957) racial threat theory. This theory simply states that ethnic minorities "threaten" the majority's hold on power, in terms of both political pull and economic factors. According to Blalock (1957), indices of discrimination, including income disparity, level of education, and roles in the labor market, should be more common in areas with higher levels of ethnic and racial heterogeneity. Thus, a modern application would suppose that hate crime is higher in areas of high heterogeneity. While Beck and Tolnay (1990) have offered findings that dispute this notion, King (2007) and others has revealed that compliance with hate crime law

tends to be at its lowest in jurisdictions with larger Black populations (in that police departments in more racially diverse communities are less likely to submit hate crime quarterly reports in compliance with the Hate Crime Statistics Act). It is important to note, though, that many agencies comply with the HCSA by submitting quarterly hate crime reports with “zero” reported hate crimes (McDevitt et al., 2003).

From analyzing the separate relationships between the dependent measure and *White population* as well as *minority change*, it is tempting to favor racial threat theory over the defended communities perspective. This is because the relationships here operated in harmony with the core tenets of the racial threat hypothesis, in which counties with higher levels of minority in-migration experienced an increased likelihood of hate crime. However, taking a closer examination of the relevant interaction term (*White population x minority*) in context of racial threat theory reveals that the relationship between hate crime and a county’s White population may not be so fragile. In other words, this research may have featured a White population that was simply not “threatened” by minority in-migration due to their “insulation”. Alternatively, the relationship between *White population* and *hate crime incidence* may be simply overpowering the influence of *minority change*. Nonetheless, neither of the defended communities perspective research hypotheses are supported by this analysis.

Political Competition

Political competition was operationalized via two county-level predictors drawn from the relevant literature: (1) the percent of third-party votes cast, and (2) the competition between the two primary political parties (Republicans and Democrats). As discussed, each was computed by averaging the results across all elections within each county for a given year. Overall, results did

not support political competition as a viable theory or conceptual framework for predicting hate crime.

The first political competition research hypothesis (Hypothesis 4) predicted that hate crime would be higher in counties that experienced higher levels of *political competition*. However, *political competition* did not emerge as a significant predictor of *hate crime incidence* in any of the models in which it was included (Models 3,4,5 and 6). Further, while the measure initially operated in the expected direction (in that it predicted increased hate crime), higher levels of political competition within a county ultimately correlated with reduced *hate crime incidence* when *violent crimes* was controlled for in later stages of the analysis. The lack of statistical significance, however, indicates that a relationship between competition and biased offending may not exist.

The second political competition research hypothesis (Hypothesis 5) predicted that counties that voted in higher rates for third-party candidates would also experience a higher likelihood of hate crime. Findings indicated that this this relationship may not exist either. The only model that rendered *third-party votes* as significant was Model 5 (the level-one full combined model), which included *violent crime* as a control measure. The level-two full contextual model (Model 6), voided this finding, which suggests that social disorganization may play a more meaningful role in predicting bias-motivated offenses than political realities.

Because this research featured relatively limited measures of political competition (in that they served only as proxies of intra-county political dynamics), it is important that its potential role not be completely ruled out. Political competition, while important in the scope of criminality, may be overwhelmed by the role of community-level structural characteristics as well as a county's racial composition. This position is supported by previous empirical research

where political measures operated as either nonsignificant or as very trivial predictors of crime when contrasted with structural variables like education and income (see McVeigh et al., 2003 or Soule & Earl, 2001).

The second perspective is that community politics do not necessarily predict the occurrence of hate crime, but instead influence the *reporting* of biased-motivated offenses. This idea is best evidenced by the work of McVeigh et al. (2003), who postulated that the reporting of hate crime is akin to a “successful social movement,” which is a function of various community-level factors including political competition. The researchers point to the discrepancy between different regions in the U.S. and reported prevalence of hate crime, suggesting that variations reflect the differences in incentives for law enforcement agencies to investigate and report hate crime. In their analysis, the authors found evidence that political competition did play a significant role in predicting hate crime reporting, especially when political competition varied in interaction with a community’s civil rights organizations and resources—revealing that political competition may have some effect on how legal authorities enforce hate crime legislation. These findings are bolstered by the fact that states tend to adopt hate crime legislation at a quicker and higher rate when they are more politically competitive (Grattet et al., 1998; Soule & Earl, 2001). Thus, the lack of support for political competition in this study may not exactly express that hate crime is not related to political competition but instead that political competition may require a more nuanced system of measurements to truly capture the relationship. Having discussed the results of the study, attention is now turned to limitations associated with the data and its methodology

Limitations

This study contained a combination of both methodological and theoretical limitations, which are important to bear in mind when pondering its findings and their implications. The

primary methodological limitation is common to most research of this nature, and relates to missing data and the dependency on law enforcement agencies to correctly identify and report hate crime. While reporting is subject to various external factors (see Soule & Earl, 2001 for a thorough discussion), a general consensus exists among researchers that hate crime is often under-reported as a function of law enforcement training and participation in the programs crafted by the Hate Crime Statistics Act of 1990 (Nolan et al., 2001). While this study's sample included states that were 100 percent NIBRS certified (by which every agency in each state reports their crimes to NIBRS), NIBRS certification does not always guarantee full reporting (Thompson, Saltzman, & Bibel, 1999).

Another limitation is the transformation of *hate crime incidence* from a count-level variable to a binary variable. While this was necessary to account for the distribution of the dependent measure (where the majority of counties reported zero hate crimes in a given year), this served to impact the statistical power of the models to predict hate crime due to a lack of variation in the measure. This was perhaps most evident when observing *time*'s emergence as a fixed (as opposed to random) effect. While this variation was not a fatal flaw in the statistical analysis, the lack of variability in the dependent measure may have impacted the various model's abilities to truly predict *hate crime incidence*.

Theoretically, the study was limited by the fact that some relevant inter-county factors were not accounted for. First, the analysis did not control for the potential for spatial autocorrelation to play a meaningful role. Although a multilevel model was utilized to account for the clustering found within the dataset, no measures were taken to adjust for the spatial distribution of hate crimes across counties. Essentially, research not including a spatial lag is based on the faulty assumption that community-level causal processes operate identically in all

places, which is certainly not the case in hate crime research (Baller, Anselin, Messner, Deane, & Hawkins, 2001). Put differently, processes at play in one county may spill over into another. However, accounting for this possibility was hampered by the fact that many counties in the sample were adjacent to other counties for which relevant data was not available (due to nonparticipation in the NIBRS program).

Perhaps more important, the current study did not include measures of collective efficacy, which constitutes a more modern view of social disorganization. Instead, only structural factors were included as proxy-measures due to a lack of available data. A more accurate test of social disorganization would mirror the methodology of Lyons (2007), who incorporated community survey results concerning social cohesion and informal crime control to measure social disorganization *and* collective efficacy. As such, the findings from this study should be viewed as a partial, albeit incomplete, assessment of the theory's applicability to the problem at hand.

Theoretical Implications

The results of this analysis have implications for social disorganization theory and the defended communities perspective in the context of predicting hate crime. First, the current study advanced social disorganization theory by suggesting that it could be extended to the county level and to rural areas. While some researchers have previously taken this approach, none have treated hate crime as their dependent measure. Scholars such as Lyons (2007) have noted that social disorganization can only explain hate crime *if* the antecedents of bias crime are similar to other types of crime ("general" crime). Thus, the findings from this analysis not only confirm that social disorganization is applicable to a more macro-level of analysis, but also that the core components of "general" crime may also apply to hate crime. This is supportive of the social constructionist view that biased offending is not fundamentally different than other forms. These findings also imply that social cohesion within a community may actually guard against the

influx of biased offending, contrary to the theoretical propositions and empirical results of former hate crime scholars, who have argued that socially cohesive locales with high levels of informal control should witness increased hate crime (Grattet, 2009; Green et al., 1998b; Lyons, 2007).

The implications for the defended communities perspective are less concrete. Instead, the implications here are more broadly applied to group conflict theories as a whole. First, the findings from this study should not be used to suggest that social disorganization is a more viable theory than the defended communities perspective or racial threat theory. While these two theories were included in the research as “competing” theories, the results from the models must be understood in the context of the level of analysis that was utilized: the county. Thus, the first theoretical implication to be taken from this study is that social disorganization serves as a more accurate predictor of biased crime than the defended communities perspective *at the county level*. Secondly, the same implication can be said of Blalock’s (1957) racial threat theory versus the defended communities perspective when using county-level hate crime data. Essentially, the findings imply that group threat theories may be more applicable to macro units of analysis, such as the county, while the effects of the defended communities perspective are less appreciable when analyzed beyond more a more urbanized, local-level setting.

Future Research and Conclusion

The current study sought to better understand the community-level characteristics that influence variation in hate crime. Findings indicated that Shaw and McKay’s (1942) theory of social disorganization was the most useful framework to explain occurrences in biased-motivated offenses. However, these findings do not come without limitations. Future research that attempts to analyze the same concept (hate crime at the county level) may achieve different results by altering a few methodological and theoretical approaches undertaken by this study.

First, researchers may want to include theories outside of the “ecological” school of criminology to explain county-level hate crime variation. These include, but are not limited to, Perry’s (2001) “doing difference” theory and Messerschmidt’s (1993) theory of “doing gender” (see the *Competing Theories* section in Chapter 2). This is especially important when considering the fact that the defended community perspective has been strictly applied to anti-racial offenses. Seeing that hate crime encompasses more than just anti-racial bias, it may behoove future researchers to expand beyond the perspective.

Next, it may be beneficial to include a comprehensive set of measurements to capture a county’s true level of political competition, including the results of local-level elections and the specific political issues that affect certain counties. Similar to using structural measures to approximate social disorganization, the operationalization of political competition in this study features potentially important limitations. Finally, future researchers may seek to utilize other sources of hate crime data, as NIBRS features reporting issues. These researchers may look to the work of Green et al. (1998), Grattet (2009), or Ruback et al. (2013), each of which utilized hate crime data from sources outside of NIBRS, UCR, or the NCVS.

In conclusion, hate crime scholars have paid little attention to analyzing the occurrence of hate crime at the county level, which served to motivate the current study. In spite of the discussed theoretical and methodological limitations, the unique nature of the current work (treating counties as the unit of analysis) and its results may serve to advance our understanding of the issue. In addition, it serves as a framework for future research into biased-motivated offenses and the application of social disorganization theory, the defended communities perspective, and political competition to problems at the macro-level.

REFERENCES

- Agnew, R. (1992). Foundation for a general strain theory of crime and delinquency. *Criminology*, 30(1), 47-87.
- Agnew, R. (2006). General strain theory: Current status and directions for further research. In F. T. Cullen, J. P. Wright, & K. R. Blevins, *Taking stock: The status of criminological theory* (pp. 101-123). New Brunswick: Transaction.
- Agnew, R. (2006). *Pressured into crime: An overview of general strain theory*. Los Angeles: Roxbury.
- Agnew, R. (2011). Revitalizing Merton: General strain theory. In F. T. Cullen, C. L. Jonson, A. J. Myer, & F. Adler, *The origins of American criminology (Advances in criminological theory)* (pp. 137-158). New Brunswick: Transaction.
- Agnew, R. (2013). When criminal coping is likely: An extension of general strain theory. *Deviant Behavior*, 34, 653-670.
- Alden, H., & Parker, K. (2005). Gender role ideology, homophobia and hate crime: Linking attitudes to macro-level anti-gay and lesbian hate crime. *Deviant Behavior*, 26, 321-343.
- Anderson, J., Dyson, L., & Brook Jr., W. (2002). Preventing hate crime and profiling hate crime offenders. *The Western Journal of Black Studies*, 26(3), 140-148.
- Appalachian Regional Commission, 40 U.S.C §§ 14301 to 14310 (2002).
- Baller, R., Anselin, L., Messner, S., Deane, G., & Hawkins, D. (2001). Structural covariates of U.S. county homicide rates: Incorporating spatial effects. *Criminology*, 39(3), 561-590.

- Baumer, E. P. (2007). Untangling research puzzles in Merton's multilevel anomie theory. *Theoretical Criminology, 11*(1), 63-93.
- Beck, E. M., & Tolnay, S. E. (1990). The killing fields of the deep south: The market for cotton and lynchings of blacks, 1882-1930. *American Sociological Review, 55*(4), 526-539.
- Bell, J. (2002). *Policing hatred: Law enforcement, civil rights, and hate crime*. New York: NYU Press.
- Bell, J. (2013). *Hate thy neighbor: Move-in violence and the persistence of racial segregation in American housing*. New York: NYU Press.
- Berk, R. (1990). Thinking about hate-motivated crimes. *Journal of Interpersonal Violence, 5*(3), 334-349.
- Blalock, H. (1957). Per cent non-white and discrimination in the south. *American Sociological Review, 22*, 677-682.
- Bobo, L., & Licari, F. (1989). Education and political tolerance: Testing the effects of cognitive sophistication and target group affect. *Public Opinion Quarterly, 53*, 285-308.
- Boeckman, R., & Turpin-Petrosino, C. (2002). Understanding the harm of hate crime. *Journal of Social Issues, 58*(2), 207-225.
- Böhnisch, L., & Winter, R. (1993). Männliche sozialisation. *Bewältigungsprobleme männlicher Geschlechtsi*.
- Bouffard, L., & Muftic, L. (2006). The "rural mystique": Social disorganization and violence beyond urban communities. *Western Criminology Review, 7*(3), 56-66.
- Bufkin, J. L. (1999). Bias crime as gendered behavior. *Social Justice, 26*, 155-176.

- Bursik, J. (1988). Social disorganization and theories of crime and delinquency: Problems and prospects. *Criminology*, 26, 519-551.
- Burton Jr, V. S., & Cullen, F. T. (1992). The empirical status of strain theory. *Journal of Crime and Justice*, 15(2), 1-30.
- Byrk, A. S., & Raudenbush, S. W. (1987). Application of hierarchical linear models to assessing changes. *Psychological bulletin*, 101(1), 147.
- Cheng, W., Ickes, W., & Kenworthy, J. (2013). The phenomenon of hate crimes in the United States. *Journal of Applied Psychology*, 761-794.
- Cloward, R. A., & Ohlin, L. E. (1960). *Delinquency and opportunity: A theory of delinquent gangs*. New York: NY: Free Press.
- Cohen, A. K. (1955). *Delinquent boys: The culture of the gang*. New York: NY: Free Press.
- Cullen, F., Wright, J., & Blevins, K. (2006). *Taking stock: The status of criminological theory*. Transaction Publishers.
- Cutler, J. E. (1969). *Lynch-law. An investigation into the history of lynching in the United States*. Chicago: Negro Universities Press.
- Dennis, D. (1984). *Black history*. New York: Writes and Readers Publishing.
- Erb, R. (1993). Ausländerfeindschaft und Jugend (gruppen) gewalt in den neuen Bundesländern. *Internationale Schulbuchforschung*, 105-119.
- Espiritu, A. (2004). Racial diversity and hate crime incidents. *The Social Science Journal*, 41, 197-208.

- Fredrickson, S. M. (1991). *White supremacy. A comparative study in American and South African history*. New York: Oxford University Press.
- Freilich, J., Adamczyk, A., Chermak, S., Body, K., & Parkin, W. (2014). Investigating the applicability of macro-level criminology theory to terrorism: A county-level analysis. *Journal of Quantitative Criminology*, *31*(3), 383-411.
- Gadd, D., Dixon, B., & Jefferson, T. (Why do they do it? Racial harrassment in North Staffordshire). 2005. Keele: Centre for Criminological Research, Keele University.
- Gimpel, Lay, & Schuknecht. (2003). *Cultivating Democracy: Civic environments and political socialization in America*. Washington DC: The Brookings Institute.
- Gladfelter, A., Lantz, B., & Ruback, B. (2017). The complexity of hate crime and bias activity: Variation across contexts and types of bias. *Justice Quarterly*, *34*(1), 55-83.
- Glaser, J., Dixit, J., & Green, D. (2002). Studying hate crime with the internet: What makes racists advocate racial violence? *Journal of Social Issues*, *58*(1), 177-193.
- Gottfredson, M., & Hirschi, T. (1990). *A general theory of crime*. Stanford: Stanford University Press.
- Grattet, R. (2009). The urban ecolgoy of bias crime: A study of disorganized and defended neighborhoods. *Social Problems*, *56*(1), 132-150.
- Grattet, R., Jenness, V., & Curry, T. (1998). Innovation and diffusion in U.S. hate crime law. *American Sociological Review*, *63*, 286-307.

- Green, D., Glaser, J., & Rich, A. (1998). From lynching to gay bashing: The elusive connection between economic conditions and hate crime. *Interpersonal Relations and Group Processes*, 82-92.
- Green, D., McFalls, L., & Smith, J. (2001). Hate crime: An emergent research agenda. *Annual Review of Sociology*, 27(1), 497-504.
- Green, D., Strolovitch, D. Z., & Wong, J. S. (1998). Defended neighborhoods, integration, and racially motivated crime. *American Journal of Sociology*, 104(2), 372-403.
- Hagan, J., & McCarthy, B. (1997). *Mean streets: Youth crime and homelessness*. Cambridge: Cambridge University Press.
- Hamm, M. (1993). *Hate crime: International perspectives on causes and control*. Cincinnati: Anderson.
- Hate Crime Statistics Act, 28 U.S.C § 534 (1990).
- Heitgard, J. L., & Bursik, R. (1987). Extracommunity dynamics and the ecology of delinquency. *American Journal of Sociology*, 92(4), 775-787.
- Hepworth, J. T., & West, S. G. (1988). Lynchings and the economy: A time-series reanalysis of Hovland and Sears (1940). *Journal of Personality and Social Psychology*, 55, 239-247.
- Hilbe, J. (2011). *Negative binomial regression*. Cambridge University Press.
- Hirschi, T. (1969). A control theory of delinquency. In *Criminology theory: Selected classic readings* (pp. 289-305).
- Hobolt, S., & Klemmensen, R. (2008). Government responsiveness and political competition in comparative perspective. *Comparative Political Studies*, 41(3), 309-337.

- Hoffman, D., & Gavin, M. (1998). Centering decisions in hierarchical linear models: Implications for research in organizations. *Journal of Management*, 24(5), 623-641.
- Howland, C., & Sears, R. (1940). Minor studies of aggression: VI. correlation of lynchings with economic indices. *Journal of Psychology*, 9, 301-310.
- Iwama, J. (2018). Hate crime research in the twenty-first century. In R. Martinez, M. Hollis, & J. Stowell, *The Handbook of Race, Ethnicity, Crime, and Justice* (pp. 87-103). Oxford: Wiley-Blackwell.
- Iwama, J. A. (2016). The role of community context in hate crimes against Latinos.
- Jaccard, J., & Turrisi, R. (2003). *Interaction effects in multiple regression*. Sage.
- Jackson, J. W. (1993). Realistic group conflict theory: A review and evaluation of the theoretical and empirical literature. *Psychological Record*, 43(3), 395-405.
- Jackson, P., & Carroll, L. (1987). Race and the war on crime: The sociopolitical determinants of municipal police expenditures in 90 non-southern U.S. cities. *American Sociological Review*, 290-305.
- Jacobs, & Potter. (1998). *Hate Crimes: Criminal Law & Identity Politics*. Oxford: Oxford University Press.
- Jacobs, D., & Carmichael, T. (2002). The political sociology of the death penalty: A pooled time-series analysis. *American Sociological Review*, 67, 109-131.
- Jordan, W. D. (1968). *White over black. American attitudes toward the Negro, 1550-1812*. Chapel Hill: University of North Carolina Press.

- Kaylen, M., & Pridemore, W. (2011). A reassessment of the association between social disorganization and youth violence in rural areas. *Social Science Quarterly*, 92(4), 978-1001.
- Kennedy, P. (1985). *A guide to econometrics*. Wiley Blackwell.
- Kent, S., & Jacobs, D. (2005). Minority threat and police strength from 1980 to 2000: A fixed-effects analysis of nonlinear and interactive effects in large U.S. cities. *Criminology*, 43, 731-760.
- Kesteren, J. V. (2016). Assessing the risk and prevalence of hate crime victimization in western Europe. *International Review of Victimology*, 22(2), 139-160.
- Kimmel, M. (1994). *Masculinity as Homophobia: Fear, Shame, and Silence in the Construction of Gender Identity*. Thousand Oaks: Sage.
- King, G., & Zeng, L. (2001). Logistic regression in rare events data. *Political Analysis*, 9(2), 137-163.
- King, R. (2007). The context of minority group threat: Race, institutions, and complying with hate crime law. *Law & Society Review*, 41(1), 189-224.
- King, R., & Sutton, G. (2013). High times for hate crimes: Explaining the temporal clustering of hate-motivated offending. *Criminology*, 51(4), 871-894.
- Kleg, M. (1993). *Hate prejudice and racism*. Albany: Albany-State University NY Press.
- Kreft, G., Leeuw, J., & Aiken, L. (1995). The effect of different forms of centering in hierarchical linear models. *Multivariate Behavioral Research*, 30(1), 1-21.

- Langton, L., & Masucci, M. (2017). *Hate crime victimization, 2004-2015*. Washington, DC: Bureau of Justice Statistics.
- Lee, M., Maume, M., & Ousey, G. (2003). Social isolation and lethal violence across the metro/nonmetro divide: The effects of socioeconomic disadvantage and poverty concentration on homicide. *Rural Sociology*, 68, 107-131.
- Levin, J., & McDevitt, J. (1993). *Hate crime: the rising tide of bigotry and bloodshed*. New York: Plenum.
- Levin, J., & McDevitt, J. (2002). *Hate crimes revisited: America's war on those who are different*. New York: Basic Books.
- Levine, R., & Campbell, D. (1972). *Ethnocentrism*. New York: Wiley.
- Lilly, J. R., Cullen, F. T., & Ball, R. A. (2015). *Criminological theory: Context and consequences*. Sage.
- Liska, A. (1992). *Social threat and social control*. Albany: State University of New York Press.
- Liska, A., Chamlin, M., & Reed, M. (1985). Testing the economic production and conflict models of crime control. *Social Forces*, 64(1), 119-138.
- Lyons, C. (2007). Community (dis)organization and racially motivated crime. *American Journal of Sociology*, 113(3), 815-863.
- Mann, C. R. (1993). *Unequal justice; An opposing viewpoints series*. Bloomington: University of Indiana Press.
- Martin, S. (1995). "A cross-burning is not just an arson": Police social construction of hate crimes in Baltimore county. *Criminology*, 33(3), 303-326.

- Mazerolle, P., & Maahs, J. (2000). General strain and delinquency: An alternative examination of conditioning influences. *Justice Quarterly*, 17(4), 753-778.
- Mazerolle, P., & Piquero, A. (1997). Violent responses to strain: An examination of conditioning influences. *Violence and Victims*, 12(4), 323.
- McCoach, D. (2010). Hierarchical linear modeling. In *The reviewer's guide to quantitative methods in the social sciences* (pp. 123-140).
- McDevitt, J., Balboni, J. M., Bennett, S., Weiss, J., Orchowsky, S., & Walbolt, L. (2003). Improving the quality and accuracy of bias crime statistics nationally. In *Hate and bias crime: A reader* (p. 77).
- McDevitt, J., Levin, J., & Bennett, S. (2002). Hate crime offenders: An expanded typology. *Journal of Social Issues*, 58(2), 303-317.
- McVeigh, R., Welch, M., & Bjarnason, T. (2003). Hate crime reporting as a successful social movement outcome. *American Sociological Review*, 68(6), 843-867.
- Merton, R. (1968). *Social theory and social structure*. New York: Free Press.
- Messerschmidt, J. (1993). *Masculinities and crime: Critique and reconceptualization of theory*. Totowa: Rowman & Littlefield.
- Messerschmidt, J. (1999). *Masculinities and Crime*. Los Angeles: Roxbury.
- Messner, S. F., McHugh, S., & Felson, R. B. (2004). Distinctive characteristics of assaults motivated by bias. *Criminology*, 42(3), 585-618.
- Mintz. (1946). A re-examination of correlations between lynchings and economic indices. *Journal of Abnormal and Social Psychology*, 41, 154-160.

- Morenoff, J. D., Sampson, R. J., & Raudenbush, S. (2001). Neighborhood inequality, collective efficacy, and spatial dynamics of urban violence. *Criminology*, 39(3), 517-558.
- Nelson, M., Wooditch, A., Martin, F., Hummer, D., & Gabbidon, S. (2016). Hate crimes in post 9/11 Pennsylvania: Case characteristics and police response revisited. *Race and Justice*, 6(4), 303-324.
- Nolan III, J., Akiyama, Y., & Brehanu, S. (2002). The hate crime statistics act of 1990: Developing a method for measuring the occurrence of hate violence. *American Behavioral Scientist*, 46(1), 136-153.
- Nolan, J., Haas, S., Turley, E., Stump, J., & LaValle, C. (2015). Assessing the "statistical accuracy" of the national incident-based reporting system hate crime data. *American Behavioral Scientist*, 59(12), 1562-1587.
- Olzak, S. (1990). The political context of competition: Lynching and urban racial violence, 1882-1914. *Social Forces*, 69(2), 395-421.
- Osgood, W., & Chambers, J. (2000). Social disorganization outside the metropolis: An analysis of rural youth violence. *Criminology*, 38(1), 81-115.
- Pacheco, J. (2008). Political socialization in context: The effect of political competition on youth voter turnout. *Political Behavior*, 30(4), 415-436.
- Papachristos, A., Meares, T., & Fagan, J. (2007). Attention felons: Evaluating project safe neighborhood in Chicago. *Journal of Empirical Studies*, 4(2), 223-272.
- Park, R., & Burgess, E. (1924). *Introduction to the science of sociology*. Chicago: University of Chicago Press.

- Perry, B. (2001). *In the name of hate: Understanding hate crimes*. New York: Routledge.
- Petrosino, C. (1999). Connecting the past to the future: Hate crimes in America. *Journal of Contemporary Criminal Justice*, 15(1), 22-47.
- Pinderhughes, H. (1993). The anatomy of racially-motivated violence in New York City: A case study of youth in southern Brooklyn. *Social Problems*, 40(4), 478-492.
- Portes, A. (1998). Social capital: Its origins and applicatoins in modern sociology. *Annual Review of Sociology*, 24(1), 1-24.
- Pratt, T. C., & Cullen, F. T. (2005). Assessing macro-level predictors and theories of crime: A meta-analysis. In M. Tonry, *Crime and justice: A review of research* (pp. 373-450). Chicago: University of Chicago Press.
- Raudenbush, S. W., Bryk, A. S., Fai Cheong, Y., Congdon Jr., R. T., & du Toit, M. (2004). *HLM& hierachial linear and nonlinear modeling user manual: User guide for scientific software international's (S.S.I) program*. Scientific Software International .
- Ray, L., & Smith, D. (2002). Hate crime, violence and cultures of racism. *The hate debate*.
- Reiker, P. (1997). *Ethnozentrismus bei jungen männern*. Weinheim: Juventa.
- Ruback, R., Gladelter, A., & Lantz, B. (2015). *An examination of hate and bias incidents in Pennsylvania, 1999-2012*. Center for Rural Pennsylvania.
- Sampson, R. (1986). Crime in the cities: The effects of formal and informal social control. *Community and Crime*, 8, 271-311.
- Sampson, R. J., & Groves, W. B. (1989). Community structure and crime: Testing social disorganization theory. *American Journal of Sociology*, 94(4), 774-802.

- Sampson, R. J., Morenoff, J. D., & Raudenbush, S. (2005). Social anatomy of racial and ethnic disparities in violence. *American Journal of Public Health, 95*(2), 224-232.
- Sampson, R., Raudenbush, S., & Earls, F. (1997). Neighborhoods and violent crime: A multilevel study of collective efficacy. *Science, 227*(5328), 918-924.
- Shaw, C., & McKay, H. (1942). *Juvenile delinquency and urban areas*. Chicago: University of Chicago Press.
- Sibbitt, R. (1997). *The perpetrators of racial harassment and racial violence, Home Office Research Study 176*. London: Home Office.
- Soule, S., & Earl, J. (2001). The enactment of state-level hate crime law in the United States: Intrastate and interstate factors. *Sociological Perspectives, 44*(3), 281-305.
- Soule, S., & van Dyke, N. (1999). Black church arson in the United States, 1989-1996. *Ethnic and Racial Studies, 22*(4), 724-742.
- Stowell, J. I. (2007). *The new Americans: Recent immigration and American society*. New York: LFB Scholarly Publishing LLC.
- Streissguth, T. (2009). *Hate Crimes: Revised Edition*. New York: Facts on File.
- Strom, K. (2001). *Hate crimes reported in NIBRS, 1997-1999*. Bureau of Justice Statistics.
- Suttles, G. D. (1972). *The social construction of communities*. Chicago: University of Chicago Press.
- Thompson, M., Saltzman, L., & Bibel, D. (1999). Applying NIBRS data to the study of intimate partner violence: Massachusetts as a case study. *Journal of Quantitative Criminology, 15*(2), 163-180.

- Tolnay, S. E., & Beck, E. M. (1995). *A festival of violence: An analysis of southern lynchings, 1882-1930*. University of Illinois Press.
- Tolnay, S. E., Beck, E. M., & Massey, J. L. (1989). The power threat hypothesis and black lynching: 'Wither' the evidence? *Social Forces*, *67*, 634-641.
- Trout, M. (2015). Federalizing hate: Constitutional and practical limitations to the matthew shepard and james byrd, jr. hate crimes prevention act of 2009. *American Criminal Law Review*, *52*(131), 131-153.
- Ulmer, J., & Johnson, B. (2004). Sentencing in context: A multilevel analysis. *Criminology*, *42*(1), 137-177.
- United States, Bureau of Justice Statistics, Office of Justice Programs. (2016). *Data Collection: National Crime Victimization Survey (NCVS)*.
- United States, Department of Justice. (2017). *National incident-based reporting system user manual*. Washington, D.C.
- United States, Department of Justice, Federal Bureau of Investigation. (2016). *Incidents and Offenses*. Washington, D.C.
- United States, Department of Justice, Federal Bureau of Investigation. (2012). *NIBRS participation by state*. Washington, D.C.
- United States, U.S. Census Bureau. (2008). *A compass for understanding and using American community survey data: What general data users need to know*. Washington, D.C.
- van Dyke, N. S., & Widom, R. (2001). The politics of hate: Explaining variation in the incidence of anti-gay hate crime. *Research in Political Sociology*, *9*, 35-58.

- Velez, M. (2001). The role of public social control in urban neighborhoods: A multi-level analysis of victimization risk. *Criminology*, 39(4), 837-864.
- Wahl, P. (1997). Wenn die Jungs mal loslegen—Anmerkungen zur Cliquen-Dynamik.
- Waldinger, R. (1995). The 'other side' of embeddedness: A case-study of the interplay of economy and ethnicity. *Ethnic and Racial Studies*, 18(3), 555-580.
- Walker, S., Spohn, C., & DeLone, M. (1996). *The color of justice*. New York: Wadsworth.
- Walters, M. (2010). A general theories of hate crime? Strain, doing difference and self control. *Critical Crimology*, 19(4), 313-330.
- Wang, L.-i. (1999). The complexities of "hate". *Ohio State Law Journal*, 60(3), 799-900.
- Watts, M. (1996). Political xenophobia in the transition from socialism: Threat, racism, and ideology among East German youth. *Political Psychology*, 17(1), 97-126.
- Websdale, N. (1998). *Rural women battering and the justice system: An ethnography*. Thousand Oaks, CA: Sage Publications.
- Wells-Barnett, I. B. (1969). *Wells-Barnett: On lynchings southern horrors a red record mob rule in New Orleans*. New York: Anro Press.
- Willems, H., Würtz, S., & Eckert, R. (1993). Fremdenfeindliche Gewalt: Eine Analyse von Täterstrukturen und Eskalationsprozessen. *Forschungsbericht für das Bundesministerium für Frauen und Jugend*.
- Young, J. (1999). *The exclusive society: Social exclusion, crime and difference in late modernity*. London: Sage Publications.

VITA

EAVEN HOLDER

- Education: East Hamilton High School, Ooltewah, TN 2012
- B.S. Political Science, University of Tennessee at Chattanooga,
Chattanooga, TN 2016
- M.A. Criminal Justice & Criminology, East Tennessee State
University, Johnson City, TN 2018
- Professional Experience: Graduate Teaching Assistant, Dept. of Criminal Justice &
Criminology, East Tennessee State University; Johnson
City, TN, 2017-2018
- Courses Taught:
CJCR 2540: Criminal Law
CJCR 3000: Statistics in Criminal Justice
- Courses Assisted:
CJCR 1100: Introduction to Criminal Justice
CJCR 1600: Forensic Science
CJCR 2540: Criminal Law
CJCR 3000: Statistics in Criminal Justice
CJCR 3440: Corrections in America
CJCR 3650: Criminal Procedure
CJCR 4580: Violence: The American Experience
- Data Specialist, Tennessee Dangerous Drugs Task Force;
Chattanooga, TN, 2016-2017
- Presentations: Holder, E. (2018). *Political Competition and Predictors of Hate
Crime: A County-level Analysis*. The American Society of
Criminology, Atlanta, Georgia
- Osborne, D., Stover A., & Holder, E. (2018). *Agricultural Crime
Prevention: An Analysis of Dedicated Agencies and
Prevention Guidelines*. Academy of Criminal Justice
Sciences, New Orleans, Louisiana
- Honors and Awards: Dean's List
- Cum Laude, University of Tennessee at Chattanooga
- Professional Affiliations: American Society of Criminology

Academy of Criminal Justice Sciences

Criminal Justice Honor Society (Alpha Phi Sigma)