RACIAL CONFLICT AND BIAS CRIMES ACROSS US CITIES: AN ANALYSIS OF THE SOCIAL THREAT PERSPECTIVE

by

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A Dissertation

Submitted to the University at Albany, State University of New York

in Partial Fulfillment of

the Requirements for the Degree of

Doctor of Philosophy

College of Arts & Sciences

Department of Sociology

2015

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ABSTRACT

This research examines racially biased crimes across US cities, utilizing social threat and a general criminality perspective based on social disorganization and strain theories. Racially biased crime is compared to violent crime in general and to unbiased racially disaggregated homicide to further examine the effects of social threat and general crime variables on different forms of violent crime. Data is compiled mainly from the 1990 and 2000 US Censuses, the 1996-2000 Uniform Crime Reports and the 1996-2000 Supplemental Homicide Reports. The research shows bias crimes cannot be explained utilizing general crime predictors. In particular, anti-Black violent bias crimes committed by Whites are mainly driven by economic forces, though not necessarily economically threatening conditions. Anti-White violent bias crimes committed by Blacks are more similar to homicides of Whites committed by Blacks, which is consistent with prior research. Additionally, the research shows the importance of complying with hate crime reporting requirements and region, again consistent with prior research. That is, the more frequently a city reports data, the higher the counts of bias crimes. Cities located in the South are less likely to have high counts of bias crimes, suggesting a lack of compliance with reporting requirements. These findings pertaining to reporting compliance offer support for social constructionist perspectives in the study of bias crimes.

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Chapter One. The Research Problem

This research examines the causes of racially motivated bias (or hate) crimes[1]. Hate crimes are of interest to the criminological community because they present an opportunity to simultaneously study criminal activity and deviance in the form of prejudice. Additionally, bias crimes are critically important to criminologists as most theoretical claims and research findings describe hate crimes as qualitatively different from non-bias crimes. Bias crimes are often presented in the theoretical and research literature as being distinct and separate from "ordinary" crime; however, little research exists examining the differences between bias and non-bias motivated crime (for exceptions, see Messner et al. 2004 for a micro-level study; Lyons 2008 and Wilson and Ruback 2003 for macro-level studies). Further, researchers disagree about the theoretical underpinnings of bias crimes. Some authors assert that social threat or defended neighborhoods best explain bias crimes, while others assert multiple theories or are atheoretical. This research will help to determine which theories are better able to explain variation in hate crimes across different cities in the United States. Last, most of the research about the causes of bias crimes remains micro-level; fewer studies have examined the causal processes of bias crimes at the macro-level (see Cheng et al 2013; D'Alessio et al. 2002; Green et al 1998a; Grattet 2009; Lyons 2007 and 2008; Van Dyke and Tester 2014; and Wilson and Ruback 2003).

I. Introduction

The primary purpose of this dissertation is to examine macro-level predictors of racially motivated violent bias crimes for a sample of U.S. cities. The analysis is informed by an analytic framework that draws upon two models of the dynamics of the commission of bias crimes: a social

[1] The terms "bias crimes" and "hate crimes" will be used interchangeably throughout the dissertation.

threat model, rooted in the conflict perspective in sociology, and a general criminality model. Most theorizing about social threat has been cast at the macro-level theory; however, criminologists interested in describing bias crimes have translated it to the micro-level. These authors typically do not credit the social threat perspective. For example, J. Levin and McDevitt (2002) state:

> Apparently, many Americans felt *personally threatened* by the rapid – in some cases, unprecedented – growth of interfaith and interracial marriages; immigration from Latin America, Asia and Eastern Europe; and movement of people of color into previously all-White neighborhoods, schools, and workplaces. (J. Levin and McDevitt 2002: 1; emphasis added)

Although the authors do not credit the social threat perspective (or any other theory, for that matter), it is clear that J. Levin and McDevitt (2002) recognize the explanatory power of threatening conditions for the commission of bias crimes. Hate crimes can be viewed as a form of conflict management. A white man angry about gains in power by minorities may deal with negative emotions by committing a hate crime. In this way, he is able to deal with his loss of power by reasserting control over those who are threatening him. Hate crimes thus differ from "ordinary" crimes in a fundamental way; they are crimes that can be usefully conceptualized as social control (Black 1983) as well as a means to manage conflicting emotions.

While not as popular as the social threat model, the general criminality model is also used to explain bias crimes at the micro-level. Bias crimes are seen as an additional form of criminal enterprise for already deviant offenders. In other words, bias crimes are simply another expression of criminality available to offenders (Messner et al. 2004). Hate crimes contain the element of prejudice; however, research has noted that a majority of bias crime offenders are motivated by the simple excitement of committing the crime rather than some form of distinct hatred (McDevitt et al. 2002).

At the macro-level, the social threat model implies that the predictors of bias crimes will be distinctive. They will be rooted in racial, economic or political conflict in an area (Eitle et al. 2002). That is, the threat of an increasing minority population relative to the White population, competition between wealthy and impoverished, gains in political power by a threatening group or some combination of competition between races, income groups and/or achievements in political power will affect the level of bias motivated crimes in an area above and beyond the level of criminality in general. While comparing hate crime and general crime offenders, Cheng et al (2013) found that White offenders are more likely to commit higher rates of hate crimes than Black offenders. The authors conclude that "Whites may commit relatively more hate crimes because of their dominant position in U.S. society and their greater motivation to preserve the *status quo*" (Cheng et al 2013: 788, emphasis in original). In contrast, the general criminality model implies that the predictors of racially motivated bias crimes are not fundamentally different from the predictors of crimes in general. As a result, the level of bias crimes should be determined by the same factors that affect the level of crime in general. In other words, is hate crime more about *hate* or *crime*?

The specific objectives of my dissertation are: 1) to develop an analytic framework that permits a comparative assessment of the social threat and general criminality explanations of bias crimes at the macro-level (for illustrations of previous efforts, see Green et al. 1998a; Lyons 2007 and 2008; and Wilson and Ruback 2003); (2) to apply this framework to explain variation in levels of racially biased violent crimes for a sample of U.S. cities; and (3) to determine whether elements of the threat framework apply to offending behavior of the racial minority group (Blacks[2]) as well as to the dominant racial group (Whites). These specific objectives can be understood in the context

[2] The terms Black and African-American will be used interchangeably throughout the paper.

of a more general question relevant to bias crime research: Are the determinants of bias crimes qualitatively different from non-bias crimes at the macro-level?

II. Nature and Importance of Bias Crimes

When one hears the term "hate crime," one logically attributes the sole motivation for the crime to "hatred." J. Jacobs and Potter (1997) argue that the term hate crime is misleading. In fact, the term hate crime serves to separate crimes motivated by *prejudice* from crimes motivated by profit, lust, or similar factors. J. Levin (2002:1) argues that during the 1980's, the term "hate" became used in a much more restricted sense to characterize an individual's negative "beliefs" about certain groups of people. He further argues that this form of hate is a motivation for violence since this definition allows an individual to perceive certain groups of people as "less than human" (J. Levin 2002: 5). Therefore, J. Levin maintains that the motivation for hate crimes is much more than prejudice; it is bigotry. However, other research suggests that the primary motive in hate crimes may in fact be "thrill-seeking" (McDevitt et al. 2002; Messner et al. 2004). This suggests that the primary motive of a hate crime at the micro-level may be more similar to general crime, although the outcomes of hate crimes have been shown to have drastically different consequences for victims than similar non-bias crimes. For example, Messner et al. (2004) found that victims of bias crimes were more likely to be injured, suggesting that biased offenders are more violent than conventional offenders. These findings suggest that the motivations of biased offenders may be more similar to conventional offenders at the micro-level, although the consequences for victims of bias crimes are radically different than victims of conventional crime. Given these contradictory findings at the micro-level, we do not know whether bias offenses have similar causes to conventional offenses at the macro-level.

Most legal sources agree that bias crime represents “an extremely serious problem” (Wang 1995: 1.02). When asked to discuss an incident of hate crime, one may think of the mass media coverage of acts of violence such as the cases of James Byrd in Jasper, Texas or Matthew Shepard in Laramie, Wyoming in 1998. Byrd was chained to a pick-up truck by three white males and dragged three miles because he was African-American. Matthew Shepard was beaten, tied to a fence and left for dead because he was a homosexual (Cogan and Marcus-Newhall 2002). These cases vividly illustrate that, in the public’s eye, bias crimes are viewed as “brutal and grisly” and extremely “bigoted” (J. Levin and McDevitt 2002: 1).

In terms of social importance, hate crimes should have a more prominent position in the study of violence. Several sources, including the American Civil Liberties Union, the Southern Poverty Law Center, and the Anti-Defamation League, collect statistics about the occurrences of “hate incidents” as well as hate crimes (J. Jacobs and Potter 1997). A hate incident is usually an occurrence where a racial, homophobic or other intolerant slur is uttered but is not accompanied by a crime. According to some academic sources, hate crimes and hate incidents have reached “epidemic” levels in the United States (see, for example, Lawrence 1994 and J. Levin and McDevitt 1993). Additionally, Torres (1999) reports that between 1992 and 1996, there was a fifty-two percent increase in the number of bias crimes reported by African-Americans. He concludes that this is evidence of a growing racial intolerance in the US. Cheng et al (2013) examined hate crimes between 1996 and 2008. They found that hate crimes steadily increased to a peak in 2002 and then began a slow decline. While many sources argue against these claims of a hate crime epidemic (see, for example, J. Jacobs and Potter 1997 and 1998), the fact remains that many in the public arena believe hate crimes to be an important political, social and criminological issue.

Despite widespread recognition of the importance of hate crimes, the available research is limited and often contradictory. Most of our current knowledge about hate crimes is presented in terms of the construction of bias crime laws (e.g., J. Jacobs and Potter 1998; Jenness 1999; Jenness and Broad 199l; Jenness and Grattet 2001; Lawrence 1999; B. Levin 2002; Soule and Earl 2001; and Wang 1995 and 1999;), the compliance with bias crime laws (e.g., Franklin 2002; King 2007; King et al. 2009; Martin 1995; McVeigh et al. 2003; and Nolan and Akiyama 1999), the identification of the offender's motivation (e.g., Boyd, Berk and Hamner 1996; Byers et al. 1999; Franklin 2000; Martin 1996; McDevitt et al. 2002; and Perry 2002), hate crime reporting (e.g., Cogan 2002 and Herek et al. 1999), or the impact of the hate crime offense on the victim or members of the victimized group (e.g., Craig 1999; Herek et al. 2002; J. Levin and Rabrenovic 2001; Martin 1996; Messner et al. 2004; Noelle 2002; and Rose and Mechanic 2002). The construction of law and hate crime reporting research is macro-level; however, these studies do not test the social structural factors that influence the *commission* of bias crimes at the macro-level. The tests of offender motivation and impact on victims are individual-level studies. We have little research into the community-level factors that influence levels hate crimes (see Grattet 2009, Green et al. 1998a; Lyons 2007 and 2008; Ruback and Wilson 2003 for notable exceptions). My research seeks to expand the knowledge of the patterns and causes of hate crimes at the macro-level.

III. The General Analytic Framework: Social Threat, Social Control and Racially Biased Crimes

As noted above, some studies on hate crimes at the micro-level allude to social threat and suggest that hate crimes can be conceptualized as a means of social control. A well-established framework for studying social threat and social control has emerged in the macro-level research literature rooted in the conflict perspective in sociology. The social threat perspective identifies group conflict and competition as the key factors determining social control. Research suggests, for example, that a threatening African-American population may be controlled through formal police sanctions, such as increases in police size (D. Jacobs 1979, Kent and Jacobs 2005, and Liska et al. 1981), increases in arrests of Blacks (D'Alessio and Stolzeberg 2003; Liska and Chamlin 1984; Liska, Chamlin & Reed 1985; Ousey and Lee 2008; Stucky 2012), or increases in the use of deadly force by police officers (D. Jacobs and O'Brien 1998). Threatening populations may also be controlled using extra-legal sanctions, such as increases in the lynching of southern Blacks (Tolnay and Beck 1990 and 1992), increases in White on Black homicides (D. Jacobs and Wood 1999), increases in referrals of African-Americans to mental health institutions (Arvanites 1992 and Liska et al. 1999), or increases in welfare controls (Chamlin 1992).

It is important to emphasize that according to the social threat model, the intensification of social control associated with conflict and competition is not merely a response to harmful conditions in society at large. Rather, the level of social control is above and beyond what would be expected given objective conditions of dangerousness. Researchers thus attempt to examine the effect of indicators of social structural arrangements that represent group threat on measures of social control net of indicators of those conditions to which social control is normally considered to be a response. The underlying logic of the social threat model of social control can be understood using the following heuristic diagram:

Structural Conditions Conducive
To Group Conflict/Threat
(e.g., Racial Composition; Racial, Economic and Political Inequality; etc.)

Intensity of Social Control
(e.g., Informal: Interracial Homicide, Lynching etc; Formal: Arrests, Police Size, etc)

Indicators of Generally Dangerous Conditions
(e.g., Officially Recorded Crime Rate, General Crime Explanations)

The distinctive prediction of the social threat model is the effect represented by the solid line, i.e., the effect of group threat that cannot be accounted for simply as a response to the objective conditions requiring social control.

The basic premise of this dissertation is that the general analytic model commonly used to study social threat and social control can be usefully extended to the study of racially biased hate crimes. This extension follows logically from the premise that bias crimes can be viewed as a type of informal, extralegal social control. Residents, rather than police, respond to the threats presented by a particular population by asserting some form of social control, such as bias crimes. Accordingly, structural conditions indicative of group conflict and threat should yield distinctive effects on the level of racially biased crimes.

The logic of the threat explanation applies most directly to the offending behavior of the dominant group. Racially motivated attacks by members of the dominant group – Whites – on members of the racial minority – Blacks – can be understood as exercises in social control. It is possible, however, that members of minority groups may react to subordination with similar behavior. Accordingly, the analysis considers whether elements of the threat model can be applied to anti-White as well as anti-Black bias offending.

Bias crime legislation is predicated on the notion that hate crimes are indeed unique forms of offending because of the prejudice involved. Critics of bias crime legislation, in contrast, argue that hate crimes may not be radically different from crime in general. While not as popular as the social threat perspective, proponents of the general criminality model argue that bias crimes are simply another form of crime. The general criminality model, which relies heavily on social disorganization and strain theories, implies that special macro-level predictors are not necessary in order to understand variation in levels of bias crime across communities. With respect to the analytic framework above, the general criminality model proposes that indicators of conditions allegedly representing group threat will have little to no effect on the level of racially biased crimes, net of adequate controls for the level of criminality and generally dangerous conditions in an area. In other words, the general criminality argument predicts that social threat variables will have little or no significant effect on bias crimes once the social disorganization and strain variables are included in the analyses.

In short, I extend the basic analytic framework informing research on group threat and social control to the macro-level study of racially motivated crimes, and more specifically, anti-White and anti-Black biased violent crimes. This framework allows for the derivation of hypotheses about the social structural correlates of the levels of hate crimes that correspond to two competing interpretations of underlying causal dynamics: the social threat and the general criminality interpretations.

IV. Methodological Approach

Three general models are utilized in this research. In Model One, I estimate the effects of general criminality variables on violent index crimes known to the police. Because my sample is based on hate crimes and reported hate crimes are very rare, it is possible that my sample of cities is biased. Thus, I would expect to see results with the preliminary model that are consistent with past research in non-biased violent criminality.

Model Two is essentially the social threat model's effects on violent anti-Black and anti-White crimes. This is the crux of the dissertation research. The purpose is to determine whether threat predictors explain biased extra-legal social control actions. That is, will socially threatening conditions cause ordinary residents to commit overtly prejudiced inter-racial crimes in order to assert social control?

Last, Model Three estimates the social threat model using interracial homicides as the dependent variable. The purpose of this model is to determine whether threatening conditions cause ordinary citizens to commit latently prejudiced[3] interracial crimes. The findings are expected to be consistent with past research; that is, I expect threatening conditions (particularly racially threatening conditions) to explain the number of interracial homicides in a city. If Models Two and Three are similar, it strengthens the support for the social threat model and its application for both biased and non-biased interracial crimes. If the Models produce different results, especially if Model Three finds support for social threat but Model Two does not, this calls into question the usefulness of the social threat perspective in predicting the overt nature of prejudice involved in bias crimes.

V. Research Contributions

The dissertation research adds to an expanding body of literature examining the causes and consequences of bias crimes by providing the first multiple jurisdiction test using the social threat

[3] Interracial crime may involve the element of prejudice; however, bias crimes are, by definition, overtly prejudiced while interracial non-biased crime is most likely not overtly prejudiced.

model while controlling for general criminality explanations to explain racially motivated violent bias crimes at the macro-level (see Grattet 2009 for a single jurisdiction study). The analyses represent an attempt to systematically apply the conflict perspective in a new domain. Conflict seems an appropriate theoretical explanation for hate crimes; however, very few tests examine the structural causes of bias crimes. With this research, I hope to expand our knowledge of hate crimes as well as apply conflict theory to a newer research agenda in criminology.

VI. Organization of the Dissertation

Chapter Two reviews the concept of bias crimes, the important legal developments, and the role of social movements in focusing attention on such crimes. I also review the macro- and micro-level studies regarding hate crimes and how these studies support the social threat and/or the general criminality argument. Next, I present the history and research regarding the general criminality argument. General criminality argues that once social disorganization and strain variables are introduced into each regression, there should be no significant effect of social threat predictors on bias crimes. Intrinsic to the study of bias crimes are the important control variables addressing the likelihood that bias crimes are the outcome of social movements. Following McVeigh et al. (2003) and King (2007), I introduce and explain why democratic voting, political competitiveness and region may have an effect on the enforcement of bias crime legislation, which in turn could explain lower levels of recorded bias crimes in certain cities. The effects of region and political climate are controlled in the models for this reason. The Chapter concludes with an enumeration of the specific hypotheses that will be tested for the general criminality argument and how the social constructionist controls might affect some regressions.

Chapter Three examines the theoretical arguments of the social threat perspective in detail. The Chapter reviews the history of the conflict paradigm in sociology and the development of the social threat perspective. The three particular dimensions of social structure that are vital to the social threat model are the racial composition of an area, the economic composition of an area, and the political climate of an area. Conflict theory predicts that as the size of the Black population increases, White attempts to control the African-American population should increase. As Blacks (and poor Whites and other minority groups) gain economic power by attaining better education and better jobs, wealthy Whites should attempt to thwart this progress. When there is a threat to the political dominance of the majority group, as in the case of a Black mayor in a city, we should expect to see a more rigorous attempt to reassert dominance. I review the research that has supported the social threat model in different arenas, including the examination of police officer killings of Blacks, the impact of the size of African-American population on residential racial composition, and interracial homicide in general. I explain why this model is the preferred explanation for bias crimes. Chapter Three ends by presenting the hypotheses based on past research in this arena.

Chapter Four discusses my overall research design, including descriptions of the data sets, sampling procedures, construction of variables, data management procedures, file formation, statistical approaches, and credibility and limitations of the data. Chapter Five presents the findings of the research and the subsequent analyses required by the results. Chapter Six discusses the conclusions of the analyses, implications for crime policy, and problems for future research.

Chapter Two. Bias Crimes and General Criminality

Chapter Two provides an overview of the bias crimes and general criminality, focusing on plausible explanations for interracial crimes and how these explanations may translate to hate crimes. I review the bias crime literature and link it to the social threat or general criminality perspectives. The chapter explains in depth the key principles underpinning this research and outlines the use of general criminological theory in hate crime research, including the key studies that examine general criminological explanations of bias crime. I conclude by presenting the general criminality hypotheses utilized in this research.

I. Bias Crimes

Bias crimes are a relatively recent criminological phenomenon; while hate crimes were certainly committed throughout U.S. history, they were not identified as such until California passed the first hate crime law in 1978 (Lyons 2008). In 1990, the federal Hate Crime Statistics Act (HCSA) introduced hate crimes into the legislative and criminal justice realms. The HCSA defines bias crimes as "crimes that manifest evidence of prejudice based on race, religion, disability, sexual orientation, or ethnicity, including where appropriate the crimes of murder, non-negligent manslaughter; forcible rape; aggravated assault, simple assault, intimidation; arson; and destruction, damage or vandalism of property" (28 US 534; FBI 1999). In 1994, the HCSA was amended to include disability[4]. The HCSA originally mandated hate crime data collection only for five years; however, in 1996, the Church Arson Prevention Act revised the collection requirement to "each calendar year" (FBI, 1999). The FBI further defines bias crimes as "a

[4] In 2009, the HCSA was again amended by the Matthew Shepherd and James R. Byrd, Jr Hate Crimes Prevention Act to include gender and gender identity as protected categories. This amendment is outside the scope of this research.

criminal offense committed against a person or property which is motivated, *in whole or in part*, by the offender's bias against a race, religion, disability, sexual orientation, or ethnicity/national origin; also known as Hate Crime" (FBI 1999: 2, emphasis added by author). The ambiguity of these definitions is a primary source of debate about what actually constitutes a hate crime (see Green et al. 2001 for a review of the literature). However, knowledge about hate crime occurrences has tangible and significant consequences for victims, police officers, and state legislatures (Wilson and Ruback 2003:373-4).

II. Bias Crimes as Qualitatively Different From General Crime

J. Levin and McDevitt (1993; 2002) note that hate crimes tend to be characterized by excessive violence. In fact, sixty percent of bias crimes are violent crimes (J. Levin and McDevitt 2002: 17, and Strom 2001). According to the *Sourcebook of Criminal Justice Statistics* for the year 2002, 82% of all reported crimes are property crimes, suggesting that bias crimes do, in fact, tend to be more violent than general crime. Messner et al. (2004) find that victims of bias assaults suffer more injuries than victims of non-bias assaults. Of particular importance to this research is the finding that a majority of violent bias crimes are racially motivated; nearly 60% of all violent bias crimes are anti-Black and 30% of all violent bias crimes tend to be anti-White (Perry 2001 and Strom 2001).

Second, J. Levin and McDevitt (1993, 2002) observe that hate crimes tend to be perpetrated by strangers rather than known offenders. Messner et al. (2004) report that assaults motivated by bias are much more likely to involve strangers than persons known to the victim. Third, bias crimes tend to involve multiple offenders (J. Levin and McDevitt 2002). Lone offenders committed 4,158,290 violent crimes (Table 3.28), while 1,091,760 violent crimes were committed by multiple offenders (Table 3.30) (*Sourcebook of Criminal Justice Statistics* 2003). That is, lone offenders committed over 79% of all violent crimes. While not based on empirical data, J. Levin and McDevitt (1993 and 2002) argue that hate crimes are more likely than non-bias crimes to involve multiple offenders. In a review of the juvenile hate crime literature, Steinberg et al. (2003) find that juvenile offenders are more likely to be lone offenders or to commit bias crimes in small groups. The authors did not contrast this to non-biased juvenile crime. It is the sum of these characteristics that make hate crimes distinctive from non-bias crimes.

III. Development of Bias Crime Legislation

It is imperative to examine the legal definition of hate crimes. At the federal level, hate crime legislation is limited to collecting statistical information about hate crimes and enhancing penalties for hate crime offenders (see the Hate Crime Sentencing Enhancement Act 28 U.S.C 994, 1994; amended 1995); however, state laws vary tremendously in terms of definition and punishment of hate crimes.

According to Wang (1995), hate crime laws at the state level have three distinct purposes. The first two purposes are somewhat related. First, state hate crime laws can define which hate crime statistics the state is responsible for collecting. Second, states may identify which categories may be protected under hate crime legislation. At first glance, this may sound relatively simple; however, states vary dramatically in terms of hate crime definitions. For example, the federal law includes the protected categories of race, religion, ethnicity, sexual orientation and disability. States are free to select whichever categories they like to protect. For example, in the year 2000, Maryland state hate crime law reflected only the protected categories of race, religion and ethnicity, while New York identified bias on the basis of race, religion, ethnicity, sexual orientation, disability, gender and age (Anti-Defamation League 2003). Therefore, states may exhibit wide variation in terms of which statistics are collected and which categories are protected under state hate crime law. Despite state differences, all states must report all of the categories protected by the HCSA to the FBI, although we cannot be certain that all states do so. Additionally, a state required to collect statistics on all five federally protected categories may more reliably report data on those five categories to the FBI than a state that only collects data on three protected categories.

The third and final type of state hate crime laws is the penalty enhancement statute. This is the most controversial in terms of legislation. These laws allow prosecutors to charge hate crime offenders with a felony rather than a misdemeanor or to recommend a harsher penalty if convicted (Anti-Defamation League 2003).

IV. Bias Crimes as a Social Movement Outcome

A third explanatory model exists and must be addressed and variables relevant to it controlled. Official bias crime rates are likely to reflect organizational processes resulting from successful social movements as well as objective levels of offending. Because bias crime laws are relatively new, law enforcement agencies may differ in their capacity to detect and report bias crime rates. Boyd, Berk and Hamner (1996) find that police officers in a large metropolitan police department showed differential recording practices of bias crimes, despite receiving the same training. Thus, official bias crime rates may be the result of differences in police training, police funding, and political support for or opposition to bias crime laws. For example, Haider-Markel (1998) finds that many hate crime laws are the result of politicians satisfying a particular interest group (e.g., the Anti-Defamation League), and other political factors (e.g., issue salience, party competition, etc). Other authors trace the formation of hate crime laws to collective action (for examples, see Jenness and Broad 1997 and Grattet, Jenness and Curry 1998). While the mechanics of their examinations and their variables differ, the results are primarily the same. The passage of hate crime laws does not occur in a vacuum. The social climate of an area, including presence of active social movement groups, political party preference, and hate group activity affects the adoption and enforcement of hate crime laws. Thus, it is important to recognize that these same factors may also affect police training and other organizational processes that ultimately influence whether a crime is deemed as racially biased or not[5].

Social movements not only affect the adoption of hate crime laws, but compliance with those laws as well. McVeigh et al. (2003) find evidence that the enforcement of hate crime laws in several US counties is due to the presence and level of activism by civil rights organizations; however, this result emerges only in politically competitive counties. King (2007) finds that compliance with hate crime law varies with racial composition and region. Following social threat/group threat theory, one would expect compliance with the HCSA to be lower in areas with larger Black populations since these laws protect minorities. This is supported in the South; however, police compliance is higher in areas with large Black populations in the Northeast. Historical racial tensions and subsequent social movements in the south, such as Jim Crow laws and lynching, negatively affect the enforcement of laws designed to protect minorities.

King et al (2009) find that historical patterns of racial violence (lynching) combined with larger Black population reduces the likelihood of police compliance with hate crime laws in the South. Similarly, a history of lynching and sizeable Black population decreases the likelihood that

[5]It is outside the scope of this research to incorporate differences in police training; thus, the findings will reflect differences in police practices as well as compliance with reporting bias crimes to the FBI.

a racially motivated crime will be prosecuted. This study is valuable in several important ways. First, it illustrates the extent to which historical social movements still affect modern compliance with hate crime laws. Lynching was most prevalent in the South and both McVeigh et al (2003) and King (2007) show that compliance with bias crime legislation is lower in the South. Second, King et al (2009) demonstrate that even when a hate crime is officially reported by police, there are factors which affect whether or not a prosecutor will try the case. This suggests that compliance with hate crime legislation is a multi-step process.

Further, Grattet and Jenness (2008) make two interesting points regarding the implementation and enforcement of hate crime law. Using California police and sheriff data, the authors find that community and activist pressures have a large and significant impact on whether or not a police agency forms a special unit to follow hate crimes. After that unit is formed and a hate crime is reported, the unit investigates it as a hate crime rather than questioning the categorization. Thus, the implementation of the law may be more community driven than the enforcement of the law, especially when a police agency reacts to pressures by creating a specific unit to address hate crimes. Boyd, Berk and Hamner (1996) find that once a police unit is created in a large metropolitan department, individual officers complied with the directives regardless of their personal opinions on the idea of a hate crime unit. Despite this compliance, the authors find evidence of variation in the officers' determination of motive as bias-related, even within the same department. Because this research is city-level and not agency-level, I cannot control for particular agency reactions to activist pressures nor for police training; however, the findings imply bias crimes could be differentially recorded by official agencies as well.

J. Jacobs and Potter (1998: 5) argue that hate crime laws are the result of "identity politics" where individuals recognize themselves as members of a persecuted group because "it is strategically advantageous to be recognized as disadvantaged and victimized. The greater the group's victimization, the stronger its moral claim on society." Hate crimes are a source of great victimization; thus, groups rally to draw attention to the issue, which eventually forces legal action.

Several authors note that police have a high level of subjectivity when determining whether a crime is bias-motivated or not (Boyd, Berk and Hamner 1996; Garofalo and Martin 1991; Martin 1995 and 1996; Wilson and Ruback 2003). In fact, this is a major point of contention in the literature. The FBI training manual provides several conditions for determining bias motivation in a crime incident (see Appendix A); however, these guidelines have been criticized for being vague, leaving the determination almost solely to the police officers' discretion (Boyd, Berk and Hamner 1996; J. Jacobs and Potter 1997). Wilson and Ruback (2003) found that police officers were more likely to respond to and identify anti-racial crimes as bias crimes. In order for a complete understanding of hate crimes, the effect of organizational funding and training differences should be incorporated into the social constructionist model and tested in future research.

To address these concerns, I will control for the effects of political climate and region on the relationships between social threat, general criminality and hate crime. Following McVeigh et al. (2003), I will determine whether or not relationships between social threat variables and hate crime (or general criminality variables and hate crime) are still strong after controlling for the democratic climate and political competitiveness of a city using data created from America Votes. Because I cannot measure police agency recording practices with the data other than controlling for number of years of data reported to the FBI, I do attempt to control for political climate in a region, which does affect organizational practices (e.g., funding for police department hate crime training, political pressures to report or not to report hate crime incidents, etc). While McVeigh et al. (2003) did not find an effect of democratic voting on the enforcement of hate crime laws, it is distinctly possible and even probable that democratic voting may affect the actual police departments' recording the number of hate crimes in a city (King 2007). By controlling for political climate, I attempt to control for the effect of social movements and political pressures on bias crime recording and to isolate the social threat and general criminality arguments.

For similar reasons, I control for region, focusing on a city's location in the South[6]. Again, King (2007) finds that the effect of size of Black population on compliance with hate crime laws is affected by region: the South has an inverse relationship between size of Black population and compliance with hate crime.

V. Racially Motivated Bias Crimes: Research Findings

While many authors attribute the cause of bias crimes with reference to different theories or are atheoretical, most research about hate crimes relates the causes of hate crimes to some form of threat by one population to the White, male, Protestant, heterosexual power structure (for examples, see Levin and McDevitt 1993 and 2002, and Perry 2001). There are few, but notable, studies that propound hate crimes as an extension of a person's general intention to commit crime. Bias crime offenders may be more prejudiced than their conventional counterparts, but they are generally seeking excitement rather than sending a message to a particular population (see Byers et al. 1999, McDevitt et al. 2002, and Messner et al. 2004)

Racially motivated hate crimes present a unique opportunity to examine the social threat perspective and compare it to general criminality at the macro-level. Most prior studies of social

[6] King (2007) found that compliance with hate crime legislation is also lower in the Midwest; however, the Midwest does not have the same historical racial tension as the South. Since this is a study of social threat and bias crimes, rather than the compliance with hate crime legislation, it is likely that the South will still affect bias crime outcomes while the Midwest will not.

threat have typically examined group conflict between African-Americans and Whites. Numerous findings suggest that African-Americans also suffer disproportionately from bias motivated violence (Cheng et al 2013; Grattet 2009; Perry 2001; Strom 2001; and Torres 1999). Torres (1999) reports a fifty percent increase in anti-African American bias crimes reported to the UCR in the time period 1992-1996. On the other hand, Wilson and Ruback (2003: 392-393) report that, due to historical racial tensions between Blacks and Whites, "police officers may be more likely to label racial incidents as hate crimes than offenses against other groups." This suggests that the official statistics to some extent reflect police labeling processes in addition to the objective reality and raises questions about the reliability of these statistics.

In light of these two differing opinions, I argue there is no "perfect" source of data; however, Perry (2001) and J. Jacobs and Potter (1998) make noteworthy observations about the nature of hate crime data. Perry (2001: 13) argues that while official data may be somewhat inaccurate, "the data nonetheless may be useful as a source of information on general trends and patterns." Second, J. Jacobs and Potter note that all hate crime data may be slightly biased and inaccurate. While official hate crime data may be biased due to police reporting tendencies, other private sources of data may be even more biased towards the organization's goal. Advocacy groups that collect hate crime statistics, such as the Anti-Defamation League and the National Gay and Lesbian Task Force, may actually benefit from inflated counts of hate crimes (J. Jacobs and Potter 1998: 46-49).

Regardless of its inadequacies, official data may be the most reliable source of data we have about the commission of hate crimes (Grattet 2009; McDevitt et al. 2003; Van Dyke and Tester 2014: specifically as to completeness of data). By using racially motivated violent crimes, I am also limiting my analyses to the most common and perhaps the most easily identifiable hate crimes. Race is an easier category to visually identify and accept than is sexual orientation, ethnicity or religion. Racial hate crimes are more reliable than are bias crimes based on sexual orientation, ethnicity, religion or disability because racially biased crimes occur more frequently and/or are more likely to be categorized (see Wilson and Ruback 2003). Additionally, police may be more likely to intensely investigate violent hate crimes because of the violence involved (Boyd, Berk and Hamner 1996: 830); therefore the data are limited to *violent* hate crimes.

While Green et al. (1998a) do not explicitly mention the social threat perspective[7], their test provides a macro-level examination of racial and economic threat as an explanation for anti-racial hate crimes. The authors find that a variant of racial threat, rather than economic threat, better explains hate crimes; however, the authors did not control for any other explanation (e.g., general criminality). The authors argue that "intuitions about the relationship between racial composition and racially motivated crime must be gleaned from cognate literatures concerning racial attitudes, housing segregation, and racial violence" (Green et al. 1998a: 373). By ignoring the possibility that bias crimes are similar to general crime, the authors fail to test alternative explanations that are not predicated specifically on racial tension.

In a macro-level study of Chicago police data, Lyons (2008) tested the racial threat, defended communities and macrostructural opportunity theories in explaining anti-Black and anti-White crimes. He finds that anti-Black incidents are more common in traditionally majority White neighborhoods and concludes that the defended communities thesis is the best explanation for anti-Black offenses. The defended communities thesis is predicated on the idea that communities are likely to share common values; the more homogeneous the community, the stronger the shared morals. Some people represent threats to these community bonds. Lyons (2008:360) states the

[7] Green et al. (1998a: 373) do credit and test the "power-threat" hypothesis offered by Blalock (1967).

"defended community perspective conceives of racial hate crimes as strategies, albeit extreme, for defending against threats posed to valued identities and ways of life … [r]acial outsiders may threaten communities whose identities are based on ideals of longstanding-standing racial homogeneity."

On the other hand, Lyons (2008) finds that anti-White biased crimes occur more frequently in racially heterogeneous communities. He attributes this to macrostructural opportunities – when Blacks and Whites are in contact more frequently, more anti-White hate crimes occur. While I do not discount or refute Lyons findings, I find his interpretations to be problematic. First, he only tests racial threat, not the political or economic threat[8] posed by the Black population. Second, his conclusions about anti-White crimes leave many unanswered issues. He attributes anti-White crimes to neighborhood spatial dynamics and infers that they could be the result of retaliations against anti-Black crimes; however, anti-Black crimes are more likely in majority White communities. Lyons (2008) does not explain how anti-Black and anti-White crimes occur in different communities yet are correlated with one another.

Grattet (2009) provides an excellent macro-level analysis of bias crimes in a single jurisdiction. In his research, Grattet (2009) limited his focus to all bias crimes that occurred in Sacramento from 1995-2002. He also tested two competing theories of bias crimes: social disorganization and defended neighborhoods. The defended neighborhoods (or communities) perspective is very similar to social threat, but at a different unit of analysis (neighborhoods rather than cities).

[8] Lyons (2008:375) does control for "economic strain" by introducing Black and White unemployment variables in his analyses. He finds no effect. His measure is incomplete, since more than one economic measure can constitute threat.

Grattet (2009) finds that concentrated disadvantage, residential turnover, and non-White migration into White neighborhoods have strong and significant impacts on bias crime in general. This suggests that both social disorganization and defended neighborhoods may operate together to explain the occurrence of bias crimes. Grattet (2009) further found that when he held the effect of the social disorganization variables constant at their means, the defended neighborhoods variables stayed significant. Additionally, Grattet (2009) finds that social disorganization variables affect robbery and assault while defended neighborhoods variables do not. Interestingly, vandalism shows a different pattern. Only residential turnover and in-migration of non-White residents have a significant effect on vandalism. Concentrated disadvantage and the influx of non-White residents into predominantly White neighborhoods emerge as strong and salient predictors of anti-Black bias crimes[9] in particular. This suggests that anti-Black bias crimes are more likely in mostly White neighborhoods and may result from social threat, above and beyond the effect of concentrated disadvantage. What would be interesting is if we separated out the effect of White concentrated disadvantage – is it simply that there is disadvantage or are the Whites in the neighborhood experiencing disadvantage and reacting against their new, non-White neighbors? Overall, Grattet (2009) concludes that bias motivated crimes share many of the same predictors as general crime with the rather important caveat that this finding changes when examining White neighborhoods experiencing an influx of non-Whites.

Van Dyke and Tester (2014: 291) examine hate crimes on college campuses, noting that "10% of the hate crimes reported nationally occur on college campuses." The authors study

[9] Grattet (2009) also tested the effects on different types of bias, but the frequencies were too small to make any reliable conclusions. He did note that anti-gay crimes provided some evidence of an effect of residential turnover; however there were only 48 anti-gay bias crimes in his sample.

racially and ethnically motivated bias crimes[10] as one unit and hypothesize that threatening conditions to White students will lead to increased bias crimes on campus. The authors hypothesize that increases in minority population (racial threat), number of fraternities on campus (indicating a hostile campus environment), and increases in tuition (economic competition) will positively affect the number of ethnic or racial hate crimes committed on campuses. Using the 2002 UCR, Van Dyke and Tester (2014) report on 349 colleges in the US.

Van Dyke and Tester (2014) find that increases in minority population sizes did not affect the number racially or ethnically motivated bias crimes committed on college campuses. Instead, the authors find that it is the size of the White population in conjunction with the size of the minority population that appears to be the driving racial factor for bias motivated crimes. When White population is high but minority population is low (0-9% of the student population), there is a reduced number of racially or ethnically motivated bias crimes. However, when White population is high and minority population is moderate (10-17% of the student population), there is an increase in the number of bias crimes on college campuses. Last, changes in tuition – their measure of economic threat – have no effect on the number of bias crimes reported on college campuses.

King and Sutton (2014) study the temporal clustering effects of hate crimes following a provocative antecedent event, such as the verdict after a contentious interracial trial, terrorist attack or court decisions regarding same-sex marriage. While this study is not equipped to address the ripple effect of hate crimes, it is important to note their findings. King and Sutton (2014) find that hate crimes do temporally cluster immediately following a provocative event, but only for racial

[10] Van Dyke and Tester (2014:296) do not note which crimes they studied, only that the dependent variable is "a count of the number of ethnic or racial-bias-motivated hate crimes the campus experienced in 2002." They also note that "20% of the racial motivation crimes that were reported targeted a White victim" (Van Dyke and Tester 2014: 297).

bias crimes (after a contentious interracial trial) and anti-Arabic/anti-Muslim bias crimes (after a terrorist attack). The authors find that the response rapidly escalates and just as quickly de-escalates, indicating the need for future research to take into account whether the study spans any time in which there is a provocative event.

VI. General Criminality Perspective

Three key criminological theories emerge as appropriate for the study of interracial crime at the macro-level; in particular, conflict theory, social disorganization theory and strain theory. Social Threat is a direct application of conflict theory to interracial crime and will be addressed in the next Chapter. Social disorganization theory and strain theory are the two additional general explanations for interracial crime in general and hate crimes in particular.

Social disorganization emerges as a strong and suitable explanation for the study of interracial violence at the macro-level, particularly in light of Grattet's (2009) findings regarding concentrated disadvantage. Concentrated disadvantage and residential turnover consistently remain strong predictors of bias crime in Sacramento, CA. The original formulation addresses community characteristics as a cause of disorganization, which lowers an area's ability to monitor itself (social control), which in turn causes an increase in crime (Shaw and McKay 1942).

More recent applications of social disorganization focus explicitly on a community's level of social control and its relationship to crime, thereby focusing on variables such as family disruption and residential mobility (Shihadeh and Steffensmeier 1994) and other community characteristics, such as collective efficacy (Sampson and Raudenbush 1999), and racial residential segregation and concentrated disadvantage (Krivo and Peterson 1993; Peterson and Krivo 2005; Sampson 1987; Wilson 1987). Areas with high levels of single-parent families, especially female-headed households, are thought to be areas where there are fewer responsible supervisors for crime-prone teenagers. That is, the level of social control will naturally be lower in communities with female-headed families because there are fewer people to supervise the young, who typically make up a majority of the criminal population (see Sampson 1987 and Shihadeh and Steffensmeier 1994).

Shaw and McKay's original social disorganization theory also addresses ethnic heterogeneity, which later researchers quantified as percent Black in an area. Shaw and McKay (1942) theorize that increased ethnic heterogeneity in an area leads to lower social control because of residents' inability to effectively communicate with one another. Thus, racial composition emerges as both a social threat variable and a social disorganization variable. The only solution is to use percent Black population as both a threat variable and a social disorganization variable.

Additional tests examine the relationship between economic factors, specifically access to employment, and crime. Social disorganization also states that many immigrants moved into the cities rather than the rural areas of the US due to the availability of low-skill work available in the cities. When access to employment dwindles, crime increases. Shihadeh and Ousey (1999) test this relationship for Whites and Blacks in 1970 and 1990. They find that decreased access to employment does increase homicide; however, decreased access to low-skill employment increases poverty and joblessness (deprivation), which increases homicide. This finding is supported for both Blacks and Whites[11].

Krivo and Peterson (1996) expand on the effects of structural disadvantage and disorganization on violent and property crime in Columbus, Ohio. The authors test two of

[11] It is important to note that there exist no tests that compare economic deprivation in social disorganization and strain to economic threat in social threat theory. In fact, the measures are typically identical. I will further address this perplexing problem in the methods section when I describe my variables and how they are measured.

Wilson's (1987) hypotheses: 1) areas with high levels of disadvantage will have high rates of violent and property crime; and 2) these differences will exist regardless of race. Krivo and Peterson (1996) find that disadvantage works particularly well when predicting violent crime, but is not a significant predictor of property crime. Second, this relationship holds for both Black and White neighborhoods.

Further research by Krivo and Peterson (2000) explains why structural disadvantage better explains White levels of violence than Black levels of violence. Specifically, the authors argue that Blacks tend to live in extremely disadvantaged areas; thus, increases in key variables would not be expected to predict increased violence. That is, in predominantly Black areas, the disadvantage is so great that any increase in disadvantage goes seemingly unnoticed. On the other hand, "whites generally live in communities with a lower-prevalence of violence-producing factors" (Krivo and Peterson, 2000: 556). Thus, even a small increase in disadvantage produces a greater impact on crime in predominantly White areas.

Lyons (2007)[12] provides a test of social disorganization to explain hate crimes. He utilizes traditional social disorganization variables, as well as defended neighborhoods and resource competition theories. Lyons (2007) finds that anti-White bias crimes are more similar to traditional crime in that anti-White crimes are more likely in socially disorganized neighborhoods. Anti-Black hate crimes are more consistent with a defended neighborhoods theory in that anti-Black crimes are more likely in organized communities. It is important to note that anti-Black crimes are "especially [likely] in internally organized white communities undergoing the threat of racial invasion" (Lyons 2007: 847). While he does not control for the social threat perspective, Lyons (2007) acknowledges that threatening conditions contribute to the level of anti-Black hate crimes.

[12] Lyons (2008) also tests anti-Black and anti-White crimes in Chicago as the result of socially threatening conditions. This piece is discussed at length in Chapter Three.

Additionally, he finds that the causes of anti-White and anti-Black hate crimes differ. Anti-White hate crimes are more similar to non-bias crimes in that they are more likely in disadvantaged neighborhoods with high levels of residential mobility.

Grattet (2009) also finds that social disorganization variables, in particular concentrated disadvantage and residential turnover, remain statistically significant predictors of bias crime even when variables measuring defended neighborhoods are introduced. Interestingly, only concentrated disadvantage remains significant for anti-Black hate crimes once the measures for defended neighborhoods are included in the models, again suggesting that anti-Black hate crimes may be committed in response to a threatening population.

Strain theory focuses on societal sources of anomie as causes of crime. Blau and Blau (1982) translate this hypothesis using economic deprivation as a source of anomie. Specifically, the authors argue that economic inequality causes frustration and aggression, which lowers support for societal norms (including norms against the commission of crime), which increases the level of anomie in an area, thereby increasing the level of crime in an area. The authors find that extreme inequality between the races is directly linked to violent crime. This finding has been difficult to replicate; some research has found partial support (e.g., Harer and Steffensmeier 1992; Messner and Golden 1992; and Shihadeh and Flynn 1996) while others fail to find a direct link (e.g., Messner and South 1986; Sampson 1987; and Shihadeh and Steffensmeier 1994).

Harer and Steffensmeier (1992) provide a unique test of this hypothesis by measuring inequality and poverty with race-specific data. They argue that it is possible that previous studies of inequality and crime did not accurately measure inequality. Prior studies typically measured interracial inequality, since Blacks suffered disproportionately from both economic discrimination and racial discrimination (Blau and Blau 1982). Harer and Steffensmeier argue that measures of intra-racial income inequality may be more relevant since Whites and Blacks tend to live in segregated communities (e.g., Massey and Denton 1993). Thus, Blacks are more likely to use other Blacks as a comparison group, while Whites are more likely to use other Whites as their comparison group when determining relative income deprivation (Harer and Steffensmeier 1992). They include three measures of inequality by race: the total measure of disadvantage (Black and White disadvantage combined), as well as intra- and interracial measures of economic disadvantage. The authors use racially disaggregated arrest rates for violent crime as the dependent variable. They find that economic inequality, regardless of how it is measured, is a more salient predictor of violent crime (rape, robbery, homicide and assault) for Whites than for Blacks. Since the authors were testing only for direct effects of inequality on crime, they suggest that Black income inequality may be less important than other social disorganization variables, such as family disruption.

The more interesting test is when these two perspectives are combined. Measures of economic discrimination (as predicted by strain theory) can be mediated by family disruption and other social disorganization variables (e.g., Sampson 1987; Shihadeh and Steffensmeier 1994). Using the 1980 Census and racially disaggregated FBI arrest data for robbery and homicide, Shihadeh and Steffensmeier (1994) find the effect of inequality is mediated by the percentage of female headed households (their measure of family disruption) for Blacks. Further, family disruption is more salient for juvenile offenders than adult offenders. A third important finding is that White to Black inequality has no effect on Black violence. The authors suggest that inequality is an important *indirect* cause of Black violence. Of particular importance to this research are the latter two findings. Juveniles and young adults commit a majority of hate crimes (McDevitt et al. 2002); thus, family disruption may be an essential but thus far neglected cause of hate crimes. The third finding suggests that the causes of White and Black violence may differ dramatically; thus providing more support that the causes of anti-White and anti-Black hate crimes may also differ.

There exist no macro-level tests of the general criminality perspective as an explanation for hate crimes; however, two micro-level studies are worth mention. First, McDevitt et al. (2002) note the existence of four distinct types of hate crime offenders in Boston. The most common hate crime offender is termed the "thrill" offender, who comprised sixty-six percent of the sample. Thrill offenders often show little prejudice or deny prejudice against their victim or their victim's group; they insist that the main purpose of the crime is excitement. Some of these offenders cite peer pressure as the main cause of their participation in the crime.

Second, Messner et al. (2004) find that while significant differences can be detected between bias motivated assaults and assaults in general, there is little support for the idea that bias crime offenders are more calculating and specific in their victim selection than other offenders. In particular, the authors find that bias assault offenders are actually *more* likely to be perceived as drunk or under the influence of drugs during an assault than non-bias offenders. Messner et al. (2004) conclude that bias offenders may simply be prone to crime and violence in general rather than reacting to a specific threatening population. Overall, it is important to note that micro-level research regarding hate crimes is mixed in terms of support for social threat and general criminality.

VII. Summary and Implications of General Criminality

Social disorganization theory and strain theory are two influential and versatile explanations for many forms of criminal behavior, including interracial crime. The main variables of interest here are economic deprivation and family disruption. Most studies find that economic deprivation has an impact on levels of violent crime in both Black and White neighborhoods, whether that effect is direct or indirect. Shihadeh and Steffensmeier (1994) clearly show that measures of intraracial economic inequality are more important in explaining levels of Black violence and more importantly, economic inequality is an indirect cause of Black violence, mediated by levels of family disruption in an area. On the other hand, Krivo and Peterson (2000) show that economic deprivation is a direct cause of violence in White communities. These important differences suggest that the effect of economic deprivation must be examined differently for Blacks and Whites.

Further, Lyons (2007) and Grattet (2009) find great support using social disorganization and defended neighborhoods as explanations for hate crimes. Of particular importance is Lyons (2007) finding that anti-White hate crimes are similar to general crime in that they are more likely in socially disorganized neighborhoods and that anti-Black hate crimes are more likely in socially organized neighborhoods experiencing the threat of racial invasion by Blacks. The latter finding is also supported by Grattet (2009). Thus, extending these findings to this research, social disorganization may better explain the causes of anti-White hate crimes as well as conventional crimes, whereas social threat may better explain the causes of anti-Black hate crimes. In their study of college campuses, Van Dyke and Tester (2014) find little support for defended neighborhoods or economic competition, but do find that a hostile campus environment (number of fraternities on campus) has a positive effect on the number of racial/ethnic motivated bias crimes. The authors base this on previous research that shows that fraternities affect the general crime rate and rate of sexual assaults on college campuses. This "hostile environment" is most likely a general criminological variable rather than an indicator of social threat.

Additionally, several micro-level studies suggest that strain and social disorganization may be just as plausible as social threat. McDevitt et al. (2002) find that most hate crime offenders are motivated by *thrill*. In other words, hate crimes are fun for most offenders, not an attempt at controlling a dangerous population. Messner et al. (2004) find that bias crime offenders may be more likely to use alcohol and drugs prior to committing an assault than are non-bias offenders, suggesting that bias crimes are the result of poor decision-making rather than a deliberate attempt to control a specific population.

VIII. General Criminality Model and Hypotheses

The general criminality model argues that the causes of violent bias crimes are identical to the causes of violent crime in general, which runs counter to the claim that hate crimes are the result of distinctive factors such as socially threatening conditions. Two theories are useful in explaining the relationship between hate crimes and general crime: social disorganization and strain theory. Thus, we would expect to see the following model:

Indicators of Social Threat
(Racial, Economic and
Political Threat) - - - - → Anti-Black Violent Hate Crime
Controls
(Democratic Voting, Political
Competition, Region) Anti-White Violent Hate Crime

Indicators of General Criminality →
(Strain and Social Disorganization
Predictors; General Dangerousness
Interracial Contacts)

This model effectively shows that the general criminality model predicts that strain and social disorganization predictors should be able to explain all forms of violent crime, regardless of social threat variables. This model will be tested for bias and non-bias violent crimes. It will also be tested specifically for anti-Black violent hate crimes, anti-White violent hate crimes and non-bias intra- and interracial homicides. This model will also control for measures of social threat. The general criminality hypotheses from social disorganization and strain theories are as follows:

G_1: Based on social disorganization theory, the percentage of Blacks in a city should be positively related to the number of bias motivated violent crimes. This pattern should hold especially for anti-White bias crimes (Lyons 2007).

Shaw and McKay (1942) propose that ethnic heterogeneity reduces social control because it inhibits effective communication between residents in an area. At the time, a high percentage of Eastern European immigrants could not communicate with neighbors as they did not speak the language; a problem that is not typically associated with a majority of African-Americans today.

On the other hand, percent Black is associated with disadvantage. A higher percentage of Blacks in an area should be indicative of disadvantage and lower social control; thus, there should a high crime rate in general, including bias motivated crime. According to Lyons (2007), both conventional crime and anti-White bias crimes are more likely in neighborhoods characterized by social disorganization; which is also expected at the city level. Anti-Black crimes should occur in socially organized cities with threatening conditions present.

G_2: As suggested by most theories of crime, an increase in concentrated disadvantage will increase all types of violent crimes, net of social threat and other control variables.

Shaw and McKay (1942) argue that higher numbers of at-risk populations results in a decrease in informal social control, which in turn increased crime. Sampson (1997) argued that in fact, several factors contribute to the deterioration of social control in an area and that it is the relationship is not linear. That is, as multiple measures of disadvantage increase, the concerted effect has a more profound impact on social control than an increase of just one single measure.

Following Grattet (2009) and Sampson (1997), I created a measure of concentrated disadvantage using unemployment, individuals living in poverty, and female headed households.[13]

G_3: The more youthful the population, the more likely a city is to have a higher number of both violent crimes and bias crimes, net of other factors.

Both violent crimes and bias crimes are more likely to involve youthful offenders. Thus, the higher the percentage aged 13-24 in a city, the higher the violent crime rate and count of violent bias crimes will be in a city.

G_4: The more dangerous the city, the more likely that city is to have a higher number of bias motivated crimes.

In general, I expect that more dangerous cities are more likely to have higher numbers of violent bias crimes; thus, cities with a high violent index crime rate in 1996 are likely to have a high number of violent bias crimes between 1996 and 2000. This seems to be a fairly simple prediction, particularly if my sample is sound and the general criminality predictors are able to explain variation in bias-motivated crimes.

IX. Controlling for Effects of Social Constructionism

I will also control for the likelihood of interracial contact, region and political competition. Cities that are more diverse in terms of racial population distribution are more likely to have citizens of different races coming into contact with one another, which may in turn affect the number of bias crimes in a city. Any effect of social threat variables above and beyond the likelihood of interracial contact can be considered a true effect of that variable. According to prior

[13] Percent Black is excluded because race is such a pivotal variable in both the social threat and general criminality models. Youthful offenders did not load onto the principal components and were not correlated with the other predictors, so it is a stand-alone variable.

research, counties that are politically competitive are more likely to enforce hate crime legislation (McVeigh et al. 2003), including reporting requirements (King 2007). Additionally, counties in the South experience a negative relationship between size of Black population and compliance with hate crime laws (King 2007). Thus, I would expect to see the following results:

C_1: Cities with higher levels of interracial contact will have higher levels of hate crimes than cities with lower levels of interracial contact, net of other factors.

Cities where Whites and Blacks have more consistent contact with each other should have higher levels of bias crimes. Additionally, these cities should have higher levels of interracial homicides.

C_2: Cities located in the South will experience a higher number of reported violent crimes than cities not located in the South. Cities located in the South will experience a lower count of recorded hate crime than cities that are not located in the South.

Because this research focuses on threatening conditions and their effect on bias crimes, I limit my control variable for region to South. While McVeigh et al (2003) and King (2007) find that Midwestern and Southern regions are less likely to pass and/or comply with hate crime legislation, only the South has a documented history of racial tension and racial violence. Following King (2007), cities located in the South will be less likely to comply with hate crime reporting; therefore, the number of recorded bias crimes for cities in the South should be lower than for cities elsewhere in the US.

C_3: Cities that are located in more politically competitive counties will experience a higher volume of hate crime than cities located in counties that are less competitive.

I expect that cities located in politically competitive counties will experience a higher volume of bias crimes due to the fact that political pressure to pass and enforce hate crime legislation is more likely in a competitive environment than a non-competitive one (McVeigh et al 2003).

In Model One, the general criminality variables are used to predict the violent index crime rate in each city. I expect the general criminality predictors to account for much of the variation in the violent crime rate. The violent index crime rate is likely to be a strong predictor of the number of violent bias crimes in a city because of this. I include all of the predictors of general crime as well as the violent index crime rate because the violent index crime rate only measures the crimes known to the police. It is likely that the remaining general criminality predictors will accurately account for more variation in the number of bias crimes in each city.

In sum, social disorganization and strain variables will adequately predict bias crimes and threat variables will have no effects on bias crimes net of the general criminality predictors. The decrease of social control in a city as measured by higher levels of violent crime, concentrated disadvantage and youthful populations should adequately predict bias and non-bias crimes, net of all other factors. Finally, political competitiveness, democratic voting and region must be controlled.

Chapter Three. Conflict Perspective and Social Threat

This chapter provides an overview of the conflict paradigm in sociology and the development of the social threat perspective, focusing specifically on plausible explanations for interracial crimes generally and how these explanations may translate to hate crimes. The chapter explains in depth the key principles underpinning this research and traces the development of conflict theory and social threat, including an examination of the research for each critical dimension of social threat (racial, economic and political threat). The conclusion presents the hypotheses utilized in this research.

I. Conflict Theory and the Social Threat Perspective

Social threat is an extension of the economic conflict perspective outlined by Karl Marx. Marx argued that society is characterized by conflict. He views capitalist society as comprised of two social and economic classes: the bourgeoisie, or the owners of the means of production, and the proletariat, or the workers. Through wealth, the bourgeoisie controls power in society, owning all of the factories and occupying all of the political offices (Marx 1988 [1848]). Later conflict theorists adapted Marx's work on economic divisions to other groups and sources of conflict in society.

The social threat perspective began with the work of Blalock (1967), and later Turk (1969) and Quinney (1977), addressing the power relationships between Whites and other races or ethnicities. These authors argue that as the minority[14] population increases, the threat to White social, political and economic dominance increases. Thus, in areas where there are larger minority

[14] Most of these studies examining social threat focus solely on the African-American and White populations.

populations, we should see direct evidence of racial discrimination because that population presents a salient social, political and economic threat to Whites.

One of the main tenets of social threat is that state offices, including the whole of the criminal justice system, represent the expression of self-interest by powerful elites in society (Liska 1992). Crimes committed by non-powerful members of society (e.g., the poor, Blacks, etc) are viewed as more threatening than those committed by powerful members (e.g., the wealthy, Whites). Because the criminal justice system is comprised of and protects the interests of powerful members of society, the criminal justice system must respond more severely to threats by non-powerful members. Liska (1987: 77) summarizes the assumptions of the social threat hypothesis in regards to its conflict origins: "Hence, the conflict perspective asserts that the greater number of acts and people threatening to the interests of the powerful, the greater the level of crime control – the threat proposition." More recent social threat researchers (e.g., Arvanites 1992; Carmichael and Kent 2014; Chamlin 1992; DeFina and Hannon 2009; Liska et al. 1999; Welch and Payne 2010) extend the social threat perspective to other systems in society, such as the educational, housing, mental health and welfare systems, and police force size.

Historically, researchers used the size of the Black population in an area to capture racial, political and economic threat since Blacks are also typically politically and economically disadvantaged. More recent researchers argue that the size of minority population should not be the sole measure of social threat (Eitle et al. 2002). With increased size of the Black population come increased economic threats to Whites, political power threats and increased fear of Black crime, especially interracial crime committed by Blacks[15]. While earlier social threat theorists address these dimensions (e.g., Blalock 1967 and Liska 1992), few attempts have been made to

[15] Measuring fear of increased Black crime is beyond the scope of this research as fear is a distinctly micro-level phenomenon. Thus, size of Black population will be used primarily as a measure of racial threat.

formulate distinct economic, political and racial threat hypotheses from the overall size of the minority population (Eitle et al. 2002: 558). To accurately examine sources of social threat, Eitle et al. (2002) argue that these three factors (racial, economic, and political threat) must be separately and distinctly measured and examined rather than being collapsed into the size of the minority population. Thus, I will address the findings of each form of threat separately.

II. Racial Threat

Racial threat is a distinct function of minority population size. An increase in the size of the Black population raises White residents' fear of a general crime rate increase, and especially a specific increase in interracial crime. For example, a White anticipates that not only will Blacks moving into a neighborhood increase the crime rate by robbing each other, but they will also rob me (see Liska et al. 1982: 762 and Lizotte and Bordua 1980). Many White residents in the United States associate African-Americans with higher crime rates in general (e.g., Downs 1973; Quillian 1995; Qullian and Pager 2001). When studying the effects of racial stereotypes on perceived crime rates, Quillian and Pager (2001:749) find that "whites (and Latinos) systematically overestimate the extent to which percentage black and neighborhood crime rates are associated; this association persists even when official crime rates are controlled." Additionally, when studying stereotypes and perception of Black crime, Gilliam et al. (2002) find that neighborhood racial composition matters. When shown stereotypical images of Black criminals in television news, Whites from majority White neighborhoods expressed more punitive views of the criminals and more negative views of Blacks overall than Whites from racially mixed neighborhoods. This clearly shows that Whites are more likely to associate percent Black with a higher crime rate, despite other evidence to the contrary. Sampson and Raudenbush (2004) find that this perception is not limited to Whites.

As the African-American population increases, **all** races perceive an increase in the level of crime in an area.

Negative beliefs about African-Americans can also influence punitive attitudes, which could be interpreted that individuals may be more likely to commit prejudiced actions if threatened. King and Wheelock (2007) find that punitive attitudes towards criminals increase as more Blacks move into an area. Further, they found the effect to be particularly salient regarding the negative attitude that Blacks are a threat to economic resources rather than a threat to increasing crime. That is, punitive attitudes towards criminals were the strongest when an individual holds a belief that Blacks "take away resources that should go to others, like jobs or welfare" (King and Wheelock 2007: 1266).

Further, an increase in the size of the African-American population in an area is a cue that crime rates will also increase, prompting Whites to leave the area. Research by Liska and colleagues (e.g., Liska and Bellair 1997; Liska et al. 1998) illustrates that this formulation may be too simplistic. In fact, the relationship between racial diversity and level of crime in a given area is reciprocal. As Blacks enter a predominantly White area, some Whites leave due to *fear* of rising crime. However, the real "White-flight" occurs after a *measured* increase in crime is observed.

Many researchers consistently find a relationship between the size of minority population and increased formal social control measures (Liska 1992). For example, a relatively large Black population is linked to police size (Carmichael and Kent 2014; D. Jacobs 1979; Kent and D. Jacobs 2005; Liska et al. 1981), private police size (D'Alessio et al. 2005), police officer killings of Blacks (D. Jacobs and O'Brien 1998), increased arrests (Beckett et al. 2006; Liska and Chamlin 1984), and increased severity of sentencing (Caravelis et al. 2011; Myers 1990; Schlesinger 2011; Stolzenberg, D'Alessio and Eitle 2004). On the other hand, Parker et al. (2005) find that a sizable

Black population and an increase in Black in-migration *decreased* the race-specific arrest rates for Blacks; however, the indicators of racial threat were significant for Blacks, but not for Whites.

D'Alessio and Stolzenberg (2003) also find that race does not play a role in the disproportionate number of Black offenders in the criminal justice system. In fact, Whites were more likely to be arrested for violent offenses than Blacks. The authors offer two alternative explanations for this unusual finding: 1) the possibility that Blacks are disproportionate participants in crime, rather than police employing racially discriminatory policies; and/or 2) police typically rely on witness reports of crime and Black victims are much less likely to cooperate with police than are Whites (the authors cited Sherman 2002 and Weitzer 2000 to support the second argument).

Second, Black in-migration increases the fear of more crime in general and more interracial crimes in particular. In Illinois, Lizotte and Bordua (1980) find that proximity to Blacks in a neighborhood did increase a respondent's fear of crime and perception of crime in their neighborhoods. Quillian and Pager (2001) find that neighborhood racial composition is a significant predictor of residents' perception of neighborhood crime rates, even controlling for the actual level of crime in the area and other criminogenic characteristics. Additionally, crime between different racial or ethnic groups may be more threatening than intra-racial crime (Liska et al. 1982). Liska et al. (1982: 767) find that Whites typically fear interracial crime and that "percent nonwhite and segregation are important structural characteristics because they influence the level of interracial crime."

An increasingly multi-racial population should also provide more opportunities to commit interracial crime in general and racially motivated hate crimes in particular. Blau (1977) argues that increased racial heterogeneity in an area leads to more interracial contacts, both positive

(Blacks and Whites in the workforce) and negative (interracial crime). Hence, an area with a relatively higher number of Blacks will have a higher level of interracial criminal incidents because Blacks and Whites come into more frequent contact. Blau's ideas have been supported by research on interracial crime in general (e.g., Sampson 1984, South and Messner 1986).

Stolzenberg, D'Alessio and Eitle (2004) provide a multilevel test of the relative size of Black population and the probability of arrest for violent crimes. This study is particularly interesting because it represents one of the few multilevel tests of social threat hypotheses. Using NIBRS data, the authors examine the size of the Black population and economic competition between Blacks and Whites in 182 cities in the year 2000 utilizing micro-level characteristics (such as offender race, additional offenses committed during the primary offense, victim injury and victim-offender relationship) in order to determine the micro-level indicators of threat that affect the likelihood of arrest. Further, they also examine macro-level characteristics, such as the size of the Black population, the ratio of Black-to-White unemployment and racial segregation, in addition to other general macro-level factors that influence race-specific arrest rates (e.g., crime rate, population density, whether the city is located in the South or not, etc).

Stolzenberg, D'Alessio and Eitle (2004) find mixed support for the racial threat argument. First and most important, the relative size of the Black population has a *negative* effect on probability of arrest, net of relevant micro- and macro-level predictors. In other words, a Black person has a lower chance of being arrested in a city with a large Black population. Second, the authors find that racial segregation appears to be a factor in Black arrests: in highly segregated cities, Blacks are more likely to be arrested, suggesting that racial segregation may be more important than size of the Black population. Interracial crimes also result in increased arrest, which is a key feature of hate crimes and finally, economic predictors have a null effect on arrest.

In terms of racial heterogeneity and bias crimes, Green et al. (1998a) present the first test of racially motivated crimes as a response to increased size of African-American, Asian and Hispanic populations in New York City. Here, the authors test three[16] main assumptions about the size of the minority population as a threat to White dominance. One assumption is that as the minority population grows larger, Whites attempt to assert dominance by increasing social control (e.g., studies of lynching in the south after the Civil War by Tolnay and Beck 1995). That is, the relationship between the size of the minority population and attempts at control is linear.

Green et al.'s (1998a) second assertion is based on Blalock (1967). The authors state that White intolerance is high when the Black population is large enough to threaten the social, economic and political dominance of Whites (or Blalock's (1967) power-threat hypothesis). Some researchers have interpreted this as a linear relationship between size and control, while others have interpreted this to mean a curvilinear relationship. In other words, when the Black population is very small, there is little threat to White dominance; when it is very large, Whites have probably fled the area and so Blacks are dominant. It is when the Black population approaches parity with Whites that we would expect an increased social threat, thus, an increase in bias motivated crimes of Blacks by Whites (e.g., South and Messner 1986).

The final test is derived from J. Levin and McDevitt (1993). They suggest that the greatest number of bias crimes will occur in areas where Blacks make up very small percentages of the population. In predominantly White areas, Whites are able to assert their dominance over Blacks with little fear of reprisal. Thus, size of the Black population may have differing effects on the level of bias crimes in an area. In terms of bias crimes, the most likely hypothesis is a negative relationship between size of the Black population relative to the White population and number of

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[16] Green et al. (1998a: 374-75) also test for a fourth "tipping hypothesis;" that the Black population must reach a certain percentage of the population (usually 25%) before attempts at social control are implemented.

anti-Black hate crimes. When there are zero Blacks living in a city, there should be zero anti-Black hate crimes; however, when Blacks begin movement into a predominantly White city, there should be a very high number of anti-Black bias crimes. The number of anti-Black bias crimes should decrease as more and more Blacks move into the city (and more Whites flee the city)[17].

Using New York City data, Green et al. (1998a) find that anti-Black, anti-Asian and anti-Hispanic crime increase when these populations moved into historically stable predominantly White areas; however, they do not find evidence of increased anti-White bias crimes committed by these populations. Thus, it is "the extent to which newcomers [minorities] cross into areas where Whites have traditionally been numerically dominant" (Green et al., 1998a: 391) that most affects White on minority bias crimes in an area. The authors are able to determine this by creating an interaction variable of minority in-migration and percent White population. This finding is also supported by Grattet (2009).

Grattet (2009) examines social disorganization and defended neighborhoods theories in Sacramento, CA. Defended neighborhoods/communities is very similar to social threat, but focuses on neighborhoods as the unit of analysis. His findings suggest support for both social disorganization and defended neighborhoods. That is, bias crimes are more likely to occur where there are higher levels of residential turnover and concentrated disadvantage (Grattet 2009: 147). However, Grattet (2009) finds support for Green's second assertion. Bias crimes are more likely to occur in neighborhoods with a majority White population that experienced an in-migration of non-White residents. This finding holds when residential turnover and concentrated disadvantage are held constant. For anti-Black bias crimes in particular, only concentrated disadvantage remains a significant social disorganization predictor and the interaction between non-white in-migration

[17] For this research, I tested for a curvilinear relationship in size of Black population (Blalock 1967) and did not find evidence that one existed, so a linear relationship is assumed.

and percent white remains a significant defended neighborhoods predictor. This latter finding supports the idea that Whites commit anti-Black offenses in response to an increased threatening population. It is important to note as well that both defended neighborhoods and social disorganization variables are salient predictors of anti-Black bias crimes.

The racial composition of the population may affect anti-White bias crimes in terms of retaliatory bias crimes (McDevitt et al. 2002). Some hate crimes may be committed to defend a specific territory from invasion by outsiders and others may be committed in retaliation against a perceived or actual hate crime committed against other Blacks in the community; however, these should not be related directly to the size of the Black population. Neither Green et al. (1998a) nor Lyons (2007) find evidence to support retaliatory hate crimes.

In a test of anti-White and anti-Black hate crimes in Chicago, Lyons (2008) did not find support for racial threat. Lyons (2008: 377) concludes that contrary to "predictions of traditional racial threat theories, anti-Black incidents are most likely when whites comprise larger proportions of the community population." However, anti-Black offenses were greater in majority White communities that experience an influx of Black in-migration. Lyons (2008) attributes this to the defended communities perspective. I argue that the defended communities perspective is a variant of the social threat perspective – people, in one community/ neighborhood, act to defend their community from a threatening population. His finding does not contradict the validity of using social threat in general or racial threat in particular as an explanation for hate crimes; however, his findings about relative size of Black population and anti-Black crimes are crucial.

Interestingly, anti-White hate crimes occur in different communities. Similar to his findings in 2007, Lyons (2008) again finds that anti-White hate crimes occur in racially heterogeneous communities. Further, he attributes these findings to two possible explanations: 1) racially diverse communities provide more interracial opportunities for contact, which also impacts the likelihood of anti-White crimes; and 2) anti-White crimes are correlated with anti-Black crimes and could possibly be retaliatory (e.g., McDevitt et al. 2003). Unfortunately, his data are not longitudinal so he cannot provide support for the latter explanation. Again, this research will control for the likelihood of interracial contact by using the Index of Dissimilarity, described in the next chapter.

III. Economic Threat

Economic threat emphasizes that competition for jobs and other scarce resources between Blacks and Whites will cause an increase in social control; furthermore, the relationship is likely to be non-linear (Blalock 1967). Economic threat cannot be easily disentangled from economic inequality or economic deprivation, which are typically associated with social disorganization and strain. However, the clearest way to measure threat versus inequality is to capture a ratio variable. When Whites are disadvantaged as compared to Blacks, that situation is particularly threatening to Whites and there should be a resulting increase in attempts at reasserting social control.

Since the relationship between income inequality and violent crime is fairly well documented in the general criminological literature (for examples see Blau and Blau 1982; Messner 1989; and Walker et al. 2011), it is more than reasonable to expect a relationship in the general criminality model. It is vital to make a distinction between the measurement of economic inequality and economic threat. The difference between economic threat and economic inequality can be summarized with the following idea: Levin and McDevitt (2002:29, italics in original) argue that "[t]hese [racial and ethnic] stereotypes best express anxiety among [White] Americans in general about *being able to compete for scarce resources* and moral outrage that a particular group might be getting *more than its share—'at my expense.'"* Thus, economic threat is not simply economic inequality, but the perception that the minority group is gaining advantages they do not deserve while the majority group is being forced to compete for resources to which they previously had open access.

Using time series analyses, Tolnay and Beck (1990) find a significant relationship between the cost of cotton and lynching in the southern United States between 1882 and 1930. The direct relationship diminishes when the authors control for price fluctuations in cotton, but the relationship is modified by increases in cotton production: with greater productivity in the cotton crop, the effect of cotton prices on mob violence against Blacks is reduced. This suggests that as long as the Whites were making money, the violence directed at Blacks decreased. Tolnay and Beck (1990) also find a strong direct effect of racial distribution of population: the larger the Black population, the greater the amount of lynching in an area; however, the authors dismissed the notion that an increase in lynching is a response to the increased threat of Black crime.

The authors report that the relationship between cotton prices and lynching remained stable and strong, even while controlling for crimes committed by Blacks. Thus, the authors suggest that economic forces are more significant than threat of Black crime when explaining lynching in the southern U.S. This finding was again stable in Tolnay and Beck (1992) when the authors examined the economic threat, political threat and threats to social position that southern Blacks posed to Whites. It is important to note that the authors were examining these threats during the Reconstruction period after the Civil War, prior to Blacks gaining the right to vote or hold political office; thus, their measure of political threat is the *size* of the Black population. The authors conclude that during the time period in question, it is "premature to accept *or* reject a political threat model of black lynchings" (Tolnay and Beck 1992: 40; italics in original).

Liska et al. (1985) describe a more complicated relationship between economics and increased arrests. The size of the police force (a variable representing the economic resources of an area) has a strong, positive effect on the ratio of arrests to crimes committed; however, when conflict variables are introduced into the equation (measures of segregation, income inequality, and percent nonwhite in the population), the economic resources variable becomes weak and non-significant. Liska et al. (1985:133) suggest that the relationship between economic conditions and crime may be spurious.

A study by Green et al. (1998b: 88) also finds a very unstable connection between hate crime (lynching in the southern U.S. 1882-1930 and anti-homosexual hate crimes in the present) and economic conditions:

> We have seen that the statistical link between hate crime and economic circumstances turned up in the case of lynching for just one time span (1882–1930), one measure of economic conditions (Ayres's index of national economic conditions), one measure of lynching (the log of lynching victims), and one test statistic (contemporaneous, as opposed to lagged, correlations). Alter, extend, or replicate this analysis, and the relationship evaporates.

In another test of bias crime and economic conditions, Green et al. (1998a) do not find a significant relationship between the White population's poor economic conditions and the frequency of anti-Black, anti-Asian and anti-Hispanic hate crimes in New York City. The authors argue that this represents a key difference for hate crime activity: organization. Green et al. (1998a: 398) suggest that prior links between economics and racist actions may reflect a coordinated and organized collective action (e.g., the Ku Klux Klan), while contemporary hate crimes are more likely to be uncoordinated actions. These diverse findings suggest that it is imperative to test the relationship between economics and anti-Black crimes; in one case, the effect of economics is spurious (Liska et al. 1985); in Tolnay and Beck (1990 and 1992), the effect of economics (cotton prices) is crucial and has a direct effect on lynching; and Green et al. (1998a and 1998b) find no definitive conclusion about the role of economic threat.

Carmichael and Kent (2014) examine the effect of racial threat and economic *inequality* on police force size in cities with more than 100,000 population between 1980 and 2010. Using a fixed-effects estimation approach, in which Census measures of race and economic inequality predict the following year's police size (e.g., 1980's Census predicts 1981's police size), the authors find that economic inequality is a robust and salient predictor of increased police force size. Further, racial threat alone has a non-linear effect: as the Black population increases to a point, police force size stops responding, possibly due to Black political pressure. Last, racial threat and economic inequality together produce an effect above and beyond racial threat and economic inequality alone.

IV. Tests of Multiple Forms of Threat

To my knowledge, there are no tests of political threat as the sole social threat explanation for crime in an area; however, more recent tests of the social threat perspective distinguish the effect of political threat from racial threat. Eitle et al. (2002) argue that many of the earlier tests of the social threat perspective make a critical error: they assume that the threat to political power of Whites, to the economic dominance of Whites, and fear of increased crime is encapsulated by the size of the minority population. The authors provide a more inclusive test by separating these factors into three distinct hypotheses: that Blacks provide a political threat, an economic threat, and an increased threat of interracial crime. Their dependent variable is the Black-to-White arrest ratio, indicating an increase in formal social control to each form of threat. Eitle et al. (2002: 570) find support only for the interracial crime threat (Black on Black crime does not increase the arrest ratio). Neither political threat (voter turnout) nor economic threat (log of Black-to-White unemployment ratio) has a significant effect on the arrest ratio (Eitle et al. 2002: 570-571).

D'Alessio et al. (2002) test the three forms of social threat as an explanation for interracial and intra-racial violent felony crime in South Carolina. To control for general crime predictors, the authors also include the divorce rate, population density, percent of population that is not White, high school dropout rates, and percent of families receiving Aid to Families with Dependent Children (D'Alessio et al. 2002: 400). Using county-level data for South Carolina from NIBRS, race-specific voting data and demographic data, the authors find that economic competition has a direct effect on the level of anti-Black violent crime. Equally important is the finding that economic competition does not have an effect on any other form of violent crime (Black on Black, Black on White or White on White). As discussed later, many other tests of economic inequality find significant associations between inequality and both interracial and intra-racial crime, although that effect is sometimes indirect (e.g., Messner 1989; Messner and Golden 1982; Messner and South 1986 and 1992; Sampson 1987; South and Messner 1987; and Shihadeh and Steffensmeier 1994). The authors find no link between political threat (measured as the ratio of Black-to-White votes in the general election) and any form of interracial or intra-racial crime. The authors suggest that this finding may be due to the fact that the percentage of Black voters did not eclipse White voters in either the 1992 or 1994 elections.

These analyses may be problematic. D'Alessio et al. (2004: 400) assert that population density serves as a measure of isolation, alienation and interracial encounters. Other research (see briefly: Alba, Logan and Stults 2000; Massey and Denton 1993) suggests that measures of interracial contact and segregation may operate somewhat independently of population density.

D. Jacobs and colleagues (D. Jacobs and O'Brien 1998; D. Jacobs and Wood 1999) illustrate how the social threat model helps to explain the use of deadly force by the police and interracial homicide. D. Jacobs and O'Brien (1998) examine whether the relative size of the African-American population, economic differences, and political inequality can explain police officer killings of Blacks. They find that cities with larger Black populations have higher rates of police killings of Blacks, which they attribute to the fact that African-Americans are traditionally viewed as a marginalized, threatening population to the White majority. They also find that the presence of a Black mayor reduces this effect, suggesting that a gain in political power by Blacks reduces the use of lethal force by police officers against Blacks. Interestingly, economic differences (measured by the GINI index) have no effect on police officer killings in general or of African-Americans in particular.

D. Jacobs and Wood (1999) examine interracial homicide rates in U.S. cities. They find that cities with greater economic competition between Whites and Blacks have higher rates of Whites killing Blacks and higher rates of Blacks killing Whites, suggesting that economic competition may be a critical factor in interracial homicide. Additionally, they find that a Black mayor reduces the amount of Blacks killing Whites, holding constant economic variables. This finding implies that political achievements by Blacks reduce the amount of Black interracial homicide. Neither political nor economic threat predicted the level of intra-racial homicide. The authors explain that these findings support the premise that areas with more political and economic competition will have a greater frequency of interracial crime.

Olzak (1990) also finds a relationship between the lynching of Blacks in the United States and political and economic power. While economic threat is a stronger predictor of violence against Blacks, political power via the Populist movement (which directly challenged White supremacy movements) also sparked an increase in the lynching of Blacks. As such, she argues that a model encompassing more than one type of threat (e.g., political and economic threat) is vital to the understanding of lynching.

While not a test of political threat, Burnett (2013) delineates how political pressure affects hate crimes in the UK. The article is more a review of the hate motivated crimes violence and the social, economic and political environs in which those crimes occur. Interestingly, Burnett (2013: 7) advises that the political climate acts more as a support for racism and racist acts of aggression:

> But in addition to these economic and social changes, a new 'common sense' racism is also permeating national policy-making and practice. It asserts that the UK is under persistent threat – from Muslims whose faith is deemed antithetical to its values and identity; from asylum seekers and migrant communities whose very presence threatens to impoverish it; and from black communities whose cultural mores are infecting it … It is a racism which is passed off as pragmatism and legitimised as economically and culturally necessary. This is the climate that fosters and sustains racial violence.

Burnett proposes an alternate explanation of how politics affect biased violence – the political climate may not directly affect bias crime but perhaps works to support racially and economically motivated threats. Unfortunately, this approach cannot be tested with this particular data since Burnett (2013) gives us little information about how to specifically capture and measure political threat.

V. Summary and Implications of Social Threat

Conflict theory and social threat are uniquely suited to explain the commission of bias crimes. The very definition of bias crime assumes some sort of conflict; however, the social threat perspective has not been adequately tested at the macro-level. The findings of social threat in regards to lynching (Tolnay and Beck 1992, 1995), interracial homicide (D. Jacobs and Wood 1999), interracial crime (D'Alessio et al. 2002), and the Black-to-White arrest ratio (Eitle et al., 2002) show that this perspective is a promising explanation for bias crimes. In particular, is it the threat of increased crime represented by a relatively large or increasing Black population, the economic threat of the Black population, or the political threat of the Black population that affects the level of violent bias crimes committed by Whites in a city? I will also address whether these conditions affect anti-White bias crimes.

Social threat does not present any arguments that would justify an increase in anti-White violent bias crimes based on population changes and economic or political gains for Blacks; however, McDevitt et al. (2002) find that some bias crimes are retaliatory in nature, suggesting that we may see this when we aggregate micro-level incidents to the city level. Neither Green et al. (1998a) nor Lyons (2007) find support for the retaliatory offender. It is important to note that Lyons (2008) does find that anti-White and anti-Black crimes *are* strongly correlated. Green et al. (1998a) and Lyons (2007) also report that anti-Black crimes are highest in areas with predominantly White populations, particularly when there is an increase in the number of minorities moving into a White neighborhood.

VI. Social Threat Model and Hypotheses

The social threat model implies that group conflict influences the level of crime and social control in an area; specifically, a large or increasing Black population, small or decreasing economic differences between Whites and Blacks or high or increasing Black political power is met with increased attempts at social control by the White majority. In particular, any Black progress will result in an increase in violent bias crimes committed by Whites. The model initially depicted in Chapter 1 reproduced below:

Indicators of Social Threat
(Racial, Economic and Political Inequality)

Anti-Black Violent Hate Crime
Anti-White Violent Hate Crime

Indicators of General Criminality
(Strain and Social Disorganization Predictors; General Dangerousness, Interracial Contacts)
Controls
(Democratic Voting, Political Competition, Region)

Social threat predictors explain increased social control independently of indicators of general criminality and social movement controls. While social threat does not provide a straightforward argument for anti-White bias crimes, it is plausible that Blacks react to powerlessness or commit retaliatory hate crimes. The hypotheses regarding anti-White bias crimes are not stated, unless there is a precedent for an effect from prior research. The model also controls for measures of general criminality and the general control variables of political climate and region. The hypotheses derived from racial threat are straightforward[18]:

ST_1: The relative size of the Black population will be positively associated with the level of anti-Black bias crimes, net of other factors.

In terms of past efforts, most research has supported a linear relationship between the relative size of population and attempts at social control; thus, H_1 is relatively simple to explain. Cities with larger Black populations should have higher levels of anti-Black bias crimes, although it is possible and likely that there is a plateau effect where increases in Black population no longer increase the numbers of the anti-Black bias crimes, suggesting a non-linear relationship (Blalock

[18] Measures will be described more fully in Chapter Four.

1967; Carmichael and Kent 2014). Since the size of Black population is also a vital social disorganization variable, it is important to capture the variable as operating as both a threat and general crime variable. Blau (1977) suggests that as the size of the Black population increases in an area, the opportunities to interact with other Blacks increases, thus anti-White crime should be low.

ST_2: An increase in size of Black population between 1990 and 2000 will be positively associated with the level of anti-Black bias crimes, net of other factors.

Changes in population composition may affect attempts at social control. Significant increases in the percentage of Black residents in a city between 1990 and 2000, or Black in-migration, should create a more threatening environment for White residents; thus, the number of anti-Black bias crimes should increase. The Census only provides detailed information about population changes every decade; a change over one decade is a reasonable indicator of the trend in racial composition for all of the years under investigation.

Again, it is unclear how Black population levels or changes in Black population will affect anti-White bias crimes.

ST_3: Cities with a larger percentage of the population that is White in 1990 will experience higher numbers of anti-Black bias crimes, net of other factors.

As Grattet (2008), Green et al. (1998a) and Lyons (2007) report, anti-Black bias crimes are more likely to occur in predominantly White areas. Thus, a city with a higher percentage of White population in 1990 is more likely to have anti-Black bias crimes. I keep the variable continuous to measure the effect of percentage changes, rather than create dummy variables for size of White population.

ST_4: A city where Blacks move into a predominantly White area will have higher numbers of anti-Black bias crimes, net of all other factors.

When Blacks move into predominantly White areas, anti-Black crime is higher (Grattet 2009, Green et al. 1998a and Lyons 2007). Thus, the interaction between the increase in percent Black population between 1990 and 2000 and percent White in 1990 is an important variable.

Economic threat proposes that there is a non-linear relationship between competition for jobs and other scarce resources. When inequality is at the extremes (that is, the economic dominance is clearly in favor of either Whites or Blacks), then there is little competition between races. It is only when the races approach parity in terms of economic competition that I expect to see high levels of bias crimes.

ST_5: As the ratio of White to Black poverty approaches parity and increases, there should be high counts of anti-Black crimes, net of other factors.

Economic threat and economic deprivation are very similar concepts. To my knowledge economic threat and economic deprivation have not been tested in the same research agenda prior to this dissertation. Thus, a distinction between threat and deprivation is crucial to this research. For the purposes of this research, economic threat occurs when Whites experience more disadvantage relative to Blacks (unemployment, poverty levels, etc). Economic deprivation is not race specific; it is the idea that those without resources experience more strain and commit more crimes, regardless of race. In other words, measures of economic threat are race-specific while measures of economic deprivation are not.

Economic threat is measured as the ratio of White to Black individuals living in poverty in 1990. In 1990, as the ratio of White to Black poverty approaches one (economic parity), then economic threat is high and anti-Black bias crimes should also be high. If the ratio exceeds one and Whites experience higher poverty relative to Blacks, then economic threat should be high and there should be a large number of anti-Black hate crimes. As the ratio approaches zero, then economic threat should be low and there should be a low or insignificant number of anti-Black hate crimes.

ST_6: As the ratio of White to Black unemployment rate approaches parity and increases, there should be high counts of anti-Black crimes, net of other factors.

In terms of economic conditions, cities where the ratio of White to Black unemployment rates is close to one, there should be a higher number of anti-Black bias crimes. As the ratio of White to Black unemployment continues to increase and more Whites are unemployed relative to Blacks, there should also be a higher number of anti-Black crimes. As the ratio approaches zero and fewer Whites are disadvantaged relative to Blacks, there should be a decrease in anti-Black crimes as Whites no longer need to assert social control.

ST_7: As the ratio of White to Black college degrees approaches parity and decreases, there should be high counts of anti-Black crimes, net of other factors.

Unlike unemployment and poverty, I expect that if the ratio of White to Black college graduates (including associates degrees, bachelor's degrees and any post-graduate degrees) is close to one or *decreasing* then anti-Black bias crimes should be high. As the ratio of White to Black college degrees increases, it shows that more Whites are graduating college relative to Blacks and therefore, Whites are not experiencing any disadvantage. However, as the ratio becomes less than one, fewer Whites are graduating college relative to Blacks and thus, Whites may be more likely to exert social control in the form of committing an increased number of anti-Black bias crimes.

Political threat will be measured by the presence of a Black mayor. While this is not a perfect measure of Black political power, D. Jacobs and colleagues (D. Jacobs and O'Brien 1998 and D. Jacobs and Wood 1999) have found that presence of a Black mayor does indeed affect interracial homicide and differential use of police force. Thus, I expect to see a relationship between the achievement of Black political power and anti-Black crimes.

ST_8: A city with a Black mayor in 1996 will have a higher number of anti-Black bias crimes than a city with a non-Black mayor, net of other factors.

Cities with Black mayors represent areas where Blacks have achieved political power; that is, Whites must work even harder to reassert social control (see Jacobs and Wood 1999). Thus, I expect to see a significant positive relationship between Black mayor and anti-Black bias crimes. I also expect to see fewer anti-White bias crimes, since Black mayor shows an increase in political power, indicating a reduced frustration among Blacks.

In sum, the size of the Black population in cities should have a direct, positive relationship with anti-Black bias crimes, particularly the change in Black population between 1990 and 2000. Cities with higher percentage White populations should experience higher levels of anti-Black bias crimes, particularly when there is an increased in-migration of Black citizens. Cities with higher ratios of White to Black poverty levels and unemployment should experience higher levels of anti-Black bias crimes. Cities where fewer Whites graduate college relative to Blacks should experience higher levels of anti-Black bias crimes. Finally, cities with Black mayors should have higher levels of anti-Black bias crimes than cities with non-Black mayors; cities with Black mayors should have lower anti-White bias crimes; and cities with non-Black mayors should have higher anti-White bias crimes.

Chapter Four. Data and Methods

Chapter Four provides an overview of the research design, including detailed descriptions of the component data sets, the final file structure and the variables used in this research. Additionally, I describe the data management techniques, the statistical methods used and the credibility and limitations of this particular dataset and research.

I. Datasets

The Uniform Crime Reporting Program[19] (UCR) is the first government-sponsored program to collect and publish hate crime statistics. The data analyzed for this research are compiled between the years 1996 and 2000. McDevitt et al. (2003) report the UCR began collecting hate crime statistics voluntarily from agencies in 1991, the year following the passage of the HCSA. Compliance with the law steadily increased until 1996, when it peaked and then declined slightly in the years following. Additionally, the original HCSA mandated hate crime data collection for only five years. In 1996, the Church Arson Prevention Act amended the hate crime data collection requirement to "each calendar year" (FBI, 1999). In order to obtain the most consistent sample, the year 1996 is the logical choice for the starting point of this research since that is the first year that the data were mandated to be collected annually. The UCR also provides the measure of region using the Census classifications and the measure of general dangerousness of an area, i.e., the violent index crime rates for each city in 1996 (the baseline year for this research).

[19] U.S. Dept. of Justice, Federal Bureau of Investigation. UNIFORM CRIME REPORTING PROGRAM DATA [UNITED STATES]: HATE CRIME DATA, 1996, 1997, 1998, 1999, 2000 [Computer file]. Compiled by the U.S. Dept. of Justice, Federal Bureau of Investigation. ICPSR ed. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [producer and distributor]. ICPSR study numbers 23841, 23840, 23821, 23800, and 23783, respectively.

I chose the year 2000 as the end point because by the year 2000, 90.1% of all agencies voluntarily reported hate crime data in all four quarters of the hate crime data collection period (FBI, 2000). While this certainly indicates a high level of compliance, a persistent criticism of the UCR's hate crime data collection effort is inconsistent reporting of hate crimes by agencies. Grattet (2009) and McDevitt et al. (2003) maintain that police agency training, departmental deficiencies and other practices make consistent reporting across jurisdictions impossible. There is also evidence to suggest that even within large, urban police departments, there may be variation in the recordation of a crime as bias motivated (Berk, Boyd and Hamner 1996). Further research by Lyons and Roberts (2014) finds that hate crimes, generally speaking, are less likely to result in arrest than non-bias crimes; however, White-on-non-White racial and ethnic bias crimes are equally likely to clear as non-biased offenses. This suggests further that officer training and political awareness of or sensitivity to racially motivated bias crimes plays an important role in the policing of hate crimes.

While police department procedures are outside the scope of this dissertation, the likelihood that police procedures affects quarterly and yearly reporting of data to the UCR remains. Thus, some measure of control over consistent reporting must be created and analyzed of the data reporting. Years reporting data to the UCR is the most effective method of controlling for differential police reporting. While years reporting cannot adequately capture police practices, and in all likelihood, it captures more than only compliance with reporting requirements, it is the most effective way to control for such compliance. Since years reported also possibly reflects police training, willingness to comply with legislation, along with various unmeasured variables, such as police department size, ability to report federal data given state hate crime data collection requirements, and other unknown variables, it is controlled for but not interpreted as a viable predictor.

Despite the voluntary nature of the reporting, I selected the UCR to obtain a larger and more complete sample of cities and to get a more accurate reflection of hate crimes that occur across the entire United States. While the other official data set – the National Incident Based Reporting System (NIBRS) – is more reliable in that reporting hate crime data is mandatory, NIBRS has been criticized for under-representing larger cities and over-representing rural areas. Other sources of data collected by advocacy groups are criticized for being biased. While there are certainly problems with studying hate crimes across multiple jurisdictions due to differences in hate crime laws, high numbers of agencies reporting zero hate crimes, differences in police hate crime investigation techniques and training, and political climate (see Nolan, Akiyama and Berhanu 2002 and McDevitt et al. 2000 for a full discussion), the UCR is still considered to be the most accurate source of national bias crime data available to researchers at this time.

Most researchers agree that while it remains imperfect, the UCR is the most representative source for hate crime data in the United States. For example, McDevitt et al. 2003 (13-14): report that agency participation has increased with hate crime reporting through the UCR, but note that while "submitting zero bias incidents may accurately reflect the number of bias crimes in many jurisdictions, it may be a low figure for some jurisdictions, particularly in larger more diverse communities." Perry's (2001) criticism of official data holds for the UCR: the data may be numerically imprecise but provides enough information to generate and analyze hate crime patterns across jurisdictions. For this research, the unit of analysis is place (or city); thus, I am aggregating the incidents and Originating Agencies by Census place code.

Since the UCR have county and state Federal Information Processing Standards (FIPS) codes but do not contain place FIPS codes, I must use the Law Enforcement Agency Identifiers Crosswalk[20] to merge the UCR with the US Census. The Crosswalk contains the originating agency identifier number (ORIs) from the UCR and FIPS state, county, and place codes from the Census dataset. These variables allow researchers to combine the incident level data of the UCR with place-level Census data.

In order to compare racially motivated bias crimes to racially disaggregated violent crime not motivated by bias, homicide data from the Supplemental Homicide Reports (SHR)[21] for the years 1996-2000 are used as the non-biased dependent variable. Because the UCR does not contain detailed offense, offender or victim data for non-bias offenses, the SHR is used as a comparable measure of non-bias violent crime. Again, incidents are aggregated to the city level and are merged with the US Census data using the Crosswalk file.

The data from the US Census comes from the Census of Population and Housing Summary Tape File 3A for the year 1990[22] and Census of Population and Housing Summary File 3 for the year 2000[23]. These Census files contain detailed demographic information from a weighted sub-sample of the US population and include information on education, income, household status,

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[20] U.S. Dept. of Justice, Bureau of Justice Statistics. LAW ENFORCEMENT AGENCY IDENTIFIERS CROSSWALK [UNITED STATES], 2000 [Computer file]. ICPSR ed. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [producer and distributor], 2004. ICPSR study number 4082.

[21] U.S. Dept. of Justice, Federal Bureau of Investigation. UNIFORM CRIME REPORTING PROGRAM DATA [UNITED STATES]: SUPPLEMENTARY Bibliographic Citation: HOMICIDE REPORTS, 1996, 1997, 1998, 1999 & 2000[Computer files]. Compiled by the U.S. Dept. of Justice, Federal Bureau of Investigation. ICPSR ed. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [producer and distributor], 2001. ICPSR study numbers 9028, 9028, 2906, 3162 and 3448, respectively.

[22] U.S. Dept. of Commerce, Bureau of the Census. CENSUS OF POPULATION AND HOUSING, 1990 [UNITED STATES]: SUMMARY TAPE FILE 3A [PUERTO RICO] [Computer file]. Washington, DC: U.S. Dept. of Commerce, Bureau of the Census [producer], 1993. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor], 1999. ICPSR study number 9782.

[23] U.S. Dept. of Commerce, Bureau of the Census. CENSUS OF POPULATION AND HOUSING, 2000 [UNITED STATES]: SUMMARY FILE 3, NATIONAL [Computer file]. Washington, DC: U.S. Dept. of Commerce, Bureau of the Census [producer], 2002. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor], 2002. ICPSR study number 13396 (national).

employment and poverty status for different racial groups in the US. The Census provides the general criminality independent variables in my analyses.

Data about race of mayor[24] comes from the Joint Center for Political and Economic Studies (JCPES). I created a data file from photocopies of all Black mayors in the states included in my sample for 1990. To my knowledge, JCPES is the only agency to collect information about Black Elected Officials in the US. The mission of JCPES is to "improve the socioeconomic status and political participation of people of color"[25]; they do not collect information about race of elected officials *unless* they are African-American. Therefore, race of mayor is a dichotomous variable: Black or non-Black. Last, JCPES only collects data about race of elected officials for cities with populations of 50,000 or larger.

Data for democratic voting is compiled from *America Votes* volumes 20, 22 and 24 for the Presidential elections in 1996[26]. McVeigh et al. (2003) hypothesize that democratic counties are more likely to enforce hate crime legislation, but this effect is only found in conjunction with civil rights organizational resources. Because this research is examining actual hate crime occurrences versus compliance with hate crime legislation, it is possible and even likely that cities which reside in Democratic counties are more likely to report and record hate crime statistics[27]. However, McVeigh et al (2003) report that political competitiveness in a county also captures political pressure to comply with hate crime legislation. A politically competitive county is one in which

[24] The data is actually collected as "Black Elected Official." I limited the data to include only "mayor." Some cities do not have mayors; they may have a city administrator or city manager. I did not include these as these positions may or may not have the same level of political power as a mayor would. Additionally, mayors who are appointed by a council are not included in the JCPES data since they are not elected positions.
[25] JCPES website. http:jointcenter.org/about/about. Accessed 07.15.2014.
[26] The year 1996 was chosen because: a) it is a Presidential election, so comparisons can be made across jurisdictions; and 2) it serves as the baseline year for the sample.
[27] Cities or towns that reside in two or more counties were coded as "not applicable" for this variable. There is no simple method to determine how to calculate how much of county A versus county B (or C) affects one city's voting process.

the voting population is almost equally split between Republicans and Democrats. In other words, politically competitive counties are ones in which Republican candidates may have to illustrate compliance with more Democratically held principles, like hate crime legislation, in order to win popular elections. After running the models with percent voting Democrat, percent voting Republican political competitiveness and *all* measures, I determined that neither percent voting Democrat nor percent voting Republican reached significance. Therefore, the variables are excluded to maintain the best specified model. Political competitiveness does reach significance and so I am confident that it captured the effect of political environments on hate crime reporting.

II. Sampling Procedures

First, I limit my analyses to agencies that have reported any bias crime data, whether that is a zero report or an incident report, to the UCR in at least one quarter of one of the years included in the study (1996-2000). The main criticism of official bias crime data is that it is often unreliable and inconsistent (Grattet 2009, J. Levin and McDevitt 2002 and McDevitt et al. 2003). On the other hand, bias crimes are very rare events and limiting the data so that there is consistent reporting during all four quarters of every year throughout five consecutive years in the study will eliminate many cases. Balancing the two needs of reliable data and sufficient cases requires flexibility. To solve this problem, I ran multiple analyses with different reporting criteria ranging from one report in any one quarter of any year in the study (6 cities reported data for only one quarter of one year in the sample), all the way through reporting in all four quarters for all five years of the study (218 cities, or 60% of the sample) to see how these restrictions affect the outcome of the analyses. Additionally, I annualized the data so that comparisons can be made across cities.

Second, I limit the analyses to violent bias crimes. Using NIBRS, Strom (2001) found that well over half of all hate crimes were violent crimes. The UCR hate crime collection considers the following as hate crimes against persons (violent crimes): murder and non-negligent manslaughter, forcible rape, aggravated assault, simple assault and intimidation[28].

In terms of city size, I limited the sample to cities with a population of 50,000 or more. This left a sample size of 521 cities. Prior research shows that bias crimes are more likely in less populated areas; however, for a macro-level study, a sufficient population size is necessary in order to optimize statistical relevance and generalizability. Bias crimes are rare events and may be unlikely in cities where there is not a significant Black population. Therefore, I limited the sample to cities with a Black population of 1,000 or more in 1990, leaving me with 415 cities. After a listwise deletion of missing cases, my final sample size is 355 cities.

For the regressions involving non-bias homicides, the SHR includes cases with multiple victims and offenders. For these cases, the event is coded according to the primary victim-offender racial relationship. If the primary victim and primary offender are White or Black, the offense is included. If the primary offender is White or Black and one of the subsequent victims is Black or White, the offense is included. If the primary offender is not White or Black, the offense is excluded.

For the violent crime, bias and non-biased homicide regressions, I will use place-level information from the 1990 and 2000 US Censuses to create the general criminality predictors. Since the UCR data utilized in this research span from 1996-2000, the 1990 Census numbers are used as a baseline for population and other key variables. The 2000 Census data is used to determine if demographic changes affect bias crime levels. Finally, data from JCPES on race of

[28] The HCSA never defined nor addressed robbery as a hate crime; thus, it is not included in this analysis.

mayor and from *America Votes* for democratic voting were collected and incorporated into the sample after cities were selected.

III. Dependent Variables

For Model One, the dependent variable is the violent index crime rate for each city averaged between 1996 and 2000. The rates are utilized since violent crimes are not skewed and can be analyzed using Ordinary Least Squares (OLS) regression. Because bias crime and homicides are rare and are therefore skewed towards zero, negative binomial regression is utilized and therefore, the dependent variables are counts. The research is focused on explaining macro-level influences of violent bias crimes; therefore, the key dependent variables in Model Two are the counts of anti-Black offenses committed by Whites and anti-White offenses committed by Blacks. Because police agencies reported differentially, I need to adjust for the number of reporting periods to make the totals comparable across cities with differential reporting. I address this later in this chapter. For Model Three, the dependent variables are the counts of non-bias homicides with Black victims committed by Whites and non-bias homicides with White victims committed by Blacks. These dependent variables are constructed as the count of all incidents between 1996 and 2000.

It is important to note that the UCR hate crime data include only the race of offender, not the race of the victim; however, the UCR does indicate whether biased offenses were anti-Black or anti-White. While absolute certainty is not possible with the UCR data, I am comfortable assuming that the vast majority of anti-Black crimes involve a Black victim. Using the SHR, I eliminated all homicides with offenders of races other than Black or White; thus I can be certain that I am measuring Blacks killed by Whites and Whites killed by Blacks.

Table 1. Dependent Variables

Variable	Description
UCR 1996 - 2000	
Total violent index crimes per 100,000 population, adjusted for year (Model 1)	Rate of murders, non-negligent homicides, robberies, forcible rapes & aggravated assaults
Anti-White Bias Crimes, Black offenders (Model 2)	Count of anti-White bias crimes committed by Black offenders
Anti-Black Bias Crimes, White offenders (Model 2)	Count of anti-Black bias crimes committed by White offenders
SHR 1996-2000	
White – Black homicide (Model 3)	Count of homicides of Whites by Black offenders
Black – White homicide (Model 3)	Count of homicides of Blacks by White offenders

There are several reasons to limit the research to these two racial groups. First, hate crime researchers find that a clear majority of victims of violent bias crimes are Blacks, followed by Whites (Cheng et al. 2013; King 2007; Lyons 2008; Martin 1996; Messner et al. 2004; Perry 2001; Strom 2001; and Torres 1999). Second, Wilson and Ruback (2003) find that a majority of all hate crimes identified in Pennsylvania counties involved Blacks and Whites. The authors offer several factors to explain the finding. Anti-racial offenses, particularly anti-White and anti-Black offenses, tend to involve more violent personal offenses rather than property offenses, and personal offenses were more likely to incur more police involvement. Additionally, police responses were highest for anti-White and anti-Black offenses. The authors (2003: 392-3) suggest that "police officers may be more likely to label racial incidents as hate crimes than offenses against other groups" due to historical racial tension between the two races. Third, it is more difficult for an offender to visibly identify a person's religion, ethnicity, or sexual orientation than it is to identify a person's race. Thus, anti-racial offenses are more reliable than any other form of biased offenses. Last, most interracial violent crime research focuses on the differences between Blacks and Whites rather than the differences between all races.

IV. Social Threat Variables

Social threat includes three dimensions: racial, political and economic threat. To measure racial threat, the percent Black population from the 1990 Census is used[29]. Additionally, the percent change in Black population from 1990 to 2000 is tested to determine if population changes affect the number of bias crimes. According to social threat, the presence of a large Black population or an increase in Black population should be met with an increase in White on Black hate crimes.

Grattet (2009), Green et al (1998a) and Lyons (2008) find that the White population plays an important role in anti-Black violence. When Blacks move into traditionally White[30] areas, Whites respond by committing more anti-Black crimes. Thus, it is essential to test how White population affects the number of bias crimes, particularly anti-Black bias crimes. Therefore, interaction between Black in-migration and percent White is tested.

To measure political threat, the race of mayor in 1996 is taken from the JCPES. A Black mayor in 1996 indicates an increase in Black political power, which should be reflected by a larger number of anti-Black bias crimes. Logically, a city with a Black mayor in 1996 should predict a low count of anti-White bias crimes, whereas a city with a non-Black mayor in 1996 should result in a high number of anti-White bias crimes; however, studies of political threat are rare. D. Jacobs and Wood (1999) find that the presence of a Black mayor reduced interracial homicides of Whites

[29] As discussed earlier, percent Black is also an important social disorganization variable. The effect of percent Black while controlling for general violent crime rate is intended to capture social threat. The effect of percent Black not controlling for general violent crime rate reflects social disorganization processes as well as social control processes manifested in hate crimes.

[30] Green et al. (1998a) test two thresholds of White population. The low predominantly White population is defined as Whites comprising 50%-89% of the population. The high threshold is defined as Whites comprising as Whites comprising ninety percent or more of the total population. In his analyses, Grattet (2009) uses the thresholds of 60% and 90% White.

committed by Blacks, while D. Jacobs and O'Brien (1998) find that presence of a Black mayor reduces police officer killings of Black victims.

Economic threat is the perceived Black economic power by the White population. For this research, economic threat is captured using three variables. First, economic threat is measured as the ratio of White to Black individuals living at or below the poverty line established by the 1990 and 2000 US Censuses[31]. Using data from the 1990 and 2000 Censuses, I will compute the ratio of White to Black individuals of any age living in poverty. Lyons (2007) finds that economic disparity is negatively related to anti-Black bias crimes in Chicago[32]. His global measure of economic disparity is similar to the more specific measures of economic threat and economic deprivation used in this research.

Another measure of economic threat computed using the 1990 and 2000 Census is the ratio of White to Black males[33] aged 16-55 who are not employed in the civilian labor force – if the ratio approaches one or greater than one (Whites are experiencing similar or higher levels of disadvantage compared to Blacks), then economic threat should be at its highest and anti-Black bias crimes should also be high. A final measure constructed using the 1990 and 2000 Censuses is the ratio of White to Black education. As the ratio of Whites to Blacks who received an Associate's Degree or higher approaches 0 (Whites are receiving fewer degrees relative to Blacks), then economic threat should be high and counts of anti-Black bias crimes should also be high.

[31] The HHS poverty level for an individual in 1990 was 6,280 and in 2000, it was 8,350 (*Federal Register*, 1990 and 2000, respectively). In comparison, the Census poverty level (called a poverty threshold) for an individual in 1990 was $6,652 and in 2000, $8,794. The poverty threshold varies by age (under 65 or 65 and over) and number of persons over age 18 in the household and the number of related children in the household. See Appendix B and C for the 1990 Poverty Thresholds and 2000 Poverty Thresholds for the US Census.
[32] Lyons (2007) did not report how economic parity affected anti-Black bias crimes.
[33] The ratio of White to Black males aged 16-55 is used, primarily because females are less likely to participate in the labor force than are males (Reed and Udry 1973; Bureau of Labor Statistics, 1996-2000).

Social threat does not provide predictions for the effect of economic threat on anti-White crimes. As discussed earlier in Chapter Three, when the economic threat to Whites is high, anti-White crimes should be low since the Black population should recognize the relative economic parity.

V. General Criminality Variables

Both social disorganization theory and strain theory are instructive explanations for interracial violent crime. The central argument of general criminality is that hate crimes are not different from crimes not motivated by bias; hence, if the level of crime in an area is high, the level of hate crime will also be high. Thus, a measure of the level of general dangerousness in an area is an important control variable for the social threat models. For non-bias general crime, the UCR collects data for the following violent index crimes: murder and non-negligent manslaughter, forcible rape, robbery, and aggravated assault. This control variable will not be racially disaggregated; that is, the non-bias violent crime rate is calculated with victims and offenders of all races.

A second important control variable is the opportunity for interracial contacts. Without interracial contact, it would be unrealistic for racially biased crimes to occur. The most appropriate measure of interracial contact is the Index of Dissimilarity (Massey and Denton 1987), which measures the uneven distribution of Whites and Blacks in a city. I am using this as a measure for the likelihood of interracial contact due to residential segregation rather than a measure of inequality. The index is computed as:

$$D = 0.5 \sum_{i=1}^{n} \left| \frac{(b_i)}{B} - \frac{(w_i)}{W} \right|$$

where b_i is the Black population of each component census tract, B is the Black population for the entire city, w_i is the White population of each component census tract and W is the White population for the city (adapted from Massey and Denton 1987: 805-6). The dissimilarity index measures whether one particular group is distributed across census tracts in the metropolitan area in the same way as another group. A high value indicates that the two groups tend to live in different tracts, meaning that the likelihood of interracial contact is low. D ranges from 0 to 100. A value of 60 (or above) is considered very high. It means that 60% (or more) of the members of one group would need to move to a different tract in order for the two groups to be equally distributed. Values of 40 or 50 are usually considered a moderate level of segregation, and values of 30 or below are considered to be fairly low.

The remaining general criminality variables are drawn from either social disorganization or strain theory. These variables will act as independent variables for general criminality argument and as control variables for the social threat models. The strain variables are based on economic deprivation. It is important to note that previous literature does not differentiate the ideas of economic threat and economic deprivation. For this research, the distinction is crucial. As previously addressed, economic threat is based on the idea that, at some economic level, the Black population becomes threatening to White economic dominance. Economic deprivation is best explained that as economic inequality increases, anomie increases, which results in increased crime, *regardless* of the racial composition of the area. In other words, it is not racial differences in economic factors which drive crime, but inequality itself. Economic inequality is a direct cause of crime, net of race. Hence, following former research efforts, economic deprivation is included in a measure of concentrated disadvantage (Grattet 2009).

Concentrated disadvantage follows Sampson (1996), who argues that as separate measures of disadvantage increase in an area, they compound each other, making the total effect of the whole greater than the sum of its component parts. Concentrated disadvantage is captured using Principal Component Analysis (PCA) in STATA, and includes percent female-headed households, percent of White and Black individuals under the poverty line and percent of White and Black males aged 16-55 unemployed or not in the labor force[34]. Grattet (2009) found that concentrated disadvantage impacts all bias crimes and anti-Black bias crimes in particular. Interestingly, Lyons (2007) found that anti-Black hate crimes are more likely to occur in affluent, socially organized communities while anti-White crimes are more likely to occur in socially disorganized communities. This suggests that the general criminality causes of anti-Black crime may differ from anti-White crime.

The traditional social disorganization model proposes that racial heterogeneity, high levels of high risk populations (in this research, the young), and high residential mobility disintegrates the level of social control in an area, which in turn increases crime. Again, it is important to note that previous literature does not differentiate between racial heterogeneity and racial threat. Thus, the percent Black in a city is used both as a measure of social disorganization and as a measure of social threat. While an increase in percent Black between 1990 and 2000 could also be conceptualized as a measure of social disorganization, it is treated more as a predictor of racial threat since it best captures *threat*, which is difficult to quantify.

Since it did not lend itself to the measure of concentrate disadvantage, percent young (ages 13-24) is captured as its own measure. Youthful offenders are traditionally associated with both

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[34] Percent Black and percent receiving public assistance are also typically included in a measure of concentrated disadvantage. Since racial threat is its own distinct measure, percent Black is kept as its own predictor. Percent receiving public assistance was not reliably measured between the 1990 and 2000 Censuses: namely, social security benefits were included in the 1990 Census as public assistance, whereas SSI benefits were captured separately in the 2000 Census. Percent young is also typically included, but did not load in the PCA for this sample.

violent and property crime. Crime is disproportionately committed by the young; hence, the more youthful the population, the more potential criminal offenders, both general and biased offenders.

Other readily available variables in the Census include rental properties and percent moved in the last 5 years. Lyons (2007) finds that anti-White hate crimes are more likely in socially disorganized communities with high population turnover. Following Lyons (2007), a measure of population instability is percentage moved in past five years[35]. Furthermore, I calculated percent rented dwellings as a traditional social disorganization variable. A high percentage of rental housing reflects a higher likelihood of residential turnover, thus indicating a low level of social control and a high level of social disorganization in an area. A higher percentage of rental properties in a city should indicate a high level of social disorganization. Cities with high percentages of the population who have moved in the past five years and high percentages of rental properties should have higher levels of bias (at least anti-White bias crimes) and non-bias violent crimes. On the other hand, areas with low population turnover and low levels of rental properties should have lower levels of all forms of violent crime, although it is possible that anti-Black crimes are higher in these neighborhoods.

VI. Control Variables

Possibly the most important control variable is the violent crime rate in 1996. This allows me to determine if the general level of dangerousness in an area explains the occurrence of bias crimes. If the independent variables exert any explanatory power on bias crime controlling for the general violence in an area, then we can be more confident in the results.

[35] The percent moved variable was drawn from the 2000 data set. This should accurately capture residential turnover for the period of 1996-2000. Using the percent moved from the year 1990 is not informative.

Another crucial alternative explanation for macro-level differences in hate crime victimization is social constructionism. As discussed earlier, hate crime laws are interesting in that they are partly the result of social movements. In particular, McVeigh et al. (2003) find that democratic and politically competitive counties are far more likely to enforce hate crime legislation than are non-democratic, non-competitive counties. The authors assert that activist organizations promoting hate crime awareness are closely tied to the Democratic party and are thus more effective in counties voting Democratic. In terms of political competition, McVeigh et al. (2003) argue that, if pressured by activist organizations, political actors are more likely to support and actively promote hate crime enforcement as a key issue in a politically competitive environment (one where there is competition for votes between Republicans and Democrats) than in areas that are less politically volatile.

King (2007) also finds that region affects the relationship between size of the Black population and compliance with hate crime legislation. The larger the Black population, the higher the compliance with hate crime laws in the Northeast, but the opposite relationship is found in the South. King explains that the South has traditionally had more interracial problems and this climate may affect the organizational application of law, including the identification and reporting of bias crimes by police officers. Police officer training is affected by social movements. It is also important to account for the region in which a city is located. At the extreme, perhaps *only* democratic, politically competitive cities in the non-South report hate crimes to the UCR; thus, any relationship between social threat and/or general criminality is dependent on the political tendencies in a city. Therefore, it is important to test for an interaction effect between region and percent voting democratic and region and political competition. To address King's (2007) findings about the effect of region, I created a dummy variable to control for the effect of a city's region, that being its location in the South or not South[36].

In order to control for the social constructionist argument, I use county-level data from *America Votes* for the 1996 Presidential election since place-level data is unavailable. The year 1996 is examined solely rather than 1992, 1996 and 2000 for several reasons. First, in 1992 and 2000, viable third party candidates (H. Ross Perot and Ralph Nader) took a rather significant portion of the votes from the two major political parties. There is no way to control for or isolate how a third party vote may affect voting. Second, 1996 is the baseline year for the dependent variables.

McVeigh et al. (2003) found that counties that are more politically competitive are more likely to strictly enforce hate crime legislation. The rationale behind this idea is that political actors are more likely to respond to activist pressures in a competitive environment than in a non-competitive environment. Following McVeigh et al. (2003: 853), the mean of the absolute difference between percentage of Republican voters and percentage of Democratic voters is multiplied by –1 so that higher scores indicate more politically competitive counties. The data for a city's region is readily available in the UCR dataset.

[36] Southern states included are: Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia, West Virginia and Washington, DC. There were no cities in Delaware that met the selection criteria.

Table 2. Independent and Control Variables

Variable	Description
UCR Measure, 1996	
Violent Crime Rate	(Number of murders, non-negligent homicides, robberies, and aggravated assaults)/100,000 population
Census Measures, 1990 & 2000	
Total city population	Total number of all persons, regardless of race
Likelihood of interracial contact	Index of Dissimilarity (equation in text) for each city in 1990 and 2000
%Black 1990	(Number of Black persons/Total population) x 100
Change in %Black (In-Migration)	%Black 2000 - %Black 1990
%White 1990	(Number of White persons/Total population) x 100
Interaction of Black in-migration and percent White population in 1990	(%Black 2000-%Black 1990) x %White 1990
Ratio of White to Black poverty	(Number of White persons below Census poverty line/Total population) / (Number of Black persons below Census poverty line/Total population)
White to Black unemployment	(Number of White males aged 16 and over who are not employed in the civilian labor force/Total population) / (Number of Black maless aged 16 and over who are not employed in the civilian labor force/Total population)
Ratio of White to Black associate degrees or higher	(Number of White persons over age 16 with associate degree or higher/Total population) / (Number of Black persons over age 16 with associate degree or higher/Total population)
Concentrated disadvantage	Principal components analysis of: percent female-headed households, percent of White and Black individuals under the poverty line, and percent of White and Black males unemployed or not in the labor force
% Rent 1990	(Number of occupied housing units that are owned / Total number of occupied housing units) x100
% Moved past 5 years (2000)	(Number of individuals ages 5 and over who moved between 1995 and 2000 / Total number of individuals ages 5 and over) x 100
%Young	(Number of residents aged 13-24 / Total number of residents) x 100
UCR 1996	
Violent crime rate (per 100,000 persons)	Number murders, non-negligent homicides, forcible rapes & aggravated assaults / per 100,000 persons in population
South	Categorical variable coded 1 if south, 0 if non-south
Joint Center for Political and Economic Studies	
Race of mayor 1996	Categorical variable coded 1 if Black, 0 if not Black
America Votes, 1996	
Political competitiveness	Mean |%Republican - %Democratic| x -1

VII. Data Management and Statistical Models

Model One is a general model that estimates the effect of general criminality predictors on the number of non-bias violent crime for the years 1996 – 2000. The purpose of this model is to test the effectiveness of my sampling procedures and to provide a baseline effect of the general criminality argument:

General Crime Indicators:

(% Black, % rental, % moved past5 years, % young, concentrated disadvantage) $\longrightarrow$ Non-bias violent crimes

The social threat model predicts that indicators of racial, political and economic threat remain strong and significant predictors of bias crimes, net of general crime indicators. While social threat does not predict results for anti-White crime, it is nonetheless the most commonly used explanation for bias crimes. Thus, some variables may have different effects for anti-White bias crimes rather than anti-Black bias crimes. For instance, an increase in Black population should have an effect on the count of anti-Black crimes but not necessarily on the number of anti-White bias crimes. Lyons (2007) found that the size of the Black population was not a significant predictor of anti-White hate crimes.

The following full Model Two represents the social threat predictors and general criminality controls for anti-White and anti-Black violent bias crimes:

Racial Threat:
(% White population, increase % Black population, increase % Black X % White population in 1990)
Political Threat:
(presence of Black mayor)
Economic Threat:
(ratio of Whites/Blacks in poverty, ratio of White/Black unemployed, ratio White/Black education)

Anti-White Bias Crimes
Anti-Black Bias Crimes
[Interracial homicides]

General Crime Indicators:
(Violent Crime rate 1996, % rental, % moved 5 years, % young, concentrated disadvantage)
Social Constructionism Controls:
(Region, Political competitiveness, Index of Dissimilarity)

The presence of a Black mayor should have a *negative* effect on anti-White bias crimes. An increase in Black political power, represented by the presence of a Black mayor, decreases the number of interracial crimes committed by Blacks (D. Jacobs and Wood 1999), which should logically include anti-White bias crimes committed by Blacks.

It would also be logical to expect that economic threat variables have a negative or small effect on anti-White crime. As Black economic power increases, their threat to the White population increases, but this should not affect anti-White bias crimes. In fact, as Black economic mobility increases, there should be an increase in Black victimization but not in the *commission* of violent bias crimes. Green et al. (1998a) find that Blacks who move into primarily White neighborhoods increase their likelihood of becoming victims of bias crime, but they did not find an increase in retaliatory bias crimes committed against Whites by Blacks. Lyons (2007) supports these results for the city of Chicago. It is possible that this finding will also be reflected in city-level hate crimes.

Variations of this model are tested. First, general crime and control predictors are tested to determine a baseline level for anti-Black bias crimes and anti-White bias crimes (model A). Next, social threat and control predictors are tested without general crime predictors for anti-Black bias crimes and anti-White bias crimes (model B). Last, the full model is tested with general crime predictors, social threat predictors and control variables (model C).

In order to determine whether or not the social threat model is a consistent explanation, I test the effect of the social threat model on interracial homicides consistent with the research of D. Jacobs and Wood (1999). In Model Three, the dependent variable is the number of homicides from the SHR committed by Whites against Blacks and Blacks against Whites. According to the D. Jacobs and Wood (1999), the social threat model has successfully predicted interracial homicide, particularly White-on-Black homicide. If Model Three produces results consistent with this finding, then I can be more confident in my sampling procedures. Further, if Models Two and Three are consistent in that social threat remains the best explanation for both prejudiced and non-prejudiced interracial crime, then the value of social threat as an explanation for crime is furthered. Model Three is identical to Model Two, except it uses interracial homicides as a dependent variable.

VIII. File Formation

Because of the complexity of the hate crime data file in the UCR, parts of the file were automatically generated using the SAS software system while other parts were hand-manipulated using Microsoft Excel. First, the 1996-2000 UCR batch header files were downloaded. Each year was sorted by the variable AGENDIC, or Agency Indicator. To control for any effect that differences in police training, police funding or other political effect of agency, I limited the analysis to city police agencies and excluded county, state, university and any agencies that were coded as being "covered by" another agency. To be certain that only city agencies were included in the analyses, I sorted the file and deleted all agencies that were not coded as city agencies. I then merged the years 1996-2000 and eliminated agencies that were not present in all five years. Last, I eliminated agencies that were listed, but did not report any data (zero or incident) in each year.

Next, I created a variable based on how many quarters per year an agency reported data. I created a categorical variable based on State Quarter Activity (QTR1ACT – QTR4ACT): if an agency reported zero hate crime incidents or reported any number of hate crime incidents, I coded this as 1. If an agency did not report any data at all, I coded this as 0. Any agency which reported data in at least one quarter of at least one year was kept in the study. I created variables for number of quarters reporting for each agency in order to adjust for differential reporting. Agencies which did not report *any* data in *any* quarter of *any* year were eliminated (1,457 agencies total). Last, I eliminated any agencies that were not present in all five years of the study – 176 in all. I was left with 8,784 participating agencies:

Table 3. Sample Attrition

Year	Total agencies	City agencies
1996	18,724	10,417
1997	18,954	10,489
1998	18,605	10,577
1999	18,753	10,685
2000	19,657	10,690
1996-2000	[-176 = agencies not present in all 5 years] [-15 "covered by" agencies]	**10,226**[37]

The full batch header file was then put to the side while I created the incident level data file. As noted earlier, the hate crime file of the UCR does not follow the hierarchy rule, so an incident can include multiple offenses. Thus, much of the file manipulation was done in Microsoft Excel to ensure that each offense within an incident was given the same weight. First, I sorted each year by bias motivation of the first offense in an incident - anti-White or anti-Black. I then deleted all incidents that were not coded as 11 (anti-White) or 12 (anti-Black) as the primary offense ***unless*** one of the remaining offenses within an incident were coded as anti-White or anti-Black. For example, the primary offense code within an incident might have been 15 (anti-Multiracial), the secondary offense code was 23 (anti-Protestant) and the third offense code within the same incident was 11 (anti-White); the entire incident was kept and coded as one anti-white incident. This was done by hand in Microsoft Excel because I found multiple errors with every attempt in SAS programming.

Second, I sorted by the UCR offense code. Only the following UCR offense codes were kept: 09A (murder and non-negligent manslaughter); 11A (forcible rape); and 13A, 13B, and 13C (aggravated assault, simple assault, and intimidation). According to the HCSA, these are the

[37] This is the total number of agencies, including 1,457 agencies which reported no data in any of the quarters in any of the years to the UCR for bias crimes.

offenses which can be defined as being motivated by bias. Again, this was done in Microsoft Excel by hand because a single incident could have multiple offense codes. As long as one offense in one incident included one of the codes listed above (and it was also coded as anti-White or anti-Black), then the incident was kept and coded.

Third, the file was uploaded to SAS and offender race was recoded into White (0) or Black (1). Last, offense codes 11 (anti-White) and 12 (anti-Black) were concatenated with offender race to create the variables for anti- anti-White/Black (110) and anti-Black/White (111) were created. I then directed SAS to count the number of 110 and 111 per incident record, and then sum the count per agency code. The full batch header file was then merged with each year of incident level data and then with the Crosswalk.

The 1990 STF3a and 2000 STF Census files were manipulated to output only the variables needed. The 1990 STF3a includes 178 population tables and 99 housing tables for each state. Data are hierarchical from the State level down to the block group level. I extracted the variables for each state. The 2000 STF Census data are comprised of 76 files for each state. Each file contains tables with links to geographic identifiers (e.g., place FIPS, county FIPS, etc). Table Four lists the variables that are extracted from the 1990 and 2000 Censuses:

Table 4. 2000 Census Variable Extraction[38]

Variable	2000 Census
Total city population	Table P1
%Black	Table P6 / Table P1
% White	Table P6 / Table P1
Index of Dissimilarity (likelihood of interracial contact)	Table P6 and Table P1
Ratio of White to Black poverty	Table P52 (Individual) Table P159a (White individuals) Table P159b (Black individuals)
White to Black unemployment	Table P150a (White males) Table P150b (Black males)
Ratio of White to Black college graduates	Table P148a (White) Table P148b (Black)
%Female-headed households	Table P10
%Rented	Table H7
%Owned	Table H7
% Moved past 5 years (2000)	Table P24
%Young	Table P8

I then merged the UCR/Crosswalk file with the 1990 and 2000 Censuses. As noted earlier, I then restricted my total population size for cities to 50,000 or more and Black population size of 1,000 or more in 1990, leaving a total sample size of 415 cities. Last, the JCPES and *America Votes* data was input manually using Microsoft Excel and then merged with the SAS dataset.

IX. Statistical Approach

The bias crime dependent variables in each model are counts of rare, discrete events (anti-White or anti-Black violent bias crimes, White-on-Black or Black-on-White homicides) that are aggregated to the city-level. Ordinary Least Squares Regression (OLS) cannot be used because: 1) the dependent variable is a count; 2) there are large numbers of zero counts; and 3) the population size of each city varies over the entire sample, which leads to different error variances across the sample (Osgood 2000). To resolve this, a Poisson regression model can be effectively

[38] Similar extraction methods were used for 1990; however, the variables are not organized by Table numbers.

utilized. The Poisson regression allows for zero counts and does not assume equal variance like OLS regressions. The Poisson regression expects variance to be a function of the number of offenses, which is also dependent on the size of the population (Osgood 2000:36). However, in order to use a Poisson regression, the mean and variance of the dependent variable must be equal, which is unlikely in the case of bias crime research (e.g., see Grattet 2009; Green et al. 1998a; King et al. 2009 and Lyons 2008). Because the mean and variance are most likely not equal, a variation of Poisson should be used, either the negative binomial regression if the residual variance is over-dispersed or the zero-inflated Poisson regression if the residual variance is under-dispersed (Long 1997)[39]. Most recent macro-level bias crime studies typically utilize the negative binomial model for this reason (see, for example, Grattet 2009; Green et al. 1998a; King et al. 2009; Lyons 2008).

The residual variance of the data is over-dispersed and so the negative binomial model is preferred (Osgood 2000: 36). In other words, the negative binomial is appropriate for over-dispersed data because it is not based on the assumption of a normal distribution. In each negative binomial regression, an appropriate population offset must be selected. In this research, the population of the offending race is used. Thus, for anti-White bias crimes and Black-on-White homicides, the average Black population is selected as the offset. For anti-Black bias crimes and White-on-Black homicides, the average White population is selected as the offset. Because negative binomial regression ultimately proved to be the best fit for the data, I chose to use STATA rather than SAS.

Regardless, the dependent variable must be counts taken over an equal time period, which means that the years reporting data should remain stable, which it does not. The solution is to

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[39] I did test the Poisson and and negative binomial regressions to determine the best fit. The negative binomial regression provided the best fit for the data.

create an average reporting over the total number of years the data was collected. In order to verify whether these results are reliable, I retested each regression using a sub-sample of cities which reported data in all four quarters of all five years of the study.

X. Credibility and Limitations of Data

Bias crime data are often criticized since there are many limitations to official data and other sources may be influenced by activist agendas. For official crime data, individual states have statutes identifying bias motivation and it is likely that some states systematically underreport certain types of bias crimes. For example, Maryland only identifies bias crimes based on religion, race or ethnicity (Martin 1996); however, the federal definition of bias crime also includes sexual orientation and disability. While the federal HCSA law *requires* states to report crimes with motivations based on race, religion, ethnicity, sexual orientation and disability, it is reasonable to expect that Maryland police officers would not accurately record sexual orientation or disability bias crimes, causing some reporting problems. In this research, all fifty US states recognize race as a protected category for bias crimes.

The whole of the UCR program is voluntary, including hate crime data reporting. Unlike the rest of the UCR program, the hate crime reporting does not follow the hierarchy rule. The hierarchy rule for the UCR dictates that in a multiple offense incident, only the most severe offense is recorded and reported. For hate crime recording in the UCR, all offenses "*which were identified as bias motivated* and occurred during the incident should be reported on the hate crime reporting form" (FBI 1999, emphasis added). It is important to note that if an additional non-bias offense occurred within an incident, it would not be recorded. It is only additional bias offenses that are recorded in the UCR hate crime reporting program.

There are numerous reasons for police agencies to *not* report hate crime data to the UCR, particularly if a city has a high level of hate crimes. Wilson and Ruback (2003) present the final three criticisms of official hate crime data. First, they argue that official crime sources only reflect crimes reported to the police. Second, there is evidence that hate crime victims are not likely to report these crimes to the police, due to fear of retaliation or belief that the police will not be able to do anything about the crime (Martin 1996). Last, even if victims do report hate crimes to the police, the police may not investigate or record the crime as a hate crime; therefore, the crime is not reported as a hate crime to the FBI. If an incident clears these three hurdles and the police record it as a hate crime, we cannot state with absolute certainty that the data would are reported to the UCR.

To address the first concern, few reliable alternative collections of hate crime data exist. J. Jacobs and Potter (1997) note that agencies that typically collect hate crime information, aside from the government, are advocacy groups. These groups may have a vested interest in inflating the occurrences of bias crimes. Additionally, some of these bias crimes may not be crimes at all. The authors note that, while the Anti-Defamation League offers an annual hate crime index, some of the "crimes" included in that index are hate incidents (J. Jacobs and Potter 1997: 47). A hate incident is not a crime: it is an occurrence where a racial, ethnic, sexual orientation, disability or religious slur is verbalized. An example of a hate incident would be a radio disc jockey making racially biased jokes on the air. Arguably, this is bad taste and offensive, but it is not a crime and should not be included in data describing hate crimes. As a result, I agree with Perry (2001: 13), who also criticizes official bias crime data as "inaccurate in absolute numbers, [but] the data nonetheless may be useful as a source of information on general trends and patterns."

The latter two concerns cannot be controlled with official data. We cannot expect that all victims report crime to the police or to researchers, nor can we control police investigations of hate crimes, whether or not these crimes are determined to be bias motivated and their subsequent accuracy in reporting to the UCR. However, by controlling for number of years an agency reported data to the UCR, I attempt to indirectly capture agency compliance with hate crime reporting.

Chapter Five. Findings

Chapter Five presents the results of the ordinary least squares (OLS) and negative binomial regressions described in Chapter Four. The sample is compared to other cities meeting similar population criteria to determine the representativeness of my sample. Then, the sample is described in terms of descriptive statistics.

The multivariate analyses begin with the OLS regression of total violent crime rate using general criminality predictors. This regression serves two purposes: 1) it again assesses the representativeness of the sample because if general criminality predictors are not associated with violent crime in this sample, then the sample comes into question; and 2) it serves as a baseline for comparison to the violent biased crimes and interracial homicide regressions.

Next are the central analyses of this research. Anti-Black violent bias crimes committed by Whites and anti-White violent bias crimes committed by Blacks are regressed on both general crime predictors and social threat predictors to determine which predictors ultimately account for biased violent crimes at the city level. While originally hypothesized the percent Democrat might indicate compliance with hate crime laws, which would increase reporting and therefore the count of bias crimes in a city, the variable did not reach significance in any of the regressions. Since political competition did reach significance, it is included as the measure in order to correctly specify the models. Two additional analyses became necessary after the bias crime regressions. A sub-sample analysis is required because the variable for years reported proved to be a salient and robust predictor of bias crimes. Also, a further analysis of the social constructionist/social movement perspective is necessary after years reported and region (South) demonstrated remarkable explanatory power in the bias regressions. The regressions were duplicated for

Midwest, West and Northeast regions.[40] Last, homicides of Blacks committed by Whites and homicides of Whites committed by Blacks are regressed on general criminality and social threat predictors to compare non-biased interracial homicides to biased violent crime.

I. Descriptive and Bivariate Results

Before presenting the results of the regression analyses, table 1 compares sample demographics to other cities of populations of 50,000 or more with 1,000 or more Black residents. There were 521 cities with populations of 50,000 or more with an African-American population of 1,000 or more in 1990. After eliminating cities that did not report any hate crime data in any of the quarters, 415 cities remain in the sample. After a list-wise deletion of all cities with missing values on any of the variables, the final sample size is 355 cities. The remaining 166 other US cities meet the selection criteria but did not report bias crimes to the UCR or have missing data on the independent variables[41]. The list of all cities included and excluded from the sample can be found in Appendix D.

The two samples are not significantly different in terms of percent White, percent Black, ratio of White to Black poverty or the violent crime rate in 1996, though the violent crime rate does come quite close. Notably, the t-statistic indicates that there are significant differences in total population size and the ratio of White to Black unemployment. Cities included in the sample

[40] The Midwest includes: Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, Ohio and Wisconsin. North Dakota, South Dakota and Wisconsin are not in the sample. Northeast includes: Connecticut, Maine, Massachusetts, New Jersey, New Hampshire, New York, Pennsylvania, and Rhode Island. Vermont is not in the sample. South includes: Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia, Washington DC, and West Virginia. Delaware is not in the sample. West includes: Alaska, Arizona, California, Colorado, New Mexico, Nevada, Oregon, Utah, Washington and Wyoming. Hawaii, Idaho and Montana are not in the sample. All excluded states did not meet the criteria of reporting zero or incident data to the UCR for all five years of the study.

[41] The N is 166 for percent White, percent Black, ratio of White to Black poverty and ratio of White to Black unemployment; however, for the Violent Crime Rate, the N is 107 due to missing or unreported data.

have larger mean populations than cities not included in the sample. Additionally, cities included in the sample have lower means for the ratio of White to Black unemployment than cities not included in the sample. This indicates that there is need for caution when generalizing the results of this sample to other cities in the US.

Table 1. Selected Demographics of Sample Cities versus Similar US Cities

Variable	**Sample Means**	**Other Cities Means**	**t**
Total population 1990	202,375.3 (478,479.7)	91,546.99 (101,414.7)	4.168
Percent White 1990	73.514 (17.213)	75.244 (20.240)	-0.952
Percent Black 1990	16.212 (16.209)	16.374 (13.606)	-0.119
Violent crime rate 1996	939.511 (649.251)	823.405 (737.663)	1.466
Ratio of White to Black poverty 1990	0.466 (.272)	0.477 (.135)	-0.617
Ratio of White to Black unemployment 1990	0.859 (.292)	0.971 (.288)	-4.118
N	355	See footnote 2	t(.05)=1.965

Standard deviation in parentheses

Table 2 presents the means and standard deviations for the dependent, independent and control variables used in the research. Since I allow for variable reporting in the dependent variables, each dependent variable is annualized and adjusted for population size to allow meaningful comparisons[42]. The mean violent crime rate per 100,000 persons between 1996 and 2000 is 837.601. One can see by the means that bias crimes and interracial homicides per 100,000 residents are rare phenomena: anti-Black bias crimes and anti-White bias crimes have a mean of less than 1, while interracial homicides have a mean of less than 3. The mean violent crime rate in 1996 of 969.605 for this sample is higher than the national average of 634.1 violent crimes per 100,000 population reported in the FBI's *Crime in the United States* for the same year. This may be attributed to the fact that my sample includes only cities of 50,000 or higher population and

[42] As a reminder, percent voting democratic does not reach significance in any of the equations. Political competitiveness does reach significance and so it is included as the predictor of political climate. Percent voting democratic is not described in any of the table.

excludes suburban and rural areas. About half of the occupied properties were leased by renters and half of the individuals reported moving their residence between 1995 and 2000 in this sample.

Table 2. Descriptive Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
Total violent crime rate per 100,000 population, 1996-2000	837.601	538.474	43.447	3,057.14
Anti-Black bias crime rate per 100,000 persons, 1996-2000	0.951	1.407	0	16.137
Anti-White bias crime rate per 100,000 persons, 1996-2000	0.321	.820	0	11.500
Homicide rate of Blacks by Whites per 100,000 persons, 1996-2000	1.240	1.591	0	9.950
Homicide rate of Whites by Blacks per 100,000 persons, 1996-2000	2.721	2.677	0	14.372
Violent Crime Rate per 100,000 persons, 1996	939.511	649.251	9.102	3,966.853
Concentrated Disadvantage	3.86e-10	1.430	-3.400	5.905
Percent Rent, 1990	45.723	11.197	14.461	78.236
Percent Moved Past 5 Years, 2000	50.856	7.013	30.104	80.356
Percent White, 1990	73.514	17.213	7.128	98.442
Percent Black, 1990	16.212	16.209	0.788	90.276
Change Percent Black, 2000-1990	0.331	0.737	-0.464	9.091
Black In-migration into Previously Majority White Cities	0.746	0.436	0	1
Black Elected Official, 1996	0.084	.292	0	1
Ratio White to Black Unemployment, 1990	0.859	.292	0.358	2.383
Ratio White to Black College, 1990	1.606	.718	0.169	5.156
Ratio White to Black poverty, 1990	0.466	.272	0.142	2.251
Dissimilarity Index, 1990	45.352	18.706	6.2	87.6
Political Competition, 1996	-18.057	13.994	-75.9	-0.2
Region (South)	0.325	.469	0	1

Demographically, these cities tend to be mainly White. Percent Black has a range of 0.788 to 90%, with a mean of 16.212[43]. Concentrated disadvantage, which is comprised of the factor scores for percent female-headed households, percent of individuals under the poverty line and percent of men aged 16-55 who are unemployed, has a mean of zero. Concentrated disadvantage

[43] It is interesting to note that the standard deviation is also 16, which is unusual but not an error.

ranges from a minimum of -3 (Naperville, IL) to almost 6 (Camden, NJ). The change in percent Black is small and positive, suggesting that very few Blacks in-migrated into these cities during the ten year period.

Slightly over 200 cities that were more than fifty percent White in 1990 experienced an increase of Black residents by the year 2000. This variable is created by combining several dummy variables. First, if a city was less than fifty percent White in 1990, it is coded zero; if fifty percent White or higher, it is coded 1 (200 cities are coded as 1). Second, a city that experienced a positive change in percent Black (percent Black 2000 – percent Black 1990), it is coded 1. If that change in percent Black is 0 or negative, it was coded 0. The in-migration of Blacks into previously White neighborhoods is coded 1 if both the fifty-percent White 90 dummy variable and the change in percent Black variables are coded as 1; and the in-migration is coded as zero if both the fifty-percent White dummy is 0 and the change in percent Black dummy are coded as 0. The mean for race of mayor is 0.084, which indicates that 31 cities in this sample report having a Black mayor in 1996. The Joint Center for Political and Economic Studies reports in 1999 that there were 40 Black mayors of cities with a population size of 50,000 or more (Bositis, 1999), so this mean is consistent with reported data.

The ratio of White to Black unemployment ranges from 0.358 to a little over 2, with a mean of 0.859. As Blacks become more equal to Whites in terms of unemployment, the ratio should be close to 1. As more Whites are unemployed compared to Blacks, the ratio should be greater than 1. As more Blacks are unemployed compared to Whites, the ratio should be less than 1. The mean tells us that more Blacks are unemployed compared to Whites in this sample. Chino, CA has the lowest ratio of White to Black unemployment at 0.358. Chino's percent Black population in 1990 is 9.77% and the percent White population is 67.37%. Corona, CA has the highest ratio of White to Black unemployment at 2.383. The Black population of Corona is extremely small, at only 2.74% and a percent White of 75.97%. Corona also has 2% of its residents living below the poverty line in 1990. The small Black population combined with a very low percentage of residents under the poverty line may explain this finding.

The ratio of White to Black college education ranges from about 0.169 to about 5, with a mean of 1.606. Again, as Blacks achieve the same levels of education as Whites, the ratio should be close to 1. As more Whites graduate from college with at least an Associate's Degree than Blacks, the ratio should be greater than 1. As more Blacks graduate compared to Whites, the ratio should be less than 1. In this sample, Whites are slightly more likely to hold Associate's Degrees or higher than are Blacks; however, the mean ratio is very close to 1. Amarillo, TX has the lowest ratio of White to Black college graduates at 0.169, indicating the highest number of Black college graduates relative to Whites in the sample. Amarillo had a 5.81% Black population and 82.89% White population in 1990. Amarillo is home to Amarillo College; however, police agencies that identified their agency type as "universities/colleges" were not included in this sample. Greenville, SC has the highest ratio of White to Black college graduates at 5.156. This ratio reflects that more Whites held Associate's degrees or higher than Blacks. The population in Greenville in 1990 was 35.20% Black and 63.89% White in 1990.

In terms of the ratio of White to Black poverty, the mean is 0.466, with a range of about 0 to about 2. Again, as Blacks and Whites reach parity in terms of poverty, the ratio should be about 1. As more Whites are in poverty than Blacks, the ratio should be greater than 1. As more Blacks are in poverty than Whites, the ratio should be less than 1. With poverty, the mean is 0.466 with a standard deviation of 0.272, indicating that in this sample, more Blacks are below the poverty line compared to Whites. Brooklyn Park, MN had the lowest ratio of White to Black poverty at

0.142. Brooklyn Park had 4.96% Black population and 90.62% White population. Additionally, the percent of residents reporting that they are unemployed is rather high at 24.57%. A very small Black population combined with a relatively high unemployment rate may explain this finding. Corona, CA again has the highest ratio of White to Black poverty at 2.251. Corona has a high White population (75.97%) and low Black population (2.74%) and a very low unemployment rate of 8.46%. Thus, this high ratio probably reflects the fact that there are so few people who are unemployed combined with a very small Black population.

The Dissimilarity Index is 45.352, suggesting that on average, about half of the Black population in each city would have to relocate in order to achieve racial balance with Whites. The standard deviation is also quite high, suggesting that the sample cities do vary in terms of the likelihood of interracial contact.

It is important to illustrate how rare the primary dependent variables are for this research. The zero counts are by far the largest frequency for all four racially disaggregated dependent variables. With the exception of Anti-Black bias and Homicides of Whites by Blacks (where the zero count and 1-5 count are essentially equal), the zero counts account for about half of the sample. Table 3 illustrates how skewed bias crimes and inter-racial homicide are towards zero counts.

Table 3. Distribution of Bias and Homicide Dependent Variables

	Anti-Black Bias	**Anti-White Bias**	**Homicide of Blacks by White**	**Homicide of Whites by Black**
0	115 (32.39%)	194 (54.65%)	157 (44.23%)	126 (35.49%)
1-5	132 (37.18%)	114 (32.11%)	149 (41.97%)	131 (36.90%)
6-10	51 (14.37%)	21 (5.92%)	24 (6.76%)	46 (12.96%)
11-25	31 (8.73%)	15 (4.22%)	17 (4.78%)	38 (10.71%)
26-50	16 (4.51%)	6 (1.69%)	4 (1.13%)	8 (2.25%)
=>51	10 (2.82%)	5 (1.41%)	4 (1.13%)	6 (1.69%)

Percentages in parentheses, N=355

The correlations for the dependent variables are displayed using the rates per 100,000 population rather than the counts. Table 4 shows the bivariate correlations of the dependent variables:

Table 4. Correlations of Dependent Variables

	Total Violent Crime	**Anti-Black Bias by Whites**	**Anti-White Bias by Blacks**	**Homicide of Black by White**	**Homicide of White by Black**
Total Violent Crime	1.00				
Anti-Black Bias by Whites	0.081	1.00			
Anti-White Bias by Blacks	-0.055	0.488**	1.00		
Homicide of Black by White	0.377**	0.019	-0.081	1.00	
Homicide of White by Black	-0.054	0.065	0.257**	-0.022	1.00

*p<.05 **p<.01 (two-tailed tests), N=355

Anti-Black bias crimes committed by Whites and anti-White bias crimes committed by Blacks show the highest correlation (0.488), followed by homicide of Blacks by Whites and total violent crime (0.377). Anti-White bias related violence and Homicides of Whites by Blacks are not significantly related to total violent crime. It is interesting that anti-Black bias crimes and homicide of Blacks by Whites are not strongly correlated (0.019), while anti-White bias crimes are correlated with homicide of Whites by Blacks (0.257), suggesting at least preliminarily that there is a reason to separate racially motivated bias crimes by race: biased violence against Whites may be similar to homicides of Whites, while biased violence against Blacks may exhibit different causal factors than non-biased homicides of Blacks.

II. Total Violent Crime as Dependent Variable

The first analysis examines the causes of the total violent crime rate from 1996-2000. It estimates the effect of general criminality predictors on non-bias violent crime rates using OLS regression. The purpose of this model is to test the effectiveness of my sampling procedures and to provide a baseline effect of the general criminality argument.

The dependent variable for the general crime OLS regression is the violent crime rate per 100,000 persons averaged between 1996 and 2000. Because the variable is skewed as noted above, I ran the regressions with the variable in its natural state and in the natural log. The natural log form of average violent crime produced a better fit for the model and so those results are reported. Region (South) is the only control variable included because political competitiveness and the likelihood of interracial contact are not typically predictors of violent crime not motivated by bias[44].

Table 5. Ordinary Least Squares Regression of Total Violent Crime Rate (Natural Log) on General Crime Variables

Variable	Coefficient	Beta
Percent Black	0.015 (.002)**	0.342
Percent young aged 13-24	-0.061 (.008)**	-0.365
Concentrated disadvantage	0.217 (.027)**	0.432
Percent Rent	0.010 (.003)**	0.161
Percent Moved 5 years, 2000	0.031 (.006)**	0.299
City located in South	0.132 (.069)	0.085
Constant	6.874	
R^2 (Adjusted R^2 in parentheses)	0.551 (.542)	
N=355		

Note: Standard errors in parentheses
N=355
*p<.05 **p<.01 (two-tailed tests)

As predicted, the results in Table 5 show significant effects of the general crime variables on total violent crimes. All of the predictors are significant and in the predicted direction, with the

[44] To be certain, I did run a model with Midwest, Index of Dissimilarity and political competitiveness. None reached significance, no matter if I added them one at a time or all three in the same model.

exception of percent young aged 13-24. This variable is to measure the youthful population, which would usually comprise the offending population. Percent young has a *negative* effect on violent crime rate; for every one standard deviation increase in the percent of the population aged 13-24, we would expect to see a 0.365 decrease in the standard deviation of the violent crime rate, net of all other factors. Recent research by McCall et al (2013) demonstrates that the age-crime relationship is not necessarily invariant; that is, youthful age will not always be a predictor of increased crime. They find that the age-crime relationship is positive when youth are not engaged in positive institutional activities such as education or employment; however, when there are high levels of participation in those institutions, the age-crime relationship is negative. Since I did not account for institutional engagement, it is feasible that the measure of age is capturing this phenomenon.

Concentrated disadvantage and percent Black have the largest impact on violent crime; for every one standard deviation increase in concentrated disadvantage, there is a 0.432 increase in the standard deviation of the violent crime rate, net of all other factors. For every one standard deviation increase in the percent Black population, there is an expected 0.342 increase in the standard deviation of the violent crime rate, all other factors held constant. Surprisingly, region only approaches significance at the .058 level. The traditional social disorganization variables of percent rent and percent moved positively affect the violent crime with betas of 0.161 and 0.299, respectively. The model explains about 55% of the variation in violent crimes, suggesting it performs relatively well.

Testing violent crime as a dependent variable illustrates that these results are consistent with what we would expect given prior research. Peterson and Krivo's (2005:347) review of the literature indicates that structural disadvantage (a combination of structural transformation, traditional social disorganization and cultural adaptation) is "a major contributor to violence" and that the main questions are exactly how these structural differences operate through intervening factors to affect levels of violence. Concentrated disadvantage (a factor score of percent males aged 16-55 who are unemployed, percent below the poverty line and percent of female-headed households), percent Black and residential instability (as measured by percentage of rental properties and percent moved) are significant predictors of the level of violent crime in a city. Recent longitudinal research by Boggess and Hipp (2010) shows that violent crime is more of a cause of residential instability (measured by home sales), while residential instability is a weaker cause of violent crime. It is notable that residential instability is still a cause of violent crime.

Additionally, Ousey (1999) finds that poverty, unemployment, income inequality, female-headed households, and deprivation affect homicide rates for White residents of US cities, but only deprivation and poverty affect homicide rates for Black residents of US cities. Last, Shihadeh and Flynn (1996) find that unemployment, poverty, and female-headed households mediated the effect of Black isolation from Whites on homicide and robbery in US cities. Violent crime is explained by social disorganization predictors. It will be interesting to see how the same predictors explain bias crimes and interracial non-biased homicides, particularly once the social threat variables are introduced.

III. Violent Bias Crime as Dependent Variable

The social threat model predicts that indicators of racial, political and economic threat will remain strong and significant predictors of anti-Black bias crimes, net of general crime indicators. The control variables of region, political competitiveness and interracial contact are introduced in each model.

Model A tests the effect of general threat predictors on anti-Black bias crimes committed by Whites. I regressed anti-Black violent bias crimes on the violent crime rate in 1996, percent Black, concentrated disadvantage, percent aged 13-24, percent rent, and the percent moved in the last five years, along with the control variables to determine which social disorganization predictors, if any, affect anti-Black violent bias crime committed by Whites in cities.

Model B tests the social threat hypothesis for anti-Black hate crimes committed by Whites. Grattet (2009) and Green et al (1998a) find that not only did percent Black population have an effect on bias crimes, but that *specifically* in-migration of non-White populations into previously White neighborhoods has a strong effect on racially motivated bias crimes and violent bias crimes. Thus, I would expect that Black in-migration to have an effect on anti-Black violent bias crimes. Additionally, the presence of a Black mayor should increase the amount of anti-Black bias crimes committed by Whites, due to the increased political threat presented by the Black population. Last, any increases in Black economic power (reflected by low levels of interracial economic inequality and poverty or increases in Black college graduates) should increase anti-Black hate crimes committed by Whites. Model C is the full model, with general crime predictors and social threat predictors.

Negative binomial regression includes an assumption that the risk of being a victim of bias crime is equally dispersed; that is, the likelihood of a bias crime occurring in one year should be the same as any other year. This sample includes cities which report hate crimes during different quarters; thus, the dependent variable was annualized so that the analyses could be performed. Anti-Black bias crimes also vary due to the size of the offending population. The likelihood of being a victim is not equally dispersed if the offending population is not equally dispersed. Following prior research (Grattet, 2009), I use the offender's average population count (White population) as my exposure variable for this set of negative binomial regressions. Even though the dependent variables are annualized, I must account for variable reporting since I cannot explain precisely why an agency may report in one year and not another year. Because the data included agencies that reported data over a variable number of quarters, I included a control variable for number of years reported and report the coefficient for all bias and homicide regressions.

It is nearly impossible to interpret what exactly the number of years reported is capturing. It could reflect a city's training level in terms of identifying hate crimes or the city's overall compliance with hate crime legislation as a result of social movements (e.g., King 2007; McVeigh et al 2003); therefore, I control for reporting but do not interpret the coefficient as a predictor variable.

The tables present estimated negative binomial regression coefficients. The dependent variables are counts and the negative binomial regression models the log of the expected count for the predictor variables. For a one unit change in a predictor variable X, the difference in the logs of expected counts of the dependent variable is expected to change by the predictor X, holding all other factors constant. This interpretation is not intuitive since it is expressing change in the expected logs of expected counts. STATA provides an option called 'listcoef' which raises the coefficient to the logistic coefficient power, or odds ratios. This option also provides a value for the odds ratios for a one standard deviation increase in the independent variable, which is useful for factor variables like concentrated disadvantage (Long and Freese, 2006). The raw coefficients are presented in the tables; however, the odds ratios are presented in the text since they are more intuitive for most readers.

Table 6. Negative Binomial Regression of Anti-Black Bias Crimes (White Offenders) on General Crime and Social Threat Variables (White Population as Exposure Variable).

	A	B	C
General Crime			
Violent Crime Rate	0.090 (.085)^		0.094 (.084)^
Percent Black, 1990	-0.002 (.007)		--
Concentrated Disadvantage	0.031 (.069)		0.053 (.069)
Percent aged 13-24	0.007 (.021)		0.006 (.021)
Percent Rent	-0.006 (.008)		-0.002 (.009)
Percent Moved	0.020 (.015)		0.013 (.016)
Social Threat			
Percent White, 1990		0.006 (.005)	.007 (.006)
Change Pct Black		0.090 (.201)	.072 (.206)
Pct White*Change Pct Black		-0.058 (.280)	0.072 (.206)
Black Official		0.082 (.239)	0.018 (.243)
Ratio White/Black unemployment		-0.693 (.319)*	-0.673 (.325)*
Ratio White/Black college		0.234 (.146)	0.193 (.151)
Ratio White/Black poverty		0.148 (.326)	0.026 (.345)
Number years reported	0.277 (.085)**	0.333 (.086)**	0.327 (.087)**
Controls			
Dissimilarity	0.011 (.005)*	0.005 (.004)	0.003 (.005)
Political Competitive	-0.003 (.005)	-0.002 (.004)	-0.004 (.005)
Region (South)	-1.158 (.180)**	-1.177 (.172)**	-1.205 (.177)**
Constant	-13.664	-12.985	-13.676
Log Likelihood	-476.192	-473.460	-471.563
Overdispersion	0.450	0.439	0.425
N=355			

Note: Standard errors in parentheses
*p<.05 **p<.01 (two-tailed tests)
^ Coefficient and standard deviation multiplied by 1,000

In model A, when regressing anti-Black violent crimes committed by Whites on only the violent crime rate in 1996, general crime and control variables, none of the general crime predictors are significant. The index of Dissimilarity (0.011) and region (-1.158) are significant control variables. For a one standard deviation increase in the index of Dissimilarity (a measure of the likelihood of interracial contact), there is a 1.227 increase in the expected count of anti-Black bias crimes committed by Whites. As Black and White city residents come into more frequent contact, anti-Black violent bias crimes committed by Whites increase. Cities located in the South have

0.314 fewer expected anti-Black bias crimes than cities not located in the South, net of all other factors.

While this is unusual given the fact that I am not addressing compliance with hate crime legislation, the result is not altogether unexpected. Cities in the South could have exerted a positive effect on bias crime given the rather stable criminological finding that violent crime is more prevalent in the South (Ellison 1991; FBI 2000b). Ellison (1991) notes that homicide rates, gun ownership rates and violent crime rates have typically been higher in the South for most of the twentieth century. This finding is typically attributed to the Southern Subculture of Violence: a set of cultural norms that accepts or even encourages violence. Using data from the General Social Survey (GSS), Ellison (1991: 1229) finds support that native Southerners are more likely to support defensive violence, thought the magnitude is modest (region explains about seven percent of the variation in support of defensive violence).

Bias crime may prove to be an exception, given McVeigh et al's (2003: 852) finding that hate crimes are unequally distributed across states and counties regionally in the United States. They note that "few hate crimes are reported in Midwestern states and in Southern states." King (2007) also finds that the South and Midwest are less likely to comply with the HCSA than are the Northeast and West. Additionally, he notes that any increase in Black population size decreases compliance with hate crime legislation and reporting in the South.

Social threat predicts that an increase in the percentage of Black residents, particularly an in-migration of Black residents into White neighborhoods will be associated with an increase in anti-Black bias crimes (Green et al 1998a; Grattet 2009; Lyons 2007). In model B, the measure of racial threat (Black in-migration into White cities) is not significant; however, the ratio of White to Black unemployment (-0.693) and region (-1.177) are significant and in the opposite direction than predicted. For a one standard deviation unit increase in the ratio of White to Black unemployment, there is a 0.816 unit decrease in the expected count of anti-Black bias crimes, controlling for all other factors. As Blacks experience unemployment levels similarly to Whites, there are fewer anti-Black violent bias crimes committed by Whites, net of all other factors. Again, this is counter to what we would expect to find, given the threat perspective. Region also remains significant and negative; cities located in the South have a 0.308 unit decrease in the expected count of anti-Black violent bias crimes committed by Whites, net of all other factors.

In the full model C, the table reports the results for anti-Black violent bias crimes committed by Whites regressed on general crime measures, social threat measures (using Black in-migration as the specific measure of racial threat), and control variables. Again, the only significant predictors are the ratio of White to Black unemployment (-0.673) and region (-1.205). For every one standard deviation unit increase in the ratio of White to Black unemployment, there is a 0.821 unit decrease in the expected count of anti-Black violent bias crimes committed by Whites, net of all other factors. Cities located in the South have an expected decrease of 0.300 counts of anti-Black biased violent crime committed by Whites than cities not located in the South, net of other factors.

It is important to note that number of years reported remains a strong and salient predictor of bias crimes, even though the bias crimes have been adjusted for reporting. Over 60% of the sample cities submitted data in all 5 years of the study. For every year reported, there is an associated increase of about 1 anti-Black bias crimes committed by Whites.

These results are notable. All models have region (South) as a significant predictor; however, anti-Black bias crimes committed by Whites are *less* likely to occur in the South, which is what we would expect to see when examining hate crimes as a social movement outcome.

Second, an increase in Black economic power, as measured by the ratio of White to Black unemployment, remains a significant predictor in the racial threat models and in the full model, but in the opposite direction than hypothesized in accordance with social threat. This is inconsistent with past research, which suggests that economic threat is an important predictor of an increase in interracial crime (D. Jacobs and O'Brien 1998; D. Jacobs and Wood 1999), although it has not been tested for racially *biased* crime in particular.

While social threat does not predict results for anti-White crime, it is important to test social threat explanations of anti-White violent bias crimes committed by Blacks. Some predictors may have different effects for anti-White bias crimes than anti-Black bias crimes. For instance, an increase in percent White should not necessarily have an effect on the number of anti-White bias crimes, unless it is a reflection of the increased likelihood of interracial contact (Lyons 2008). Thus, we would expect the relationship to disappear once the index of Dissimilarity is controlled. Lyons (2008:379) further suggests that anti-White bias crimes "parallel those for other types of interracial crime, including interracial victimization (Sampson 1984) and interracial homicide (South and Messner 1986; Wadsworth and Kubrin 2004), which may or may not be explicitly motivated by bias." If this is the case, then we would expect the model for anti-White crimes to be very similar to the model of homicides of Whites committed by Blacks.

Black in-migration should not be an important predictor of anti-White bias crimes, unless it is capturing the effect of an increase of potential offenders. Lyons (2008) finds that increases in non-White populations in turn increases anti-White crime but only in communities that are racially heterogeneous or majority White. In fact, he finds that anti-White hate crimes are the most likely to have a curvilinear relationship with the influx of non-White populations. At very low White populations, there are lower frequencies of anti-White crimes than in more heterogeneous or majority White communities.

As for political threat, the presence of a Black mayor should have a negative effect on anti-White bias crimes since it reflects an increase in Black political power. D. Jacobs and Wood (1999) find that Black mayors have a protective effect on the interracial homicides of Whites by Blacks. That is, cities with greater economic competition have higher rates of interracial homicide (both Blacks killing Whites and Whites killing Blacks); however, race of mayor intervenes. Cities with Black mayors have lower rates of Blacks killing Whites and higher rates of Whites killing Blacks, holding constant all other variables.

Last, I expect that economic threat variables have little to no effect on anti-White crime. As Black economic power increases, their threat to the White population increases, but this should not affect anti-White bias crimes. If anything, there may be a decrease in anti-White crimes as Black economic power increases.

Table 7 shows the anti-White bias crimes committed by Blacks. Model A again shows the effect of the violent crime rate in 1996, the general crime variables and the control variables to determine whether the violent crime rate better predicts bias crime than general crime predictors.

Model A includes the general predictors of crime and control variables. For the social threat model B, it is difficult to determine which population is the threatening population for anti-White violent bias crimes. Thus, to maintain comparability between the models, Black in-migration is used as the measure of racial threat, even though Blacks in this instance are the offending population. Model C is the full model with general crime, social threat - with Black in-migration to White neighborhoods as the measure of racial threat – and control variables. All models use the average Black population count as the offset variable.

In Model A, percent Black (-0.041) and region (-0.946) exert significant effects on anti-White bias crimes committed by Blacks. For a one unit increase in a city's percent Black, there is an expected 0.960 unit decrease in anti-White bias crimes committed by Blacks. This is interesting; as a city's percent Black increases, and therefore the proportion of potential offenders increase, its count of anti-White bias crimes committed by Blacks decreases by almost one. This also suggests that the fewer Blacks in a city, the more frequently anti-White bias crimes may occur. A city located in the South has an expected 0.388 unit decrease in expected anti-White hate crimes committed by Blacks than cities not located in the South, net of all other factors.

For model B, percent White in 1990 (0.038) is the only significant threat predictor: as the percent White in a city increases by one percent in 1990, anti-White violent bias crimes committed by Blacks increase by 1.039, controlling for all other factors. The other social threat predictors are not significant. This is as predicted and consistent with Lyons (2008)[45]: as Whites comprise more of the population, there are more anti-White hate crimes; however, I expected this to disappear after controlling for the likelihood of interracial contact. Race of mayor is not significant, which is not consistent with prior research conducted by D. Jacobs and O'Brien (1998) and D. Jacobs and Wood (1999). Region (-1.223) is also a significant predictor of anti-White biased violent crimes committed by Blacks. A city in the South is expected to have 0.294 fewer expected anti-White bias crimes committed by Blacks than cities not located in the South, net of all other factors.

[45] Lyons (2008) actually finds a more curvilinear relationship between percent White and anti-White hate crimes. As percent White approached 60% of the population, anti-White hate crimes increased. In fact, anti-White hate crimes peaked as Whites comprised 40-60% of the population. 23% of the cities in my sample have a population of 60% White or less.

Table 7. Negative Binomial Regression of Anti-White Bias Crimes (Black Offenders) on General Crime and Social Threat Variables (Black Population as Offset Variable).

	A	B	C
General Crime			
Violent Crime Rate	0.061 (.117)^		0.080 (.118)^
Percent Black, 1990	-0.041 (.009)**		--
Concentrated Disadvantage	-0.002 (.106)		-0.015 (.108)
Percent aged 13-24	0.008 (.034)		-0.006 (.036)
Percent Rent	-0.006 (.012)		0.004 (.013)
Percent Moved	0.024 (.024)		0.019 (.025)
Social Threat			
Percent White, 1990		0.038 (.008)**	0.039 (.009)**
Change Pct Black		-0.234 (.409)	-0.261 (.423)
Pct White*Change Pct Black		-0.148 (.492)	-0.139 (.507)
Black Official		-0.258 (.291)	-0.272 (.304)
Ratio White/Black unemployment		-0.684 (.589)	-0.643 (.607)
Ratio White/Black college		0.267 (.194)	0.194 (.204)
Ratio White/Black poverty		-0.457 (.633)	-0.605 (.712)
Number years reported	0.234 (.127)	0.446 (.129)**	0.408 (.133)**
Controls			
Dissimilarity	0.008 (.007)	-0.011 (.007)	-0.010 (.008)
Political Competitive	-0.006 (.007)	-0.009 (.006)	-0.011 (.007)
Region (South)	-0.946 (.254)**	-1.223 (.232)**	-1.267 (.246)**
Constant	-12.306	-14.189	-15.200 (1.445)
Log Likelihood	-289.289	-284.084	-283.056
Overdispersion	0.621	0.566	0.548
N=355			

Note: Standard errors in parentheses
*p<.05 **p<.01 (two-tailed tests)
^ Coefficient and standard deviation multiplied by 1,000

For model C, consistent with model A, the general crime predictors are insignificant. As for social threat, percent White (0.039) remains a significant predictor of anti-White violent bias crimes committed by Blacks, even when controlling for interracial contact as captured by the Index of Dissimilarity. As the percent White in a neighborhood increases by one percent, the expected count of anti-White violent hate crimes committed by Blacks increases by 1.040, controlling for all other factors. Again, we find that region (-1.267) exerts a significant effect on anti-White bias crimes, but again in the opposite direction. Cities located in the South have an expected decreased count of anti-White bias crime by a factor of 0.282.

In the full model, aside from percent White, none of the hypothesized social threat or general crime predictors adequately explain anti-White violent bias crimes committed by Blacks. It is clear that not only are bias crimes substantively different from non-biased violent crimes, but that anti-White and anti-Black violent bias crimes also have different causal processes.

It is important to note that, for bias crimes, years reporting data is a significant and rather robust predictor. Two subsequent analyses result from the robustness of years reported. First, in order to establish whether the effects of the social threat predictors are somehow related to differential reporting, I ran the models on a restricted sample of cities that reported data in all quarters for all five years of the study (the list of cities included in the full sample and in the sub-sample are presented in Appendix D). The restricted sample included 214 cities, or 60% of the full sample. If the results of the regressions for the restricted sample are similar to the full sample, it should provide evidence of the robustness for the significant predictors. Alternatively, if the predictors in the full sample become not significant or other predictors emerge as significant in the restricted sample, it would give me less confidence in the results.

Second, it is clear that years reporting data indicates that agency-level reporting is affecting city level counts of bias crime. Thus, other regions must be controlled for to determine whether or not patterns associated compliance with hate crime legislation in other regions are also measurable at the city level. In terms of *racial threat*, only the South was hypothesized to have an effect on interracial bias crimes due to historical racial tensions; however, I re-test all of the regressions for the effect of other regions.

IV. Violent Bias Crime in the Restricted Sample

It is interesting that years reporting does not exert any significant effects on the homicide models (yet to be presented), yet are so robust in the bias crime models. This leads me to believe that future studies addressing bias crimes as criminal events should control for compliance with hate crime reporting laws. Even after annualizing the data, number of years reported makes an impact on biased crimes, but not on interracial crimes in general. I wanted to explore this further and ran the full model using the restricted sample that submitted data in all of the quarters in all of the years of the study. The first model is anti-Black violent bias offenses committed by Whites and the second is anti-White violent bias crimes committed by Blacks. The restricted sample contains 214 cities, or 60% of the full sample.

First, the sub-sample model for anti-Black violent bias crimes committed by Whites fairly supports the full-sample model. For anti-Black violent bias crimes committed by Whites, the ratio of White to Black unemployment (-0.752) and region (-1.191) are significant, in the same direction and about the same magnitude as the full-sample model. The one difference is that percent moved (0.049) is significant for the sub-sample. For every one percent increase in residents who reported moving between 1995 and 2000, there is an expected 0.016 increase in the count of anti-Black biased violent crimes committed by Whites, net of all other factors.

Table 8. Negative Binomial Regressions for the Restricted Sample

	Anti-Black committed by Whites	Anti-White committed by Blacks
General Crime		
Violent Crime Rate	0.006 (.009)^	0.039 (.156)^
Percent Black, 1990	--	--
Concentrated Disadvantage	0.030 (.083)	-0.191 (.137)
Percent aged 13-24	-0.014 (.025)	-0.037 (.048)
Percent Rent	-0.006 (.010)	-0.005 (.015)
Percent Moved	0.049 (.020)*	0.041 (.032)
Social Threat		
Percent White, 1990	-0.889 (6.468)^	0.028 (.011)**
Change Pct Black	0.164 (.224)	0.189 (.408)
Pct White*Change Pct Black	0.112 (.337)	-0.641 (.652)
Black Official	-0.085 (.250)	-0.383 (.314)
Ratio White/Black unemployment	-0.752 (.356)*	-0.506 (.660)
Ratio White/Black college	0.054 (.190)	0.117 (.254)
Ratio White/Black poverty	0.198 (.346)	-0.285 (.736)
Controls		
Dissimilarity	0.011 (.006)	0.004 (.009)
Political Competitive	-0.011 (.006)	-0.018 (.009)*
Region (South)	-1.191 (.208)**	-1.538 (.308)**
Constant	-13.075	-13.452
Log Likelihood	-302.880	-169.611
Overdispersion	.338	.369
N=214	Exposure = White population	Exposure = Black population

Note: Standard errors in parentheses
*p<.05 **p<.01 (two-tailed tests)
^ Coefficient and standard deviation multiplied by 1,000

For anti-White biased crimes committed by Blacks, percent White (0.028) and Region (-1.538) remain significant in the same direction and about the same magnitude as the full sample. Political competition (-0.018) is significant for the sub-sample but not in the full sample. There is an expected 0.772 count decrease in anti-White biased violent crimes committed by Blacks for a one standard deviation increase in political competitiveness of a county, net of all other factors. This suggests that in counties where Republicans and Democrats compete for votes, anti-White bias crimes committed by Blacks are lower in frequency. This is contrary to McVeigh et al (2003) who find that political competitiveness increases the frequency of bias crimes; however, their measure of bias crimes were not racially disaggregated and included *all* forms of bias crimes. As a whole, the sub-sample results support the full-sample results. Predictors that were significant for the full-sample models remain significant in the sub-sample models. Political competition also becomes significant in the sub-sample models, suggesting that the social constructionist argument has a significant impact on bias crimes at the macro-level. But the issue remains that number of years reported is the most robust predictor of the full-sample models.

V. Violent Bias Crime and Social Constructionist Analyses

Years reporting data and Region (South) have strong and significant effects on bias crimes. It is logical that the count of bias crimes increase as reporting increases. What is problematic is that failure to comply with bias crime reporting requirements artificially suppresses the count of bias crimes in a city.

It is unlikely that bias crimes are less likely to occur in the South than in other regions, especially given the strong history of racial tension in the South. What is more probable is that cities located in the South are less likely to report bias crimes to the UCR in compliance with the HCSA. This finding is supported by King (2007) and McVeigh et al (2003); however, those studies also find that compliance with bias crime legislation is also lower in the Midwest and higher in the Northeast. Those regions do not have the same historical racial tension or documented links between race and violent crime that is common in the South; thus, would not make theoretical sense in a study designed to test social threat and the *occurrence* of violent bias crime.

Given the strong support in the social threat models (and lack of support in the violent crime model (Table 5) and interracial homicides (Tables 10 and 11), I present a small analysis of social movement variables and their effects on bias crime. The first notable finding is that South is the only region that consistently predicts violent bias crimes in the models. Midwest is significant only in the general crime model, but not in the social threat or full models. Northeast and West are significant as sole predictors of bias crime, but do not reach significance once general crime variables are introduced. Results for these regional variables are not presented since they do not reach significance once any other variable is introduced into the regressions.

Table 9 presents the effects of general crime variables on anti-Black violent bias crimes committed by Whites for the Midwest region. The first regression shows the effects of social constructionist, general crime and control variables for anti-Black violent bias crimes committed by Whites. The second regression presents the effects of social constructionist, general crime and control variables for anti-White violent bias crimes committed by Blacks.

For anti-Black violent bias crimes committed by Whites, unlike Model A in Table 6, the only variables that are significant are percent Black (-0.019), years reported and Midwest (0.798). Concentrated disadvantage is almost significant ($p=0.058$), indicating that regional variations exist in the impact of predictor variables. The expected count of anti-Black violent bias crimes committed by Whites decreases by 0.981 for every one percent increase in percent Black, net of all other factors. This finding is not consistent with social disorganization theory, nor is it consistent with Model A in Table 6, where percent Black is not significant. It could be that more integrated communities experience fewer biased incidents. What may be more likely, given that the Index of Dissimilarity is not significant, is that cities with larger Black populations may be more segregated, so that Blacks and Whites are less likely to come into contact with one another, resulting in fewer hate crimes.

Table 9. Negative Binomial Regressions in the Midwest Region

	Anti-Black	Anti-White
Social Constructionist		
Political Competitive	-0.008 (.005)	-0.008 (.007)
Region (Midwest)	0.798 (.185)**	0.919 (.236)**
General Crime		
Violent Crime Rate	1.03 (1.62)^	0.179 (.194)^
Percent Black, 1990	-0.019 (.007)**	-0.054 (.009)**
Concentrated Disadvantage	0.145 (.077)	0.016 (.106)
Percent aged 13-24	-0.023 (.023)	0.677 (3.351)^
Percent Rent	0.005 (.009)	0.014 (.012)
Percent Moved	0.005 (.016)	
Controls		
Number years reported	0.322 (.095)**	0.312 (.129)*
Dissimilarity	-0.007 (.005)	-0.442 (7.155)
Constant	-9.541	-12.180
Log Likelihood	-503.195	-288.139
Overdispersion	.637	.737
N=355		

Note: Standard errors in parentheses
*p<.05 **p<.01 (two-tailed tests)
^ Coefficient and standard deviation multiplied by 1,000

Unlike the South, cities located in the Midwest have an expected count increase of 2.221 anti-Black hate crimes than cities not located in the Midwest, net of other factors. It appears that being located in the Midwest either increases the counts of anti-Black violent bias crimes committed by Whites or increases compliance with hate crime reporting. King (2007) finds that the Midwest and South regions showed the least compliance with the HCSA. The main explanation for this discrepancy is that King's (2007) study included *all* states, whereas the main parameter for inclusion in this study is reporting data to the UCR. 9 states are excluded because for cities larger than 50,000, city police agencies did not report zero or incident data for any quarter in any of the five years of the study: Delaware, Hawaii, Idaho, Montana, North Dakota, Oregon, South Dakota, Vermont and Wisconsin. Three of those states (ND, SD, WI) are located in the Midwest region. King (2007:211, footnote 30) notes that "particular states may influence regional comparisons with respect to statistical significance." The fact that three states in the Midwest did not comply with hate crime reporting at all indicates that their absence could explain why the effect of Midwestern region is positive in these regressions.

For anti-White violent bias crimes committed by Blacks, percent Black (-0.054), region (0.919) and years reported exert a significant effect, which is similar to Model A in Table 7. There is an expected 0.947 count decrease in anti-White bias crimes committed by Blacks for every one percent increase in percent Black. As there are more potential offenders in a city, there are fewer anti-White violent bias crimes committed by Blacks. A city located in the Midwest is expected to have 2.508 more anti-White violent bias crimes committed by Blacks, net of other factors. Again, number of years reported is significant and positive for both regressions.

The finding that Midwest region becomes not significant once social threat variables are introduced into the regression is notable. South remains significant in the social threat and full models, which may indicate that historical racial tensions in the South are so deeply ingrained that any policy that addresses minority populations will be problematic. The Midwest is similar to the South in terms of political conservatism, Black representation in Congress and compliance with hate crime legislation (King 2007), yet once socially threatening conditions are accounted for in the Midwest, region becomes not significant. This finding shows that the South is the most problematic region to study for officially reported racially biased hate crimes.

VI. Interracial Homicide as Dependent Variable

According to prior research, the social threat model has successfully predicted interracial homicide, particularly White-on-Black homicide. D. Jacobs and O'Brien (1998) find that cities with higher percentages of Blacks have higher rates of police officer killings of Blacks, which is indicative of a response to a socially threatening population. Race of mayor also affected this relationship: cities with Black mayors had fewer police officer killings of Blacks, regardless of size of Black population. D. Jacobs and Wood (1999) find that the greater the economic competition between Whites and Blacks, the greater the rates of interracial homicide, with Black mayors again having an intervening effect. Cities with Black mayors had reduced killings of Whites by Blacks and increased killings of Blacks by Whites.

If we look to general crime predictors and homicide, racial and economic inequality are also factors in interracial homicide, particularly in homicides of Blacks (Parker and McCall 1999; Messner and South 1992), suggesting that concentrated disadvantage should be a salient predictor of homicides of Blacks committed by Whites. Further, it is likely that increased Black in-migration to predominantly White cities will exert an effect for homicides of Black victims by White offenders. Political power, in the form of Black mayor, probably should increase homicides of Blacks by Whites, but should act as a protective factor for homicides of Whites by Blacks.

Table 10 shows the homicides of Blacks committed by Whites. Model A uses the violent crime rate in 1996, general crime variables and the control variables to explain homicides of Blacks by Whites. Model B uses Black in-migration as the measure of racial threat; and model C is the full model with general crime variable, social threat variables and control variables. All models use the average White population count as the offset variable.

Consistent with predictions for model A, percent Black (0.019), concentrated disadvantage (0.153) and the Index of Dissimilarity (0.014) exert significant effects on homicides of Blacks committed by Whites. There is a 1.019 increase in expected count of homicides of Blacks committed by Whites for a one percent increase in percent Black, net of all other factors. There is a 1.241 change in expected count of homicides of Blacks committed by Whites for a one standard deviation increase in concentrated disadvantage. This finding is consistent with past research regarding concentrated disadvantage and interracial homicide (see, for example, Krivo and Peterson 2000; Messner and Golden 1992; and Peterson and Krivo 1993). There is a 1.302 increase in expected count of homicides of Blacks committed by Whites for a one standard deviation increase in the index of Dissimilarity, net of other factors. That is, as opportunities for interracial contact increase, there are more interracial homicides of Blacks committed by Whites. It is interesting to note that number of years reported and region are not significant.

Again, model B uses Black in-migration into White neighborhoods as the measure of racial threat. D. Jacobs and Wood (1999) find that economic competition and race of mayor are the strongest predictors of homicides of Blacks committed by Whites. Following D. Jacobs and Wood (1999), I expect that Black in-migration and race of mayor will be associated with an increase in homicides of Blacks committed by Whites. Additionally, economic threat should act similarly to economic competition in the form of the ratio of White to Black unemployment, the ratio of White to Black poverty and ratio of White to Black educational attainment should also have a positive and significant impact on homicides of Blacks committed by Whites. Cities with Black mayors should have increased rates of homicides of Blacks committed by Whites.

The only significant predictors in model B are percent White (-0.028) and the Index of Dissimilarity (0.011). As the White population increases by one percent, homicides of Blacks committed by Whites decrease by a factor of 0.973, controlling for all other factors. This may be a reflection that Whites tend to live in more affluent, low crime areas. There is a 1.224 increase in expected count of homicides of Blacks committed by Whites for a one standard deviation increase in the Index of Dissimilarity, holding all other variables constant. Again, it is surprising that Black in-migration, race of mayor or economic competition (the ratio of White to Black unemployment) are not significant, given past research efforts by D. Jacobs and Wood 1999.

Table 10. Negative Binomial Regression of Homicides of Black Victims Committed by Whites on General Crime and Social Threat Variables (White Population as Offset Variable).

	A	B	C
General Crime			
Violent Crime Rate[46]	0.078 (.084)		0.093 (.095)
Percent Black, 1990	0.019 (.007)**		--
Concentrated Disadvantage	0.153 (.081)*		0.236 (.084)**
Percent aged 13-24	-0.026 (.030)		-0.043 (.033)
Percent Rent	-0.004 (.009)		-0.016 (.009)
Percent Moved	0.026 (.019)		0.038 (.020)
Social Threat			
Percent White, 1990		-0.028 (.006)**	-0.028 (.006)**
Change Pct Black		0.322 (.356)	0.201 (.387)
Pct White*Change Pct Black		-0.577 (.505)	-0.485 (.530)
Black Official		0.059 (.206)	-0.249 (.223)
Ratio White/Black unemployment		-0.847 (.555)	-1.044 (.573)
Ratio White/Black college		-0.023 (.181)	-0.035 (.188)
Ratio White/Black poverty		-0.088 (.497)	-0.175 (.553)
Number years reported	0.089 (.064)	0.047 (.069)	0.065 (.066)
Controls			
Dissimilarity	0.014 (.006)*	0.011 (.006)*	0.008 (.007)
Political Competitive	-0.002 (.006)	0.001 (.005)	-0.004 (.005)
Region (South)	-0.092 (.187)	-0.015 (.177)	-0.008 (.175)
Constant	-14.550	-10.396	-10.699
Log Likelihood	-234.915	-229.351	-223.012
Overdispersion	0.064	0.028	.009
N=355			

Note: Standard errors in parentheses
*p<.05 **p<.01 (two-tailed tests)
^ Coefficient and standard deviation multiplied by 1,000

For model C, concentrated disadvantage (0.236) and percent White (-0.028) exert significant effects on homicides of Blacks committed by Whites. It is interesting to note that three other variables approach significance: percent rent (p=.057), percent moved (p=.061) and the ratio of White to Black unemployment (p=.069). There is a 1.397 increase in expected count of

[46] I was concerned about using an index including homicide rates to predict interracial homicide counts. I tested the violent crime rate in 1996 including homicides and excluding homicides. There was no difference in the predictors; thus, the violent crime rate in 1996 including homicide is used so that it is consistent with the bias equations.

homicides of Blacks committed by Whites for a one standard deviation increase in concentrated disadvantage, holding all other variables constant. This result is inconsistent with what we would expect since Whites are unlikely to live in areas with high levels of concentrated disadvantage, but again suggests that interracial homicides are impacted by social disorganization. For the social threat predictors, as the city's White population increases by one percent, the count of homicides of Blacks by Whites decreases by 0.973, net of all other factors.

Last, D. Jacobs and Woods (1999) find that some social threat variables also predict homicides of Whites committed by Blacks. As the Black population increases, so do the homicides of Whites committed by Blacks. As economic competition between Whites and Blacks increases, so do the homicides of Whites committed by Blacks; however, when the city's mayor is Black, the homicides of Whites committed by Blacks decrease.

Table 11 shows homicides of White victims by Black offenders. Model A uses the violent crime rate and general crime variables; model B uses only social threat and control variables; and model C is the full model with general crime, social threat and control variables. The population offset for these models is the average count of the Black population.

For model A, percent Black (-0.027) and percent rent are significant (-0.015). For a one percent increase in Black population, there is an expected 0.974 decrease of homicides of Whites committed by Blacks, net of other factors. An increase by one percent in rental units decreases Black homicides of Whites by 0.985, net of other factors. These findings are counter to the typical social disorganization prediction that argues that any increase in percent Black or residential turnover will increase crime. However, it could be that as a city becomes more predominantly Black, the number of available White victims decrease.

Table 11. Negative Binomial Regression Homicides of White Victims Committed by Blacks on General Crime and Social Threat Variables.

	A	B	C
General Crime			
Violent Crime Rate[47]	0.089 (.050)^		0.066 (.059)^
Percent Black, 1990	-0.027 (.005)**		--
Concentrated Disadvantage	0.096 (.056)		0.063 (.063)
Percent aged 13-24	-0.208 (21.128)		-0.024 (.023)
Percent Rent	-0.015 (.006)*		-0.009 (.007)
Percent Moved	0.018 (.013)		0.032 (.015)*
Social Threat			
Percent White, 1990		0.013 (.004)**	0.012 (.005)*
Change Pct Black		-0.074 (.278)	-0.101 (.286)
Pct White*Change Pct Black		0.023 (.159)	0.018 (.331)
Black Official		-0.210 (.159)	-0.319 (.167)
Ratio White/Black unemployment		-0.678 (.411)	-0.691 (.419)
Ratio White/Black college		-0.125 (.129)	-0.158 (.135)
Ratio White/Black poverty		0.158 (.338)	0.166 (.358)
Number years reported	0.069 (.046)	0.045 (.052)	0.048 (.051)
Controls			
Dissimilarity	-0.002 (.004)	-0.009 (.004)*	-0.008 (.005)
Political Competitive	-0.001 (.004)	0.003 (.004)	-0.002 (.004)
Region (South)	0.002 (.130)	-0.179 (.132)	-0.198 (.135)
Constant	-10.078	-0.898	-10.704
Log Likelihood	-320.541	-330.076	-326.715
Overdispersion	0.013	0.044	0.036
N=355			

Note: Standard errors in parentheses
*p<.05 **p<.01 (two-tailed tests)
^ Coefficient and standard deviation multiplied by 1,000

In model B, percent White (0.013) and the Index of Dissimilarity (-0.009) are significant predictors of homicides of Whites committed by Blacks. For every one percent increase in the White population of a city, there is an expected 1.014 increase in homicides of Whites committed by Blacks, net of all other factors. Black mayors have no protective effect on this, which contradicts the findings of D. Jacobs and Wood (1999). Additionally, there is a 0.840 decrease in

[47] See footnote 46.

expected count of homicides of Whites committed by Blacks for a one standard deviation increase in the Index of Dissimilarity. These two findings are related: as a city's White population increases, the interactions between Whites and Blacks decrease.

Percent moved (0.032) and percent White (0.012) are significant predictors of homicides of Whites committed by Blacks in model C; however, the presence of a Black mayor (p=.057) approaches significance in the full model and has a negative effect on homicides of Whites committed by Blacks, which is consistent with past research (D. Jacobs and Wood 1999). As the percent of residents who report moving in the last five years increases by one percent, there is an expected increase of 1.033 homicides of Whites committed by Blacks. This suggests that residential turnover plays a role in homicides of Whites committed by Blacks. As the White population of a city increases by one percent, there is an expected count increase of 1.012 homicides of Whites committed by Blacks, net of all other factors. This finding is significant even when controlling for interracial contact. Overall, these findings support that homicides of Whites committed by Blacks are more similar to general crime than they are to biased crime.

Chapter Six. Conclusion and Implications

This research supplements previous efforts to explain biased crime at the macro-level. It is the first examination of biased and non-biased crimes across multiple cities in the US. In doing so, it has provided useful support for previous research and identified a few discrepancies that should be pursued in future research.

Initially, the research was designed to test the feasibility of the social threat perspective vis a vis social disorganization theory in explaining biased violent crime. This test provides support for perspectives that separate bias crimes from other forms of crime; however, it does not provide unequivocal support for the social threat perspective. Surprisingly, the results also focus attention on the social constructionist perspective in terms of complying with hate crime legislation and reporting hate crime data. Social threat and social disorganization provide relatively poor macro-level predictors for biased crime once number of years reported is introduced into the regressions. In fact, social disorganization variables do not explain racially biased crime at all. Social threat variables are better predictors, but are sometimes in the opposite direction than predicted.

In this chapter, I will review the negative binomial regressions of anti-White violent hate crimes committed by Blacks and anti-Black violent hate crimes committed by Whites. Next, I will present the more notable findings regarding the social constructionist perspective. Then, I will discuss limitations of the current research. Last, I will present the implications for future research.

I. Social Threat, Social Disorganization and Violent Biased Crime

The first finding is that anti-Black violent bias crimes committed by Whites and anti-White violent bias crimes committed by Blacks appear to have different causal processes than non-biased violent crime in general and non-biased interracial homicides. Violent crimes not motivated by bias were clearly explained by social disorganization predictors. Additionally, while region did not meet significance at the .05 level, it was positive and approached significance at the .058 level. That is, cities located in the South experienced higher levels of violent crimes than cities not located in the South. Social disorganization predictors were unable to reach significance in the biased equations, except for percent moved in the sub-sample of cities that reported data in all five years for anti-Black biased crimes committed by Whites. Even in that sub-sample analysis, the ratio of White to Black unemployment was still significant. Additionally, region was significant in every biased equation, but in the opposite direction to that of unbiased violent crimes. Rather than a lower count of biased crimes occurring in the South, the significance of region seems to indicate that police agencies located in Southern cities are less likely to report biased crimes than cities not located in the South. Region was not a significant predictor for interracial homicides.

Comparing biased crimes to unbiased interracial homicides is murky. Percent White is not significant for anti-Black biased crimes committed by Whites, but is a significant predictor of anti-White biased violent crimes and unbiased interracial homicides of Whites and Blacks. Percent White is negative for homicides of Blacks committed by Whites and positive for anti-White biased crimes and homicides of Whites committed by Blacks. This suggests that anti-Black biased violent crimes are distinct from anti-White biased violent crimes and also implies that anti-White bias crimes may have more in common with non-biased motivated interracial violence.

Comparing anti-White biased violent crimes committed by Blacks and anti-Black biased violent crimes committed by Whites illustrates different causal processes at work. In both the full sample and sub-sample analyses, anti-Black violent bias crimes appear to be driven by economics; however, it is in the opposite direction than that predicted by economic threat. As Whites experience higher unemployment compared to Blacks, counts of anti-Black bias crimes decrease rather than increase. Social threat would predict that as Whites become more economically disadvantaged, they become threatened by those who they perceive are gaining advantages (Blacks) and will attempt to reassert dominance over the threatening population. Instead, as Whites become more economically disadvantaged than Blacks, the expected counts of bias crimes against Blacks decrease.

This research suggests that biased crime may not be a typical response to the economic threat posed by Blacks to Whites. This finding is actually supported by recent research on college campuses. Van Dyke and Tester (2014: 301) found that a "$1,000 [U.S. dollars] increase in tuition is associated with 25% fewer racist hate crimes. This analysis suggests that *economic* competition is not influencing ethnic conflict on campus" (italics in original). Van Dyke and Tester's (2014) measure of tuition increases is arguably not the best representation of competition for scarce resources; however, it does indicate that perhaps the role of economics and bias crimes might need to be re-conceptualized completely.

An alternate explanation is that perhaps as Blacks achieve economic parity with Whites, the Black population becomes less threatening. The image of the typically threatening "urban black male" is that he is not employed (Wilson 1987; Quillian and Pager 2001; Quillian 2003). Perhaps as Blacks become gainfully employed, they become less threatening to Whites. Quillian (2003) found that male joblessness is greatest in predominantly Black neighborhoods, supporting Wilson's (1987) and Massey and Denton's (1993) hypothesis that as disadvantage becomes concentrated, mostly in Black neighborhoods, it acts as an active barrier to achieving economic success. Quillian (2003) also found that male joblessness was not as troublesome in less disadvantaged Black neighborhoods, White or multi-ethnic neighborhoods. Recent work by Wagmiller (2008) supports some of these findings. Male joblessness is highest in economically disadvantaged Black neighborhoods; however, between 1970 and 2000, male jobless rates increased at about the same pace for males in less disadvantaged Black, Hispanic and multi-ethnic neighborhoods. That is, male residents in less disadvantaged Black, Hispanic and multi-ethnic neighborhoods are more likely to experience similar increased rates in joblessness to disadvantaged Black neighborhoods than are males in White neighborhoods. One could argue that Blacks living in White neighborhoods are less likely to be jobless and therefore, not as threatening to his neighbors. Thus, the Black residents in a predominantly White neighborhood may be somewhat protected from biased crimes.

A final interpretation is that perhaps Whites are more likely to compare economic situations with other Whites rather than with Blacks, and therefore may not compare their own unemployment to Blacks. Krivo et al (2013) found that Whites living in disadvantaged neighborhoods in Los Angeles are more likely to engage in routine activities (shopping, working, etc) in areas where there are fewer Blacks and Latinos. The situation is even more pronounced for Whites living in advantaged neighborhoods where there are few minorities. Whites in advantaged neighborhoods are likely to use other wealthy Whites as their economic reference group; however, even disadvantaged Whites are more likely to find other slightly more advantaged Whites as their reference group, rather than comparing themselves with economically similar Blacks.

Political threat, represented by the presence of a Black mayor, also fails to reach significance in any of the models, although it does approach significance in the full model of homicides of Whites committed by Blacks. This is slightly contrary to work by D. Jacobs and colleagues (1998 and 1999) who find that race of mayor reduces the number of police officer killings of Blacks and homicides of Whites committed by Blacks. While not significant (p=0.057), the effect of race of mayor is negative for homicides of Whites committed by Blacks, consistent with D. Jacobs and Woods (1999). Bias crimes, particularly anti-Black violent bias crimes committed by Whites, appear to have different causal paths than that of unbiased interracial crime. While unexpected, this result is not unexplainable. It is unusual in terms of anti-White bias crimes committed by Blacks since the causal processes seem to be more similar to interracial homicides of Whites committed by Blacks.

An anomalous result is that Black in-migration failed to reach significance in any of the regressions, yet was such a robust predictor in previous studies (Green et al 1998a; Grattet 2009; Lyons 2007). One possible explanation is that the unit of analysis may be critically important for this particular measure. Previous research focused on neighborhoods rather than cities as the unit of analysis. Cities may be too large a demographic region for one to notice Black in-migration. Van Dyke and Tester (2014) found that increases in the minority population on college campuses have no effect on the number of racial or ethnic hate crimes committed on campus. Their findings at yet another different unit of analysis do not support defended neighborhoods theory on college campuses.

Another possible explanation is that these prior studies failed to take region into consideration. King (2007) found Midwestern and Southern police agencies are less likely to comply with the HCSA, but not for agencies located in the Northeast or West. Grattet (2009) studied Sacramento, CA in the West and Green et al (1998a) studied NYC in the Northeast. The police agencies in these regions have not demonstrated problematic compliance with federal hate crime laws, which in turn might influence how Black in-migration affects bias crimes.

Anti-White bias crimes committed by Blacks are more likely to occur in cities with higher percentage White population, net of all other factors. This includes controlling for the measure of interracial contact, which indicates that the mere presence of more Whites in a city may lead to more anti-White biased violent crime. This does not necessarily lend itself to supporting social threat. From a threat perspective, Whites do not pose a threat, since they are the powerful group. Percent White does not affect anti-Black biased crimes committed by Whites, nor does change in percent Black population or Black in-migration.

Also observed are the social constructionist variables playing an important role for biased violence but no role whatsoever in unbiased violence. Years reporting data and region are statistically significant and salient predictors in the bias regressions, but not regressions of unbiased violent crime or homicides. This finding suggests that bias crimes are the result of social constructionism, at least to some degree. To place these results in theoretical context, it is useful to summarize briefly key studies in the constructionist tradition.

II. Social Construction and Biased Violent Crime

Social constructionist research generally examines the factors that affect compliance with public policies once they are enacted, and how the presence or absence of certain groups or organizations factor into that compliance (McVeigh et al 2003). Additionally, compliance with legislation varies in terms of police agency training and decision-making (King 2007). Hate crime legislation is a prime topic for discussion since hate crime laws are relatively recent, both at the federal and state levels. Because hate crime legislation aims to protect historically disenfranchised populations, there are likely to be activist groups which promote the necessity of the laws, as well as those that see little incentive to actively cooperate with the legislation, or at the extreme, actively fight against hate crime legislation.

In their study of hate crime reporting as a result of social movements, McVeigh et al (2003) find that counties with higher populations, higher per capita incomes, active hate groups, active civil rights organizations, and that are politically competitive have higher compliance with hate crime reporting laws, even if the reports are zero counts. Rural counties and counties with higher rates of Black-on-White homicide have lower compliance with hate crime legislation. Last, counties in the Southern and Midwestern US are less likely to comply with hate crime reporting.

King (2007) examines minority group threat in conjunction with compliance with the HCSA. His study examined 2,985 police departments and whether they complied, complied partially or did not comply at all with the HCSA. He finds that the South and Midwest are the least likely to comply with the HCSA[48]. King (2007) further finds that Black population size negatively affects police department compliance with the HCSA in the South (it positively affects compliance in the North and has no effect on compliance in the Midwest or West). Last, community policing (his measure of the degree of governmental and community interaction, also called institutional arrangements) has a positive effect on both partial and full compliance with the HCSA.

As noted above, region is a very important predictor of biased crimes. A city's location in the South negatively affected the number of hate crimes reported to authorities; however, being located in the South was not a significant predictor of either interracial homicide or violent crimes in general. In fact, being located in the South was almost significant for violent crimes in general (0.058), but the effect is positive. This further bolsters McVeigh et al's (2003) and King's (2007) finding that cities located in the South are less likely to comply with hate crime legislation.

The effect of region is not consistent. Southern cities are less likely to have recorded numbers of bias crimes, regardless of which variables are included in the regression. The

[48] King (2007) qualifies his results as to Southern police departments when it comes to partial compliance: Southern states are less likely to comply with the HCSA overall; however, once an agency does comply, it is more likely to fully comply – rather than partially comply - with the reporting requirements.

relationship between reporting and bias crimes for Midwestern cities is inconsistent with past research. Years reporting has a positive effect on the number of bias crimes reported in Midwestern cities, but only when social disorganization and strain variables are included in the regression. The relationship between Midwestern cities and bias crime disappears in the social threat and full models. Caution must be issued because three Midwestern states were excluded from the sample for not reporting data to the UCR for any of the quarters in any of the years of the study. However, it is interesting to note that social threat may modify the relationship between region and compliance with hate crime reporting legislation. Once social threat variables are introduced into the regressions, the relationship between years reported and bias crimes becomes not significant for Midwestern cities, while the relationship between years reported and bias crimes remained significant for Southern cities.

Political competition is also a social constructionist predictor that is significant in the sub-sample of cities for anti-White violent bias crimes committed by Blacks. In cities that reported data in all five years of the sample, those cities located in politically competitive counties reported a decreased number of anti-White violent bias crimes committed by Blacks. McVeigh et al (2003) reported that bias crimes in general increased in politically competitive counties; however, those bias crimes were not racially disaggregated and included *all* forms of bias crimes, including property crimes. While not supporting McVeigh et al's (2003) finding regarding political competitiveness, it does support my finding that anti-White violent biased crimes have different causal processes than anti-Black violent biased crimes. Lyons (2007) found that anti-White biased crimes are more similar to unbiased crime in general than they are to biased crimes, suggesting that future studies of racially motivated violent hate crimes should be racially disaggregated. This research shows that anti-White violent bias crimes are more similar to interracial violent crime than it is to anti-Black violent bias crimes or unbiased violent crimes.

Perhaps the most important finding is that years reported is a strong, salient and consistent predictor in the biased negative binomial regressions, yet had no effect on the non-biased interracial homicides. Every year reporting increased the expected counts of a biased crime by about 1, even controlling for region. King (2007) reports that cities located in the South are less likely to comply with hate crimes, a finding which is supported by this research. Years reported exerts a positive effect on anti-White and anti-Black bias crimes. For every year an agency complied with hate crime legislation and reported data to the FBI, there was an increase of about one biased crime per year. This finding, along with region, suggests that compliance with hate crime legislation is an important variable to control for and to explain when studying hate crimes.

III. Limitations of the Current Research

First, this research relies on reported bias crimes to the police, which then are investigated by officers and deemed to be violent biased crimes. Once the determination is made that an incident is racially motivated, the officer must comply with a federal law to report the crimes to the FBI. There are many reasons why this presents a problem (as reviewed in McDevitt et al 2000; and Nolan, Akiyama and Bernhau 2002). Most important to this research appears to be the fact that each additional year of reporting data, even zero counts of bias crimes, positively affects both anti-White and anti-Black violent bias crimes. That is, merely complying with the reporting requirement is associated with an increase in violent biased crimes for a city.

A possible solution to this would be to use victimization data to see if reported victimization coincides with investigated and "officially" tracked bias crimes. One must be cautious though of the source of that victimization data, since some may be tracking biased activity rather than biased crime.

Second, it is vital that regional variations in reporting be addressed. The stable finding that Southern cities report lower counts of bias crimes is important and because all Southern states except Delaware were included in this sample, we can rely on those results. Midwestern states reported higher counts of bias crimes; however, these results must be interpreted with caution because three Midwestern states did not meet the reporting criteria in that cities of over 50,000 persons with a minimum population of 1,000 African-Americans did not report data in any quarter of any year in the study.

A surprising finding in this research is that in-migration of Blacks into previously majority White cities is not a predictor of anti-Black violent biased crimes committed by Whites. The most likely explanation is that cities are too large a unit of analysis to capture the effect of in-migration.

IV. Implications for Future Research

As supported by this research, anti-White and anti-Black crimes have different predictors (Green et al, 1998a), and are substantively different from unbiased violent crime and unbiased interracial homicides. Anti-White violent biased crimes seem driven by racial composition of a city, while anti-Black violent bias crimes appear to have foundations in economics – though that foundation does not appear to be economic threat. When both races appear to be doing well economically, there are fewer anti-Black violent biased crimes committed by Whites. Threat theories cannot explain why this is the case, although Van Dyke and Tester (2014) found that increases in tuition (their measure of economic competition) also operated to reduce the number of ethnic and racially motivated hate crimes committed on campus. Future research attempts should hone in on why economic threat has a protective effect on anti-Black hate crimes. As discussed earlier, it is possible that as Black males achieve equal rates of employment, they become less threatening to Whites.

In terms of anti-White biased violence, the one significant predictor is percent White in a city. Percent White was also a significant predictor for homicides of Whites committed by Blacks, although percent moved also had an effect on homicides. Anti-White violent bias crimes committed by Blacks have more causal processes in common with homicides of Whites committed by Blacks than can be said for anti-Black hate crimes and homicides of Blacks committed by Whites.

If future studies wish to focus on the effects of population changes on bias crimes, the researchers will need to pay particular attention to the unit of analysis. Cities appear to be too large to effectively utilize changes in racial composition as a predictor variable. Neighborhoods may be the appropriate size to examine the effects of minority in-migration on bias crimes, although Van Dyke and Tester (2014) found that increased minority population had no effect on ethnic and racially motivated crimes on college campuses, again illustrating that researchers must adequately address the unit of analysis before progressing with hate crime research. Additionally, macro-level hate crime studies should take into account region (South and Midwest, when available), number of years reporting data and other social constructionist variables, such as political climate, presence of active hate groups in an area, and presence of active civil rights organizations (McVeigh et al 2003, King 2007).

In a recent paper, Green and Spry (2014) delineate the problems of determining causality in hate crime research efforts. They note that most attempts have been cross-sectional thus far and have therefore not been effective at determining the causal order of hate crimes. The authors suggest that quasi-experimental research should be the main focus for future researchers. In terms of macro-level studies of hate crimes and the apparent effect of social constructionist variables, quasi-experimental research should be appropriate. Researchers could examine Southern neighborhoods with social activist groups and compare them to Southern cities without social activist groups. The same could be done for active hate groups, or for neighborhoods in the Midwest versus the South.

V. Summary

Several important findings can be drawn from this research. First, this research provides more evidence that violent bias crimes should be racially disaggregated. Anti-Black violent bias crimes are distinct from anti-White violent bias crimes, interracial unbiased homicides and violent crime in general. Research that fails to disaggregate violent bias crimes by race may miss important differences in the predictors of biased crimes. In particular, anti-Black bias crimes are best explained by economic threat, although not in the hypothesized direction. Rather than recognizing the threat the Black population poses, Whites may be comparing their levels of unemployment to other Whites rather than to Blacks, which might explain why anti-Black violence decreases as White disadvantage increases. Second, research that aims to address demographic shifts in populations on bias crimes must correctly identify the unit of analysis. This study suggests that cities are too large a unit to effectively analyze changed in population characteristics when it comes to bias crimes. Third, macro-level studies must take into account regional variations in complying with hate crime reporting, particularly in the South and Midwest.

Probably the most important finding of this research is that future macro-level and possibly even micro-level studies must address data reporting and compliance with reporting statutes.

Years reporting data is a strong and salient predictor in every bias regression, showing consistently that for every year reporting data, the expected count of bias crimes increases by one. Thus, any study of bias crimes may be misspecified without controlling for compliance with the HCSA and other hate crime reporting legislation.

Sources

Addington, Lynn A. 2008. "Assessing the Extent of Nonresponse Bias on NIBRS Estimates of Violent Crime." *Journal of Contemporary Criminal Justice*, V24 N1: 32-49.

Akiyama, Yoshio and James Nolan. 1999. "Methods for Understanding and Analyzing NIBRS Data." *Journal of Quantitative Criminology*, 15 (2): 225-238.

Alba, Richard D., John R. Logan and Brian J. Stults. 2000. "How Segregated are Middle-Class African Americans?" *Social Problems*, 47(4): 543-559.

Allison, Paul D. 1978. "Measures of Inequality." *American Sociological Review*, 43(6): 865-880.

Arvanites, Thomas M. 1992. "The Mental Health and Criminal Justice Systems: Complementary Forms of Coercive Control." Pages 131-150 in *Social Threat and Social Control,* ed. Allen E. Liska. Albany, NY: SUNY Press.

Beckett, Katherine, Krisy Nyrop and Lori Pfingst. 2006. "Race, Drugs and Policing: Understanding Disparities in Drug Delivery Arrests." *Criminology*, 44: 105-37.

Berk, Richard A. 1983. "An Introduction to Sample Selection Bias in Sociological Data." *American Sociological Review*, 48: 386-98.

Boggess, Lyndsay N. and John R. Hipp. 2010. "Violent Crime, Residential Instability and Mobility: Does the Relationship Differ in Minority Neighborhoods?" *Journal of Quantitative Criminology*, 26: 351-370.

Bositis, David A. 1999. *Black Elected Officials: A Statistical Summary 1998.* www.jointcenter.org/research/black-elected-officials-a-statistical-summary-1998. Retrieved 28 March 2014.

Boyd, Elizabeth A., Richard A. Berk and Karl M. Hammer. 1996. "Motivated by Hate or Prejudice: Categorization of Hate-Motivated Crimes in Two Police Divisions." *Law & Society Review*, 30(4): 819-850.

Black, Donald. 1983. "Crime as Social Control." *American Sociological Review*, 48: 34-45.

Blalock, Hubert M. 1967. *Towards a Theory of Minority-Group Relations.* New York: John Wiley.

Blau, Peter M. 1977. *Inequality and Heterogeneity*. New York: Free Press.

Blau, Judith R. and Peter M. Blau. 1982. "The Cost of Inequality: Metropolitan Structures and Violent Crime." *American Sociological Review*, 47: 114-129.

Bureau of Labor Statistics. 2014. "Labor Force Statistics from the Current Population Survey (SIC)." http://data.bls.gov/cgi-bin/surveymost. Retrieved 4 December 2014.

Burnett, John. "Britain: Racial Violence and the Politics of Hate." *Race & Class*, v54 n5: 5-21.

Byers, Bryan, Benjamin W. Crider and Gregory K. Biggers. 1999. "Bias Crime Motivation: A Study of Hate Crimes and Offender Neutralization Techniques Used Against the Amish." *Journal of Contemporary Criminal Justice*, 15(1): 78-96.

Caravelis, Cyndy, Ted Chiricos and William Bales. 2011. "Static and Dynamic Indicators of Minority Group Threat in Sentencing Outcomes: A Multi-Level Analysis." *Journal of Quantitative Criminology*, 27: 405-425.

Carmichael, Jason T. and Stephanie L. Kent. 2014. "The Persistent Significance of Racial and Economic Inequality on the Size of Municipal Police Forces in the United States, 1980-2010." *Social Problems,* 61(2): 259-282.

Chamlin, Mitchell B. 1992. "Intergroup Threat and Social Control: Welfare Expansion Among States During the 1960s and 1970s." Pages 151-164 in *Social Threat and Social Control,* ed. Allen E. Liska. Albany, NY: SUNY Press.

Cheng, Wen, William Ickes and Jared B. Kenworthy. 2013. "The Phenomenon of Hate Crimes in the United States." *Journal of Applied Social Psychology*, v43(4): 761-794.

Cogan, Jeanine C. 2002. "Hate Crime as a Crime Category Worthy of Policy Attention." *American Behavioral Scientist*, 46(1): 173-185.

Cogan, Jeanine C. and Amy Marcus-Newhall. 2002. "Introduction." *American Behavioral Scientist*, 46(1): 8-13.

Craig, Kellina M. 1999. "Retaliation, Fear, or Rage: An Investigation of African American and White Reactions to Racist Hate Crimes." *Journal of Interpersonal Violence*, 14(2): 138-151.

D'Alessio, Steward J. and Lisa Stolzeberg. 2003. "Race and the Probability of Arrest." *Social Forces*, 81: 1381-97.

D'Alessio, Stewart J., Lisa Stolzenberg and David Eitle. 2002. "The Effect of Racial Threat on Interracial and Intraracial Crimes." *Social Science Research*, 31(3): 392-408.

Dasgupta, Partha, Amartya Sen and David Starrett. 1973. "Notes on Measurement of Income Inequality." *Journal of Economic Theory*, V6: 180-187.

DeFina, Robert and Lance Hannon. 2009. "Diversity, Racial Threat and Metropolitan Housing Segregation." *Social Forces*, 88(1): 373-394.

Downs, Anthony. 1973. *Opening up the Suburbs: An Urban Strategy for America.* New Haven, CT: Yale University Press.

Eitle, David, Stewart J. D'Alessio and Lisa Stolzenberg. 2002. "Racial Threat and Social Control: A Test of the Political, Economic, and Threat of Black Crime Hypotheses." *Social Forces* 81(2): 557-576.

Ellison, Christopher G. 1991. "An Eye for an Eye? A Note on the Southern Subculture of Violence Thesis." *Social Forces*, 69(4) 1223-1239.

Federal Bureau of Investigation (FBI). 1999a. *Uniform Crime Reports: Hate Crime Reporting Statistics (Annual).* Washington, DC.

Federal Bureau of Investigation (FBI). 1999b. *Hate Crime Data Collection Guidelines (Revised)*. Washington, DC.

Federal Bureau of Investigation (FBI). 2000a. *Hate Crime Statistics, 2000*. Washington, DC: Government Printing Office.

Federal Bureau of Investigation (FBI). 2000b. *Uniform Crime Reports*. Washington, DC.

Federal Register. 1990. Vol. 55, No. 33, February 16, 1990: 5664-5666.

Federal Register. 2000. Vol. 65, No. 31, February 15, 2000: 7555-7557.

Franklin, Karen. 2000. "Antigay Behaviors Among Young Adults: Prevalence, Patterns and Motivators in a Noncriminal Population." *Journal of Interpersonal Violence*, 15(4): 339-362.

Franklin, Karen. 2002. "Good Intentions: The Enforcement of Hate Crime Penalty-Enhancement Statutes." *American Behavioral Scientist*, 46(1): 154-172.

Gilliam, Franklin D., Nicholas A. Valentino and Matthew N. Beckmann. 2002. "Where You Live and What You Watch: The Impact of Racial Proximity and Local Television News on Attitudes About Race and Crime." *Political Research Quarterly,* 55(4): 755-780.

Grattet, Ryken. 2009: "The Urban Ecology of Bias Crime: A Study of Disorganized and Defended Neighborhoods." *Social Problems*, 56(1): 132-150.

Grattet, Ryken and Valerie Jenness. 2008. "Transforming Symbolic Law into Organizational Action: Hate Crime Policy and Law Enforcement Practice." *Social Forces*, 87(1): 501-27.

Grattet, Ryken, Valerie Jenness and Theodore R. Curry. 1998. "The Homogenization and Differentiation of Hate Crime Law in the United States, 1978-1995: Innovation and Diffusion in the Criminalization of Bigotry." *American Sociological Review,* 63(2): 286-307.

Green, Donald P., Dara Z. Strolovitch, and Janelle S. Wong. 1998a. "Defended Neighborhoods, Integration, and Racially Motivated Crime." *American Journal of Sociology*, 104(2): 372-403.

Green, Donald P., Jack Glaser and Andrew Rich. 1998b. "From Lynching to Gay-Bashing: The Elusive Connection Between Economic Conditions and Hate Crime." *Journal of Personality and Social Psychology*, 75(1): 82-92.

Green, Donald P., Laurence H. McFalls, and Jennifer K. Smith. 2001. "Hate Crime: An Emergent Research Agenda." *Annual Review of Sociology* 27:479-504.

Green, Donald P. and Amber D. Spry. 2014. "Hate Crime Research: Design and Measurement Strategies for Improving Causal Inference." *Journal of Contemporary Criminal Justice*, 30(3): 228-246.

Haider-Markel, Donald P. 1998. "The Politics of Social Regulatory Policy: State and Federal Hate Crime Policy and Implementation Effort." *Political Research Quarterly*, 51(1): 69-88.

Harer, Miles D. and Darrell Steffensmeier. 1992. "The Different Effects of Economic Inequality on Black and White Rates of Violence." *Social Forces*, 70: 1035-1054.

Herek, Gregory M., Jeanine C. Cogan and J.R. Gillis. 2002. "Victim Experiences in Hate Crimes Based on Sexual Orientation." *Journal of Social Issues*, 58(2): 319-339.

Hipp, John R., George E. Tita and Lyndsay N. Boggess. 2009. "Intergroup and Intragroup Violence: Is Violent Crime an Expression of Group Conflict or Social Disorganization?" *Criminology*, 47(2): 521-564.

Jacobs, David. 1979. "Inequality and Police Strength: Conflict Theory and Coercive Control in Metropolitan Areas." *American Sociological Review*, 44(9): 913-25.

Jacobs, David and Robert M. O'Brien. 1998. "The Determinants of Deadly Force: A Structural Analysis of Police Violence." *The American Journal of Sociology*, 103(4): 837-62.

Jacobs, David and Katherine Wood. 1999. "Interracial Conflict and Interracial Homicide: Do Political and Economic Rivalries Explain White Killings of Blacks or Black Killings of Whites?" *The American Journal of Sociology,* 105(1): 157-90.

Jacobs, James B. and Kimberly A. Potter. 1997. "Hate Crimes: A Critical Perspective." *Crime and Justice*, University of Chicago.

Jacobs, James B. and Kimberly A. Potter. 1998. *Hate Crimes: Criminal Law & Identity Politics.* New York, NY: Oxford University Press.

Jenness, Valerie. 1999. "Managing Difference and Making Legislation: Social Movements and the Racialization, Sexualization, and Gendering of a Federal Hate Crime Law in the U.S., 1985-1998." *Social Problems*, 46(4): 548-571.

Jenness, Valerie and Kendal Broad. 1997. *Hate Crimes: New Social Movements and the Politics of Violence*. New York, NY: Aldine.

Jenness, Valerie and Ryken Grattet. 2001. *Making Hate A Crime: From Social Movement to Law Enforcement*. New York: Russell Sage Foundation.

Kent, Stephanie L. and David Jacbos. 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.

King, Ryan D. 2007. "The Context of Minority Group Threat: Race, Institutions and Complying with Hate Crime Law." *Law & Society Review* 41: 189-224.

King, Ryan D. and Darren Wheelock. 2007. "Group Threat and Social Control: Race, Perceptions of Minorities and the Desire to Punish." *Social Forces*, 65(3): 1255-80.

King, Ryan D., Steven F. Messner and Robert D. Baller. 2009. "Contemporary Hate Crimes, Law Enforcement, and the Legacy of Racial Violence." *American Sociological Review*, 74: 291-315.

Krivo, Lauren J. and Ruth D. Peterson. 1996. "Extremely Disadvantaged Neighborhoods and Urban Crime." *Social Forces*, 75: 619-650.

Krivo, Lauren J., Heather M. Washington, Ruth D. Peterson, Christopher R. browning, Catherine A. Calder, and Mei-Po Kwan. 2013. "Social Isolation of Disadvantage and Advantage: The Reproduction of Inequality in Urban Space." *Social Forces*, 92: 141-164.

Land, Kenneth C., Patricia L. McCall and Lawrence E. Cohen. 1990. "Structural Covariates of Homicide Rates: Are There Any Invariances Across Time and Social Space?" *The American Journal of Sociology*, 95(4): 922-63.

Lawrence, Frederick M. 1999. Punishing Hate: Bias Crimes Under American Law. Cambridge, MA: Harvard University Press.

Levin, Brian. 2002. "From Slavery to Hate Crime Laws: The Emergence of Race and Status-Based Protection in American Criminal Law." *Journal of Social Issues*, 58(2): 227-245.

Levin, Jack. 2002. *The Violence of Hate: Confronting Racism, Anti-Semitism, and Other Forms of Bigotry.* Boston, MA: Allyn and Bacon.

Levin, Jack and Gordana Rabrenovic. 2001. "Hate Crimes and Ethnic Conflict: An Introduction." *American Behavioral Scientist*, 45(4): 574-587.

Levin, Jack and Jack McDevitt. 1993. *Hate Crime: The Rising Tide of Bigotry and Bloodshed*. New York, NY: Plenum.

Levin, Jack and Jack McDevitt. 2002. *Hate Crimes Revisited: America's War on Those Who Are Different.* Boulder, CO: Westview Press.

Liska, Allen E. 1987. "A Critical Examination of Macro Perspectives on Crime Control." *Annual Review of Sociology*, 13: 67-88.

Liska, Allen E. 1992. *Social Threat and Social Control*. Albany, NY: SUNY Press.

Liska, Allen E., Joseph J. Lawrence and Michael Benson. 1981. "Perspectives on the Legal Order: The Capacity for Social Control." *American Journal of Sociology*, 87:413-26.

Liska, Allen E., Joseph J. Lawrence and Andrew Sanchirico. 1982. "Fear of Crime as a Social Fact." *Social Forces*, 60(3): 760-770.

Liska, Allen E., Mitchell B. Chamlin and Mark B. Reed. 1985. "Testing the Economic Production and Conflict Models of Crime Control." *Social Forces*, 64(1): 119-138.

Liska, Allen E., Fred E. Markowitz, Rachel Bridges Whaley and Paul Bellair. 1999. "Modeling the Relationship Between the Criminal Justice and Mental Health Systems." *The American Journal of Sociology*, 104(6): 1744-1775.

Lizotte, Alan J. and David J. Bordua. 1980. "Firearms Ownership for Sport and Protection: Two Divergent Models." *American Sociological Review*, 45(2): 229-44.

Long, J. Scott. 1997. *Regression Models for Categorical and Limited Dependent Variables*. Thousand Oaks, CA: Sage.

Long, J. Scott. and Freese, J. (2006). *Regression Models for Categorical Dependent Variables Using Stata*, Second Edition. College Station, TX: Stata Press.

Lyons, Christopher J. 2007. "Community (Dis)Organization and Racially Motivated Crime." American Journal of Sociology, 113(3): 815-63.

Lyons, Christopher J. 2008. "Defending Turf: Racial Demographics and Hate Crime Against Blacks and Whites." Social F*orces*, 87(1): 357-85.

Maltz, Michael. 1999. "Bridging Gaps in Police Crime Data." *Bureau of Justice Statistics*, US Department of Justice Statistics: NCJ 176365.

Martin, Susan E. 1996. "Investigating Hate Crimes: Case Characteristics and Law Enforcement Responses." *Justice Quarterly*, 13(3): 455-480.

Martin, Susan E. 1999. "A Cross-Burning is Not Just an Arson: Police Social Construction of Hate Crimes in Baltimore County." *Criminology*, 33: 303-326.

Marx, Karl. 1988 [1848]. *The Communist Manifesto.* Edited by Frederic L. Bender. New York, NY: W.W. Norton & Company.

Massey, Douglas. 2001. "The Prodigal Paradigm Returns: Ecology Comes Back to Sociology." In Alan Booth and Ann Crouter (eds), *Does It Take a Village? Community Effects on Children, Adolescents and Families.* Mahwah, NJ: Lawrence Erlbaum Associates.

Massey, Douglas and Nancy A. Denton. 1987. "Trends in Residential Segregation of Blacks, Hispanics and Asians: 1970-1980." *American Sociological Review*, 52(6): 802-25.

Massey, Douglas and Nancy A. Denton. 1993. *American Apartheid: Segregation and the Making of the Underclass.* Cambridge, MA: Harvard University Press.

McCall, Patricia L., Kenneth C. Land, Cindy Brooks Dollar and Karen F. Parker. 2013. "The Age Structure-Crime Rate Relationship: Solving a Long-Standing Puzzle." *Journal of Quantitative Criminology*, 29(2): 167-190.

McDevitt, Jack, Jack Levin and Susan Bennett. 2002. "Hate Crime Offenders: An Expanded Typology." *Journal of Social Issues,* 58(2): 303-317.

McDevitt, Jack, Shea Cronin, Jennifer Balboni, Amy Farrell, James Nolan and Joan Weiss. 2003. "Bridging the Information Disconnect in National Bias Crime Reporting." Institute on Race and Justice Technical Report.

McVeigh, Rory, Michael R. Welch and Thoroddur Bjarnason. 2003. "Hate Crime Reporting as a Successful Social Movement Outcome." *American Sociological Review*, 68(6): 843-867.

Messner, Steven F. 1989. "Economic Discrimination and Societal Homicide Rates: Further Evidence on the Cost of Inequality." *American Sociological Review,* 54:597-611.

Messner, Steven F. and Reid M. Golden. 1992. "Racial Inequality and Racially Disaggregated Homicide Rates." *Criminology*, 30: 421-445.

Messner, Steven F., Suzanne McHugh, and Richard Felson. 2004. "Distinctive Characteristics of Assaults Motivated by Bias." *Criminology*, 42(3): 585-618.

Messner, Steven F. and Scott J. South. 1986. "Economic Deprivation, Opportunity Structure and Robbery Victimization: Intra- and Interracial Patterns." *Social Forces*, 64: 975-991.

Messner, Steven F. and Scott J. South. 1992. "Interracial Homicide: A Macrostructural-Opportunity Perspective." *Sociological Forum*, 7: 517-536.

Morenoff, Jeffrey D, Robert J. Sampson and Stephen W. Raudenbush. 2001. "Neighborhood Inequality, Collective Efficacy and the Spatial Dynamics of Urban Violence." *Criminology* 39(3): 517-559.

Myers, Martha A. 1990. "Black Threat and Incarceration in Postbellum Georgia." *Social Forces*, 69(2): 373-93.

Noelle, Monique. 2002. "The Ripple Effect of the Matthew Shepard Murder: Impact on the Assumptive Worlds of Member of the Targeted Group." *American Behavioral Scientist,* 46(1): 27-50.

Nolan, James J. III and Yoshio Akiyama. 1999. "An Analysis of Factors That Affect Law Enforcement Participation in Hate Crime Reporting." *Journal of Contemporary Criminal Justice*, 15(1): 111-127.

Nolan, James J. III, Yoshio Akiyama, and Samuel Berhanu. 2002. "The Hate Crime Statistics Act of 1990: Developing a Method for Measuring the Occurrence of Hate Violence." *American Behavioral Scientist,* 46: 136-153.

Nolan, James J. III, Jack McDevitt, Shea Cronin and Amy Farrell. 2004. "Learning to See Hate Crimes: A Framework for Understanding and Clarifying Ambiguities in Bias Crime Classification." *Criminal Justice Studies*, 17(1): 91-105.

Olzak, Susan. 1990. "The Political Context of Competition: Lynching and Urban Racial Violence, 1882-1914." *Social Forces*, 69(2): 395-421.

Osgood, D. Wayne. 2000. "Poisson-Based Regression Analysis of Aggregate Crime Rates." *Journal of Quantitative Criminology*, 16(1): 21-43.

Ousey, Graham C. and Matthew R. Lee. 2008. "Racial Disparity in Formal Social Control: An Investigation of Alternative Explanations of Arrest Rate Inequality." *Journal of Research in Crime and Delinquency*, 45(3): 322-55.

Perry, Barbara. 2001. *In the Name of Hate: Understanding Hate Crimes*. New York: Routledge.

Perry, Barbara. 2002. "Defending the Color Line: Racially and Ethnically Motivated Hate Crime." *American Behavioral Scientist,* 46(1): 72-92.

Peterson, Ruth D. and Lauren J. Krivo. 2005. "Macrostructural Analyses of Race, Ethnicity, and Violent Crime: Recent Lessons and New Directions for Research." *Annual Review of Sociology,* 31: 331-356.

Quillian, Lincoln. 1995. "Prejudice as a Response to Perceived Group Threat: Population Composition and Anti-immigrant and Racial Prejudices in Europe." *American Sociological Review,* 60: 586-611.

Quillian, Lincoln. 2003. "The Decline of Male Employment in Low-Income Black Neighborhoods, 1950-1990." *Social Science Research*, 32(2):220-250.

Quillian, Lincoln and Devah Pager. 2001. "Black Neighbors, Higher Crime? The Role of Racial Stereotypes in Evaluations of Neighborhood Crime." *American Journal of Sociology*, 107(3): 717-67.

Quinney, Richard. 1977. *Class, State and Crime.* New York, New York: McKay.

Reed, Fred W. and J. Richard Udry. 1973. "Female Work, Fertility and Contraceptive Use in a Bi-Racial Sample." *Journal of Marriage and Family*, 35(4): 597-602.

Regoeczi, Wendy C. and John P. Jarvis. 2013. "Beyond the Social Production of Homicide Rates: Extending Social Disorganization Theory to Explain Homicide Case Outcomes." *Justice Quarterly,* 30(6): 983-1014.

Rose, Suzanna M. and Mindy B. Mechanic. 2002. "Psychological Distress, Crime Features and Help-Seeking Behaviors Related to Homophobic Bias Incidents." *American Behavioral Scientist,* 46(1): 14-26.

Sampson, Robert J. 1987. "Urban Black Violence: The Effect of Male Joblessness and Family Disruption." *American Journal of Sociology*, 93(2): 348-382.

Sampson, Robert J., Stephen W. Raudenbush and Felton Earls. 1997. "Neighborhoods and Violent Crime: A Multilevel Study of Collective Efficacy." *Science*, 5328: 9180924

Sampson, Robert J. and Stephen W. Raudenbush. 1999. "Systematic Social Observation of Public Spaces: A New Look at Disorder in Urban Neighborhoods." *American Journal of Sociology*, 105(3): 603-651.

Sampson, Robert J. and Stephen W. Raudenbush. 2004. "Seeing Disorder: Neighborhood Stigma and the Social Construction of 'Broken Windows.'" *Social Psychology Quarterly,* 67: 319-342.

Schlesinger, Traci. 2011. "The Failure of Race Neutral Policies: How Mandatory Terms and Sentencing Enhancements Contribute to Mass Racialized Incarceration." *Crime & Delinquency*, 57: 56-81.

Shihadeh, Edward S. and Nicole Flynn. 1996. "The Effect of Black Social Isolation on the Rates of Black Urban Violence." *Social Forces*, 74(4): 1325-1352.

Shihadeh, Edward S. and Darrell J. Steffensmeier. 1994. "Economic Inequality, Family Disruption and Urban Black Violence: Cities as Units of Stratification and Social Control." *Social Forces*, 73(2): 729-751.

Shaw, Clifford R. and Henry D. McKay. 1942. *Juvenile Delinquency in Urban Areas.* Chicago, IL: University of Chicago Press.

Soule, Sarah A. and Jennifer Earl. 2001. "The Enactment of State-Level Hate Crime Law in the United States: Intrastate and Interstate Factors." *Sociological Perspectives*, 44(3) 281-305.

South, Scott J. and Steven F. Messner. 1986. "Structural Determinants of Intergroup Association: Interracial Marriage and Crime." *The American Journal of Sociology,* 91(6): 1409-1430.

Sourcebook of Criminal Justice Statistics. 2003. Section 3: Nature and Distribution of Known Offenses. http://www.albany.edu/sourcebook/. Retrieved 1 September 2009.

Steinberg, Annie (M.D.), Jane Brooks (M.Ed.) and Tariq Remtulla (B.A.). 2003. "Youth Hate Crimes: Identification, Prevention and Intervention." *American Journal of Psychiatry,* 160: 979-989.

Stolzenberg, Lisa, Stewart J. D'Alessio, and Davide Eitle. 2004. "A Multilevel Test of Racial Threat Theory." *Criminology*, 42(3): 673-698.

Strom, Kevin J. 2001. "Hate Crimes Reported in NIBRS, 1997-99." *Bureau of Justice Statistics Special Report*, US Department of Justice Statistics: NCJ 186765.

Stucky, Thomas D. 2012. "The Conditional Effects of Race and Politics on Social Control: Black Violent Crime Arrests in Large U.S. Cities, 1970-1990." *Crime and Delinquency*, 49: 3-30.

Tolnay, Stewart E. and E. M. Beck. 1990. "The Killing Fields of the Deep South: The Market for Cotton and the Lynching of Blacks, 1882-1930." *American Sociological Review,* 55(4): 526-539.

Tolnay, Stewart E., Glenn Deane and E.M. Beck. 1996. "Vicarious Violence: Spatial Effects on Southern Lynchings, 1890-1919." *The American Journal of Sociology*, 102(3): 788-815.

Tolnay, Stewart E. and E. M. Beck. 1992. "Toward a Threat Model of Southern Black Lynchings." Pages 33-52 in *Social Threat and Social Control,* ed. Allen E. Liska. Albany, NY: SUNY Press.

Tolnay, Stewart E. and E. M. Beck. 1995. *A Festival of Violence: An Analysis of Southern Lynchings, 1882-1930.* Urbana, IL: University of Illinois Press.

Torres, Sam. 1999. "Hate Crimes Against African Americans: The Extent of the Problem." *Journal of Contemporary Criminal Justice*, 15(1) 48-63.

Turk, Austin T. 1969. *Criminality and Legal Order.* Chicago, IL: Rand McNally.

Van Dyke, Nella and Griff Tester. 2014. "Dangerous Climates: Factors Associated With Variation in Racist Hate Crimes on College Campuses." *Journal of Contemporary Criminal Justice*, 30(3): 290-309.

Wadsworth, Tim and Charis E. Kubrin. 2004. "Structural Factors and Black Interracial Homicide: A New Look at the Causal Process." *Criminology,* 42(3): 647-72.

Wagmiller, Robert L., Jr. 2008. "Male Nonemployment in White, Black, Hispanic and Multi-Ethnic Urban Neighborhoods, 1970-2000." *Urban Affairs Review*, 44(1): 85-125.

Walker, Samuel, Cassia Spohn and Miriam DeLone. 2011. *The Color of Justice: Race, Ethnicity and Crime in America.* Belmont, CA: Thomson Wadsworth.

Wang, Lu-in. 1995. *Hate Crimes Laws.* New York: Clark, Boardman, Callaghan.

Wang, Lu-in. 1999. "The Complexities of 'Hate.'" *Ohio State Law Journal*, 60(3): 799-900.

Welch, Kelly and Allison Ann Payne. 2010. "Racial Threat and Punitive School Discipline." *Social Problems*, 57(1): 25-48.

Wilson, Mindy S. and R. Barry Ruback. 2003. "Hate Crimes in Pennsylvania, 1984-99: Case Characteristics and Police Responses." *Justice Quarterly,* 20(2): 373-98.

Wilson, William Julius. 1987. *The Truly Disadvantaged: The Inner-City, the Underclass, and Public Policy*. Chicago, IL: The University of Chicago Press.

APPENDIX A. FBI Hate Crime Data Guidelines

The FBI has published guidelines for the collection of hate crime data (http://www.fbi.gov/ucr/hatecrime.pdf). Selected text provided verbatim from the guidelines is presented below. The FBI training manual is available at http://www.fbi.gov/ucr/traingd99.pdf.

Section II, Definitions (p2):

To ensure uniformity in reporting nationwide, the following definitions have been adopted for use in hate crime reporting:

Bias—A preformed negative opinion or attitude toward a group of persons based on their race, religion, disability, sexual orientation, or ethnicity/national origin.

Bias Crime—A criminal offense committed against a person or property which is motivated, in whole or in part, by the offender's bias against a race, religion, disability, sexual orientation, or ethnicity/national origin; also known as Hate Crime.

> **Note:** Even if the offender was mistaken in his/her perception that the victim was a member of the group he or she was acting against, the offense is still a bias crime because the offender was motivated by bias against the group.

Section IIIB, Objective evidence that the crime was motivated by bias (pp. 4-6):

An important distinction must be made when reporting a hate crime. The mere fact that the offender is biased against the victim's race, religion, disability, sexual orientation, and/or ethnicity/national origin does not mean that a hate crime was involved. Rather, the offender's criminal act must have been motivated, in whole or in part, by his/her bias.

Because motivation is subjective, it is difficult to know with certainty whether a crime was the result of the offender's bias. Therefore, before an incident can be reported as a hate crime, sufficient objective facts must be present to lead a reasonable and prudent person to conclude that the offender's actions were motivated, in whole or in part, by bias. While no single fact may be conclusive, facts such as the following, particularly when combined, are supportive of a finding of bias:

1. The offender and the victim were of different race, religion, disability, sexual orientation, and/or ethnicity/national origin. For example, the victim was black and the offender was white.

2. Bias-related oral comments, written statements, or gestures were made by the offender which indicate his/her bias. For example, the offender shouted a racial epithet at the victim.

3. Bias-related drawings, markings, symbols, or graffiti were left at the crime scene. For example, a swastika was painted on the door of a synagogue.

4. Certain objects, items, or things which indicate bias were used. For example, the offenders wore white sheets with hoods covering their faces or a burning cross was left in front of the victim's residence.

5. The victim is a member of a racial, religious, disability, sexual-orientation, or ethnic/national origin group which is overwhelmingly outnumbered by other residents in the neighborhood where the victim lives and the incident took place. This factor loses significance with the passage of time; i.e., it is most significant when the victim first moved into the neighborhood and becomes less and less significant as time passes without incident.

6. The victim was visiting a neighborhood where previous hate crimes were committed against other members of his/her racial, religious, disability, sexual-orientation, or ethnic/national origin group and where tensions remained high against his/her group.

7. Several incidents occurred in the same locality, at or about the same time, and the victims were all of the same race, religion, disability, sexual orientation, or ethnicity/national origin.

8. A substantial portion of the community where the crime occurred perceived that the incident was motivated by bias.

9. The victim was engaged in activities promoting his/her race, religion, disability, sexual orientation, or ethnicity/national origin. For example, the victim was a member of the NAACP or participated in gay rights demonstrations.

10. The incident coincided with a holiday or a date of particular significance relating to a race, religion, disability, sexual orientation, or ethnicity/national origin, e.g., Martin Luther King Day, Rosh Hashanah.

11. The offender was previously involved in a similar hate crime or is a hategroup member.

12. There were indications that a hate group was involved. For example, a hate group claimed responsibility for the crime or was active in the neighborhood.

13. A historically established animosity existed between the victim's and the offender's groups.

14. The victim, although not a member of the targeted racial, religious, disability, sexual-orientation, or ethnic/national origin group, was a member of an advocacy group supporting the precepts of the victim group.

Section IIIC, Cautions (p. 6)

1. Need for Case-by-Case Assessment of the Facts — The aforementioned factors are not all-inclusive of the types of objective facts which evidence bias motivation. Therefore, reporting agencies must examine each case for facts which clearly provide evidence that the offender's bias motivated him/her to commit the crime.

2. Misleading Facts — Agencies must be alert to misleading facts. For example, the offender used an epithet to refer to the victim's race, but the offender and victim were of the same race.

3. Feigned Facts — Agencies must be alert to evidence left by the offenders which is meant to give the false impression that the incident was motivated by bias. For example, students of a religious school vandalize their own school, leaving anti-religious statements and symbols on its walls in the hope that they will be excused from attending class.

4. Offender's Mistaken Perception — Even if the offender was mistaken in his/her belief that the victim was a member of a racial, religious, disability, sexual-orientation, or ethnic/national origin group, the offense is still a hate crime as long as the offender was motivated by bias against that group. For example, a middle-aged, non-gay man walking by a bar frequented by gays was attacked by six teenagers who mistakenly believed the victim had left the bar and was gay. Although the offenders were wrong on both counts, the offense is a hate crime because it was motivated by the offenders' anti-gay bias.

5. Changes in Findings of Bias — If, after an initial incident report was submitted, a contrary finding regarding bias occurs, the national file must be updated with the new finding. For example, if an initial finding of no bias was later changed to racial bias or a finding of racial bias was later changed to religious bias, the change should be reported to the FBI's UCR Program.

APPENDIX B. Poverty Guidelines 1990

Poverty Thresholds in 1990, by Size of Family and Number of Related Children Under 18 Years (Dollars)

Size of family unit	Weighted average thresholds	Related children under 18 years: None	One	Two	Three	Four	Five	Six	Seven	Eight or more
One person (unrelated individual)..	$6,652									
Under 65 years....................	6,800	6,800								
65 years and over................	6,268	6,268								
Two persons........................	8,509									
Householder under 65 years.......	8,794	8,752	9,009							
Householder 65 years and over....	7,905	7,900	8,975							
Three persons......................	10,419	10,223	10,520	10,530						
Four persons.......................	13,359	13,481	13,701	13,254	13,301					
Five persons.......................	15,792	16,257	16,494	15,989	15,598	15,359				
Six persons........................	17,839	18,693	18,773	18,386	18,015	17,464	17,137			
Seven persons......................	20,241	21,515	21,650	21,187	20,864	20,262	19,561	18,791		
Eight persons......................	22,582	24,063	24,276	23,839	23,456	22,913	22,223	21,505	21,323	
Nine persons or more...............	26,848	28,946	29,087	28,700	28,375	27,842	27,108	26,445	26,280	25,268

Source: U.S. Census Bureau, Current Population Survey

SOURCE: U.S. CENSUS BUREAU, HOUSING AND HOUSEHOLD ECONOMIC STATISTICS DIVISION
Retrieved from http://www.census.gov/hhes/www/poverty/threshld/thresh90.html on October 20, 2008

APPENDIX C. Poverty Thresholds 2000

Poverty Thresholds in 2000, by Size of Family and Number of Related Children Under 18 Years (Dollars)

Size of family unit	Weighted average thresholds	Related children under 18 years: None	One	Two	Three	Four	Five	Six	Seven	Eight or more
One person (unrelated individual)....	8,794									
Under 65 years.....................	8,959	8,959								
65 years and over..................	8,259	8,259								
Two persons..........................	11,239									
Householder under 65 years.........	11,590	11,531	11,869							
Householder 65 years and over......	10,419	10,409	11,824							
Three persons........................	13,738	13,470	13,861	13,874						
Four persons.........................	17,603	17,761	18,052	17,463	17,524					
Five persons.........................	20,819	21,419	21,731	21,065	20,550	20,236				
Six persons..........................	23,528	24,636	24,734	24,224	23,736	23,009	22,579			
Seven persons........................	26,754	28,347	28,524	27,914	27,489	26,696	25,772	24,758		
Eight persons........................	29,701	31,704	31,984	31,408	30,904	30,188	29,279	28,334	28,093	
Nine persons or more.................	35,060	38,138	38,322	37,813	37,385	36,682	35,716	34,841	34,625	33,291

SOURCE: U.S. CENSUS BUREAU, HOUSING AND HOUSEHOLD ECONOMIC STATISTICS DIVISION

SOURCE: U.S. CENSUS BUREAU, HOUSING AND HOUSEHOLD ECONOMIC STATISTICS DIVISION
Retrieved from http://www.census.gov/hhes/www/poverty/threshld/thresh00.html on October 20, 2008.

Appendix D. Cities Included in Sample, Included in Sub-Sample and Excluded from Sample

Cities Included in Sample, by State and City Name (355)

ALASKA
1. ANCHORAGE

ALABAMA
1. BIRMINGHAM
2. DOTHAN
3. HUNTSVILLE
4. MOBILE
5. MONTGOMERY
6. TUSCALOOSA

ARIZONA
1. CHANDLER
2. GLENDALE
3. MESA
4. PHOENIX
5. SCOTTSDALE
6. TEMPE
7. TUCSON

ARKANSAS
1. FORT SMITH
2. LITTLE ROCK
3. NORTH LITTLE ROCK
4. PINE BLUFF

CALIFORNIA
1. ALAMEDA
2. ALHAMBRA
3. ANAHEIM
4. ANTIOCH
5. BAKERSFIELD
6. BALDWIN PARK
7. BERKELEY
8. BUENA PARK
9. BURBANK
10. CHINO
11. CHULA VISTA
12. COMPTON
13. CONCORD
14. CORONA
15. COSTA MESA
16. DALY CITY
17. DOWNEY
18. EL CAJON
19. ESCONDIDO
20. FAIRFIELD
21. FONTANA
22. FREMONT
23. FRESNO
24. FULLERTON
25. GLENDALE
26. HAWTHORNE
27. HUNTINGTON BEACH
28. IRVINE
29. LA MESA
30. LONG BEACH
31. LOS ANGELES
32. MERCED
33. MILPITAS
34. MODESTO
35. MORENO VALLEY
36. MOUNTAIN VIEW
37. NATIONAL CITY
38. OAKLAND
39. OCEANSIDE
40. ONTARIO
41. ORANGE
42. PALO ALTO
43. PASADENA
44. RANCHO CUCAMONGA
45. REDLANDS
46. REDWOOD CITY
47. RIALTO
48. RICHMOND
49. RIVERSIDE
50. SACRAMENTO
51. SALINAS
52. SAN BERNADINO
53. SAN BUENAVENTURA
54. SAN DIEGO
55. SAN FRANCISCO
56. SAN JOSE
57. SAN LEANDRO
58. SANTA ANA
59. SANTA BARBARA
60. SANTA CLARA
61. SANTA MARIA

62. SANTA MONICA
63. SANTA ROSA
64. SIMI VALLEY
65. SOUTH GATE
66. SOUTH SAN FRANCISCO
67. STOCKTON
68. SUNNYVALE
69. TORRANCE
70. TUSTIN
71. UNION CITY
72. UPLAND
73. VACAVILLE
74. VALLEJO
75. VISALIA
76. WEST COVINA
77. WEST HOLLYWOOD

COLORADO

1. AURORA
2. COLORADO SPRINGS
3. DENVER
4. LAEKWOOD
5. PUEBLO

CONNECTICUT

1. BRIDGEPORT
2. BRISTOL
3. DANBURY
4. EAST HARTFORD
5. GREENWICH
6. HAMDEN
7. HARTFORD
8. MANCHESTER
9. MERIDEN
10. NEW BRITAIN
11. NEW HAVEN
12. NORWALK
13. STAMFORD
14. WATERBURY
15. WEST HARTFORD
16. WEST HAVEN

DISTRICT OF COLUMBIA

1. WASHINGTON

FLORIDA

1. BOCA RATON
2. CLEARWATER
3. FORT LAUDERDALE
4. HIALEAH
5. HOLLYWOOD
6. JACKSONVILLE
7. MELBOURNE
8. MIAMI
9. MIAMI BEACH
10. ORLANDO
11. POMPANO BEACH
12. SAINT PETERSBURG
13. SARASOTA
14. TALLAHASSEE
15. TAMPA

GEORGIA

1. ATLANTA

ILLINOIS

1. CHICAGO
2. NAPERVILLE
3. PEORIA
4. SPRINGFIELD

INIDANA

1. BLOOMINGTON
2. EVANSVILLE
3. FORT WAYNE
4. HAMMOND
5. INDIANAPOLIS
6. MUNCIE
7. SOUTH BEND

IOWA

1. DAVENPORT
2. DES MOINES
3. SIOUX CITY
4. WATERLOO

KANSAS

1. WICHITA

KENTUCKY

1. LEXINGTON
2. LOUISVILLE
3. OWENSBORO

LOUISIANA

1. BATON ROUGE
2. BOSSIER CITY
3. KENNER
4. LAFAYETTE
5. LAKE CHARLES
6. MONROE
7. NEW ORLEANS
8. SHREVEPORT

MARYLAND

1. BALTIMORE

MASSACHUSETTS

1. BOSTON
2. BROCKTON
3. BROOKLINE
4. CAMBRIDGE
5. CHICOPEE
6. FALL RIVER
7. FRAMINGHAM
8. LAWRENCE
9. LOWELL
10. LYNN
11. MALDEN
12. MEDFORD
13. NEW BEDFORD
14. NEWTON
15. SOMERVILLE
16. SPRINGFIELD
17. WALTHAM
18. WORCESTER

MICHIGAN

1. ANN ARBOR
2. BATTLE CREEK
3. EAST LANSING
4. FARMINGTON HILLS
5. FLINT
6. GRAND RAPIDS
7. KALAMAZOO
8. LANSING
9. SAGINAW
10. SOUTHFIELD
11. TAYLOR
12. TROY
13. WESTLAND

MINNESOTA

1. BLOOMINGTON
2. BROOKLYN PARK
3. MINNEAPOLIS
4. SAINT PAUL

MISSISSIPPI

1. JACKSON

MISSOURI

1. COLUMBIA
2. FLORISSANT
3. INDEPENDENCE
4. KANSAS CITY
5. SAINT CHARLES
6. SAINT LOUIS
7. SPRINGFIELD

NEBRASKA

1. LINCOLN
2. OMAHA

NEVADA

1. HENDERSON
2. RENO
3. SPARKS

NEW HAMPSHIRE

1. NASHUA

NEW JERSEY

1. BAYONNE
2. CAMDEN
3. CHERRY HILL
4. CLIFTON
5. EAST ORANGE
6. ELIZABETH
7. IRVINGTON
8. JERSEY CITY
9. MIDDLETOWN
10. NEWARK
11. PASSAIC
12. PATERSON
13. TRENTON
14. UNION CITY
15. UNION TOWNSHIP
16. VINELAND

NEW MEXICO

1. ALBUQUERQUE
2. LAS CRUCES

NEW YORK

1. ALBANY
2. AMHERST
3. BUFFALO
4. CLAY
5. MOUNT VERNON
6. NEW ROCHELLE
7. NEW YORK CITY
8. NIAGARA FALLS
9. ROCHESTER
10. SYRACUSE
11. TROY
12. UTICA

13. YONKERS

NORTH CAROLINA

1. ASHEVILLE
2. CHARLOTTE
3. DURHAM
4. FAYETTEVILLE
5. GASTONIA
6. GREENSBORO
7. HIGH POINT
8. RALEIGH
9. WILMINGTON
10. WINSTON-SALEM

OHIO

1. AKRON
2. CINCINNATI
3. CLEVELAND
4. CLEVELAND HEIGHTS
5. COLUMBUS
6. DAYTON
7. EUCLID
8. LORAIN
9. MANSFIELD
10. SPRINGFIELD
11. TOLEDO
12. YOUNGSTOWN

OKLAHOMA

1. BROKEN ARROW
2. EDMOND
3. LAWTON
4. MIDWEST CITY
5. NORMAN
6. OKLAHOMA CITY
7. TULSA

OREGON

1. EUGENE
2. PORTLAND
3. SALEM

PENNSYLVANIA

1. ABINGTON
2. ALLENTOWN
3. BENSALEM
4. BETHLEHEM
5. ERIE
6. HARRISBURG
7. PHILADELPHIA
8. PITTSBURGH
9. READING

RHODE ISLAND

1. CRANSTON
2. EAST PROVIDENCE
3. PAWTUCKET
4. PROVIDENCE

SOUTH CAROLINA

1. CHARLESTON
2. COLUMBIA
3. GREENVILLE
4. NORTH CHARLESTON

TENNESSEE

1. CHATTANOOGA
2. CLARKSVILLE
3. KNOXVILLE
4. MEMPHIS
5. NASHVILLE

TEXAS

1. ABILENE
2. AMARILLO
3. ARLINGTON
4. AUSTIN
5. BAYTOWN
6. BEAUMONT
7. BRYAN
8. CARROLLTON
9. COLLEGE STATION
10. CORPUS CHRISTI
11. DALLAS
12. DENTON
13. EL PASO
14. FORT WORTH
15. GARLAND
16. GRAND PRAIRIE
17. HOUSTON
18. IRVING
19. KILLEEN
20. LONGVIEW
21. LUBBOCK
22. MESQUITE
23. MIDLAND
24. ODESSA
25. PLANO
26. PORT ARTHUR
27. RICHARDSON
28. SAN ANGELO

29. SAN ANTONIO
30. TYLER
31. VICTORIA
32. WACO
33. WICHITA FALLS

UTAH

1. OGDEN
2. SALT LAKE CITY

VIRGINIA

1. ALEXANDRIA
2. CHESAPEAKE
3. DANVILLE
4. HAMPTON
5. LYNCHBURG
6. NEWPORT NEWS
7. NORFOLK
8. PORTSMOUTH
9. RICHMOND
10. ROANOKE
11. SUFFOLK
12. VIRGINIA BEACH

WASHINGTON

1. BELLEVUE
2. FEDERAL WAY
3. SEATTLE
4. SPOKANE
5. TACOMA
6. YAKIMA

WEST VIRGINIA

1. CHARLESTON
2. HUNTINGTON

WISCONSIN

1. KENOSHA
2. MADISON
3. MILWAUKEE
4. RACINE

WYOMING

1. CHEYENNE

Cities Included in Sub-Sample, by State and City Name (214)

ARIZONA

1. GLENDALE
2. PHOENIX
3. TEMPE
4. TUCSON

CALIFORNIA

1. ALAMEDA
2. ALHAMBRA
3. ANAHEIM
4. ANTIOCH
5. BAKERSFIELD
6. BALDWIN PARK
7. BERKELEY
8. BUENA PARK
9. BURBANK
10. CHINO
11. CHULA VISTA
12. COMPTON
13. CONCORD
14. CORONA
15. COSTA MESA
16. DALY CITY
17. DOWNEY
18. EL CAJON
19. ESCONDIDO
20. FAIRFIELD
21. FONTANA
22. FREMONT
23. FRESNO
24. FULLERTON
25. GLENDALE
26. HAWTHORNE
27. HUNTINGTON BEACH
28. IRVINE
29. LA MESA
30. LONG BEACH
31. LOS ANGELES
32. MERCED
33. MILPITAS
34. MODESTO
35. MORENO VALLEY
36. MOUNTAIN VIEW
37. NATIONAL CITY
38. OAKLAND
39. OCEANSIDE
40. ONTARIO
41. ORANGE
42. PALO ALTO
43. PASADENA
44. RANCHO CUCAMONGA
45. REDLANDS
46. REDWOOD CITY
47. RIALTO
48. RICHMOND
49. RIVERSIDE
50. SACRAMENTO
51. SALINAS
52. SAN BERNADINO
53. SAN BUENAVENTURA
54. SAN DIEGO
55. SAN FRANCISCO
56. SAN JOSE
57. SAN LEANDRO
58. SANTA ANA
59. SANTA BARBARA
60. SANTA CLARA
61. SANTA MARIA
62. SANTA MONICA
63. SANTA ROSA
64. SIMI VALLEY
65. SOUTH GATE
66. SOUTH SAN FRANCISCO
67. STOCKTON
68. SUNNYVALE
69. TORRANCE
70. TUSTIN
71. UNION CITY
72. UPLAND
73. VACAVILLE
74. VALLEJO
75. VISALIA
76. WEST COVINA
77. WEST HOLLYWOOD

COLORADO

1. AURORA
2. COLORADO SPRINGS
3. DENVER
4. LAEKWOOD
5. PUEBLO

CONNECTICUT
1. NEW BRITAIN

FLORIDA
1. BOCA RATON
2. CLEARWATER
3. FORT LAUDERDALE
4. HIALEAH
5. HOLLYWOOD
6. JACKSONVILLE
7. MELBOURNE
8. MIAMI
9. MIAMI BEACH
10. ORLANDO
11. POMPANO BEACH
12. SAINT PETERSBURG
13. SARASOTA
14. TALLAHASSEE
15. TAMPA

GEORGIA
1. ATLANTA

ILLINOIS
1. CHICAGO

INIDANA
1. BLOOMINGTON

KANSAS
1. WICHITA

LOUISIANA
1. NEW ORLEANS

MARYLAND
1. BALTIMORE

MASSACHUSETTS
1. BOSTON
2. SPRINGFIELD
3. WORCESTER

MICHIGAN
1. BATTLE CREEK
2. FARMINGTON HILLS
3. KALAMAZOO
4. LANSING
5. SAGINAW
6. SOUTHFIELD
7. TROY

MINNESOTA
1. MINNEAPOLIS

MISSOURI
1. COLUMBIA
2. KANSAS CITY
3. SAINT CHARLES
4. SAINT LOUIS

NEW JERSEY
1. BAYONNE
2. CAMDEN
3. CHERRY HILL
4. CLIFTON
5. EAST ORANGE
6. ELIZABETH
7. IRVINGTON
8. JERSEY CITY
9. MIDDLETOWN
10. NEWARK
11. PASSAIC
12. PATERSON
13. TRENTON
14. UNION CITY
15. UNION TOWNSHIP
16. VINELAND

NEW MEXICO
1. ALBUQUERQUE

NEW YORK
1. ALBANY
2. AMHERST
3. BUFFALO
4. CLAY
5. MOUNT VERNON
6. NEW ROCHELLE
7. NEW YORK CITY
8. NIAGARA FALLS
9. ROCHESTER
10. SYRACUSE
11. UTICA
12. YONKERS

NORTH CAROLINA
1. ASHEVILLE
2. DURHAM
3. GREENSBORO
4. RALEIGH
5. WILMINGTON
6. WINSTON-SALEM

OHIO
1. CINCINNATI
2. CLEVELAND
3. COLUMBUS

4. DAYTON
5. EUCLID
6. LORAIN
7. SPRINGFIELD

OKLAHOMA

8. BROKEN ARROW
9. EDMOND
10. LAWTON
11. MIDWEST CITY
12. NORMAN
13. OKLAHOMA CITY
14. TULSA

PENNSYLVANIA

1. ABINGTON
2. ALLENTOWN
3. BENSALEM
4. BETHLEHEM
5. HARRISBURG
6. READING

RHODE ISLAND

1. CRANSTON
2. EAST PROVIDENCE
3. PAWTUCKET
4. PROVIDENCE

SOUTH CAROLINA

1. CHARLESTON
2. COLUMBIA
3. GREENVILLE
4. NORTH CHARLESTON

TEXAS

1. ABILENE
2. ARLINGTON
3. AUSTIN
4. BAYTOWN
5. BRYAN
6. CARROLLTON
7. COLLEGE STATION
8. CORPUS CHRISTI
9. DENTON
10. EL PASO
11. FORT WORTH
12. GARLAND
13. GRAND PRAIRIE
14. HOUSTON
15. IRVING
16. KILLEEN
17. LONGVIEW
18. LUBBOCK
19. MESQUITE
20. MIDLAND
21. PLANO
22. PORT ARTHUR
23. SAN ANGELO
24. SAN ANTONIO
25. VICTORIA
26. WACO
27. WICHITA FALLS

UTAH

1. SALT LAKE CITY

VIRGINIA

1. CHESAPEAKE
2. NEWPORT NEWS

WASHINGTON

1. BELLEVUE
2. SEATTLE
3. SPOKANE
4. TACOMA

WYOMING

1. CHEYENNE

Cities Excluded from Sample, by State and City Name (166)

ALABAMA
1. MOBILE

ARIZONA
1. FLAGSTAFF
2. PEORIA
3. YUMA

ARKANSAS
1. JONESBORO

CALIFORNIA
1. ARDEN ARCADE
2. BELLFLOWER
3. CARSON CITY
4. CERRITOS
5. CITRUS HEIGHTS
6. DAVIS
7. DIAMOND BAR CITY
8. EAST LOS ANGELES
9. EL MONTE
10. EL TORO
11. FLORENCE GRAHAM
12. GARDENA
13. GARDEN GROVE
14. HACIENDA HEIGHTS
15. HAYWARD
16. HESPERIA
17. INGLEWOOD
18. LAKEWOOD
19. LANCASTER
20. LYNWOOD
21. NORWALK
22. NOVATO
23. OXNARD
24. PALMDALE
25. PARAMOUNT
26. PITTSBURG
27. POMONA
28. SAN MATEO
29. SAN RAFAEL
30. SANTA CLARITA
31. SANTA CRUS
32. SPRING VALLEY
33. THOUSAND OAKS
34. VISTA

COLORADO
1. BOULDER

CONNECTICUT
1. STRATFORD

DELAWARE
1. WILMINGTON

FLORIDA
1. BOYNTON BEACH
2. BRANDON
3. CAROL CITY
4. CORAL SPRINGS
5. DAVIE
6. DAYTONA BEACH
7. DELRAY BEACH
8. DELTONA
9. FORT MYERS
10. GAINESVILLE
11. KENDALL
12. LAKELAND
13. LARGO
14. MELBOURNE
15. PALM BAY
16. PEMBROKE PINES
17. PENSACOLA
18. PLANTATION
19. PORT ST. LUCIE
20. SUNRISE
21. WEST PALM BEACH

GEORGIA
1. ALBANY
2. ATHENS
3. COLUMBUS
4. MACON
5. ROSWELL
6. SANDY SPRINGS
7. SAVANNAH
8. SOUTH AUGUSTA

HAWAII
1. HONOLULU

IDAHO
1. BOISE

ILLINOIS
1. AURORA
2. BLOOMINGTON
3. CHAMPAIGN
4. DECATUR
5. ELGIN

6. EVANSTON
7. HOFFMAN ESTATES
8. JOLIET
9. OAK PARK
10. ROCKFORD
11. SCHAUMBURG
12. SKOKIE
13. WAUKEGAN
14. WHEATON

INDIANA
1. ANDERSON
2. GARY
3. TERRE HAUTE

IOWA
1. AMES
2. CEDAR RAPIDS
3. IOWA CITY

KANSAS
1. KANSAS CITY
2. LAWRENCE
3. OLATHE
4. OVERLAND PARK
5. TOPEKA

LOUISIANA
1. ALEXANDRIA
2. METAIRIE

MAINE
1. PORTLAND

MARYLAND
1. BETHESDA
2. COLUMBIA
3. DUNDALK
4. SILVER SPRING
5. WHEATON GLENMONT

MASSACHUSETTS
1. HAVERHILL
2. PITTSFIELD
3. QUINCY
4. TAUNTON

MICHIGAN
1. CANTON
2. CLINTON
3. DETROIT
4. PONTIAC
5. WARREN
6. WEST BLOOMFIELD
7. WYOMING

MINNESOTA
1. BURNSVILLE
2. EAGAN
3. PLYMOUTH
4. ROCHESTER

MISSISSIPPI
1. BILOXI
2. GREENVILLE

MISSOURI
1. ST. JOSEPH
2. ST. PETERS

NEVADA
1. LAS VEGAS
2. NORTH LAS VEGAS
3. PARADISE
4. SPRING VALLEY
5. SUNRISE MANOR

NEW HAMPSHIRE
1. MANCHESTER

NEW JERSEY
1. EDISON
2. NORTH BERGEN
3. PARSIPPANY
4. PISCATAWAY
5. PLAINFIELD

NEW YORK
1. BINGHAMMPTON
2. CHEEKTOWAGA
3. HEMPSTEAD
4. SCHENECTADY
5. WIHTE PLAINS

NORTH CAROLINA
1. ROCKY MOUNT

OHIO
1. CANTON
2. ELYRIA
3. HAMILTON
4. LIMA
5. MIDDLETON
6. WARREN

OKLAHOMA
1. ENID

PENNSYLVANIA
1. BENSALEM
2. LANCASTER

3. PENN HILLS
4. SCRANTON
5. WILKES BARRE

SOUTH DAKOTA

1. SIOUX FALLS

TENNESSEE

1. JACKSON
2. JOHNSON CITY

TEXAS

1. GALVESTON
2. LEWISVILLE
3. PASADENA
4. TEMPLE

VIRGINIA

1. ANNANDALE
2. ARLINGTON
3. BURKE
4. EVERETT

WASHINGTON

1. LAKEWOOD