CRIMINALIZING OUR WAY TO RACIAL EQUALITY?

AN EMPIRICAL LOOK AT HATE REGULATION

by

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DISSERTATION ABSTRACT

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Title: Criminalizing Our Way to Racial Equality? An Empirical Look at Hate Regulation.

Does regulating hate promote racial equality? This dissertation proposes a method for beginning an empirical examination into the benefits and burdens of anti-hate laws. The effects of criminalization are particularly important given the U.S. history of racialized and colorblind justice and some evidence indicating criminalization may harm racial minorities.

Chapter 2 examines whether hate crime laws have the unintended consequence of promoting racial inequality by contributing to racial disparities in arrests. It finds that while police are more likely to recognize assaults as hate crimes when the suspects are white, African Americans are nonetheless significantly overrepresented among hate crime arrestees.

Chapter 3 examines how race affects victim perception of potential hate crimes, and how this, in turn, affects police response. While research suggests people tend to have a preconceived notion of the quintessential hate crime in which African Americans are victims, it also shows a negative racial bias in which people ascribe greater culpability and are more punitive towards African Americans. This study looks at how people act under the real-world stresses of crime. Findings provide evidence of a tendency to label African Americans as hate crime offenders and to report them to police

at significantly higher rates. Further, while African American suspects experience relatively high arrest rates generally, the magnitude of this effect is significantly greater for hate crimes.

Chapter 4 explores the nefarious uses of hate crime laws, examining how they may be weaponized to inoculate police and undermine movements for racial justice. Specifically, it looks at the case of "Blue Lives Matter" legislation, which extends hate crime protections to police. Findings reject the officer safety rationale: States with BLM proposals do not differ significantly from other states in terms of violence against police. However, African American arrests do predict these bills, indicating they are a continuation of past police repression. Further research is needed to fully understand how officials enforce hate regulations, and the reverberations of this enforcement on society.

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CHAPTER I

CRIMINALIZING OUR WAY TO RACIAL EQUALITY?

AN EMPIRICAL LOOK AT HATE REGULATION

I. Introduction

What is the role of government in addressing hateful expression or conduct? Does greater government intervention address racial subordination and persecution, thereby creating an environment in which equal citizenship can be realized? Alternatively, does invoking and empowering the government result in abuse of power and institutionalized racial repression? How can we effectively address hate and promote racial equality?

Answering these questions is no simple task. This is partially because it requires balancing the benefits and burdens of individual liberty and government regulation. Such inquiries are often normative; they have moral and ideological dimensions and involve subjective value judgments. Compounding these difficulties is the lack of systematic empirical research to inform the discussion.

This dissertation proposes a method for beginning a social scientific examination into the benefits and burdens of regulating hate. It does so by identifying a type of regulation, hate crime, and narrowly focusing on a particular type of burden, penal enforcement. This burden is of particular interest given the United States history of racialized and colorblind justice and some evidence indicating criminalization may, in fact, work to the detriment of racial minorities. Thus, this dissertation will examine who bears the burden of criminalization under these provisions. This research examines hate crime enforcement at its earliest phases: victim reports and police responses. It further examines police responses by looking into how they may weaponize anti-hate laws to ward off legitimate criticism and oversight. The findings serve as a small but important piece of the empirical puzzle regarding whether regulating hate actually promotes racial equality.

II. Addressing Hate: A State Minimalist v. State Interventionist Approach

A longstanding division exists in liberal thought regarding the extent to which regulating hate advances freedom and equality (Fiss 1996). Nineteenth century liberalism focused on individual liberty from government intrusion. However, there was a shift in perspective beginning with the abolition of slavery, and later, the decision of *Brown v. Board of Education* (1954). Equality became central to liberal ideology. This perspective called for greater state intervention (e.g., federal courts overseeing school desegregation; the creation of an Office for Civil Rights to ensure compliance with federal antidiscrimination law). The demand for a more heavy-handed government challenges the traditional liberal commitment to state minimalism. This newer strain of liberalism insists, under certain circumstances, liberty must give way to efforts to address social stigmatization and subordination. It views unencumbered individual autonomy as a force of oppression.

The liberal fissure is most exemplified in the context of hate speech. One the one hand, free speech advocates defend strong individual freedoms, arguing robust expressive rights ultimately protect politically and socially marginal groups and are foundational to free thought and democratic self-governance (see, e.g., Chemerinsky and Gillman 2017; Stone 2004; Romero 2017; Cole 2017; Greenwald 2017). They assert, among other things, that history and experience have taught us the importance of strong protections, which developed as result of government overreach including the Sedition Act, the McCarthy era, and the repression of civil rights advocacy and anti-war protests. They are deeply skeptical that the government can be trusted with the power to decide what speech is and is not permissible. Moreover, free speech advocates contend a robust First Amendment has been particularly important to racial minorities and activists for racial equality, who have relied on non-violent discourse as a major tool to fight oppression. These individual freedoms have created and preserved a space for social change and racial equality. Under this approach, universal free speech rights have benefitted racial minorities. On the other hand, advocates for greater government suppression counter unfettered free speech is harmful to minorities and undermines principles of the Equal Protection Clause, as well as the First Amendment (see, e.g., Matsuda 1993; Lawrence 1993; Delgado 1993; MacKinnon 1993; Ogletree 1996; Tsesis 1999; Park 2017). They argue, in part, that hate speech promotes racial hierarchy and violence, or, at the very least, occurs within a context of violence and acts as an implicit threat and dignitary affront. Hate speech creates a climate in which minorities cannot safely engage in free expression, work, school, and other democratic pursuits. Thus, unchecked hateful rhetoric undermines the promise of *Brown* to address stigma and subordination and to promote equality. From this standpoint, the First Amendment has, at times, been harmful to racial minorities because of its blindness to social power.

The liberal tension between state minimalism and interventionism extends to the context of regulating hateful conduct; we address similar questions regarding the role of government. It is true that hate crime laws differ significantly from proposed prohibitions on hate speech, namely because they purport to punish acts rather than expression (Jenness and Grattet 2001; *Wisconsin v. Mitchell* 1993). Hate crime laws merely provide new or enhanced penalties for already prohibited behavior when it is motivated by the victim's real or perceived membership in a protected class (e.g., race, ethnicity, gender, sexual orientation, religion, or national origin) (Levin 2002). However, despite these differences, regulating hate crime resembles regulating hate speech in a few noteworthy regards. First, it strives to address stigmatization and subordination by stopping the expression of hate. Second, it punishes objectionable ideas because it treats otherwise similar acts more severely due to the words and thoughts ascribed to them, and it usually relies on words (i.e., speech) as evidence of a violation (Jenness and Grattet 2001; Gellman 1991; Jacobs and Potter 1998). Finally, it involves the same sort of government intervention: penal enforcement. In sum, like proposed hate speech laws, hate crimes strive to promote equal citizenship by showing zero tolerance for racial subjugation by invoking the criminal justice system. Accordingly, we contend with the tension between liberty and equality, as well as grapple with the question of whether the government can be trusted to regulate hate or whether such enforcement will ultimately lead to the repression of racial minorities.

III. Research Question: Does Criminalizing Hate Promote Racial Equality?

It is an empirical question whether invoking and empowering government to regulate hate promotes or undermines racial equality. Yet, few scholars have systematically examined the societal burdens or benefits regulating hate or attempted to compare them. In the hate speech context, the lack of systematic research may be due, in part, to methodological barriers: namely, how can we measure the effects of stricter hate speech regulations in the U.S. context when they are constitutionally forbidden and do not exist (see, e.g., *Colin v. Smith* 1978; *Cohen v. California* 1971; *Gooding v. Wilson* 1972; *R.A.V. v. St. Paul* 1992)? The answer requires testing a counterfactual, and is therefore inherently speculative and difficult to operationalize. However, we can evaluate hate crime laws because they are both legal and prevalent in the United States. Accordingly, this dissertation examines who bears the burden of criminalizing hateful conduct.

Criminalization is an important metric for understanding the consequences of regulating hate for racial equality because it involves a particular type of burden racial minorities have disproportionately borne. Thus, some scholars have highlighted the irony of relying on the criminal justice system as an avenue for promoting racial justice (Franklin 2002). Though the penal system is often invoked to solve social problems, as a historical matter, it has overwhelmingly been a purveyor of racial inequality. Regulating hate speech necessarily involves a high degree of trust in the criminal justice system that is, perhaps, undeserved. Given its record of racial subjugation, a little caution is warranted. Criminalizing hate may have the unintended consequence of creating another vehicle through which racial minorities are funneled into the carceral system. This section outlines mechanisms in the criminal justice system contributing to racial inequality. It then considers how these structural problems, unaddressed, may lead to similar racialized outcomes in the hate crime context.

a. The Criminal Justice System Institutionalizes Racial Hierarchy

Since the abolition of slavery, the criminal justice system has been the major legal institution producing and reproducing racial hierarchy in the United States. It has facilitated and legitimized the mass incarceration, enslavement, disenfranchisement, and discrimination of racial minorities, legally enshrining a racial caste system (Alexander 2012). This section describes the connection between the criminal justice system and racial inequality, providing a backdrop for understanding why criminalizing hate-driven speech and conduct may actually harm racial minorities.

The criminal justice system promotes inequality at every step, including lawmaking, enforcement, sentencing, and corrections. While laws that explicitly discriminate on the basis of race are generally impermissible, legislators continue to enact race-neutral statutes to control racial minorities. A significant example can be found in the "War on Drugs," which arose as part of a broader strategy to promote "law and order" and capitalize on fears surrounding civil disobedience, affirmative action, and integration (Alexander 2012). Further, legislatures have criminalized a wide range of conduct such that most people violate the law regularly, making criminality ubiquitous. This gives police and prosecutors broad authority to enforce it when and against whom they see fit, and the judiciary is highly deferential to these officials, providing very little oversight (Carbado 2017; Carbado 2002). Social psychological research suggests such ambiguity and discretion facilitate racial bias (see Girvan and Marek 2016 for a review of the literature). Sure enough, racial discrimination is widespread in police encounters – including stops, searches, arrests, and uses of force – even though bias-based policing is not efficacious (see, Fagen et al. 2009; Harris 2002; Civil Rights Division of the U.S. Department of Justice 2016; Civil Rights Division 2015; Civil Rights Division and U.S. Attorney's Office 2017).

Likewise, disparities occur at every prosecutorial decision-making point – including detention, dropping or reducing charges, and plea offers – even though racial minorities are more likely to benefit from dismissals (Kutateladze, et al. 2014; Berdijo 2018). Thereafter, race greatly determines the sentence one receives. Notably, in a meta-analysis of 85 studies, researchers found blacks and Latinos were sentenced more punitively than whites regardless of criminal history or seriousness of offense (Mitchell and MacKenzie 2004). Blacks also serve a greater portion of their sentences in prison than whites, awaiting parole for a much longer time (Huebner and Bynam 2008).

Unequal treatment in the criminal justice system contributes greatly to social inequality overall. It has led to the mass incarceration of minorities, with nearly ten percent of black individuals in the United States in prison or jail or under probation or parole supervision (Warren et al. 2009). Criminalization has tremendous collateral consequences, as well. In the short term, arrests, court appearances, and jail time get in the way of going to school, finding and maintaining work, attending social service appointments, and other activities that allow a person to pursue a stable and prosperous existence (Fisher et al. 2015). Even the most minor of crimes can have serious and long-term ramifications, including health problems, as well as the loss or denial of employment, housing, government benefits, mental and drug treatment, or social services (Adock et al. 2016; Massoglia 2008; Alexander 2012; Pager 2008; National Law Center on Homelessness and Poverty 2015). Involvement in the justice system carries with it hefty fines and fees, and failure to pay those debts can result in suspension of a driver's license, poor credit, and even incarceration (Shapiro 2014; Civil Rights Division 2015). Individuals accused or convicted of certain crimes face banishment from geographic areas through civil injunctions (Davis 1998; Becket and Herbert 2009). Criminalization also directly impacts basic rights of citizenship, including (for immigrants) the ability to be lawfully present or become a U.S. citizen, and (for U.S. citizens) the ability to vote or serve on juries (Alexander 2012; 8 U.S.C. §§ 1182, 1227, 1182). For all of these reasons, criminalization itself increases the likelihood of recidivism, future incarceration, and extreme destitution (Gowan 2002; National Healthcare for Homeless Council 2013).

These harsh realities undermine the legitimacy of the justice system itself. Sure enough, there are notable differences regarding the extent to which groups trust the law and its administration. Black and Hispanic populations perceive police bias as a problem at a much higher rate than white populations, with a lower proportion of minorities attributing police action to legitimate criminality (Weitzer and Touch 2005; Weitzer 2000). Similarly, blacks are much more likely to view the criminal justice system overall as unfair (Hurwitz and Peffley 2005). These negative experiences and perceptions have broad ramifications. Importantly, they affect whether individuals report crime victimization (Zaykowski 2010). Further, research suggests racism in the penal system discourages minorities from participating in civil cases (Greene 2015). Blacks are particularly skeptical of the notion that they can receive equal treatment, and they have diminished confidence in the court's handling of their cases (Brooks 2001). It is not hyperbole to suggest that many black people see the justice system – whether criminal or civil – as a source of oppression more so than a place of refuge.

In sum, significant scholarship has highlight the ways in which racial bias permeates every level of the criminal justice system, including the creation of laws and their implementation. Moreover, the criminal justice system is so integrated into other social institutions, like voting, education, employment, and housing, that it promotes racial hierarchy on a societal level. These problems are systemic and profound, and may influence anti-hate statutes and their administration.

b. The Contradiction: How Can an Institution of Racial Injustice Promote Racial Justice?

The need to combat racist conduct is uncontroversial, but, in light of the foregoing discussion, there appears to be a mismatch of means and ends. In criminalizing hate, we are invoking a system of racial injustice to promote racial justice. The criminal justice system is a compromised institution: Its severe systemic shortcomings – namely, over-criminalization, lack of judicial oversight, and unchecked executive discretion – have created a climate wherein racial bias thrives. During a time of heightened awareness among scholars, policymakers, and advocates for the need to limit its reach, how can we simultaneously argue for its fortification? This section outlines some of the evidence suggesting the criminalization of hate-driven speech and conduct may actually harm racial minorities.

Some may conceptualize hate crime statutes as merely another form of antidiscrimination law (see, e.g., MacKinnon 1993; Levin 2002). Through this perspective, it is easy to understand the appeal of such regulations. Antidiscrimination laws have done much to promote racial equality in a variety of contexts (employment, public accommodations, education, credit, mortgages, housing, and voting) and also prohibited interference with important civil rights (voting, obtaining government funded benefits or services, accessing employment, participation in jury service, enrollment in public education, interstate travel, and the benefits of various types of public accommodations) (Reskin 2012; Levin 2002). However, these laws have been largely civil, or they criminalized narrow categories of conduct that specifically targeted racial minorities. For example, an employer who discriminates against an employee will not face penal sanctions like prison or a criminal record, even if punitive damages are awarded. Those laws that do involve penal sanctions, like burning a cross on the property of another without consent, address a very particular behavior and context, and leave little room for ambiguity, discretion, and biased attitudes among government officials.

Anti-hate regulations therefore differ significantly from other forms of equality-promoting legislation. They involve criminalization, setting into motion the racialized criminal justice system that has been so devastating to minority communities. Further, anti-hate regulations involve a high degree of ambiguity. No bright line rules exist to determine whether words or actions involve hate. Such ambiguous standards invite inconsistent and arbitrary applications of the law because they fail to provide explicit direction as to the correct outcome in a case. (Girvan 2016). Without clear criteria, decision makers must rely on their common sense, attitudes, and stereotypes, with potentially capricious results.

Accordingly, research on hate crime reveals variation in its enforcement. Differences exist across police department in policies, procedures, training, and resource allocation (Franklin 2002; Bell 2002; Jenness and Grattet 2001). In addition, implementation depends on subjective factors, like the attitudes, beliefs, and practices of individual officers (Franklin 2002; Bell 2002; Jenness and Grattet 2001). Officers have a particularly high level of discretion when it comes to enforcing hate crime laws because it is difficult to prove that hate or bias is the primary motivation behind a crime. This ambiguity introduces a high level of subjectivity into the process to determining whether a hate crime occurred, inviting arbitrary and uneven application of penalties (Franklin 2002). It is particularly difficult to determine whether a hate crime occurred because it will always involve conduct that would be criminal regardless of the bias motive (Jenness and Grattet 2001). Thus, police rely on their preconceived notions of what a 'typical' hate crime looks like and eliminate offenses that do not meet these expectations, such as cases involving drugs, fights, neighbor or domestic disputes, or that otherwise have multiple potential motives (Bell 2002; Jenness and Grattet 2001). Police also evaluate the victims to determine whether some explanation other bias may be involved. For example, police may be less likely to attribute victimization to bias when the target lives in a poor neighborhood or has a criminal record (Bell 2002). In sum, hate crime classifications depend greatly on the meaning-making processes of police (Jenness and Grattet 2001).

Additionally, anti-hate laws operate within the confines of a colorblind constitution, and are therefore incapable of recognizing racial dynamics, power asymmetries, and other social context. Colorblind jurisprudence pretends racial equality has already been realized and fails to acknowledge the vastly different circumstances of groups in society (Gotanda 1991). Under this approach, the law is skeptical of all racial distinctions, regardless of whether the government action favors or disfavors racial minorities, promotes equality or inequality, or corrects or continues historical racism (Bell 2008). Thus, it greatly hinders judicial intervention that could address historical subordination, and it ignores the central role of race in social relations, thereby legitimizing unfair and disparate treatment in situations where racism is difficult to prove (Carbado 2002; Butler 2010). This perspective, which only recognizes explicit – not subtle or structural – forms of racism, enables severe racial disparities to persist throughout criminal justice process, including in policing (*Whren v. United States* 1996), jury selection (*Batson v. Kentucky* 1986), and sentencing (*McClesky v. Kemp* 1987).

Likewise, anti-hate laws apply with equal vigor to all groups, regardless of their particular histories and contemporary place in society. Notably, hate crime statutes protect universal categories, like race, ethnicity, religion, sexual orientation, etc., as opposed to particular groups within a category, like blacks, Jews, homosexuals, etc. (Jenness and Grattet 2001). Under this acontextual and ahistorical scheme, advocates for racial justice have been characterized as hate groups. For instance, the FBI has identified black activists as "Black Identity Extremists." (Winter and Weinberger 2017). Similarly, lawmakers have signaled their desire to designate Black Lives Matter a hate group (Phillips 2017; Cohen 2016). True to the colorblind anti-discrimination framework, the mere acknowledgement of race is itself deemed racist. Even critiques of police are suspect. The FBI was particularly concerned about criticisms of law enforcement, which it alleged fueled anti-police sentiment and violence (Winter and Weinberger 2017). Indeed, black activism around policing has led some jurisdictions to give law enforcement protected class status under hate crime statutes (Craven 2017). This creates an inverted reality wherein police killing of unarmed black people – which the United Nations has likened to lynching – is not labeled hate activity, but protesting it is (Miles 2016).

Given these considerations – namely, that anti-hate laws criminalize groups without taking into account their social positions – it is unsurprising that enforcement thereof may reflect disparities seen throughout the criminal justice system. For example, in the late 1990s, blacks comprised a disproportionate contingent of hate crime offenders according to FBI statistics (Franklin 2002). Data available in Florida, New York, and California revealed similar trends (Franklin 2002). In addition, a sizeable portion of the victims was white. Similarly, research indicates police are more likely to become involved in incidents targeting white victims than those targeting black victims (Wilson and Ruback 2003). These disparities may reflect police bias or differences in the willingness of certain groups to contact the police for assistance. Data from the National Crime Victimization Survey reveal that, while minority victimizations are generally less likely to be reported, the magnitude of this effect is far greater for racial hate crimes (Zaykowski 2010). Other research shows that hate crime enforcement depends on a place's legacy of racism. A jurisdiction's history of lynching, and law enforcement's failure to protect minority groups, is predictive of contemporary law enforcement responses to hate-motivated crimes (King, Messner, and Baller 2009). Specifically, past lynching is negatively correlated with hate crime law compliance, i.e., enforcement and reporting by policing agencies.

In sum, some evidence suggests anti-hate laws benefit whites more than racial minorities and, conversely, burden racial minorities more than whites. Anti-hate laws, despite good intentions, may be nothing more than a microcosm of the larger criminal justice system, which, as discussed, promotes racial inequality. Therefore, an honest assessment of anti-hate regulation requires looking into the consequences of criminalization.

IV. An Empirical Look at Hate Crime Laws

Can we trust the government to regulate hate, or will it lead to the mass criminalization of racial minorities? Despite the longstanding interest and obvious significance of this issue, we lack systematic research. This is a particularly important question given the United States history of racialized and colorblind justice and some evidence indicating criminalization may harm racial minorities. This dissertation will therefore examine who bears the burden of criminalization under these provisions. It will provide important empirical evidence pertaining to the question of whether regulating hate actually promotes racial equality, though much more research will be necessary to answer the question. This dissertation is but a small first step.

Chapter 2 initiates the empirical exploration into the potentially perverse impacts of hate crime enforcement, looking at how police handle these crimes. Specifically, it examines whether hate crime laws have the unintended consequence of promoting racial inequality by contributing to racial disparities in arrests. It proposes and tests the following theory regarding hate crime enforcement: While police recognize whites as more likely to commit hate-motivated offenses, they nevertheless arrest African Americans at disproportionately high rates due to biases that overwhelm the criminal justice system. It does so by looking at police-level decisions regarding who has committed a hate crime, examining whether any racial or ethnic groups are overrepresented among hate crime offenders, and comparing these disparities to those among non-hate offenders. The data set is comprised of statistics from the FBI's Uniform Crime Report, innovatively combining the NIBRS and Hate Crime Data series. It also relies on demographic information from the Decennial Censuses of 2000 and 2010. The sample includes incidents of intimidation, simple assault, and aggravated assault for years 2000-15. Preliminary findings suggest there is cause for concern. While police are less likely to designate an assault a hate crime for African American suspects than white, African Americans are nonetheless significantly overrepresented among hate crime offenders. These disparities persist regardless of broader community-level enforcement patterns, though they are significantly lower among hate crimes than comparable non-hate crimes. Major disparities also exist among American Indians. The effects on Hispanics remain unknown. Further research is needed to fully understand how police – as well as other criminal justice officials – enforce hate crime laws, and the reverberations of this enforcement on society.

Chapter 3 continues the exploration into enforcement. It examines how race affects victim perception of potential hate crimes, and how this, in turn, affects police response. Research suggests people tend to have a preconceived notion of the quintessential hate crime in which African Americans are victims. At the same time, other research indicates the public and criminal justice system tend to have a preconceived notion of the prototypical criminal, in which African Americans are seen as the offender. This study asks which holds true in real life scenarios: are African Americans more likely to be seen victims or offenders overall? It proposes that, when individuals personally encounter the stresses of a real (rather than hypothetical) crime, negative biases prevail. Victims will most likely identify an incident as a hate crime and report it to police when the perpetrator is African American, and police will treat suspects more punitively by arresting them when they are African American. To test this theory, I look at victim accounts of their recent victimizations. The data set is comprised of statistics from the Bureau of Justice Statistics' National Crime Victimization Survey for years 2003-15, as well as demographic information from the Decennial Census of 2000 and 2010. Findings provide clear evidence of a tendency to label African Americans as hate crime offenders and report them to police at significantly higher rates. Further, while African American suspects experience relatively high arrest rates generally, these disparities increase precipitously for purported hate crimes. Other non-white offenders and Hispanics are also treated more harshly. At a minimum, this analysis demonstrates the need for further research to show the potentially perverse consequences of hate crime enforcement, and whether this approach is the most efficacious means for addressing bigotry and violence.

Chapter 4 explores the nefarious uses of hate crime laws, examining how they may be weaponized to inoculate police, undermine movements for racial justice, and perpetuate racial repression. Specifically, it looks at the case of so-called Blue Lives Matter legislation. Since 2016, a wave of states has introduced bills into their legislatures that propose extending hate crime protections to police. Hate crime laws have, since their inception, aimed to protect historically oppressed groups. Police do not fit that description, so why provide hate crime protections to police? This chapter tests two explanations for the introduction of these laws. First, it considers conventional wisdom that police face heightened or new violence that justifies new protections. Second, it examines whether past police repression predicts the Blue Lives Matter bills, indicating they are a continuation of such practices. This chapter argues that Blue Lives Matter laws, unlike other types of anti-hate legislation, aim to undermine equality rather than promote it by suppressing movements for racial justice. The data set is comprised of five data sources: legislation introduced at state legislatures in the years 2016 and 2017; the Law Enforcement Officers Killed or Assaulted series from the FBI's Uniform Crime Reporting Program (UCR); Law Enforcement Management and Administrative Statistics (LEMAS); the Arrests by Age, Sex, and Race series from the UCR; and the U.S. Census Bureau Decennial Censuses of 1990, 2000, 2010. Findings reject the officer safety rationale for hate crime protections. States in which lawmakers proposed BLM protections do not differ significantly from other states in terms of violence against police. However, states with more repressive police practices – as measured through arrests of African Americans – are significantly more likely to introduce legislation extending hate crime protections to law enforcement. The results indicate states proposing BLM laws are those in which police have historically exercised broad powers and wish to continue doing so. This suggests states are using hate crime laws – which mean to protect the vulnerable – to protect the powerful. It appears states are weaponizing civil rights laws to suppress movements for racial justice. Further research is needed to fully understand the social context of these laws and their future consequences for racial equality.

Chapter 5 synthesizes these findings, and situates them within the broader question of whether criminalization of hate perpetuates racial inequality. This chapter also seriously considers the limitations of the research. Notably, even if criminalization disproportionately burdens people of color, regulating hate may nevertheless have redeeming equality-promoting effects. In other words, the inquiry does not stop here. We cannot weigh the burdens and benefits of regulation without a full accounting of what those entail. This chapter will explore these limitations, as well as other areas ripe for future exploration.

In conclusion, this dissertation draws attention to the need for greater empirical evidence regarding the potential impacts of regulating hate. It proposes a method for beginning a social scientific examination by identifying a type of regulation that targets hate driven conduct and narrowly focusing on a particular type of burden which has historically afflicted racial minorities, penal enforcement. It then modestly embarks on this empirical journey by examining enforcement at its earliest phases: victim reports and police responses. It further examines police responses by looking into how they may weaponize anti-hate laws to ward off legitimate criticism and oversight. This dissertation is a small but nevertheless necessary first step into the empirical inquiry regarding whether regulating hate actually promotes racial equality.

CHAPTER II

UNINTENDED CONSEQUENCES:

RACIAL DISPARITIES IN HATE CRIME ARRESTS

I. Introduction

Hate crimes have reentered the public spotlight as of late. Laws prohibiting such acts were largely passed in the latter part of the twentieth century out of a convergence of civil rights, women's rights, the gay and lesbian rights, and victim's rights movements. (Jenness and Grattet 2001). They aimed to raise awareness about bigotry directed at minority groups and respond to violence stemming from it. Recently, many advocates, including prominent groups like the Southern Poverty Law Center, the NAACP, the Anti-Defamation League, and the Lawyers Committee on Civil Rights, among others, have reported an "explosion of bias incidents," due to a political climate that permits – or even encourages – hate (see, e.g., Southern Poverty Law Center 2017; National Association for the Advancement of Colored People, "Monitoring and Preventing Hate Crimes"; Anti-Defamation League 2018; Lawyers Committee on Civil Rights, "Stop Hate Project"). Like the anti-hate movement decades ago, these groups look to the criminal justice system, particularly law enforcement, as a primary means for addressing the problem.

But what might be the unintended consequences of demanding greater police intervention? Many groups sounding the alarm and hailing the criminal justice system have at other times led the charge to dismantle that same system because of its role in promoting racial inequality (see, e.g., National Association for the Advancement of Colored People, "Pathways"; Southern Poverty Law Center 2018; Lawyers Committee for Civil Rights, "Criminal Justice"). Police have faced particularly fierce and intense scrutiny as anecdotes and studies surface exposing discriminatory treatment towards people of color and people in poverty or mental health crisis, with regards to stops, searches, arrests, and, most notably, violence (see, Fagen et al. 2009; Harris 2002; Civil Rights Division of the U.S. Department of Justice 2016; Civil Rights Division 2015; Civil Rights Division and U.S. Attorney's Office 2017). Police face a crisis of legitimacy, in large part due to their systemic racism (Vitale 2017). Can the institution of policing effectively address racial subordination, or will greater police involvement translate into higher numbers of minority individuals (particularly African Americans) entering the criminal justice system, as has historically been the case? (See, e.g., Alexander 2012).

This chapter explores whether anti-hate enforcement, which purports to promote racial equality, works to the detriment of racial minorities by contributing to their disproportionate criminalization. As discussed in the Chapter 1, racial disparities exist at every decision-making point in the criminal justice system, from police, to prosecutors, to judges, to juries, to parole boards. Seeing whether these disparities persist in the hate crime context requires a similar examination of key decision-making points. The following study starts this inquiry by focusing on police. It theorizes that, while police recognize whites as more likely to commit hate-motivated offenses, they nevertheless arrest African Americans at disproportionately high rates due to biases that overwhelm the criminal justice system. Using multilevel models nesting incidents of assault within communities (cities or counties), controlling for incident-level characteristics (severity of the offense) and community-level factors (such as racial demographics and racial inequality), I test this theory by modeling whether suspect race or ethnicity determines when police label an incident a hate crime. I then examine the extent to which racial and ethnic groups are overrepresented among hate crime offenders, and how this measures up to inequality in the criminal justice system outside the hate crime context. This shows whether biases within the criminal justice system permeate hate crime enforcement, despite good intentions. Police are a particularly important focal point because of their central role in enforcing hate crime laws and acting as gatekeepers to the system. Moreover, they have been widely regarded as a source of racial subjugation among scholars, advocates, and activists concerned with racial equality. Thus, this investigation is both necessary and timely.

II. Methods

a. Data Sources

This analysis employs four sources of data: the National Incident-Based Reporting System (NIBRS) from the Uniform Crime Reporting Program (UCR); Hate Crime Data from the UCR; the U.S. Census Bureau Decennial Census; and the Law Enforcement Agency Identifiers Crosswalk (LEAIC). Each serves a necessary function. The UCR Hate Crime Data provides statistics on incidents of hate crime offenses, whereas NIBRS offers information on comparable non-hate offenses. The Decennial Census has community-level demographic information that enables the calculation of crime rates for the different racial or ethnic groups and the exploration of relationships between city/county characteristics and enforcement. Finally, LEAIC provides linkage variables that facilitate merging of UCR and Census data. These data sources together allow the analysis of hate crime on multiple levels, collectively providing information about both the incidents and the communities in which they occur. Significantly, incident-level characteristics include details on the offender (race) and the offense (the type and whether it involved bias). The community-level characteristics include demographic and socioeconomic attributes (like racial breakdown, median income, educational attainment, and unemployment and poverty rates). This multilevel analysis will reveal the extent to which incident and community-level characteristics influence incidence of hate crime, among whom, and the odds a crime is deemed hate-driven. Each data source is described in greater detail below.

i. <u>UCR NIBRS and Hate Crime Data</u>

The Federal Bureau of Investigation (FBI) compiles the UCR. City, county, and state law enforcement agencies nationwide submit data on crimes known to police in their respective jurisdictions. Under the UCR, hate crimes are defined as those that “manifest evidence of prejudice based on race, religion, gender, gender identity, sexual orientation, ethnicity, or disability” (Uniform Crime Reporting Program Data: Hate Crime Data 2015 Codebook).

NIBRS includes information at the incident level, including characteristics of the crime, offender, victim, and reporting agency. The UCR’s main Summary Reporting System does not include incident-level information. The FBI implemented NIBRS in 1991, and agencies have incrementally shifted to that method of reporting. As of 2015, 6,648 agencies reported via NIBRS, a little more than one third of those participating in the UCR overall (“FBI Releases 2015 Crime Statistics from the National Incident-Based Reporting System, Encourages Transition”). These agencies collectively covered approximately 93,509,938 of the U.S. population, according to agency population estimates provided by the LEIAC (discussed in subsection ii below). Only 2,988 agencies participated in 2000, collectively covering 42,919,325 of the U.S. population. The agencies participating in NIBRS cannot be presumed random. As a result, NIBRS is not a representative sample of crime in the United States (ICPSR 2009). Yet, it is the only available data source that allows a direct comparison of incidents at the agency level. Thus, NIBRS creates a window – albeit one with a limited and imperfect view – into whether and when police determine crimes as having a hate motive.

The Hate Crime Data series is a separate segment of the UCR. It began in 1990 with passage of the Hate Crime Statistics Act of 1990, and became a permanent feature of the UCR in 1996 under the Church Arson Prevent Act of 1996 (Uniform Crime Reporting Program Data: National Incident-Based Reporting System, 2015). It similarly includes incident-level information pertaining to offenses, offenders, and victims. The overwhelming majority of agencies reporting hate crimes do so via this system. However, in 2000, Hate Crime Data only included data from 1,892 agencies, whose jurisdictions covered 134,900,000 of the U.S. population. In 2015, it included data from 1,742 agencies, whose jurisdictions covered 141,600,000 of the U.S. population. Most agencies report no hate crime at all; FBI hate crime statistics come from a fraction of agencies nationwide. (see, e.g., Hate Crime Data 2016).

Comparisons between hate and non-hate statistics are rare, likely because agencies overwhelmingly report them separately via the Hate Crime Data and NIBRS systems respectively in different formats. Thus, this study is innovative in bringing together two typically siloed data sources, thereby providing a more complete picture of hate crime enforcement within the criminal justice system.

ii. U.S. Census Bureau Decennial Census

The U.S. Census Bureau conducts the Decennial Census, surveying households across the country to provide, among other things, population estimates. Pertinent to this study, the Decennial Census provides demographic information on households and geographic areas, including racial and ethnic composition and socioeconomic attributes (median income, poverty rates, educational attainment, and unemployment rates). Table 2-1 provides descriptive statistics for these geographic units of analysis.

Table 2-1: Geographic Units of Analysis (Cities and Counties)

Total Number of Units	6,455		
	Mean	*Min*	*Max*
Number Incidents	26,568	1	436,446
Population (Count)	91,395	8	3,376,741
White (%)	83.46%	1.52%	100.00%
African American (%)	7.26%	0.00%	95.31%
Asian/PI (%)	1.18%	0.00%	27.69%
AI (%)	1.05%	0.00%	85.74%

Data include only NIBRS reporting agencies, but include statistics from NIBRS and Hate Crime Data sources for those agencies.

This study includes data from the 2000 and 2010 decennial censuses (Manson, et al. 2017). UCR data from years 2000-2009 were paired with the 2000 census, and years 2010-2015 the 2010 census. This means a lag exists between the decennial census and subsequent years. However, this lag exists across geographic areas. Decennial Census and UCR data were merged by city (FIPS place codes) for Census places, and by county (FIPS county codes) for non-place geographic areas (e.g., counties).

iii. LEIAC

The U.S. Bureau of Justice Statistics creates the LEIAC. It contains common match keys for merging UCR and Census Bureau data. Linkage variables include the Originating Agency Identifier (ORI) code, Federal Information Processing Standards (FIPS) codes for states, counties, and cities (places). For this study, the 2012 LEIAC linked UCR years 2010-2015 to 2010 Decennial Census data, and the 2000 LEIAC linked UCR years 2000-2009 to 2000 Decennial Census data.

b. Sample

This study includes UCR NIBRS and Hate Crime Data for the years 2000 through 2015. All years are combined. The sample has only assault-related offenses: intimidation, simple assault, and aggravated assault. Several considerations prompted the decision to focus on these offenses. Notably, they comprise the majority of hate-related crimes, whereas the remaining incidents are diffuse. Hate Crime Data for this time period spanned 41 offense types, 58.53 percent assaults, 32.85 percent vandalism and destruction of property, and 9 percent the remaining 37 categories (each less than 2 percent of cases respectively). Thus, these 37 offenses were eliminated due to sparseness among hate crime offenses. In addition, the nature of assaults is such that the offender's race is usually known. This was true for 77 percent of cases in the Hate Crime Data. In contrast, vandalism and destruction of property indicated offender race in just 16 percent of cases, and was therefore excluded (see Table 2-2 for the distribution of offenses in the sample).

Table 2-2: Distribution of Offenses in Sample

	Intimidation	*Simple Assault*	*Aggravated Assault*	*Total*
Non-Hate	2,625,791	9,212,060	2,193,087	14,030,938
	18.71%	65.66%	15.63%	100%
Hate	9,220	10,223	4,777	24,220
	38.07%	42.21%	19.72%	100%
Total	2,635,011	9,222,283	2,197,864	14,055,158
	18.75%	65.61%	15.64%	100%

Data include only NIBRS reporting agencies, but include statistics from NIBRS and Hate Crime Data sources for those agencies.

Some changes were required to ensure comparability between NIBRS and Hate Crime Data. First, since non-hate data only included NIBRS reporting agencies, the Hate Crime Data was similarly limited to NIBRS reporting agencies to prevent the influence of agency-level differences. Second, Hate Crime Data aggregates all offenders in a given incident, leaving the incident (not offender) as the unit of analysis. Thus, while NIBRS provided a within-incident breakdown of offenders, this information was collapsed to match the Hate Crime Data incident-level aggregation. Third, Hispanic was omitted from the entire data set because Hate Crime Data does not include that variable, and it appears in NIBRS only for years 2012 through 2015, and is rarely reported even then (see Table 2-3 for a breakdown of the distribution of incidents by racial and ethnic category). Fourth, Hate Crime Data provides no racial/ethnic information on victims, and thus this information was removed altogether. All cases for which offender race is unknown were excluded from the analysis (1,230,657 cases dropped out of 15,285,815, constituting just 8 percent of the sample). With all restrictions, the final sample equaled 14,055,158 incidents.

Table 2-3: Distribution of Incidents in Sample by Racial Category of Offenders*

	White	*African American*	*Asian/PI*	*AI*	*Multi*	*Total*
Non-Hate	8,681,862	4,962,928	85,858	105,073	195,217	14,030,938
	61.88%	35.37%	0.61%	0.75%	1.39%	100%
Hate	16,815	5,964	191	254	996	24,220
	69.43%	24.62%	0.79%	1.05%	4.11%	100%
Total	8,698,677	4,968,892	86,049	105,327	196,213	14,055,158
	61.89%	35.35%	0.61%	0.75%	1.4%	100%

*Asian/PI includes Asian and Pacific Islanders. AI refers to American Indian. Multi refers to groups comprised of offenders of different racial identities. Data include only NIBRS reporting agencies, but include statistics from NIBRS and Hate Crime Data sources for those agencies.

c. Measures

This multilevel analysis will reveal the extent to which incident- and community-level characteristics influence incidence of hate crime enforcement, among whom, and the odds a crime is deemed hate-driven. It involves two separate statistical tests: Bernouli and a negative binomial regressions.

For the first series of Bernouli models, the dependent outcome is whether police designated an incident a hate crime or a not. Thus, incidents were categorized into a binary variable as either having a bias motive or the lack thereof. Blank and negative responses were coded as “0” to indicate police noted no bias, and all others were coded as “1” to indicate police positively identified a form of bias. This allows us to see how police labeled each incident, and whether various fixed effects predict either outcome.

For the next Bernouli model, the dependent is whether the incident involved an African American suspect. For this test, incidents were categorized into a binary variable as either involving an African American suspect or not. This will show whether the difference in African American representation among arrestees differs signficiantly between the hate and non-hate contexts.

The negative binomial regressions then examine bias and non-bias crimes separately (those labeled “1” and then those labeled “0”), using counts of those incidents by geographic area to calculate incidence rates for every racial and ethnic group. This allows for a direct comparison of arrest rates for non-hate crimes and hate crimes, thereby illuminating whether similar racial/ethnic disparities occur in both contexts.

The primary predictor of interest is offender race. Hate Crime Data aggregates the race of all offenders involved in a particular incident into a single group. If multiple offenders of one race are involved in a given incident, the race variable will reflect their shared group identity (e.g., African American, white, etc.). However, if the incident involves multiple offenders of more than one race, the race variable merely indicates the group was multiracial without a demographic breakdown. Thus, NIBRS data was coded to match the Hate Crime Data categories such that multiracial refers to groups of suspected assailants of different racial or ethnic identities. Both UCR data sets combine Asian and Pacific Islander offenders in years preceding 2012, and so the demographic groups were combined all years for consistency.

Another important incident-level covariate is the severity of the offense. Severity of offense refers to the level of violence used in the assault, and was based on FBI definitions (“Uniform Crime Reporting Handbook”). Intimidation is the least severe, involving the use of threatening words or conduct without a weapon or actual physical attack. Simple assault is more severe, involving a physical attack but no weapon or serious bodily injury. Aggravated assault is the most severe, as it entails serious bodily injury, and is often accompanied by the use of a weapon or other means likely to produce death or great bodily harm. These were coded as “1,” “2,” and “3,” respectively to create a categorical variable.

The community-level characteristics of interest are population and racial inequality. Population allows for the calculation of arrest rates for each demographic group. The first series of Bernouli models do not include population because there was no theoretical reason to believe population sizes affects whether or not police label a crime as bias motivated. The negative binomial regression uses populations of each racial and ethnic category for the city or county wherein the law enforcement agency exists (based on place and county FIPS codes from the Decennial Censuses). Measurement of racial inequality required calculating dissimilarity between white and African American populations in a given geographic area (again using place and county FIPS codes) for median income, educational attainment, and unemployment. See Appendix A for these calculations. In brief, this involved calculating the ratios for income, educational attainment, and unemployment between African Americans and whites. Higher numbers on the index denote greater disparities between African Americans and whites in these combined categories. For income, a positive number indicates African Americans are better off. For educational attainment and unemployment, a positive number indicates whites are better off. These metrics are useful because they show the extent to which African Americans occupy a marginalized position within their given communities compared to the dominant white group. The inequality ratios do not show the level of educational attainment, unemployment, and income for all populations within an entire city or county. Instead, it measures the relative disadvantage of African Americans specifically. These ratios will allow us to see whether there is an interaction between racial inequality and the criminalization of African Americans.

d. Analysis

This study examines whether hate crime enforcement, which purports to promote racial equality, works to the detriment of racial minorities by leading to their disproportionate criminalization. It does so by asking who bears the burden of hate criminalization by police and whether disparities exist. This analysis therefore explores the relationship between race and the enforcement of hate crime laws. It predicts that police will recognize whites as more likely to commit hate-motivated offenses, but their enforcement will nonetheless succumb to systemic bias throughout the criminal justice system, resulting in disparate enforcement against African Americans of the variety known to other criminal contexts. This leads to the following hypotheses:

> H1: Offender race is a significant predictor of whether police label a crime as bias-motivated, with the odds of white offenders receiving such a designation significantly greater than that of African American offenders. Offenses involving a white offender will be most likely to be recognized as a hate crime.
>
> H2: African Americans are overrepresented in arrests among hate crime offenders to a similar degree as they are overrepresented in arrests among non-hate offenders; i.e., we see similar disparities in arrest rates between African Americans and whites across hate and non-hate crimes, with no significant difference between the two contexts.
>
> H3: Communities with more extreme racial inequality have greater disparities in enforcement.

Answering these questions requires measurement of key variables on multiple levels: it involves the regression of police actions (bias motive designation and incidence of arrest) on suspect racial identifiers. The model must also control for other factors that may explain variation, like seriousness of offense, as well as community-level characteristics, including crime rates for comparable non-hate crimes, the racial composition of the geographic area, and level of racial inequality. Other relevant variables are excluded from the study due to limitations in how the UCR currently compiles Hate Crime Data (see section IV below).

If the coefficient for African Americans is a significant negative predictor of whether police ascribe bias to a crime, it will show police recognize white criminality as more frequently hate-driven. If racial disparities in hate crime enforcement mirror those in the criminal justice system, it will signify that it suffers from similar systemic bias. A finding that racial inequality predicts disproportionate enforcement against African Americans will indicate hate criminalization is an extension of the racial subordination occurring in communities in which they are most marginalized. If no significant relationship exists between race and police action, it will suggest anti-hate regulations successfully avoided the racial disparities endemic to the criminal justice system.

This study employs several statistical tests. To test H1, Bernouli logistic models measure the relative odds of an incident receiving a bias designation based the offenders' race or ethnicity (odds ratios). Put another way, these models take into account all assaults, and calculate the odds police will label one a hate crime if the offender is white, African American, or of another racial or ethnic group. This will reveal whether offender race or ethnicity is a significant predictor of police recording a crime as bias-motivated.

The analysis then uses a combination of Bernouli logistic and negative binomial regression models to test H2. First, a Bernouli logistic model measures the relative odds of an incident involving an African American suspect based on whether it was bias-motivated. It controls for offense type and the relative population of each demographic group. This shows whether African American arrest rates significantly differ between the hate and non-hate contexts.

Then, to facilitate a closer examination of the relative arrest rates in both contexts, the analysis uses negative binomial regression models to test H2. The first of these models measures incidence rates ratios of arrests among hate crimes, and the second repeats the test for non-hate crimes. This statistic considers the counts of arrests for each racial group, and calculates their arrest rates based on their relative populations while also controlling for overall population. This determines the extent to which groups are overrepresented based on their population size, notably showing the degree to which African Americans comprise a disproportionately large segment of alleged offenders.

Due to overdispersion, the negative binomial regression model provides the best fit. Overdispersion occurs when more variability exists around the model's fitted values than possible for a Poisson formulation (Berk and MacDonald 2008). Negative binomial regression tests require the exposure (i.e., population of a given racial group) to be greater than zero and known. Thus, the models omit observations not meeting the exposure criteria, dropping: (1) those for which the population is zero; and (2) those for which population is unknown, i.e., incidents with multiple offenders comprised of more than one racial or ethnic category whose population cannot be determined.

The Bernouli and negative binomial models mentioned will also provide opportunities to test H3, revealing whether significant interactions exist between offender race and community-level racial inequality. In other words, they will measure whether communities with greater racial inequality treat African Americans more harshly in their hate crime enforcement.

The first series Bernouli models has three iterations: Model 1A is a null model without fixed effects; Model 1B adds level-1 fixed effects (race and severity of offense); and Model 1C adds the level-2 fixed effect (inequality metrics for income, education, and unemployment). This allows for a comparison for level-2 variance.

The mathematical formula for the final Bernouli model is as follows:

$$biaspresent_{ij} \sim Bernoulli\ (\pi_{ij})$$
$$\text{logit}(\pi_{ij}) = \beta_0 + \beta_{1\text{-}5}(race_{ij}) + \beta_{6\text{-}8}(offense_{ij}) + \beta_9(income\ ratio_j) + \beta_{10}(education\ ratio_j) + \beta_{11}(employment\ ratio_j) + \beta_{12-16}(race_{ij})(income\ ratio_j) + \beta_{17-21}(race_{ij})(education\ ratio_j) + \beta_{22-26}(race_{ij})(employment_j) + \mu_{0j}$$
$$\text{Level 2: } \mu_{0j} \sim \text{N } [0, \sigma^2{}_{\text{u0}}]$$
$$\text{Level 1: Var}(biaspresent_{ij} |\ \pi_{ij}) = \pi_{ij}\ (1 - \pi_{ij})$$

The next Bernouli model segment has one iteration: Model 2 measures the relative odds of an incident involving an African American suspect based on whether it was bias-motivated. It is a single level analysis. The mathematical formula is as follows:

$$offender\ AA_{ij} \sim Bernoulli\ (\pi_{ij})$$
$$\text{logit}(\pi_{ij}) = \beta_0 + \beta_1(biaspresent_{ij}) + \beta_{2\text{-}4}(offense_{ij}) + \beta_5(white\ population_j) + \beta_6(AA\ population_j) + \beta_7(biaspresent_{ij})(AA\ population_j) + \mu_{0j}$$
$$\text{Level 1: Var}(offender\ AA_{ij} |\ \pi_{ij}) = \pi_{ij}\ (1 - \pi_{ij})$$

The negative binomial regression has two iterations: Model 3A, which measures hate-related incidents with level-1 and level-2 fixed effects; and Model 3B, which measures non-hate-related incidents with level-1 and level-2 fixed effects. This model is similar to a Poisson, with the exception of the level 1 variance, which is a function of the mean and scale parameter, notated as follows:

Model 3A Level 1: $\text{Var}(hate\ incidents_{ij} |\ \pi_{ij}, \upsilon) = \pi_{ij} + \pi_{ij}^2\upsilon$

Model 3B Level 1: $\text{Var}(non - hate\ incidents_{ij} |\ \pi_{ij}, \upsilon) = \pi_{ij} + \pi_{ij}^2\upsilon$

III. Results

To test H1, bias designations were regressed on available variables for offender race or ethnicity (white, African American, Asian/Pacific Islander, American Indian) and severity of offense (intimidation, simple assault, aggravated assault) using all indicator codes. The models are multilevel, with level-1 representing incident-level variables, and level-2 representing city/county-level variables. Model 1A is a null model without fixed effects. Model 1B adds level-1 fixed effects (race and severity of offense). Model 1C adds level-2 fixed effects (income, education, and unemployment disparities).

The substantive conclusions were consistent across Models 1B and 1C (Table 2-4). The coefficient for African American was a significant negative predictor in these models, whereas the coefficients for American Indian and multiracial offender groups (i.e., those with multiple assailants of different identities) were significant positive predictors (see Model 1C, Table 2-4). The coefficient for Asian/Pacific Islander offenders was not statistically significant. In the median city/county, incidents involving African American offenders had .81 the odds of receiving a hate designation than those involving white offenders. Incidents with American Indian offenders had 1.49 the odds of receiving a hate designation than those with white offenders. Multiracial groups had 3.5 times the odds of receiving a hate designation than white offenders. The coefficients for severity of offense were significant negative predictors of whether an officer labeled a crime as hate-motivated, with simple and aggravated assault having far smaller odds than intimidation in the median city/county (see Model 1C).

Table 2-4: Bernouli Logistic Regressions of Bias Designation on Race and Inequality

	Model 1: Null	*Model 2: Level-1 Fixed Effects*					*Model 3: Level-2 Fixed Effects*				
	OR	OR	P>z		95% Conf. Interval		OR	P>z		95% Conf. Interval	
Race											
White (ref.)											
African Am	-	**0.73**	0.00	***	0.71	0.76	**0.81**	0.00	***	0.76	0.87
Asian/PI	-	1.01	0.89		0.87	1.17	0.89	0.45		0.67	1.19
AI	-	**1.22**	0.01	**	1.06	1.40	**1.49**	0.00	**	1.24	1.78
Multi	-	**2.99**	0.00	***	2.80	3.20	**3.50**	0.00	***	3.14	3.91
Income	-	-			-		**1.08**	0.04	*	1.00	1.17
Unemp.	-	-			-		**0.98**	0.01	*	0.97	1.00
Educ.	-	-			-		1.04	0.71		0.84	1.29
*Income*Race*	-	-			-						
African Am.	-	-			-		0.99	0.89		0.82	1.19
Asian/PI	-	-			-		0.55	0.12		0.25	1.16
AI	-	-			-		**1.49**	0.01	**	1.11	2.00
Multi	-	-			-		1.08	0.57		0.83	1.39
*Unemp.*Race*	-	-			-						
African Am.	-	-			-		**0.53**	0.00	***	0.43	0.64
Asian/PI	-	-			-		0.62	0.12		0.34	1.13
AI	-	-			-		0.77	0.31		0.46	1.39
Multi	-	-			-		**0.48**	0.00	***	0.36	0.36
Offense											
Intimidation (ref)											
Simple	-	**0.29**	0.00	***	0.28	0.30	**0.29**	0.00	***	0.28	0.30
Aggravated	-	**0.59**	0.00	***	0.57	0.61	**0.58**	0.00	***	0.56	0.61
Intercept	**0.00**	**0.00**	0.00	***	0.00	0.00	**0.00**	0.00	***	0.00	0.00
City/County Variance	3.85	3.75			3.48	4.05	3.95			3.66	4.28

Coefficient superscripts indicate these significance levels: * (p < .05), ** (p < .01), *** (p< .001). Bolded coefficients indicate those that are significant at p < .05 or less in all models. OR means odds ratio. Asian/PI refers to Asian and Pacific Islander. AI denotes American Indian. Multi means the offender group was comprised of multiple individual, and they have different racial or ethnic identities.

Testing of H2 involved two steps. In step one, offender race (African American or not) was regressed on the variable for whether the crime was hate-motivated and offense type. The coefficient indicating the crime involved hate is a significant negative predictor of whether the suspect was African American (Model 2, Table 2-5). An arrest involving a hate-motivated offense has two-thirds the odds of a non-hate offense of involving an African American offender, and a hate crime is significantly less likely to involve an African American suspect, even when controlling for the population of African Americans. Put another way, hate crimes are significantly less likely than non-hate crimes to involve African Americans, even as African American population increases.

In step two, the number of times police cited/summoned/arrested people for hate-related assaults was regressed on the variables for race and ethnicity and the coefficients for racial inequality in terms of income, educational attainment, and unemployment. (Model 3A, Table 2-6). This was offset by the population of each racial and ethnic group in a given geographic area (exposure), controlling for overall population, as well.

The coefficients for African American and American Indian offenders were significant positive predictors of incidence rates, and the coefficient for Asian/Pacific Islander offenders was a significant negative predictor (Model 3A, Table 2-6). The expected number of hate-related assault citations/summons/arrests was 2.85 times higher for African Americans than whites, and 1.34 times higher for American Indians than whites. Asian/Pacific Islander offenders were cited/summoned/arrested for hate-related assaults at less than one-fifth the rate of whites.

Table 2-5: Bernouli Logistic Regression of African American Suspect on Hate and Non-Hate Offenses and Group Populations

	Model 2				
	Odds Ratio	P>z		95% Conf. Interval	
Hate Crime					
Non-Hate (ref)					
Hate	**0.676125**	0.00	***	0.62	0.74
Population					
White	**0.999998**	0.00	**	1.00	1.00
African Am.	**1.000008**	0.00	***	1.00	1.00
*Hate*African Am. Population*					
Non-Hate (ref)					
Hate	**0.999997**	0.00	***	1.00	1.00
Offense					
Intimidation (ref)					
Simple	**1.349706**	0.00	***	1.27	1.43
Aggravated	**1.502125**	0.00	***	1.38	1.63
Intercept	**0.289414**	0.00	***	0.26	0.33

Coefficient superscripts indicate these significance levels: * (p < .05), ** (p < .01), *** (p< .001). Bolded coefficients indicate those that are significant at p < .05 or less in all models. OR means odds ratio.

Table 2-6: Negative Binomial Regressions of Arrests on Race and Inequality for Hate and Non-Hate Offenses

	Model 3A: Hate					*Model 3B: Non-Hate*				
	IRR	P>z		95% Conf. Interval		IRR	P>Z		95% Conf. Interval	
Race										
White (ref)										
African Am.	**2.85**	0.00	***	2.58	3.16	**3.09**	0.00	***	3.01	3.18
Asian/PI	**0.19**	0.00	***	0.13	0.26	**0.28**	0.00	***	0.27	0.29
AI	1.34	0.01		1.08	1.65	**0.54**	0.00	***	0.52	0.55
Income	**0.89**	0.05	*	0.79	1.00	0.98	0.71		0.87	1.11
Unemp.	0.99	0.13		0.97	1.00	**1.00**	0.00	***	1.00	1.00
Educ.	**0.72**	0.01	*	0.56	0.92	0.98	0.78		0.87	1.11
*Race*Income*										
White (ref.)										
African Am.	**1.60**	0.00	***	1.27	2.00	**0.92**	0.00	**	0.88	0.97
Asian/PI	0.37	0.03	*	0.15	0.89	0.90	0.02		0.84	0.96
AI	1.20	0.37		0.80	1.80	**0.87**	0.00	***	0.82	0.92
*Race*Unemp.*										
White (ref.)										
African Am.	1.02	0.41		0.98	1.06	**1.01**	0.00	***	1.00	1.01
Asian/PI	1.03	0.46		0.95	1.12	1.00	0.87		1.00	1.01
AI	1.04	0.07		1.00	1.08	**1.00**	0.00	***	1.00	1.01
*Race*Educ.*										
White (ref.)										
African Am.	**0.63**	0.01	***	0.44	0.90	**0.81**	0.00	***	0.73	0.90
Asian/PI	0.96	0.91		0.44	2.07	1.00	0.97		0.86	1.15
AI	1.12	0.72		0.59	2.15	1.15	0.08		0.98	1.34
Intercept	**0.00**	0.00	***	0.00	0.00	**0.06**	0.00	***	0.03	0.03
Exposure	1					1				
Total Pop.	**1.00**	0.00	***	1.00	1.00	**1.00**	0.00	***	1.00	1.00
City/County Variance	1.22			1.12	1.33	3.16			3.04	3.29

Coefficient superscripts indicate these significance levels: * ($p < .05$), ** ($p < .01$), *** ($p < .001$). Bolded coefficients indicate those that are significant at $p < .05$ or less in all models. IRR means incidence rates ratio.

To see whether these results were unique to hate-related offenses, the same model was run on non-hate incidents (Model 3B, Table 2-6). The number of times police cited/summoned/arrested someone for non-hate assaults was regressed on the variables for race and ethnicity and the level of inequality, offset by sub-group populations (exposure). The coefficient for African American offenders was a significant positive predictor of incidence rates, whereas the coefficients for American Indian and Asian/Pacific Islander offenders were significant negative predictors. The expected number of non-hate citations/summons/arrests for non-hate assaults was three times higher for African Americans than whites. Asians/Pacific Islanders and American Indians were cited/summoned/arrested a little more than one-quarter and one-half the rate of whites respectively.

To test H3, bias designations were regressed on available variables for offender race or ethnicity (white, African American, Asian/Pacific Islander, American Indian) and severity of offense (intimidation, simple assault, aggravated assault), as well as the metrics for racial inequality. The coefficient signifying the disparities in income had a significant positive effect on hate designations, whereas the coefficient representing disparities in employment had a significant negative effect (Model 1C, table 2-4). Disparities in educational attainment were not significant. The interaction between income disparities and whether the offender was American Indian had a significant positive effect. The interaction between whether the disparities in unemployment and whether the offender was African American had a significant negative effect.

Disparities in income and educational attainment had significant negative effects on incidents rates of arrests for hate crimes, but not for non-hate crimes (Model 3A,

Table 2-6). For non-hate arrests, the coefficient for inequality in unemployment had a significant negative effect (Model 3B, Table 2-6). However, when considering the interaction between these inequality metrics and the race of the offender, the patterns change. The interaction between the coefficients for African American suspects and income equality has a significant positive effect on incidence rates of arrests for hate crimes, but a significant negative effect for non-hate crimes. The interaction between the coefficients for the interaction between African American suspects and educational inequality had a significant negative effect on incidence rates of arrests for hate crimes and non-hate crimes. The interaction between the coefficients for African American suspects and disparities in unemployment had a significant positive effect on incidence rates ratios for arrests in non-hate crimes, but no significant effect for hate crimes. However, the interaction between inequality and race was significant for African American and American Indian offenders, with higher rates of inequality translating into smaller disparities between these groups and the reference group, whites (Model 3B, Table 2-6). Relatedly, there was significant between-city/county variation in both Models 3A and 3B. However, the number more than doubled between the former and the latter, with level-2 variance at 1.22 for hate incidents and 3.16 for non-hate incidents.

IV. Discussion

a. Evidence of Racial Disparities

This study set out to explore whether anti-hate regulations contribute to the mass criminalization of African Americans, looking at police-level decisions regarding who has committed a hate crime. It examines whether suspect race predicts police labeling incidents as hate-driven, the extent to which racial or ethnic groups are overrepresented among hate crime offenders, and whether these disparities resemble those seen in the non-hate context. If hate crime enforcement is plagued with the same racial bias characteristic of the criminal justice system, we should see that, even when police recognize whites as the majority of hate crime perpetrators, African American offenders still represent a disproportionate share of those arrested for hate crimes, and those disparate arrests rates do not differ significantly from those for non-hate offenses.

The results provide equivocal support for that theory. Consistent with H1, offender race is a significant predictor of whether police label a crime as bias-motivated. The odds of an African American offender receiving such a designation is significantly less than that of a white offender. Put another way, assaults have significantly higher odds of being labeled a hate crime when committed by white rather than African American suspects. This held true when controlling for geographic location as well as the type and severity of offense. Standing alone, this outcome seems consistent with conventional wisdom that anti-hate laws address aggression from the dominant group in society (i.e., white aggressors), and it appears to counteract concerns that colorblind anti-hate laws, in combination with systemic racial bias and discrimination, lead to disparate enforcement against African Americans. However, the subsequent statistical tests provide evidence to the contrary.

As predicted in H2, the results reveal disparities. When taking into account relative populations, African American suspects are significantly overrepresented among hate-related assault suspects. African Americans are the targets of police action for these crimes at significantly higher rates than whites. However, these disparities are still significantly lower than those in the non-hate context. The expected number of citations/summons/arrests for non-hate assaults was 3.09 times higher for African Americans than whites. The numbers for hate crime assaults are less extreme, but bear a close resemblance, with the expected number of citations/summons/arrests for hate-related assaults still 2.85 times higher for African Americans than whites. Despite their similarities, the arrest rates for non-hate and hate offenses differ significantly (Model 2, Table 2-5). This outcome suggests that biases within the criminal justice system do permeate hate crime enforcement, despite good intentions, but to a significantly lesser degree. Racial disparities are present, though attenuated, for hate crimes. Nonetheless, these findings resonate with early research warning African Americans would comprise an unequal contingent of hate crime offenders (for a discussion of this research, see Franklin 2002). Thus, even though the hate crimes police are learning about and responding to involve whites as perpetrators, there is reason to believe structural forces perpetuating bias and discrimination are still at play.

All of the models suggest American Indians are significantly burdened by hate crime enforcement. An assault involving an American Indians suspect is approximately 1.49 times more like to be designated a hate crime than one involving a white suspect (Model 1C, Table 2-4). Similarly, American Indians are 1.34 times as likely to be cited/summoned/arrested for a hate-related assault as whites (Model 3A, Table 2-6). This is in stark contrast to non-hate assaults, in which they are only half as likely as whites to be involved (Model 3B, Table 2-6). American Indians are disproportionately subject to hate crime enforcement.

Asian and Pacific Islanders are only about a quarter as likely as whites to be involved in either hate or non-hate assaults, and when they are involved, the odds of police labeling their conduct hate-motivated does not differ significantly from the odds for whites.

Interestingly, groups comprised of offenders from multiple racial/ethnic categories had about 3 times the odds of receiving a hate designation than white offenders. A post-hoc Bernouli analysis was conducted adding the number of offenders as a control to determine whether this significance was attributable to the size or the racial character of the group. Notably, while offender group size was also a significant positive predictor of whether a crime received the hate designation, the racial composition maintained its significance with the addition of this control. This suggests that something about the racialized nature of the offender group affects how the officers interpret its conduct. These findings support claims that groups of racial minorities are often characterized and perceived as threatening. For example, critics have noted the media portrays non-whites as “rioting” when engaged in protest, or “looting” when responding to natural disasters, while depicting comparable white actions in a more empathetic and favorable light (see, e.g., Jones 2005; Finley 2015). The public sees non-white and multiracial groups as more disorderly and dangerous. This tendency seems to carry over to the hate crime context.

The results show some support for H3, depending on the inequality metric. Hate crime enforcement is greater in communities with African Americans who have higher earnings than their white counterparts (Model 1C, Table 2-4). While income inequality leads to lower incidence rates of hate crimes overall, it has a significant positive effect when interacted with African American offenders (Model 3A, Table 2-6). In other words, the better off African Americans are relative to their white counterparts, the more likely it is they will be arrested for hate crimes. Interestingly, the trend is the opposite for non-hate crimes, where greater disparities representing higher African American incomes translate into lower arrest rates of African Americans overall. However, these findings change when focusing on educational attainment. Inequality in educational attainment has a significant negative effect on African American arrest rates in both the hate and non-hate contexts. The greater the difference between whites and African Americans in education, the lower the disparities in arrests. No discernible pattern exists for unemployment inequality. Thus, disparities in income positively predict African American arrest rates for hate crimes, but disparities in education and employment do not show the same pattern.

b. Limitations and Future Opportunities

This study faced significant methodological limitations. Most notably, it excludes all jurisdictions that report crime statistics via programs outside NIBRS. As a result, the sample omits at least two-thirds of UCR reporting agencies for any given year. This means entire states are missing. Quite possibly, missing states (notably New York, Florida, and California), which have large and diverse populations, may have very different patterns in hate crime enforcement. Further, because agencies may differ within a state regarding their mode of reporting, those states represented in the sample may be missing key jurisdictions. NIBRS is not a representative sample of crime in the United States, and this greatly affects the generalizability of the models.

Further, valuable information was lost in an effort to harmonize NIBRS and Hate Crime Data. NIBRS collects important incident-level data that was omitted to be consistent with the Hate Crime Data, like information on the crime (e.g., whether it was attempted or completed and the severity of the injury), how police handled it (e.g., citation, summons, arrest), and victim characteristics (e.g., race, sex, and age). NIBRS also provided an offender-level breakdown of racial characteristics, which was diluted to match the Hate Crime Data offender group aggregates. Until the FBI achieves its goal of having all agencies report via NIBRS, it will be difficult to systematically measure these important incident- and offender-level differences. As a result, this study may have overlooked significant variables.

Like other hate crime research, this study is limited in its ability to accurately measure crime rates. First, it is greatly hindered by discrepancies in enforcement and reporting. Much variation exists in how departments approach the issue, including in policies, procedures, training, and resource allocation (Franklin 2002; Bell 2002; Jenness and Grattet 2001). Importantly, most agencies report no hate crime at all; the hate crime data in this study come from a fraction of agencies nationwide. For example, 88.4 percent of agencies participating in the Hate Crime Data Program reported no hate crimes occurred in the jurisdictions in 2016 (Hate Crime Data, 2016).

Second, hate crimes are underreported, particularly among racial minorities. Indeed, Zaykowski (2010) used data from the National Crime Victimization Survey to explore the influence of the victim's race on reporting hate crimes to the police. Controlling for other demographic and incident characteristics, her results revealed that minority victimizations are less likely to be reported for hate crimes, and the magnitude of this effect is even greater for those motivated by race specifically. Racial minority victimizations were approximately 35 percent less likely to be reported than white victimizations. Other researchers have found an incident with a white victim significantly increases the probability of police involvement, possibly due to the willingness of certain groups to contact the police for assistance. (Wilson and Ruback 2003). This issue of underreporting means official statistics may understate the hate crime, particularly for those involving non-white victims. This could also mean the number of white offenders is underreported. This likely skews the distribution of victims and attendant offenders in the sample.

Another noteworthy issue with this study is its lack of pertinent ethnic information. The UCR began compiling data on Hispanic origin in 2012. However, even in subsequent years, many agencies lacked that level of detail. Thus, while the criminal justice system disproportionately punishes Hispanics, this study fails to examine whether hate crime enforcement contributes to the problem. Further, the data lack nuance and may provide a simplistic and inflated picture of whites in the sample. According to the 2010, 53 percent of Hispanics identified as white, as opposed to 2.5, 1.4, 0.5, and 0.1 percent who identified as African American, American Indian, Asian/Pacific Islander respectively (Humes, Jones, and Ramizerz 2011). Thus, lacking a Hispanic option likely has a greater effect on white than African American suspects in the sample. This study suggests the odds of police labeling an assault as a hate crime are significantly higher for whites than African Americans. However, distinguishing between Hispanic and non-Hispanic whites may alter that statistic and erode its significance. Data on Hispanic origin is needed to provide an accurate measure of how hate crime enforcement impacts both white and non-white Hispanic communities.

Thus, looking forward, researchers should refine the method for measuring how police enforce hate crime laws and the effects of this enforcement on various racial and ethnic communities. More detailed and reliable information will be available as the number of agencies reporting to NIBRS increases. Researchers may consider other sources of hate crime data too, including victimization surveys, as well as reports generated in response to public records requests or for government agencies engaged in police oversight or human rights work. These analyses should also try to capture data on incidents that do not result in arrest or other formal police action.

Future research should also examine hate crime enforcement at other stages in the criminal justice system. Many decision-making points exist throughout the process wherein broad discretion and racial and ethnic bias invite disparities. Prosecutors, judges, juries, and parole boards play significant roles in determining who is punished and to what extent. Research scrutinizing decisions around charging, plea bargaining, pretrial release, conviction, sentencing, and parole may illuminate significant disparities. This empirical work is necessary to truly appreciate the impacts of criminalization.

Finally, scholars should study the effects of hate crime laws more broadly. Conventional wisdom suggests strict regulation will communicate zero tolerance for bigotry and violence. However, limited research exists on whether hate crime statutes actually have a deterrent effect. In fact, some research indicates otherwise: prosecution may increase resentment towards minorities because it plays into the offenders' perceptions that they were the victims of oppression by a more socially privileged and powerful group (Franklin 2002). Moreover, in other criminal justice contexts, social science has shown therapeutic approaches to have superior outcomes to punitive ones (see, e.g., Warren 2009). Therefore, more work is needed to evaluate the efficacy of hate crime laws in combating hate and promoting racial equality.

V. Conclusion

While it is true that racial inequality is a significant problem in contemporary U.S. society, it is also undeniable that the criminal justice system has been a major culprit in creating and perpetuating that inequality. Accordingly, an honest assessment of the efficacy of hate crime laws must include an analysis of its effects on those it punishes. This study set out to begin that analysis into whether hate crime laws have the unintended consequence of promoting racial inequality by contributing to the mass criminalization of African Americans. It did so by looking at police-level decisions regarding who has committed a hate crime, examining whether any racial ethnic groups are overrepresented among hate crime offenders, and the extent to which disparities in hate crime enforcement resemble those throughout the criminal justice system. These preliminary findings suggest there is cause for concern. Police are less likely to designate an assault a hate crime for African American suspects than white, but African Americans are nonetheless significantly overrepresented among hate crime offenders, though these disparities are significantly lower than those seen in non-hate contexts. Likewise, major disparities exist among American Indians. The effects on Hispanics remain unknown. These results indicate hate crime enforcement may indeed be a double-edged sword that cuts against those it aims to protect. Further research is needed to fully understand how police – as well as other criminal justice officials – enforce hate crime laws, and the reverberations of this enforcement on society.

CHAPTER III

THE QUINTESSENTIAL HATE CRIME?

VICTIM BIAS AD RACIAL DISPARITIES IN HATE CRIME ENFORCEMENT

I. Introduction

This chapter explores whether offender race/ethnicity predicts how victims and police interpret and respond to crime. Are they more or less likely to label an incident a hate crime or to react punitively by reporting the incident or executing an arrest based on the perpetrator's demographic characteristics? As Chapter 1 discussed, the decision on whether to categorize an incident as a hate crime involves a high level of subjectivity. Victims, police officers, prosecutors, judges, and juries look at the circumstances and infer whether the bias motive exists. Thus, several researchers have explored how race influences the perception of hate crime, and the findings present an interesting contradiction. On the one hand, people tend to have a preconceived notion of the quintessential hate crime in which African Americans are *victims*. On the other hand, the public and criminal justice system tend to have a preconceived notion of the prototypical criminal, in which African Americans are seen as *offenders*. This begs the question: which preconception predominates in the context of real-world hate crime incidents, that which sympathizes with African Americans as victims, or that which villainizes them offenders? While we cannot directly measure the thoughts of those involved in a crime, we can examine whether, in the aggregate, race predicts how victims interpret their offenses or how victims and police respond. If similarly situated offenders are treated more punitively – by being labeled a hate criminal, being reported to police, and being arrested – based on race, it will strongly indicate a negative bias towards African Americans occurs in anti-hate enforcement.

A notable body of social psychological research suggests that individuals are particularly sympathetic towards African Americans in the hate crime context. People are more likely to interpret a crime as bias-motivated when committed by a white perpetrator against an African American victim. Lyons (2006) examined the influence of social status on the assignment of blame in hate crime scenarios, using a quasi-experimental factorial vignette design. He found the status of the victim and offender influenced attributions of blame, with respondents showing sensitivity to racial status asymmetry. Specifically, respondents blamed white offenders more than African American offenders. Further, they blamed offenders more for victimizing African Americans than whites and assigned less blame to African American victims than white. Similarly, in three experiments with mock jurors, Marcus-Newhall, Blake, and Baumann (2002) evaluated the influence of race on perceptions of hate crime perpetrators and victims. They found mock jurors had a greater certainty of guilt and gave longer sentences when the victim was African American than white. They also found the perpetrator's race had a marginally significant effect: mock jurors were more certain of guilt when the perpetrator was white than African American. Participants perceived hate crimes committed by white perpetrators against African American victims most negatively. Saucier et al. (2008) also found that mock jurors generally assigned greater blame and recommended longer sentences to white perpetrators of violence against African American victims than to African American perpetrators against white victims.

These sympathetic perceptions of hate crime are even more accentuated among racial minorities. Craig and Waldo (1996) conducted surveys on college students to understand how they conceptualize hate crimes. Respondents of color were twice as likely as their white counterparts to associate hate crime victimization with minority group status. Similarly, while 19 percent of all respondents indicated the typical hate crime perpetrator was white, 4 percent of white respondents and 46 percent of African American respondents expressed this view. In another study, researchers found that minority participants evaluated incidents as more severe when the victim was African American than white, but that effect did not occur for white participants (Marcus-Newhall, Blake, and Baumann 2002). However, white participants would give longer sentences for defendants when the victim was African American if their white peers encouraged them to do so.

At the same time, research also reveals people associate African Americans with criminality. African Americans are seen as more suspicious, and people tend to overestimate their culpability (Pickett et al. 2012; Chiricos, Welch, and Gertz 2004; Carbado 2016; see also Carbado and Roithmayr 2014; Goff 2014). Further, people see African Americans as more threatening and dangerous, evoking more severe reactions, including support for punitive policies and the use of lethal force (Barkan and Cohn 2005; Unnever and Cullen 2012; King and Wheelock 2007; Eberhardt et al. 2004; Sim et al. 2013; Correll et al. 2002). These racial biases distort our legal institutions, as well, with officials throughout the system treating African Americans more harshly, irrespective of their conduct or history (see, e.g., Fagen et al. 2009; Kutateladze, et al. 2014; Berdijo 2018; Mitchell and MacKenzie 2004; Huebner and Bynam 2008).

Some evidence indicates these trends carry over to hate crime contexts. Studies show a relationship between racist and pro-punishment ideology and an anti-African American perception and response to crime scenarios potentially involving hate. In a study using responses from a national telephone survey of 1,300 American adults, Steen and Cohen (2004) explored factors that affect public support for enhanced punishment for hate crimes. Respondents who believed that minorities have too few rights requested more lenient sentences for non-hate crimes, but not for hate crimes. The authors speculate that individuals who are concerned with minority rights may be more aware than others of the overrepresentation of minorities in prison and wish to mitigate that problem. However, respondents with pro-punishment attitudes were less likely to request imprisonment when asked about hate crimes. In fact, they requested more lenient punishments for hate crime offenders than for the average offender. Saucier et al. (2008) found a high level of participant racism was associated with less severe sentencing for crimes by whites against African Americans and more severe sentencing for crimes by African Americans against whites. Similarly, in subsequent research, Saucier et al. (2010) found higher levels of racism resulted in longer sentences for African American assailants, but not white. The authors hypothesized this relationship may have emerged because the racist participants may see African American violence as a confirmation of their negative stereotypes about African American people. In addition, participants with more racist views blame victims more and perpetrators less when the perpetrators are white, though no such relationship exists for African American perpetrators. The researchers also found a relationship – though not one of significance – between participant racism and whether they categorize a crime as a hate crime: individuals with higher levels of racism were more likely to associate hate crime commission with African American perpetrators. A marginally significant relationship existed between racism scores and the belief that hate crimes should be punished more severely, with lower racism levels predicting a greater support.

Thus, social psychological research reveals two competing biases at play: one oriented towards civil rights, another oriented towards negative racial biases. On the one hand, studies repeatedly show people attribute bias to crimes involving white perpetrators and African American victims. Indeed, hate crime legislation grew from an effort by civil rights and social justice advocates to raise awareness about bigotry directed at minority groups and respond to violence stemming from it (Jenness and Grattet 2001). Consistent with this vision, the public appears to recognize hate crimes as phenomena in which the dominant group victimizes historically vulnerable and marginalized factions of society. This is what many consider the quintessential hate crime. I refer to this as a civil rights orientation to hate crime.

On the other hand, racial animus may distort this typical understanding of hate crime dynamics. Studies show negative racial stereotypes are strong in the criminal justice context, individuals with racist views are more likely to attribute bias to crimes involving African American perpetrators than white, and to advocate for harsher treatment of the former. These findings reflect broader patterns of public opinion and criminal justice in the United States, wherein crime is racialized and race is criminalized; criminality is associated with African Americans, and African Americans are associated with criminality (Carbado and Roithmayr 2014; Alexander 2012). African Americans are seen as more culpable (see, e.g., Goff et al. 2014). The desire to crack down on African American offenders is likely an extension of historical ‘get tough’ approaches to crime, as discussed in Chapter 1, which strive to tame, control, and subordinate African Americans, who are seen as a threat (see, e.g., Alexander 2012). For many, African Americans are the prototypical criminal. I refer to this as the racial bias orientation to hate crime.

Meanwhile, research also shows the effect of bias may be situational. Individuals are more susceptible to their implicit biases in certain contexts. Significantly, we rely more heavily on our attitudes and stereotypes under stressful circumstances. Fear, time pressure, fatigue, and ambiguity can exacerbate bias and shape a person's interpretation of an incident and their subsequent decision-making (see, e.g., Smolkowsi et al. 2016; Payne 2005; Correll et al. 2007; Girvan 2016; Girvan and Marek 2016; Danziger, Levav, and Avnaim-Pesso 2011). These studies suggest individuals revert to negative stereotypes under duress. This is particularly important since victims and police are dealing with stressful events when determining whether a hate crime occurred and how to respond.

As the foregoing discussion illustrates, scholarly work on race and public perception of hate crime is contradictory and inconclusive. Moreover, significant gaps exist. Most notably, research is very limited regarding how biases operate in the real-world context. Most studies involve experimental designs with hypothetical vignettes, but do not capture how people actually perceive incidents in their daily lives. This chapter builds upon the existing body of knowledge by exploring whether race predicts how crime victims perceive their victimization, and the degree to which it contributes to racial disparities in hate crime enforcement. It theorizes the racial bias orientation to hate crime prevails in real-world hate crime scenarios: victims will most likely identify an incident as a hate crime, as well as respond punitively by reporting the crime to police, when the perpetrator is African American; and police will treat African Americans more punitively than whites by arresting them at significantly higher rates. These hypotheses are consistent with the research above suggesting that: (1) a widely-held and deeply-engrained stereotype of African Americans exists conflating them with criminality; (2) the criminal justice system is highly racialized, with African Americans disproportionately criminalized and punished; (3) racial animus has been shown to distort the typical understanding of hate crime dynamics; and (4) negative racial biases are especially acute in stressful situations, such as crime scenes.

Using statistical tests, and controlling for victim race/ethnicity and type and severity of offense, I model whether suspect race/ethnicity predicts when a victim will identify an incident as hate-driven, as well as their decision to report it to police. I also measure the extent to which racial and ethnic groups are overrepresented among hate crime arrestees, and whether police are significantly more likely to act punitively towards an African American by arresting them when the victim labels the incident as hate motivated. This analysis whittles away at the broader question of whether a society with deeply engrained biases regarding race and crime, as well as pervasive systemic racism, can rely on its criminal justice system to promote racial equality, as is the goal of anti-hate legislation.

II. Methods

a. Data Sources

This study employs data from the National Crime Victimization Survey (NCVS) and the U.S. Census Bureau Decennial Census. The NCVS provides data on the frequency, characteristics, and consequences of crime victimization, including race/ethnicity information on the offender and victim and whether the victim perceived the crime to have a bias motive. The Decennial Census has demographic information that enables the calculation of arrest rates for the different racial or ethnic groups.

The Bureau of Justice Statistics within the U.S. Department of Justice administers the NCVS. This study uses the "National Crime Victimization Survey, Concatenated File, 1992-2015," available via the Inter-university Consortium for Political and Social Research, and the following description of the NCVS comes from the codebook for that data set (U.S. Department of Justice 2016).

The NCVS began in 1973 (under the name National Crime Surveys), and hate crime data collection started in 2003. The NCVS involves an ongoing survey of a nationally-representative sample of residential addresses in the United States. U.S. Census Bureau provides a list of respondents monthly for the NCVS using a "rotating panel" sample design. Households are selected at random, and all individuals of eligible age become part of the panel. Respondents in the sample are interviewed every six months for three years. Two interviews occur face-to-face, and the remainders are by telephone.

NCVS respondents report their victimization and that the household as a whole (for example, burglary or motor vehicle theft). The data include basic demographic information, including the race and ethnicity of the victim and the perceived race and ethnicity of the offender. The NCVS also measures crimes perceived by victims to be motivated by an offender's bias against them for race, ethnicity/national origin, religion, disability, sex, and/or gender.

The U.S. Census Bureau conducts the Decennial Census, surveying households across the country to provide, among other things, population estimates. Pertinent to this study, the Decennial Census provides nationwide racial and ethnic information. This study includes data from the 2000 and 2010 decennial censuses (Manson, et al. 2017). NCVS data from years 2000-2009 were paired with the 2000 census, and years 2010-2015 the 2010 census. This means a lag exists between the decennial census and subsequent years.

b. Sample

This study includes NCVS data for the years 2003 through 2015, as 2003 is when the NCVS began collecting information on hate crimes. All years are combined. The data include all offenses reported during this period. However, they omit incidents in which the race and/or ethnicity of the offender is unknown since offender race/ethnicity is the major predictor of interest. Tables 1 and 2 provide information on the racial composition of the victims and offenders in the sample. As the tables illustrate, whereas many categories exist for victim race and ethnicity, the NCVS coded offender race into three narrow categories: white, black/African American, and other for years preceding 2012, and therefore they are reported as such throughout this study. Also of note, race and Hispanic/Latino origin are not mutually exclusive categories, and thus all individuals of Hispanic/Latino origin also fall within another racial or ethnic category. The NCVS provides an option for Hispanic/Latino origin for victims all years, but only 2010 through 2015 for offenders. The final sample constitutes 23,473 observations, 1,305 (approximately 6 percent) of which the victims deemed to have a bias motive.

Table 3-1: Race and Ethnicity of Victims in Sample

	White	African American	AI	Asian	NH/PI	Two +	Total
Non-Hispanic	15,806	3,185	269	419	47	713	20,439
Hispanic	2,697	128	47	32	8	122	3,034
Total	18,503	3,313	316	451	55	835	23,473
Percent	*79%*	*14%*	*1%*	*2%*	*.002%*	*4%*	*100%*

AI refers to American Indian, NH/PI refers to Native Hawaiian/Pacific Islander, and Two+ refers to individuals reporting two or more racial backgrounds. Race and Hispanic/Latino origin are not mutually exclusive categories, and thus all individuals of Hispanic/Latino origin also fall within another racial or ethnic category.

Table 3-2: Race and Ethnicity of Offenders in Sample

	White	African American	Other	Total
Unknown (2003-09)	10,007	4,428	2,140	16,575
Non-Hispanic	3,691	2,002	333	6,026
Hispanic	731	60	81	872
Total	14,429	6,490	2,554	23,473
Percent	*61%*	*28%*	*11%*	*100%*

The NCVS began collecting information on offender Hispanic/Latino origin in 2010, and therefore this characteristic is unknown for the preceding years, 2003-09. The NCVS coded offender race into three categories, White, Black/African American, and Other, for years preceding 2012, and therefore they are reported as such for all years here.

Tables 3 through 6 provide descriptive statistics on hate crimes specifically. Men and women are victims equally (Table 3-3). Whites account for most of those reporting hate crime victimization, comprising three-quarters of this population (Table 3-3). African Americans equal 14 percent of purported hate crime victims, and victims of other racial backgrounds account for the remaining 10 percent (Table 3-3). These demographics change noticeably for offenders. Men and women are offenders in 79 and 28 percent of cases respectivly (some incidents involve both) (Table 3-4). Whites and African Americans comprise an equal share of offenders, around 40 percent each, and other racial/ethnic groups account for 16 percent (Table 3-4).

Table 3-3: Characteristics of Hate Crime Victims

Sex	*Freq.*	*Percent*
Male	673	52%
Female	630	48%
Total	1303	100%
Race	*Freq.*	*Percent*
White	984	75%
African American	186	14%
American Indian	22	2%
Asian	43	3%
NH/PI	4	0%
Two or More	66	5%
Total	1305	100%
Hispanic/Latino (2010-15)	*Freq.*	*Percent*
No	1084	83%
Yes	217	17%
Total	1301	100%
Age	*Freq.*	*Percent*
Under 18	228	17%
18-25	211	16%
26-40	351	27%
41-65	475	36%
66+	40	3%
	1305	100%

Many victims report their incident as involving more than one type of bias (Table 3-5). Racial bias is the most common type of bias reported, followed by that based on ethnicity and national origin (Table 3-5). This trend is true regardless of victim race/ethnicity.

More than three-quarters of purported bias crimes involved assault (intimidation, simple assault, or aggravated assault) (Table 3-6). The remainders involved robbery, sexual assault, or property offenses.

Table 3-4: Perceived Characteristics of Hate Crime Suspects

Sex	*Freq.*	*Percent*		
Male	932	72%		
Female	267	21%		
Involved Both	95	7%		
Total	1294	100%		
Race	*Freq.*	*Percent*		
White	563	42%		
African American	533	41%		
Other	209	16%		
Total	1305	100%		
Hispanic/Latino (2010-15)	*Freq.*	*Percent*		
No	297	83%		
Yes	62	17%		
Total	359	100%		
Age	*Under 18*	*18-29*	*30+*	*Total*
Single Offender	15%	31%	54%	100%
Multiple Offenders				
Youngest	46%	40%	14%	100%
Oldest	26%	55%	19%	100%

Table 3-5: Type of Bias Motive by Victim Race

	Percent of Respondents from Each Group Reporting Yes					
Victim Race	*Race*	*Religion*	*Eth./Nat'l. Or.*	*Disability*	*Gender*	*Sex*
White	55%	10%	28%	15%	26%	9%
African American	62%	10%	34%	19%	37%	5%
American Indian	73%	5%	50%	14%	32%	9%
Asian	84%	7%	67%	7%	19%	2%
Two or More	58%	9%	21%	9%	33%	21%

Table 3-6: Hate Crimes by Offense Type

Offense Type	*Number*	*Percentage*
Rape	20	2%
Other Sexual Assault	16	1%
Robbery	125	10%
Aggravate Assault	157	12%
Simple Assault	431	33%
Intimidation	442	34%
Property	114	9%
Total	1305	100%

c. Measures

This analysis explores the extent to which race and ethnicity influence who is labeled and punished as a hate criminal and the degree to which it contributes to racial disparities in hate crime enforcement. Specifically, it measures whether offender race/ethnicity affects how victims understand, and subsequently report, the offense. It also compares incidence rates of arrests to see if racial minorities are disproportionately represented among those policed. To this end, the analysis will involve multiple models.

In the first model, the dependent outcome is whether the victim designated the incident a hate crime. Thus, incidents are categorized into a binary variable as either having a bias motive or not. Blank and negative responses were coded as "0" to indicate the victim noted no bias, and all others were coded as "1" to indicate the victim positively identified a form of bias. In 2010, the NCVS added a question asking whether the individual believed the incident was motivated by bias. However, until that time, the survey asked a series of questions regarding why the offender targeted the victim, each relating to a different type of bias (race, ethnicity/national origin, religion, disability, gender, or sexual orientation). Specifically, it asked: "An offender/Offenders can target people for a variety of reasons, but we are only going to ask you about a few today. Do you suspect the offender(s) targeted you because of your [protected classification]?" If a victim answered yes to any of these questions, the data were coded as "1" to indicate a positive response.

In the second set of models, the dependent outcome is whether the victim or another member of their household reported the crime to police. Incidents were categorized into a binary variable as either having been reported or not, with "1" indicating the victim or another household member reported the crime, and "0" indicating the police found out by other means or not at all.

In the third segment, the dependent variable is whether the incident resulted in an arrest. Three NCVS questions comprised this variable. The first asked whether police executed an arrest while they were present. The second asked whether police followed up with an arrest after the fact. The third asked generally whether anyone was arrested or charged. Incidents were categorized into a binary variable as either involving an arrest or not, with "1" indicating the affirmative and "0" the negative, and all other responses were coded as missing.

In the final series of models, the dependent outcome is the incidence rates of arrests for each demographic group of offenders. This is calculated using counts of arrests. Thus, the variable is coded based on whether the police arrested the individual during the incident or at any time subsequently. Three NCVS questions comprise this variable: one asking whether the police made an arrest while on the scene, another asking whether police made an arrest as follow-up to the incident, and final question asking whether any arrests or charges were made. The outcome variable was coded as "1" if respondents answered affirmatively to any of these questions, and "0" otherwise.

For all models, the primary predictor of interest is offender race. For years 2003-11, the NCVS coded offender race into three categories, white, black/African American. In 2012, the NCVS expanded the offender racial categories to include the following: white, black/African American, Asian, American Indian, and Pacific Islander. For consistency, the racial categories conform to the pre-2012 standards throughout this study, with Asian, American Indian, and Pacific Islander offenders grouped into the 'other' category. The

NCVS did not ask whether the offender was of Hispanic/Latino origin until 2012, and therefore separate analyses examine this variable since its addition greatly reduces the number of observations by eliminating all incidents occurring prior to the introduction of that question. Hispanic/Latino is coded as a binary variable. The survey also indicates whether incident involved a single offender or multiple, and their respective races. Beginning in 2012, victims could indicate multiple races, regardless of the number of offenders. All incidents involving one offender or multiple offenders of a single shared racial category were coded as belonging to that race ("white," "African American," or, if in another category, "other"). Incidents involving offenders of multiple racial categories were coded as "other."

Another important fixed effect is victim race and ethnicity. Unlike offender data, the NCVS offers a broad menu of options here, including: white only, black/African American only, American Indian/Alaska native only, Asian only, Hawaiian/Pacific Islander only, plus fifteen other categories that are various combinations thereof. Victims of one race/ethnicity retained their original label. However, individuals of multiracial backgrounds were combined into one group for two or more races, "2+." Two major considerations informed this decision: first, each of these multiracial categories was alone quite sparse; and, second, the difficulty of categorizing multiracial individuals into an existing group (e.g., is a person identifying as white-African American best described as white or African American?). Race and Hispanic/Latino origin are not mutually exclusive categories, and thus all individuals of Hispanic/Latino origin also fall within another racial or ethnic category. These are two distinct variables in the NCVS and this study. Hispanic/Latino is coded as a binary variable.

This analysis includes a third race variable to measure the combined effect of offender and victim race. This variable includes a distinct category for every offender-victim race combination (e.g., white offender-African American victim, African American offender-white victim, etc.).

Another covariate of interest is offense. This encompasses 34 categories, including attempted and completed offenses spanning violent and property crimes. This variable provides an important control both for offense type as well as severity, allowing us to measure whether similarly situated individuals of differing racial/ethnic categories are perceived and treated alike.

The final covariate is population. The populations for each racial and ethnic category permit the calculation of incidence rates of arrests. Since The NCVS keeps the location of respondents confidential to protect anonymity, the analysis cannot calculate arrest rates by jurisdiction. Accordingly, it uses national-level demographic estimates.

d. Analysis

This study examines the role of victim bias in promoting racial disparities in hate crime enforcement. It does so by asking how crime victims understand the incident, examining whether they attribute it to bias. The study then looks at how these interpretations contribute to systemic disparities through a series of analyses. It first explores the circumstances under which victims invoke the criminal justice system by reporting their crimes to police. This shows how victim bias directly leads to involvement with police, which, in turn, increases the likelihood of criminalization. The analyses then examines whether racial disparities exist in police response, looking who police arrest for hate crimes, the extent to which this is explained by victim actions (reporting), and whether these arrest rates are worse than those seen in other contexts. This leads to the following hypotheses:

> H1: Offender race is a significant predictor of whether victims interpret a crime to be hate-motivated, with victims most likely to ascribe bias to offenses involving African American offenders.
>
> H2: Offender race is a significant predictor of whether victims report a crime to police, with victims most like to report offenses involving African American offenders.
>
> H3: Offender race is a significant predictor of arrest, with police most likely to arrest African Americans. Further, while police generally arrest African Americans at higher rates than whites relative to their respective populations, the magnitude of the effect is significantly greater for hate crimes than non-hate crimes.

Testing these hypotheses requires measurement of key variables: it involves the regression of victim and police responses (the attribution of a bias motive, the decision to report, and the incidence rates of arrest) on suspect racial and ethnic identifiers. The model must also control for other factors explaining variation, like victim race and ethnicity, the incidence of non-hate crimes, and the type and severity of the offense.

A finding that the coefficient for African American suspects is a significant positive predictor of whether victims attribute bias to a crime, even when controlling for offense characteristics and crime rates overall, will suggest negative racial stereotypes about African Americans shape victims' understanding of their victimization. A significant negative effect will indicate the opposite, supporting the inference that conventional conceptions of the quintessential hate crime prevail (i.e., dominant groups victimizing the historically marginalized ones). If offender race predicts whether victims report crimes to police, this will suggest victims are more punitive towards African Americans, because they are more likely to invite a penal response. Further, it will demonstrate how these biases contribute to criminalization overall, because involving police necessarily increases the likelihood of arrest and subsequent punishment. If offender race predicts whether arrest occurs, and if the results show disparities in arrests, it will indicate police share these biases. If the magnitude of this effect is significantly greater for hate crimes than non-hate crimes, it will show how labeling an incident as hate-motivated exacerbates systemic inequality. Measuring the effect of victim reporting and victim labeling of the crime as hate-motivated will further indicate whether victim or police bias plays a greater role in arrest disparities. A lack of significant relationships at any stage in the analysis will support the inference that incident-level circumstances other than race or ethnicity have greater relevance.

Multiple Bernouli logistic models test H1. Model 1A calculates the relative odds of a victim labeling an incident as bias-motivated based on offender race or ethnicity. It controls for victim race and ethnicity, as well as the type and severity of offense. The mathematical formula is as follows:

$$biaspresent_{ij} \sim Bernoulli\ (\pi_{ij})$$
$$\text{logit}(\pi_{ij}) = \beta_0 + \beta_{1\text{-}3}(offender\ race_i) +$$
$$\beta_{4-9}(victim\ race_i) + \beta_{10}(victim\ Hispanic_i) + \beta_{11}(offense_i)$$
$$\text{Level 1: Var}(biaspresent_i \mid \pi_i) = \pi_i\ (1 - \pi_i)$$

Model 1B mirrors Model 1A, with the addition of offender ethnicity as a fixed effect. The mathematical formula is as follows:

$$biaspresent_{ij} \sim Bernoulli\ (\pi_{ij})$$
$$\text{logit}(\pi_{ij}) = \beta_0 + \beta_{1\text{-}3}(offender\ race_i) +$$
$$\beta_{4-9}(victim\ race_i) + \beta_{10}(victim\ Hispanic_i) + \beta_{11}(offense_i)$$
$$+ \beta_{12}(offender\ Hispanic_i)$$
$$\text{Level 1: Var}(biaspresent_i \mid \pi_i) = \pi_i\ (1 - \pi_i)$$

Model 2 calculates the relative odds of a victim labeling an incident as bias-motivated based on the combined effect of offender and victim race/ethnicity. It controls for the type and severity of offense, as well as Hispanic ethnicity. The mathematical formula is as follows:

$$biaspresent_{ij} \sim Bernoulli\ (\pi_{ij})$$
$$\text{logit}(\pi_{ij}) = \beta_0 + \beta_{1\text{-}17}(race\ combo_i) +$$
$$\beta_{18-23}(victim\ Hispanic_i) + \beta_{24}(offender\ Hispanic_i) +$$
$$\beta_{25}(offense_i)$$
$$\text{Level 1: Var}(biaspresent_{ij}|\ \pi_i) = \pi_i\ (1 - \pi_i)$$

Two Bernouli logistic models test H2. Model 3A measures the relative odds that a victim will report an incident to police when the offender is white, African American, or of another race/ethnicity. It controls for victim race and ethnicity, the type and severity of the offense, as well as whether it was perceived as a hate crime. The mathematical formula is as follows:

$$reported_{ij} \sim Bernoulli\ (\pi_{ij})$$
$$\text{logit}(\pi_{ij}) = \beta_0 + \beta_{1\text{-}3}(offender\ race_i) +$$
$$\beta_{4-9}(victim\ race_i) + \beta_{10}(victim\ Hispanic_i) + \beta_{11}(offense_i)$$
$$+ \beta_{12}(biaspresent_i)$$
$$\text{Level 1: Var}(reported_i|\ \pi_i) = \pi_i\ (1 - \pi_i)$$

Model 3B mirrors Model 3A, but with the addition of offender ethnicity as a fixed effect. The mathematical formula is as follows:

$$reported_{ij} \sim Bernoulli\ (\pi_{ij})$$
$$\text{logit}(\pi_{ij}) = \beta_0 + \beta_{1-3}(offender\ race_i) +$$
$$\beta_{4-9}(victim\ race_i) + \beta_{10}(victim\ Hispanic_i) + \beta_{11}(offense_i)$$
$$+ \beta_{12}(biaspresent_i) + \beta_{13}(offender\ Hispanic_i)$$
$$\text{Level 1: Var}(reported_i|\ \pi_i) = \pi_i\ (1 - \pi_i)$$

Several models test H3. The first of these is Model 4A, a Bernouli model measuring the relative odds of an incident resulting in an arrest based on the race of the suspect, whether the victim labeled the crime as hate-motivated, and whether the victim reported it to police. It also tests the interactions of offender race and whether the victim labeled the crime as hate-motivated or reported it to police respectively. The mathematical formula is as follows:

$$
\begin{aligned}
&arrested_{ij} \sim Bernoulli\ (\pi_{ij}) \\
&\text{logit}(\pi_{ij}) = \beta_0 + \beta_{1-3}(offender\ race_i) + \\
&\beta_{4-9}(victim\ race_i) + \beta_{10}(victim\ Hispanic_i) + \beta_{11}(offense_i\ ) \\
&+ \beta_{12}(biaspresent_i\ ) + \\
&\beta_{13}(reported_i\ ) + \beta_{14-16}(biaspresent_i\ )(offender\ race_i) + \\
&\beta_{17-19}(reported_i\ )(offender\ race_i) \\
&\text{Level 1: Var}(offender\ AA_{ij} |\ \pi_{ij}\ ) = \pi_{ij}\ (1 - \pi_{ij})
\end{aligned}
$$

The same model is repeated for Model 4B, but with the addition of offender ethnicity as a fixed effect. It also tests the interactions of offender ethnicity and whether the victim labeled the crime as hate-motivated or reported it to police respectively.

$$
\begin{aligned}
&arrested_{ij} \sim Bernoulli\ (\pi_{ij}) \\
&\text{logit}(\pi_{ij}) = \beta_0 + \beta_{1-3}(offender\ race_i) + \\
&\beta_{4-9}(victim\ race_i) + \beta_{10}(victim\ Hispanic_i) + \beta_{11}(offense_i\ ) \\
&+ \beta_{12}(biaspresent_i\ ) + \\
&\beta_{13}(reported_i\ ) + \beta_{14-16}(biaspresent_i\ )(offender\ race_i) + \\
&\beta_{17-19}(reported_i\ )(offender\ race_i) \\
&+ \\
&\beta_{20}(offender\ Hispanic_i) + \beta_{21}(biaspresent_i\ )(offender\ Hispanic_i) \\
&+ \beta_{21}(reported_i\ )(offender\ Hispanic_i) \\
&\text{Level 1: Var}(offender\ AA_{ij} |\ \pi_{ij}\ ) = \pi_{ij}\ (1 - \pi_{ij})
\end{aligned}
$$

To further test H3, two Poisson regression models measure arrests rates across racial and ethnic groups of offenders, providing incidence rates of arrests given relative populations nationwide. Model 5A examines non-hate incident rates ratios of offender groups based on racial categories, controlling for the population of each racial group as an exposure variable. Model 5B repeats the test, examining offender groups based in Hispanic ethnicity, controlling for Hispanic population as an exposure variable. The models are multilevel because they involve counts by geographic area (United States), with level one representing incident-related characteristics (victim, offender, and offense attributes), and level two representing nationwide demographic characteristics. The mathematical formula for Model 5A is as follows:

$$
\begin{aligned}
&non-hate\ incidents_{ij} \sim Poisson\ (\pi_{ij}) \\
&\ln(\pi_{ij}) = \beta_{0j} + \beta_{1-3}(offender\ race_{ij}) + \\
&\beta_{4-9}(victim\ race_{ij}) + \beta_{10}(victim\ Hispanic_{i}j) + \beta_{11}(offense_{ij}) + \\
&\ln(racial\ group\ population_{ij}) \\
&\text{Level 2: } \mu_{0j} \sim \mathrm{N}\ [0, \sigma^2{}_{u0}] \\
&\text{Level 1: Var}(non\text{-}hate\ incidents_{ij} \mid \pi_{ij}) = \pi_{ij}
\end{aligned}
$$

The mathematical formula for Model 5B is as follows:

$$
\begin{aligned}
&non-hate\ incidents_{ij} \sim Poisson\ (\pi_{ij}) \\
&\ln(\pi_{ij}) = \beta_{0j} + \beta_{1-3}(offender\ race_{ij}) + \\
&\beta_{4-9}(victim\ race_{ij}) + \beta_{10}(victim\ Hispanic_{i}j) + \beta_{11}(offense_{ij}) + \\
&\ln(Hispanic\ group\ population_{ij}) + \beta_{12}(offender\ Hispanic_{i}) \\
&\text{Level 2: } \mu_{0j} \sim \mathrm{N}\ [0, \sigma^2{}_{u0}] \\
&\text{Level 1: Var}(non\text{-}hate\ incidents_{ij} \mid \pi_{ij}) = \pi_{ij}
\end{aligned}
$$

Models 6A and 6B duplicate 5A and 5B respectively, substituting hate-motivated incidents for those non-hate incidents.

III. Results

To test H1, victims' attributions of bias were regressed on available variables for offender race and ethnicity (white, African American, other, and then – for years 2012-15 – Hispanic), controlling for victim race and ethnicity (white, African American, Asian, American Indian, Native Hawaiian/Pacific Islander, 2 or more races, and Hispanic) as well as type and severity of offense. Model 1A calculates the relative odds of a victim labeling an incident as bias-motivated based on offender race (Table 3-7). Model 1B adds offender ethnicity as a fixed effect (Table 3-7). Model 2 examines the combined effect of offender and victim race/ethnicity, controlling for the type and severity of offense (Table 3-8).

Offender race and ethnicity are significant. The coefficients for offenders who were African American and 'other' are significant positive predictors of whether a victim interprets the incident as hate-motivated (Models 1A and 1 B, Table 3-7). Likewise, the coefficient for Hispanic offenders has a significantly positive effect (Model 1B). Incidents involving African American offenders have about 2.5 the odds of receiving a hate designation than those involving white offenders. Incidents with offenders of other non-white categories have about twice the odds of whites, and Hispanic offenders have 1.75 the odds of non-Hispanics.

Victim race and ethnicity have mixed significance. Across models, the coefficient for African American victims is a significant negative predictor of whether a crime is considered hate-motivated (Models 1A and 1B, Table 3-7). The coefficients for American Indian, Asian, and Hispanic victims have a significant positive effect (Model 1A, Table 3-7) that is lost with the addition Hispanic offender as a fixed effect (Model 1B, Table 3-7). The coefficient for Native Hawaiian/Pacific Islander victims is not significant. African American victims have about two-thirds the odds of labeling their incidents bias-motivated than whites. Victims who are Asian, two or more races, and Hispanic had 1.38, 1.31, and 1.18 the odds of whites respectively, but the effect is insignificant when controlling for whether the offender was Hispanic.

Table 3-7: Odds of Victims Interpreting Incident as Hate-Motivated Based on Offender Race/Ethnicity

	Model 1A: Race					Model 1B: Race & Hispanic				
	Odds Ratio	P>z		95% Conf. Interval		Odds Ratio	P>z		95% Conf. Interval	
Offender Race										
White (ref)										
Black	**2.47**	0.00	***	2.15	2.82	**2.61**	0.00	***	2.02	3.37
Other	**2.10**	0.00	***	1.77	2.49	**1.90**	0.00	**	1.27	2.86
Victim Race										
White (ref)										
Black	**0.64**	0.00	***	0.54	0.77	**0.65**	0.02	**	0.46	0.92
AI	1.14	0.55		0.73	1.79	1.06	0.90		0.42	2.68
Asian	**1.38**	0.05	*	0.99	1.92	1.44	0.25		0.77	2.71
PI	1.24	0.68		0.44	3.5	1.86	0.42		0.42	8.33
Two +	**1.31**	0.04	*	1.01	1.71	1.48	0.08		0.96	2.3
Ethnicity										
Non-Hispanic (ref)										
Victim										
Hispanic	**1.18**	0.04	*	1.01	1.38	1.14	0.40		0.84	1.53
Offender										
Hispanic						**1.74**	0.00	**	1.27	2.39
Offense	**0.97**	0.00	***	0.96	0.97	**0.97**	0.00	***	0.96	0.97
Constant	**0.08**	0.00	***	0.07	0.09	**0.07**	0.00	***	0.06	0.09

Coefficient superscripts indicate these significance levels: * (p < .05), ** (p < .01), *** (p< .001). Bolded coefficients indicate those that are significant at p < .05 or less in all models. NH/PI refers to Native Hawaiian and Pacific Islander. AI denotes American Indian. Other refers to all offenders who are neither identified as just white or just African American, including those of multiple racial/ethnic identities. 2 or more means victims who identify with more than a single racial/ethnic backgrounds.

Table 3-8: Odds of Victims Interpreting Incident as Hate-Motivated By Offender-Victim Race/Ethnicity Combinations

	Model 2				
	Odds Ratio	*P>z*		*95% Conf. Interval*	
Offender-Victim Combination					
White-White	**0.14**	0.00	***	0.08	0.22
White-AI	**0.24**	0.03	**	0.07	0.84
White-Asian	0.60	0.31		0.22	1.62
White-NH/PI	0.45	0.47		0.05	3.84
White-Two+	**0.15**	0.00	***	0.06	0.36
African Am.-White	**0.52**	0.01	**	0.31	0.87
African Am.-African Am.	**0.13**	0.00	***	0.07	0.24
African Am.-AI	0.49	0.37		0.10	2.33
African Am.-Asian	0.53	0.21		0.20	1.41
African Am.-NH/PI	1.00				
African Am.-Two+	0.80	0.58		0.37	1.75
Other-White	**0.30**	0.00	***	0.37	0.58
Other-African Am.	0.46	0.18		0.15	1.43
Other-AI	NA				
Other-Asian	NA				
Other-NH/PI	1.53	0.73		0.14	16.49
Other-2+	0.66	0.41		0.24	1.77
Ethnicity					
Non-Hispanic (ref)					
Victim Hispanic	1.11	0.49		0.83	1.50
Offender Hispanic	**1.53**	0.01	**	1.11	2.12
Offense	**0.97**	0.00	***	0.96	0.97
Constant	**0.47**	0.00	**	0.28	0.77

Coefficient superscripts indicate these significance levels: * ($p < .05$), ** ($p < .01$), *** ($p < .001$). Bolded coefficients indicate those that are significant at $p < .05$ or less in all models. NH/PI refers to Native Hawaiian and Pacific Islander. AI denotes American Indian. Other refers to all offenders who are neither identified as just white or just African American, including those of multiple racial/ethnic identities. 2 or more means victims who identify with more than a single racial/ethnic backgrounds.

A few offender-victim combinations had a significant negative effect, including: the coefficients for African American offender plus white or African American victims; the coefficients for white offender plus white, American Indian, or two +; and the coefficient for other offender and white victim (Model 2, 8). These combinations were less likely to be labeled a hate crime than those incidents in which the offender was white and the victim was African American. All other coefficients for offender-victim combinations lacked significance.

The coefficients for type and severity of offense are also significant across models (Models 1A and 1B, Table 3-7; Model 2, Table 3-8). However, the tests did not categorize this variable in any particular order or designate a reference group, having no theoretical impetus to do so. Accordingly, neither table provides a breakdown by offense category.

To test H2, the variable representing whether the victim (or another household member) reported the crime to police was regressed on available variables for offender race – white, African American, other, and then – for years 2012-15 – Hispanic), controlling for victim race and ethnicity (white, African American, Asian, American Indian, Native Hawaiian/Pacific Islander, 2 or more races, and Hispanic), type and severity of offense, and whether the crime was bias-motivated. Model 3A calculates the relative odds of a victim reporting the crime to police based on the offender race. Model 3B adds offender ethnicity as a fixed effect. See Table 3-9 below.

Table 3-9: Odds of a Victim Reporting Crime to Police

	Model 3A: Race					*Model 3B: Hispanic Offender Added*				
	Odds Ratio	*P>z*		*95% Conf. Interval*		*Odds Ratio*	*P>z*		*95% Conf. Interval*	
Offender Race										
White (ref)										
Black	**1.18**	0.00	***	1.10	1.27	1.13	0.07		0.99	1.29
Other	0.92	0.06		0.80	1.00	0.87	0.22		0.69	1.09
Victim Race										
White (ref)										
Black	1.05	0.27		0.96	1.15	1.01	0.88		0.86	1.20
AI	**0.75**	0.03	*	0.59	0.97	0.71	0.16		0.45	1.14
Asian	0.95	0.61		0.78	1.16	0.86	0.45		0.58	1.27
NH/PI	0.80	0.46		0.44	1.46	0.82	0.68		0.31	2.12
Two or more	**0.83**	0.02	*	0.71	0.97	**0.77**	0.05	*	0.60	0.99
Ethnicity										
Non-Hispanic (ref)										
Victim Hispanic	1.00	0.45		1.00	1.12	1.13	0.12		0.97	1.32
Offender Hispanic						1.1	0.25		0.94	1.30
Hate Crime										
Non-Hate (ref)										
Hate	**0.74**	0.00	***	0.66	0.84	0.8	0.07		0.64	1.02
Offense	**0.99**	0.00	***	0.99	0.99	0.99	**0.00**	***	0.99	0.99
Constant	0.65	0.00		0.62	0.70	0.67	**0.00**	***	0.60	0.75

Coefficient superscripts indicate these significance levels: * (p < .05), ** (p < .01), *** (p< .001). Bolded coefficients indicate those that are significant at p < .05 or less in all models. NH/PI refers to Native Hawaiian and Pacific Islander. AI denotes American Indian. Other refers to all offenders who are neither identified as just white or just African American, including those of multiple racial/ethnic identities. 2 or more means victims who identify with more than a single racial/ethnic backgrounds.

The coefficient for African American offender is a significant positive predictor of whether the victim reported the incident to police. The odds of the victim doing so are about one-and-one-fifth times higher for African Americans than whites. However, this coefficient is only marginally significant (P>z = .068) with the addition of the fixed effect for Hispanic offender (Model 3B, Table 3-9). The coefficient for 'other' and Hispanic offenders has no statistical significance.

For the most part, the coefficients for victim race are not significant predictors of whether a crime was reported to police (Models 3A and 3B, Table 3-9). The exceptions are the coefficients for American Indian victims and victims of two or more racial identities, each having a significant negative effect. These victims have .75 and .83 the odds of reporting their crimes to police respectively compared to whites.

The coefficient for type and severity of offense is significant across models (Models 3A and 3B, Table 3-9). Like before, the tests do not categorize this variable in any particular order or designate a reference group, and therefore Table 3-8 provides no breakdown by offense category. The perceived presence of a bias motive has a significant negative effect, though this significance disappears with the addition of Hispanic offender as a fixed effect.

Testing H3 involved several tests. In the first of these, the binary variable signifying whether the incident resulted in an arrest (yes or no) was regressed on offender race, whether the incident was a hate crime, whether the incident was reported, as well as the interactions between either of these latter two variables and offender race (Models 4A and 4B, Table 3-10). The models also controlled for victim race, victim ethnicity, and offense type. Model 4B added a fixed effect for offender ethnicity. The coefficient for African American offenders was a significant negative predictor of whether an incident resulted in arrest (OR=.81). The coefficient for whether the incident was labeled a hate crime was also significantly negative (OR=.45), as was that which represented whether the incident was reported (OR=.83). However, the interaction between the coefficients for African American offenders and whether the incident was a hate crime was significantly positive (OR=1.72). These coefficients lost their significance when reducing the sample in Model 4B to only incidents in which offender ethnicity was known (Model 4A N=10,595; Model 4B N=3,028). Victim ethnicity was significantly negative across models (OR=.81 in Model 4A; OR=.67 in Model 3B). Offense type was also significant. The models showed no other significant relationships.

To further test H3, arrests were regressed on available variables for offender race – white, African American, other, and then – for years 2012-15 – Hispanic), controlling for each group's respective nationwide population (exposure), victim race and ethnicity (white, African American, Asian, American Indian, Native Hawaiian/Pacific Islander, 2 or more races, and Hispanic), as well as type and severity of offense. Model 5A calculates the incidence rates of arrests based on offender race for non-hate offenses, and Model 5B adds offender ethnicity as a fixed effect (Table 3-11). Model 6A measures the incidence rates of arrests based on offender race for hate-motivated offenses, and Model 6B adds offender ethnicity as a fixed effect (Table 3-12). Models 5B and 6B cannot calculate incident rates ratios for racial groups because the models employ the exposure variable for Hispanic population, not racial populations. For this reason, these two models omit the breakdown of incident rates ratios for these groups. However, Models 5A and 6A provide incident rates ratios by racial group.

Table 3-10: Odds of Arrest Based on Race, Bias Motive, and Whether Reported

	Model 4A: Race					*Model 4B: Ethnicity*				
	Odds Ratio	*P>z*		*95% Conf. Interval*		*Odds Ratio*	*P>z*		*95% Conf. Interval*	
Offender Race (White ref)										
African Am.	**0.81**	0.03	*	0.67	0.98	0.95	0.78		0.66	1.36
Other	1.08	0.55		0.84	1.38	1.11	0.75		0.58	2.12
Hate Crime (Non-Hate Ref)										
Hate	**0.45**	0.00	***	0.33	0.63	0.54	0.06		0.28	1.02
Hate*Offender Race (No-White ref)										
Yes-African Am.	**1.70**	0.03	*	1.04	2.69	0.99	0.99		0.41	2.42
Yes-Other	1.16	0.65		0.62	2.17	0.88	0.88		0.16	4.93
Reported (No ref)										
Yes	**0.83**	0.00	**	0.74	0.94	1.03	0.85		0.80	1.32
Reported*Offender Race (No-White Ref)										
Yes-African Am.	0.88	0.228		0.71	1.09	0.83	0.36		0.55	1.24
Yes-Other	0.84	0.259		0.63	1.13	0.99	0.98		0.46	2.11
Victim Race (White ref)										
African Am	1.13	0.10		0.98	1.30	0.96	0.75		0.73	1.25
AI	1.38	0.07		0.98	1.95	1.24	0.51		0.66	2.33
Asian	0.75	0.11		0.53	1.06	0.66	0.24		0.33	1.31
Two or more	0.80	0.19		0.61	1.05	0.88	0.57		0.56	1.38
Ethnicity (Non-Hispanic ref)										
Victim	**0.81**	0.00	**	0.71	0.93	**0.67**	0.00	**	0.52	0.87
Offender	-	-	-	-	-	1.00	0.99		0.61	1.66
Hate*Hispanic Offender (No-Non-Hispanic ref)										
Yes-Hispanic	-	-	-	-	-	1.03	0.96		0.35	3.04
Reported*Hispanic Offender (No-Non-Hispanic ref)										
Yes-Hispanic	-	-	-	-	-	0.90	0.72		0.51	1.60
Offense	**0.98**	0.00	***	0.98	0.98	**0.98**	0.00	***	0.97	0.98
Intercept	**0.77**	0.00	***	0.69	0.87	**0.69**	0.00	**	0.54	0.88

Coefficient superscripts indicate these significance levels: * ($p < .05$), ** ($p < .01$), *** ($p < .001$). Bolded coefficients indicate those that are significant at $p < .05$ or less in all models. Pacific Islander victims were included as a control, but omitted from the table due to small sample size.

The coefficients for African American, ‘other,’ and Hispanic offenders are significant positive predictors of incidence rates ratios of arrests. This holds true for both non-hate and hate crimes (Tables 3-11 and 3-12). The expected number of arrests is 4.88 times greater for African Americans than whites for non-hate crimes, and 7.24 times greater for hate crimes (Models 5A, Table 3-11; Model 6A, Table 3-12). The expected number of arrests is 5.85 times greater for ‘other’ offenders than whites for non-hate crimes, and 6.76 times greater for hate crimes (Models 5A, Table 3-11; Model 6A, Table 3-12). The expected number of arrests is nearly seven times greater for Hispanics than non-Hispanics for both non-hate and hate offenses (Models 5B, Table 3-11; Model 6B, Table 3-12).

The coefficient for Hispanic victim is a significant negative predictor of arrest for non-hate crimes, with the expected number of arrests .85 that of whites (Model 5A, Table 3-11). This number changes to .71 with the addition of Hispanic offender as a fixed effect, and when controlling Hispanic population by designation it as the exposure variable (Model 5B, Table 3-11). The coefficient for Hispanic victim is not statistically significant for hate crimes (Table 3-12). The coefficients for other victim racial and ethnic categories are not significant predictors for either non-hate or hate crimes.

The coefficient for type and severity of offense is significant across models, except for Model 6B which measures hate crime arrests with the addition of Hispanic offender as a fixed effect. As was the case previously, these tests do not categorize the variable or designate a reference group, and therefore neither Tables 11 nor 12 provide a breakdown by offense category.

Table 3-11: Incidence Rates Ratios for Arrests for Non-Hate Crimes

	Model 5A: Race					*Model 5B: Ethnicity*				
	IRR	*P>z*		*95 % Conf. Interval*		*IRR*	*P>z*		*95 % Conf. Interval*	
Offender Race						0.95	0.40		0.84	1.07
White (ref)										
Black	**4.88**	0	***	4.41	5.41					
Other	**5.85**	0	***	5.17	6.63					
Victim Race						0.97	0.50		0.91	1.05
White (ref)										
Black	1.09	0.16		0.97	1.24					
AI	1.25	0.12		0.94	1.65					
Asian	0.83	0.24		0.61	1.13					
NH/PI	1.07	0.88		0.45	2.58					
Two or more	0.85	0.18		0.67	1.08					
Ethnicity										
Non-Hispanic (ref)										
Victim Hispanic	**0.85**	0.02	**	0.76	0.96	**0.71**	0.00	**	0.57	0.9
Offender Hispanic						**6.89**	0.00	***	5.45	8.71
Offense	**0.98**	0.00	***	0.98	0.99	**0.98**	0.00	***	0.98	0.99
Constant	**0.00**	0.00	***	0.00	0.00	**0.00**	0.00	***	0.00	0.00
Exposure (Population)	1					1				

Coefficient superscripts indicate these significance levels: * (p < .05), ** (p < .01), *** (p< .001). Bolded coefficients indicate those that are significant at p < .05 or less in all models. NH/PI refers to Native Hawaiian and Pacific Islander. AI denotes American Indian. Other refers to all offenders who are neither identified as just white or just African American, including those of multiple racial/ethnic identities. 2 or more means victims who identify with more than a single racial/ethnic backgrounds. Model 5B merely uses racial categories as controls, and omits their respective incidence rates ratios since the model already had an exposure variable (Hispanic/non-Hispanic population) and therefore could not control for their populations.

Table 3-12: Incidence Rates Ratios for Arrests for Hate Crimes

	Model 6A: Race					Model 6B: Ethnicity				
	IRR	P>z		95 % Conf. Interval		IRR	P>z		95 % Conf. Interval	
Offender Race						0.92	0.80		0.50	1.70
White (ref)										
Black	**7.24**	0.00	***	4.82	10.88					
Other	**6.76**	0.00	***	3.9	11.72					
Victim Race						0.98	0.90		0.70	1.32
White (ref)										
Black	0.96	0.86		0.58	1.61					
AI	1.48	0.51		4.67	4.69					
Asian	0.59	0.36		0.18	1.86					
NH/PI	0	0.98								
Two or more	0.64	0.45		0.20	2.03					
Ethnicity										
Non-Hispanic (ref)										
Victim Hispanic	0.92	0.75		0.55	1.52	1.36	0.48		0.60	3.20
Offender Hispanic						**6.92**	0.00	***	2.70	17.44
Offense	**0.97**	0.02	*	0.95	1	0.96	0.15		0.90	1.01
Constant	**0.00**	0.00	***	0.0	0.0	**0.00**	0.00	***	0.00	0.00
Exposure (Population)	1					1				

Coefficient superscripts indicate these significance levels: * ($p < .05$), ** ($p < .01$), *** ($p < .001$). Bolded coefficients indicate those that are significant at $p < .05$ or less in all models. NH/PI refers to Native Hawaiian and Pacific Islander. AI denotes American Indian. Other refers to all offenders who are neither identified as just white or just African American, including those of multiple racial/ethnic identities. 2 or more means victims who identify with more than a single racial/ethnic backgrounds. Model 6B merely uses racial categories as controls, and omits their respective incidence rates ratios since the model already had an exposure variable (Hispanic/non-Hispanic population) and therefore could not control for their populations.

IV. Discussion

a. Evidence Consistent With the Racial Bias Orientation to Hate Crime

This chapter set out to explore whether offender race/ethnicity shapes how victims interpret and respond to crime. Outside of the experimental setting and under real world duress, do people view African Americans as the quintessential hate crime victim or the prototypical criminal offender? In other words, which predominates with regards to hate crimes: the civil rights orientation or the racial bias orientation? To answer these questions, this study examines whether offender race/ethnicity predicts if victims will interpret incidents as hate-driven or report incidents to police. It also explores the extent to which racial and ethnic groups are overrepresented among arrestees for both non-hate and hate crimes. If negative racial stereotypes about African Americans shape victims' understanding of their victimizations, we should find the odds of victims labeling their crimes as hate-driven are significantly greater when the perpetrator is African American, regardless of crime rates or the type and severity of offense. Similarly, they will act more punitively by reporting crimes involving African Americans to police.

The results provide preliminary evidence consistent with the racial bias orientation to hate crime. As H1 predicts, offender race and ethnicity are significant predictors of whether victims interpret crimes as hate-motivated (Models 1A and 1B, Table 3-7). The odds of incidents involving African Americans receiving such a label are about two-and-a-half times greater than those involving whites. Incidents with offenders of other non-white or multiracial categories ("other") have about twice the odds. Hispanic offenders are 1.75 times as likely as non-Hispanics to receive this designation. These results hold true while controlling for the type and severity of the offense, as well as victim racial and ethnic characteristics. Victims are significantly more likely to consider their victimization a hate crime when the perpetrator is non-white and/or Hispanic, especially if that perpetrator is African American.

At the same time, African American victims are significantly less likely to ascribe bias to their victimization (Models 1A, 1B, 1C, Table 3-7). In fact, they are about two-thirds as likely to do so. Put another way, the odds of a white victim interpreting their victimization as a hate crime are significantly higher than that of an African American victim. This is in contrast to other racial minorities, where we see the opposite effect: Victims who are Asian or two or more races have 1.38 and 1.31 the odds of whites respectively (Models 1A and 1B, but not 1C, Table 3-7); and Hispanics have 1.18 the odds of non-Hispanics (Model 1C, Table 3-7).

Examining offender-victim race/ethnicity combinations has little effect on the analysis. White-on-black offenses are no more likely to be called a hate crime than most other inter-racial duos (Model 2, Table 3-8). The only inter-racial combinations that differ significantly are those involving African American offenders with white victims (which had half the odds), and those involving white offenders with victims who are American Indian or of two or more racial backgrounds (.24 and .15 the odds respectively). The fact that incidents involving African American offenders and white victims have significantly lower odds of receiving a hate crime designation supports an inference that victims have a civil rights orientation towards their hate crimes. However, this inference quickly loses footing when considering the entire picture: crimes purportedly involving hate are nearly twice as likely to involve African Americans (Model 4, Table 3-10), African American offenders are two-and-a-half times more likely to be considered hate criminals (Models 1A and 1B, Table 3-7), and most offender-victim combinations involving African American offenders having similar odds being considered bias-motivated as those involving white offenders and African American victims (i.e., those involving victims of American Indian, Asian, Native/Hawaiian/Pacific Islander, or two or more racial backgrounds) (Model 2, Table 3-8).

As predicted in H2, offender race is a significant predictor of whether victims take the extra step to report their victimizations to police (Model 3A, Table 9). The significant relationship exists regardless of victim race/ethnicity, the offense type and severity, or whether the crime is hate-motivated. Incidents involving African Americans have about one-and-one-fifth the odds of being reported to police compared to whites (though Model 3B reveals this relationship becomes only marginally significant when controlling for whether the offender is also Hispanic). Victims are significantly more likely to react punitively towards African American offenders, invoking the penal system by reporting the crime to police.

Collectively, these results paint a very different picture of the typical hate crime than that which is widely accepted. The quintessential hate crime is anything but that. White-on-black offenses are not the most likely to be seen as hate-motivated. Rather, acts of African American offenders have the greatest odds of being labeled hate crimes. Meanwhile, offenses perpetrated against African Americans are least likely to be attributed to bias. As is the case throughout the criminal justice system, the culpability of African Americans is overestimated while the suffering underestimated. Faced with the stress of a real-world crime, these findings are consistent with – though do not conclusively prove – the conclusion that victims revert to a racial bias orientation towards African Americans.

b. Evidence that Victim Bias Contributes to Systemic Racial Disparities

This chapter also aimed to measure whether offender race and ethnicity influence police response to hate crime. If victims' negative racial stereotypes about African Americans affect enforcement, we should see significantly higher arrest rates for African Americans, regardless of the type or severity of the offense. These disparities should differ significantly from those seen in the non-hate context.

The results mixed evidence as to whether victim bias contributes to systemic racial disparities. As discussed in the previous subsection, victims are significantly more likely to label their victimizations as hate crime, as well as report crimes to police, when the perpetrator is African American (Tables 7 and 9). This suggests victims are invoking the criminal justice system more for African American suspects, which would logically lead to greater police response. However, incidents that victims reported to police are significantly less likely to result in an arrest than those reported or discovered by other means (Mode 4A, Table 3-10). This indicates the mere act of a victim reporting the offense does not significantly increase the extent to which African Americans are arrested for hate or non-hate crimes.

Even still, the fact that the victim labeled the incident as hate-motivated does have a significant effect on arrests for African American suspects. Crimes involving a bias motive are significantly less likely to result in an arrest, even when controlling for whether they are reported to police; arrests are half as likely for hate crimes (Model 4A, Table 3-10). Likewise, crimes involving African Americans lead to arrest at significantly lower rates, as well, with .81 the odds of those involving whites (Model 4A, Table 3-10).[1] Nonetheless, police are significantly more likely to arrest African Americans accused of hate crimes than whites who commit non-hate crimes; the odds of arrest are 1.72 times as great (Model 4A, Table 3-10). The combined effect of the victim labeling the offense a hate crime, and the offense involving an African American, significantly increases the odds that police will react punitively by taking the suspect into custody.

Models 5A (Table 3-11) and 6A (Table 3-12) further reveal how these biases translate into broader inequalities in enforcement. Police are generally more likely to arrest African Americans, but the magnitude of this effect is much greater for hate crimes. For non-hate crimes, the incidence rates of arrest are 4.88 times higher for African Americans than whites. In startling contrast, the incidence rates of arrest for hate crimes are 7.24 times greater for African Americans than whites. In other words, the gap between African American and white arrest rates widens by a third between non-hate and hate crimes. A similar, though less extreme, trend occurs for other non-white and/or Hispanic offenders, though it differs in significant respects. As is the case with African Americans, victims are much more likely to say they suffered a hate crime when the offender is ‘other’ and/or non-Hispanic (2 higher than white and 1.75 higher than non-Hispanic reference groups respectively). In addition, like African Americans, both groups have disproportionately high arrest rates. For ‘other’ offenders, the expected number of arrests is 5.85 greater for non-hate crimes, and 6.76 times greater for hate crimes (Model

[1] These findings that police are significantly less likely to arrest African Americans may seem counterintuitive given the abundance of research to the contrary (see Chapter 1). These unusual findings may be explained by a variety of factors. First, NCVS, by definition, excludes victimless crimes (like drug offenses), where racial disparities in arrests are often the most egregious. Second, this finding may further illustrate victim bias by showing people think they are victims of crime more often when they interact with an African American, even when no probable cause exists to support an arrest, thus incidents involving African Americans would be less likely to lead to arrest.

5A, Table 3-11; Model 6A, Table 3-12). Hispanic offenders have seven-times the odds of non-Hispanic offenders of being arrested (Model 5B, Table 3-11; Model 6B, Table 3-12). However, incidence rates for Hispanic arrests are the same for non-hate and hate offenses; they are very high either way, but do not grow worse.

These results support, though differ considerably from, the findings in Chapter 2. Recall, Chapter 2 used UCR data to regress the number of times police cited/summoned/arrested people for hate-related assaults on variables for race and ethnicity, and it repeated this test for non-hate assaults. It found the expected number of citations/summons/arrests for hate and non-hate assaults was 2.41 and 2.80 times higher for African Americans than whites respectively. Thus, both chapters show substantial racial disparities in arrests for non-hate and hate-related offenses. However, Chapter 2 estimates were significantly lower than those in Chapter 3. Also, racial disparities in arrests for hate-related assaults were lower, not higher, than those of non-hate crimes. Why?

One explanation may be that the two chapters sample different offenses. The UCR analysis included just assault-related offenses (intimidation, simple assault, and aggravated assault), whereas the NCVS analysis includes all offense categories. Accordingly, a post-hoc analysis was conducted to see whether limiting the current study to assaults changed the outcome (this cut 9,387 incidents, 40 percent of the sample). This involved replicating Models 1A, 4, 5A, and 6A. Interestingly, constraining the sample to assault-related offenses had little effect on racial disparities in non-hate arrests: African Americans were 5.38 times more likely than whites to be arrested. However, it did alter the results for hate crimes: 5.77 times more likely than whites to be arrested for a hate crime. However, African Americans were still 2.4 times more likely to be labeled a hate criminal, and hate crimes were twice as likely to involve an African American offender. Further, even when limiting this sample to assaults, the disparities still double those in the UCR. Clearly, offense type does not account for these extremely different outcomes.

Another compelling explanation for the UCR-NCVS discrepancy is the UCR data was limited and skewed. As Chapter 2 elucidates, a fraction of agencies report any hate crime to the FBI whatsoever (around 12 percent). Moreover, Chapter 2's sample excludes all jurisdictions that report crime statistics via programs outside NIBRS. As a result, the sample omits at least two-thirds of UCR reporting agencies for any given year, meaning entire states were missing, including New York, Florida, and California, which have diverse populations that likely affect patterns of hate crime enforcement. Unlike the NCVS, NIBRS is not a representative sample of crime in the United States, especially hate crime, and this greatly affects the generalizability of Chapter 2's models. The NCVS provides a more complete and reliable picture of hate crime enforcement. In any event, both studies show significant disparities, with African Americans greatly overrepresented among arrestees for hate and non-hate offenses alike.

In sum, victim perceptions of hate crime appear to influence police enforcement. There mere fact a victim reported the crime to police does not increase the likelihood of arrest. However, the combined effect of the victim labeling the offense a hate crime, and the offense involving an African American, significantly increases the odds that police will react punitively by taking the suspect into custody. Further, if a victim believes bias drove an African American offender to target them, disparities in incidence rates of arrests grow precipitously. A similar but subtler trend occurs with other non-white offenders. Hispanics are also more likely to be considered hate criminals, and they endure consistently high arrest rates regardless of whether the crime has this designation. These results provide intriguing evidence of a negative victim bias towards racial and ethnic minorities that may perpetuate systemic racial disparities.

c. Limitations and Future Opportunities

This study provided entree into how people actually perceive crime day-to-day and the effects of race and ethnicity. The NCVS offered an excellent starting point for this inquiry because it directly measures how victims subjectively understand and experience hate crime under real-world conditions. Further, the results are generalizable because of the demographically representative sampling method.

Despite its virtues, this research design has its limitations. Most notably, we can neither detect nor control for every aspect of a crime that may explain variation. In an experimental design, researchers would present subjects with identical scenarios and manipulate a single variable, like race or ethnicity, in an attempt to measure its effects. This benefit the NCVS cannot provide (although, as discussed, experimental settings may lack important real-world effects – like stress – that can alter the results, particularly as they relate to racial bias). As a result, the possibility exists this study does not account for some factors that may be significant. The NCVS has increasingly added questions that allow victims to provide context about the incidents and, over time, comparisons will likely become more sophisticated. For instance, the NCVS started gathering information on the evidence supporting the inference the crime was hate-motivated beginning 2010. However, only half of respondents who experienced a hate crime between 2010-15 provided a response (277 out of 546), and a large portion of those responses were coded as “don’t know” to indicate uncertainty or “residue” to indicate a response that fell outside of the yes/no binary. Thus, the remaining sample is too small for statistically relevant analysis. However, future data may provide fruitful information that allows for a more qualitative analysis of how and why racial disparities exist in hate crime labeling and enforcement.

Another drawback of the NCVS is its metrics for offender race and ethnicity pre-2012. During that period, offenders fell into one of three categories: white, black/African American, and other. In addition, no variable for Hispanic/Latino ethnicity existed. Beginning 2012, the survey underwent significant improvement. Victims could indicate the offender was white, black/African American, Asian, American Indian, Native Hawaiian/Pacific Islander, or any combination thereof. It also established a new variable for Hispanic/Latino. However, any analysis including pre-2012 data must conform to the older method, and thereof lacks accuracy and nuance.

Looking forward, future research should examine how other members of the public, as well as officials throughout the criminal justice system, understand and respond to hate crime. Of particular interest is whether actors farther removed from the stressful incident can retain a civil rights orientation, and if so, whether that mitigates racial disparities. Witnesses, prosecutors, judges, juries, and parole boards play significant roles in determining who is punished and to what extent. The media also greatly influences public perception, discourse, and action around crime and punishment. Scholars should explore whether these players influence racial disparities in hate crime enforcement and the nature of this effect.

Finally, as discussed in Chapter 2, researchers should also focus on the efficacy of hate crime statutes more broadly. Limited research exists pertaining to whether these laws and their enforcement effectively address bigotry and violence. Similarly, more research is needed to see whether less-restrictive policies, like education and anti-poverty campaigns, restorative justice, or therapeutic models, may have more meaningful, longer-lasting, positive impacts. More empirical work is needed to adequately evaluate the value of hate crime legislation and to identify evidence-based approaches.

V. Conclusion

It has taken centuries for the public, policymakers, and the legal system to recognize the effect of bigotry and violence on racial equality and develop institutional responses. Hate crime legislation is understandably seen as a major victory for civil rights. It is no surprise that, facing a potential white supremacist revival, minority rights groups urge stronger and harsher enforcement of these laws to communicate zero tolerance and promote public safety and security. However, in so doing, they ironically place their faith in a system that has time and again been exposed for its deeply engrained racial bias.

During these times of political turmoil and public panic, researchers have the crucial responsibility of empirically assessing the efficacy of policies, as well as their unforeseen consequences, to ensure adequate information is available for the development of evidence-based responses. Do hate crime laws operate as intended, and what are their potentially perverse impacts? This study set out to assess how hate crime laws play out on the ground, examining whether offender race/ethnicity shapes how victims and police interpret and respond to a crime. Specifically, it asks whether they are more or less likely to label an incident a hate crime or react punitively by calling police based on the perpetrator’s demographic characteristics. When individuals are personally engrossed in a stressful criminal event, do they rely on a civil rights preconception of hate crime or do they revert to a racial bias orientation that disproportionately villainizes and punishes African Americans?

The results provide compelling preliminary evidence for the latter. Acts of African American offenders have the greatest odds of being labeled and punished as hate crimes. Meanwhile, offenses perpetrated against African Americans are least likely to be attributed to bias. Further, victim perceptions of crime appear to influence police enforcement. Victims are more likely to report crimes involving African American offenders. While reporting a crime to police, in and of itself, does not increase the likelihood of arrest for African Americans, labeling it as hate-motivated does. If a victim believes bias drove the offender to target them, the incident is significantly more likely to result in arrest, and arrest disparities grow immensely. Police are also more likely to arrest other non-white offenders, as well as those of Hispanic ethnicity, for hate crimes. These results show some support for the inference that victims have negative bias towards racial and ethnic minority offenders, and that these biases perpetuate systemic racial disparities. At a minimum, this analysis demonstrates the need for further research on whether deeply engrained biases regarding race and crime and pervasive systemic racism hinder the ability of the criminal justice system to promote racial equality, as is the goal of hate crime legislation.

CHAPTER IV

WEAPONIZING CIVIL RIGHTS: 'BLUE LIVES MATTER' AND THE USE OF HATE LAWS TO PROTECT THE POWERFUL

I. Introduction

This chapter explores a new iteration of hate crime laws and its implications for racial justice. Since 2016, a wave of states has introduced bills into their legislatures that propose extending hate crime protections to police. These are widely known as "Blue Lives Matter" (hereafter "BLM") measures. Traditionally, hate crime laws have aimed to protect historically oppressed groups. However, police do not fit that description; they are not a vulnerable group needing governmental protections. Quite the opposite: Police are empowered by the government as an appendage of it, and they have often wielded this power to perpetrate the very acts that hate crimes laws aim to prevent. So why provide hate crime protections to police? This study tests two explanations for the introduction of BLM laws. First, using data on assaults and felonious killings of police, it considers whether heightened or new violence towards police predicts BLM bills. Second, using data on police use of force and arrests, it examines whether past police repression predicts the BLM bills. This paper cautions that BLM laws, unlike other types of anti-hate legislation, may undermine equality rather than promote it.

a. Hate Crime Laws Arose to Protect the Vulnerable from Oppression

An examination of the historical origins and development of hate crime legislation reveals the incredible irony of BLM proposals. Hate crime laws aim to protect historically oppressed groups. Police do not fall in this category. In fact, police have, at times, engaged in the types of repression these laws aimed to prevent.

Hate crimes are a form of civil rights legislation that arose from efforts to address racial repression. Their origins can be traced back to the first status-based legal protections, the post-Civil War constitutional amendments: the Thirteenth Amendment, ending slavery; the Fourteenth Amendment, extending citizenship and equal protection of the law to African Americans and other groups, and prohibiting state interference with many constitutional rights; and the Fifteenth Amendment, guaranteeing voting rights regardless of race, color, or prior slave status (Levin 2002). A series of federal statutes followed to ensure these protections would be realized: the 1871 Force Act, providing enhanced federal authority to protect the franchise of African American people; the Ku Klux Klan Act of 1871, criminally punishing government officials and private conspiracies that deprive citizens of equal protection or interfere with federal protection of civil rights; and the Civil Rights Act of 1875, guaranteeing “full and equal enjoyment” to all citizens of public accommodations and conveyances, regardless of race, color, or prior servitude. These signified the U.S. government’s first attempt to combat race-based mistreatment, and are the earliest versions anti-hate legislation.

Subsequent forms of legislation also emerged to address bias-based criminality targeting African Americans (Levin 2002). With the rise of racial terrorism, sixteen states passed anti-lynching laws between the 1890s and 1930s. In response to race riots directed at African Americans, states passed group-libel statutes, punishing defamatory statements against racial, religious, or ethnic groups. In response to a Klan renaissance in the 1920s, states enacted a variety of new policies, including prohibiting masks in public, confiscating materials, and banning the group from meeting or parading.

In recent decades, hate crime laws have broadened their focus, beyond protecting racial minorities to encompass other historically oppressed groups. The contemporary anti-hate movement emerged in the latter part of the twentieth century to respond to violence stemming from bigotry (Jenness and Grattet 2001). It grew out of a convergence of the modern civil rights movement, the contemporary women's movement, the gay and lesbian movement, and the victim's rights movements. This work has focused on raising awareness of, and addressing, bias directed towards minority groups that lead to their subjugation.

Modern day anti-bias laws continue to focus on equality. They often prohibit conduct that has historically prevented minority groups from enjoying full citizenship. For instance, in the federal arena, these laws include legislation punishing interference with civil rights (18 U.S.C. §§ 241-42); interference with enumerated rights including voting, obtaining government funded benefits or services, obtaining employment, participation in a jury, enrollment in public education, participation in state programs, interstate travel, and access to public accommodations (18 U.S.C. § 245); and interference with housing rights (42 U.S.C. § 3631) (Levin 2002).

Hate crime laws are another form of equality-promoting legislation. The federal government and most states have penalty enhancement statutes that provide tougher sentencing for certain offenses committed because of group identities that have, as a historical matter, been the basis for violence: race, color, religion, national origin, ethnicity, gender, disability, or sexual orientation (Levin 2002). These laws vary on who exactly they protect, and as discussed in Chapter 1, they can be invoked to protect the dominant group (e.g., whites) because they cover universal categories like race and do not differentiate within the group (e.g., between whites and African Americans) (Jenness and Grattet 2001). Nonetheless, hate crime laws today focus on characteristics that have, empirically speaking, been the basis of violence, exclusion, and other forms of oppression. This has always been the purpose. That is, until now.

b. Police Have Been the Oppressors, not the Oppressed

So how do police fit within this anti-discrimination, equality-promoting framework? Police are not a group that has been marginalized in any sense of the word. The characterization of police as a vulnerable class is abstracted from historical and contemporary context; it misrepresents their past and present social position. Police are not a group needing governmental protections. Quite the opposite: Police are empowered by the government as an appendage of it, and they have often wielded this power to perpetrate the very acts hate crimes laws aim to prevent.

Indeed, police enjoy tremendous power in the United States politically, legally, and physically. Police have significant political clout through their unions and other law enforcement interest groups (e.g., Bies 2017). These organizations advocate for policies and employment contracts that prevent officer oversight and accountability. Police also enjoy strong public support. Most Americans have “a great deal” or “quite a lot” of confidence in law enforcement (Jones 2015). Further, the law powers police to stop, search, and arrest people for the smallest of infractions, regardless of their underlying motives (*Atwater v. City of Lago Vista* 2001; *Whren v. Untited States* 1996). Police can also use a continuum of force, sometimes lethal, and courts largely defer to police as to what is reasonable and therefore constitutional (*Graham v. Connor* 1989). In addition, departments equip their officers with military-style weaponry, including tanks, grenade launchers, surveillance equipment, and more (Balko 2013).

Important scholarship has shown police have more often been the perpetrators, not victims, of systemic oppression. This is especially true in the context of racial justice. Throughout the United States history, police have greatly hindered racial equality. In the southern United States, early police emerged from slave patrols, whose main purpose was to prevent slaves from escaping to the North (Vitale 2017). With the abolition of slavery, this role evolved. Police ensured slavery effectively continued through the enforcement of vagrancy laws, arresting African Americans and leasing them to private employers for profit (Alexander 2012; Vitale 2017). Police were also central to voter suppression, preventing African American participation in the political process thereby ensuring white domination of the system (Vitale 2017). In the North, police helped contain and control African Americans, who were feared by other segments of the population, through physical violence.

Researchers have also outlined how police actively repressed civil rights movements of African Americans and other people of color (Vitale 2017). They impeded protest by denying permits and beating and arresting protesters. They enabled private violence – including bombings and assassinations – through acquiescence. Local police and the FBI collaborated to infiltrate, surveil, and entrap individuals in these movements, thereby legitimizing arrest. They also conspired to assassinate prominent civil rights leaders. Largely in response to these civil rights movements, the Nixon Administration waged the Drug War as a race-neutral means to subordinate and control people of color

(Alexander 2012). Police have been on the frontlines, leading the charge to criminalize and imprison, en masse, people of color throughout the country (Alexander 2012).

In recent decades, scholars have noted how police continued to play a vital role in maintaining the political and economic status quo. Due to austerity beginning in the 1980s, widespread poverty followed, especially among people of color, and jurisdictions responded by enacting laws punishing low-level "public order" behaviors associated with poverty (Camp and Heatherton 2016). This is widely known as "broken windows policing." Practically speaking, it gave police the unfettered power to crack down on people of color, and that has been the result. As discussed in Chapter 1, study after study documents the racial discrimination that pervades police encounters, from stops, to searches, to arrests, to uses of force, to murders (see, Fagen et al. 2009; Harris 2002; Civil Rights Division of the U.S. Department of Justice 2016; Civil Rights Division 2015; Civil Rights Division and U.S. Attorney's Office 2017).

This body of empirical work shows police are not a defenseless group in need of governmental protection. They are not a class that has faced historical or contemporary persecution. Police have awesome powers that allow them to not only defend themselves, but also to overpower others, and they have wielded these powers to commit the very acts hate crimes laws aim to prevent. Thus, police do not fit within the anti-discrimination, equality-promoting framework of hate crime laws.

c. What Explains Blue Lives Matter Legislation?

What, then, explains the introduction of legislation extending hate crime protections to police? This chapter tests two theories: (a) states consider BLM legislation when police face heightened or new violence; or (b) states consider BLM legislation as means to continue controlling and repressing African American communities.

Proponents of BLM measures claim police need hate crime protections due to an increase in hostility and aggression towards police. In recent years, law enforcement interest groups, politicians, and the media have sounded the alarm on a new "war on cops" (Casey 2018; National Public Radio 2016; Mac Donald 2016; see also Balko 2015 for several examples). They argue anti-police resentment and violence has intensified, presenting an existential threat to officers and impeding their ability to protect public safety. The "war on cops" narrative relies heavily on two sources of evidence to support its claims: first, anecdotes of violence towards police, like the 2016 killings of officers in Dallas, Texas; and second, protests of police which allegedly create an antagonistic dynamic that cultivates anti-police animus and violence. Some call this latter phenomenon the "Ferguson effect," suggesting the increased scrutiny and criticism of police following the killing of Michael Brown in Ferguson, Missouri, fueled an increase in violence towards police and crime overall (Mac Donald 2016).

An alternative explanation exists for why states propose extending hate crime protections to law enforcement. The threat BLM laws wish to suppress may be a democratic one: public discourse around and advocacy for police reform. The Black Lives Matter movement arose as a response to police violence towards African American communities (Camp and Heatherton 2016), and its protests are most likely to occur in places where police have killed African Americans (Williamson, Vanessa, Trump, and Levine Einstein 2018). Blue Lives Matter, as the name suggests, launched in response to Black Lives Matter (Lynch 2017). The "Ferguson effect," mentioned above, is a euphemism for the protest activity by Black Lives Matter, which was sparked by Michael Brown's death in Ferguson. BLM proponents insinuate those who critique police are actually inciting violence, and therefore presenting a public safety threat that demands a severe legal response. I propose states may introduce BLM measures as a means to chill protest, not to protect police. If so, we would see BLM proposals in states where police have repressed African Americans and where protests are likely to occur. People are challenging police power in these states by shining a light on abuse and misconduct and demanding greater oversight and accountability. BLM laws may be part of a historical effort to keep African Americans in line and maintain the social order by preventing advocacy for racial justice and equality.

Accordingly, this study tests two explanations for the introduction of BLM laws. First, using data on assaults and felonious killings of police, it considers whether heightened or new violence towards police predicts BLM bills, like BLM advocates suggest. Second, using data on police use of force and arrests, it examines whether past police repression predicts the BLM bills.

II. Methods

a. Data Sources

This study employs five sources of data: a list of BLM bills introduced at state legislatures; Law Enforcement Officers Killed or Assaulted (LEOKA) from the UCR; Law Enforcement Management and Administrative Statistics (LEMAS); Arrests by Age, Sex, and Race (ASR) from the Uniform Crime Reporting Program (UCR); and the U.S. Census Bureau Decennial Census. The list of BLM bills provides the dependent variable, showing what states are acting to provide extra protections to law enforcement officers.

Other data sets include predictors of interest: LEOKA shows the number of officers killed or assaulted; LEMAS provides the number of incidents involving use of force; and ASR offers arrest rates by race. The Decennial Census provides demographic data by state, allowing us to control for populations of each racial group.

i. BLM Bills

The Huffington Post conducted an analysis of every state legislature to determine where BLM bills were introduced in the years 2016 and 2017 (Craven 2017). This study uses that analysis. BLM bills are those that propose extending hate crime protections to law enforcement officers. Generally, these laws try to achieve this by adding police to the list of protected classes, which typically include categories such as race, sex, national origin, sexual orientation, and disability. Sometimes (as is the case in South Carolina) no hate crime protections currently exist, and so police would constitute the sole protected class for these purposes. Table 4-1 provides a list of states that have introduced BLM legislation. This study focuses on the introduction stage of bills for two reasons. First, BLM laws are a relatively recent phenomenon, and so too few states have passed them to allow for statistical analysis of implantation. Second, it provides a meaningful metric for measuring where lawmakers and other advocates pushing for the passage of BLM laws, even though this does not measure popular support.

Table 4-1: States in Which Lawmakers Introduced BLM Bills, 2016-17

Alabama	Mississippi
California	New Jersey
Connecticut	New Mexico
District of Columbia	New York
Illinois	Pennsylvania
Kentucky	South Carolina
Louisiana	Tennessee
Maryland	Texas
Missouri	Washington
	Wisconsin

i. <u>LEOKA</u>

The Federal Bureau of Investigation (FBI) compiles the UCR. City, county, and state law enforcement agencies nationwide submit data on crimes known to police in their respective jurisdictions. LEOKA contains information agencies submit to the FBI through a monthly report in which they provide information on killings and assaults of police. In relevant part, agencies report whether the killings were accidental or felonious, and they provide information on all assaults that involved more than verbal abuse or minor resistance during the course of arrest. This study includes LEOKA data for years 1995 through 2015. Table 4-2 provides a tally of felonious killings and assaults of officers for these years combined by state.

Table 4-2: Totals by State for Each Data Source, All Years Combined

	LEOKA: Officers		*LEMAS: Force*	*ASR: Arrests*	
State	*Killed*	*Assaulted*	*Incidents (2013)*	*AA*	*White*
AK	6	5375	313	49732	363054
AL	**16**	**5551**	**913**	**1310041**	**1266535**
AR	11	5021	967	748141	1231156
AZ	27	42471	4657	482793	5398527
CA	**89**	**168742**	**12456**	**4659072**	**2.35E+07**
CO	11	17028	2377	496844	3900359
CT	**2**	**14149**	**2502**	**816905**	**1764105**
DC	**3**	**5178**	**487**	**105771**	**15143**
DE	2	9376	346	309062	331830
FL	42	152805	12733	275701	399745
GA	38	20173	6529	3251251	1704418
HI	1	6474	215	32345	344128
IA	1	10121	892	222837	1197327
ID	7	5272	272	5303	1127135
IL	**0**	**4243**	**6905**	**2914570**	**1187694**
IN	32	25968	4481	1050719	1993312
KS	4	15304	2829	107647	637913
KY	**6**	**13700**	**1456**	**514185**	**876780**
LA	**55**	**40819**	**1429**	**2263509**	**1421609**
MA	3	12393	1106	429171	1522122
MD	**22**	**81620**	**813**	**3705112**	**2517238**
ME	0	5097	53	8635	611873
MI	31	21863	2455	1856421	2614786
MN	5	4061	706	733577	2166241
MO	68	49292	3312	2034549	2884023
MS	**22**	**5295**	**543**	**888723**	**485174**
MT	1	2692	322	1277	247874
NC	40	49652	3928	3674021	3550568
ND	1	1733	241	6533	299732
NE	2	4107	646	320210	1194270
NH	5	4330	510	9551	472985
NJ	**20**	**56642**	**2158**	**2546109**	**2605366**
NM	**10**	**15888**	**561**	**57061**	**1424818**
NV	8	9796	311	692133	2118028
NY	**26**	**34771**	**4119**	**5748567**	**7437605**
OH	17	21417	3405	1670073	2930340
OK	21	17762	1404	424759	1325610
OR	5	10464	2081	160755	2300542
PA	**33**	**57987**	**1307**	**2373778**	**3939599**
RI	2	9127	148	98537	470691
SC	**26**	**14840**	**1901**	**1395131**	**1373578**
SD	10	2428	594	11918	304732
TN	**16**	**35600**	**2975**	**1629173**	**2397683**

TX	**95**	**97071**	**11169**	**4667584**	**1.39E+07**
UT	4	7915	1319	48153	1983145
VA	41	29469	3519	2151734	2531472
VT	0	758	205	1224	88500
WA	**12**	**24008**	**3154**	**352610**	**3285255**
WI	**14**	**14418**	**2141**	**1279905**	**3928816**
WV	4	6037	539	52103	299068
WY	1	1322	263	8106	476394

Data include totals for year 1995-2015, with the exception of LEMAS (use of force), which includes only 2013 data. AA denotes African American. Bolded states are those in which BLM bills have been introduced.

ii. LEMAS

The Bureau of Justice Statistics conducts LEMAS, a periodic survey of all state and local law enforcement agencies. It gathers information from all agencies that employ 100 or more sworn officers, and also collects a nationally representative sample of smaller agencies. Data obtained include a variety of administrative information about agency responsibilities, expenditures, responsibilities of employees, demographic characteristics of officers, policies, training, technology, and more. Relevant here, LEMAS asks the number of incidents involving the use of force in the prior year. This study includes data from only the most recent LEMAS survey, administered in 2013, because that is the first year the survey included a question on the number of use of force incidents. Table 4-2 provides the number of use of force incidents by state for 2013.

iii. ASR

ASR is another series of the UCR. The ASR provides arrest counts by age, sex, and race and offense type for each reporting agency. This study includes ASR data for years 1995 through 2015. Table 4-2 provides the total number of arrests by state and race for all years combined.

iv. U.S. Census Bureau Decennial Census

The U.S. Census Bureau conducts the Decennial Census, surveying households across the country to provide, among other things, population estimates. Pertinent to this study, the Decennial Census provides demographic information on households by state, including racial and ethnic composition. This study includes data from the 1990, 2000, and 2010 decennial censuses (Manson, et al. 2017).

b. Sample

This sample encompasses LEOKA and ASR data for all years beginning 1995 and ending 2015. It includes LEMAS data from the year 2013, and data from the 1990, 2000, and 2010 decennial censuses. LEOKA, LEMAS, and ASR data from years 1995-1990 were paired with the 1990 Census, years 2000-2009 with the 2000 Census, and years 2010-2015 with the 2010 Census. A lag exists between the decennial census and subsequent years, but it is consistent across all geographic areas. The sample has 1,071 observations: one for each state and the District of Columbia (51 geographic areas) for every year (21 years).

c. Measures

This analysis explores what factors predict whether state legislators introduce BLM legislation. Specifically, it measures whether these decisions are motivated by officer safety, as measured through assault and murder rates over time. In the alternative, it measures whether these decisions are merely states doubling down on historically repressive policies, as measured through use of force and arrests. To this end, the analysis involves multiple models.

In all models, the dependent outcome is whether state legislators introduced BLM legislation in 2016 or 2017. States are accordingly categorized into a binary variable as either having a BLM bill introduced or not, with "0" denoting the negative and "1" denoting the affirmative.

Model 1 has two predictors of interest: the number of assaults on officers, and the number of murders. LEOKA asks agencies for the totals of felonious killings (murders) and assaults of police. These two variables are collapsed by state for each year. This analysis uses those yearly statewide counts. This model also includes a fixed effect for the total number of officers employed as a control. This number is provide by LEOKA, as well, and was similarly collapsed into a yearly statewide count for this study. In other words, each geographic area has 21 observations, one for each year (1995-2015) for each variable (total assaults and total murders).

Model 2 has two predictors of interest: the rate of change in assaults between the years 1995 and 2015, and the rate of change in murders for that same period. I calculated the rate of change by regressing the number of assaults on years for states separately, controlling for the total number of officers serving. I then did the same for murders. The coefficients for every state were used to create two new variables – one for assaults, another for murders – representing the slope for every state. Therefore, each state has one number associated with it: the slope for all years (1995-2015). Note, the rates of change for assaults and murders tend to be monotonic, with a relatively linear trend in either direction (see Appendix B).

Model 3 has one predictor of interest: police use of force. LEMAS asks agencies a series of questions regarding how they record incidents involving the use of force. For those responding departments that provide a report for every incident, the survey inquires as to the total number of incidents involving force. Agencies can respond with a number, including "0," or indicate "unknown." This sample uses only those answers in which the number of incidents was known, and the values reflect the total number of incidents noted by the responding agency (thus, 301 of the 1,767 responses were dropped since they were missing this information). The data lack a demographic breakdown of individuals against whom police used force, and so the variable here provides the aggregate counts for all racial and ethnic groups for the year 2013 (which, as discussed, is the only year this information is available).

Model 4 has one predictor of interest: the number of African Americans arrested. It also includes a fixed effect for the number of whites arrested as a control. ASR data include state totals of arrests for African Americans and whites separately. ASR provides the total number of arrests by each racial and ethnic group for adults and juveniles in every offense type by agency. For African Americans and whites, I added the arrest counts for juveniles and adults together. I then collapsed the two variables by state for each year, combining all offenses into one total. The result is two variables: total arrests for African Americans by state for each year, and total arrests for whites by state for each year. In other words, each geographic area has 21 observations, one for each year (1995-2015) for each variable (total arrests of African Americans and total arrests of whites). This analysis uses the annual statewide counts by racial group. Further, because the number of arrests if often in the tens of thousands, I divide the number by 10,000 for the statistical calculations to ensure a more meaningful and discernable odds ratio.

Models 3 and 4 each include fixed effect variables based on statewide populations. Model 3 uses the total population of all racial and ethnic groups combined as a control. Model 4 uses the population of African Americans as a control. These estimates come from the Decennial Censuses.

d. Analysis

This study examines what factors predict whether state legislators introduce BLM legislation. It does so by measuring whether a relationship exists between these efforts and officer safety, or whether these policies are a continuation or escalation of repressive police practices, and therefore predicted by a pattern of such practices historically. This leads to the following hypotheses:

> H1: The relationship between assaults on police and the introduction of BLM legislation is not positive. The same holds true for officer murders.
>
> H2: The relationship between the change over time in assault on police and the introduction of BLM legislation is not positive. The same holds true for change over time in officer murders.
>
> H3: The number if incidents in which officers use force is a significant positive predictor of whether a state introduces BLM legislation.
>
> H4: African American arrests are a significant positive predictor of whether a state introduces BLM legislation.

Testing these hypotheses requires measurement of key variables. First, it involves regressing whether states introduced BLM bills on the number of assaults and murders of officers, the number of incidents involving use of force, and the number of arrests for African Americans. The models must also control for other factors explaining variation, like the total number of officers serving, the counts of arrests for people other than African Americans, and population estimates.

A finding that the coefficients for assaults or murders of officers is insignificant or negative will suggest decisions to introduce BLM legislation are not actually based on founded concerns around officer safety. Similarly, if the coefficients representing the rate of change in assaults or murders of police are insignificant or negative predictors, we can infer the introduction of these bills is not a response to a growing need for enhanced officer protection.

A finding that the coefficients for use of force or arrests of African Americans will indicate the introduction of BLM bills is fundamentally about maintaining or increasing police powers over African Americans. States with repressive policies are fighting to protect the social order.

The four models below employ Bernouli logistic analyses. In all models, *i* represents the geographic area (each state or the District of Columbia) for a given year between 1995-2015. Model 1 calculates the relationship between a state's introduction of BLM legislation and the number of assaults and murders of officers by year, controlling for the number of officers serving in each state in that year. The formula is as follows:

$$blm_i \sim Bernoulli\ (\pi_i)$$
$$\text{logit}(\pi_i) = \beta_0 + \beta_1(assaults_i) + \beta_2(murders_i) + \beta_3(total\ officers_j)$$
$$\text{Var}(blm_i | \pi_i) = \pi_i\ (1 - \pi_i)$$

Model 2 measures the relationship between a state's introduction of BLM legislation and the overall rate of change over years in assaults and murders of officers respectively. The formula is as follows:

$$blm_i \sim Bernoulli\ (\pi_i)$$
$$\text{logit}(\pi_i) = \beta_0 + \beta_1(change\ in\ assaults_i) + \beta_2(change\ in\ murders_i)$$
$$\text{Var}(blm_i | \pi_i) = \pi_i\ (1 - \pi_i)$$

Model 3 calculates the relationship between a state's introduction of BLM legislation and the number incidents involving police use of force in the year 2013. It controls the overall population. The formula is as follows:

$$\begin{aligned}
&blm_i \sim Bernoulli\ (\pi_i) \\
&\text{logit}(\pi_i) = \ \beta_0 \ + \ \beta_1(force\ incidents_i) + \beta_2(total\ population_i\ ) \\
&\text{Var}(blm_i |\ \pi_i\ ) \ = \pi_i\ (1\ -\ \pi_i)
\end{aligned}$$

Model 4 measures the relationship between a state's introduction of BLM legislation and the number of African Americans arrested each year. It controls for the number of whites arrests by year, as well as the African American population. The formula is as follows:

$$\begin{aligned}
&blm_i \sim Bernoulli\ (\pi_i) \\
&\text{logit}(\pi_i) = \ \beta_0 \ + \ \beta_1(AA\ arrests_i) + \beta_2(white\ arrests_i\ ) \\
&+ \beta_3(AA\ population_j) \\
&\text{Var}(blm_i |\ \pi_i\ ) \ = \pi_i\ (1\ -\ \pi_i)
\end{aligned}$$

III. Results

To test H1, the introduction of BLM legislation was regressed on variables for assaults and murders of officers, controlling for the total number of officers serving (Model 1, Table 4-3). The odds ratios for assaults and murders are both insignificant. The odds ratio for total officers is a significant positive predictor, though the coefficient is very small (odds ratio of 1.00, indicating a nearly 1:1 ratio).

To test H2, the introduction of BLM legislation was regressed on variables representing the rate of change for assaults and murders of officers (Model 2, Table 4-3). The odds ratio for change in assaults over time was a significant negative predictor, though the coefficient is very small (odds ratio of 1.00, indicating a nearly 1:1 ratio). The odds ratio for change in murders over time was not significant.

Table 4-3: Officer Safety

Model 1: Number of Assaults and Murders

	Odds Ratio	*P>z*		*95% Conf. Interval*	
Assaulted	1.00	0.63		1.00	1.00
Murdered	1.07	0.13		0.98	1.16
Total Officers	**1.00**	0.00	***	1.00	1.00
Intercept	**0.25**	0.00	***	0.20	0.30

Model 2: Rates of Change in Assaults and Murders

	Odds Ratio	*P>z*		*95% Conf. Interval*	
Change in Assaults Over Time	**1.00**	0.00	**	1.00	1.00
Change in Murders Over Time	0.89	0.80		0.37	2.16
Intercept	**0.56**	0.00	***	0.49	0.64

Coefficient superscripts indicate these significance levels: * ($p < .05$), ** ($p < .01$), *** ($p < .001$). Bolded coefficients indicate those that are significant at $p < .05$ or less in all models.

To test H3, the introduction of BLM legislation was regressed on the number of incidents in which officers used force, controlling for population (Model 3, Table 4-4). The odds ratio for use of force was not significant, but population had a significant positive effect.

To test H4, the introduction of BLM legislation was regressed on the variable for African American arrests, controlling for white arrests and African American population. All coefficients were significant positive predictors of whether states introduced BLM bills (Model 3, Table 4-4). As the number of African American arrests increases by 10,000, the odds of a state introducing BLM legislation increases by 1.12. As the number of white arrests increases by 10,000, the odds of a state introducing BLM legislation increases by 1.02.

Table 4-4: State Repression

Model 3: Number of Incidents Involving Use of Force

	Odds Ratio	*P>z*		*95% Conf. Interval*	
Use of Force	1.00	0.12		1.00	1.00
Total Population	**1.00**	0.03	*	1.00	1.00
Intercept	**0.23**	0.00	**	0.09	0.63

Model 4: Arrests of African Americans

	Odds Ratio	*P>z*		*95% Conf. Interval*	
AA Arrests	**1.12**	0.00	***	1.08	1.17
White Arrests	**1.02**	0.03	*	1.00	1.04
AA Population	**1.00**	0.01	**	1.00	1.00
Intercept	**0.20**	0.00	***	0.60	0.25

Coefficient superscripts indicate these significance levels: * ($p < .05$), ** ($p < .01$), *** ($p < .001$). Bolded coefficients indicate those that are significant at $p < .05$ or less in all models. AA refers to African American. In Model 4, the parameters represent the unit of change in odds ratios for every 10,000 arrests (see Section 2(c) above).

IV. Discussion

a. Evidence Undermining Officer Safety Rationale for Hate Crime Protections

This chapter set out to explore what factors predict whether states introduce legislation extending hate crime protections to law enforcement officers. Historically, such protections have covered classes of people who were the targets of violence. Does violence towards police predict whether lawmakers propose BLM laws? Even if rates of violence are low, has there been a significant uptick in violent incidents to spur such efforts? If states propose these bills out of a legitimate concern for officer safety, we should expect to see significantly higher rates of assaults or murders against police or, at a minimum, a relative increase in violence in those states.

The results provide compelling evidence undermining the officer safety rationale for hate crime protections. Consistent with H1, neither the rates of assaults nor murders predict whether states propose the measures. Put another way, states in which lawmakers proposed BLM protections do not differ significantly from other states in terms of violence against police.

Moreover, the introduction of BLM legislation does not appear to be driven by an increase in assaults or murders of police. In fact, a significant negative relationship exists between changes in assaults over time and these measures (though the coefficient diminutive). BLM proposals are associated with a decline in assaults; states in which lawmakers propose these bills are seeing a drop. Further, no significant relationship exists between the change in murders and BLM bills. States with BLM bills in the legislative queue have not seen an increase in police murders. In sum, the data provide no support for the claim that police in these states need enhanced protections. If anything, the opposite appears to be the case.

b. *Evidence Consistent With a State Repression Rationale for Hate Crime Protections*

This chapter proposed an alternative theory for why states consider extending hate crime protections to law enforcement. This theory posits lawmakers propose BLM laws not to protect police from violence, but rather democratic challenges to police power. Under this theory, states with historical patterns of police repression towards African Americans will be most likely to put forth legislation further protecting and empowering police and, likewise, punishing and disempowering African Americans.

The results are consistent with this state repression theory. States with more repressive police practices are significantly more likely to introduce legislation extending hate crime protections to law enforcement. African American arrests predict the introduction of BLM legislation (Model 4, Table 4-4). This finding holds true when controlling for the number of whites arrested as well as the African American population. As the number of African American arrests increases by 10,000, the odds of a state introducing BLM legislation increases by 1.12. White arrests are also significant, though to a lesser degree (with an odds ratio of 1.02). Repression of African Americans and also whites, as measured through arrests, predict BLM bills in state legislatures. No significant relationship exists between use of force and the introduction of BLM legislation. However, as discussed in Section VI, I attribute this to underreporting by police and sample size. In conclusion, the results indicate that states proposing BLM laws are those in which police have historically exercised broad powers and wish to continue doing so.

c. Limitations and Future Research

This study took the important first step in examining some of the factors that may predict the introduction of laws extending hate crime protections to law enforcement. Notably, it employed five distinct data sources provided by the federal government to test the dominant justification, officer safety, and an alternative explanation, state repression.

This study merely examined BLM laws at their conception. At least two states – Louisiana and Kentucky – have enacted this legislation. Others may follow. Much more research will be needed to understand the effects. For instance, researchers should examine the circumstances under which police invoke their newfound protections, and against whom. Also, scholarship should focus on the possible negative consequences, including the potential chilling effect on speech critiquing police and demanding reform. Along these lines, research should scrutinize how these policies affect historically oppressed groups – like African Americans – and whether these laws have the consequence of undermining civil rights. Finally, as is true for all hate crime legislation, researchers should measure the efficacy of these policies in achieving their purported public safety goals, and the availability of less restrictive alternatives.

This research design has noteworthy limitations. Importantly, it relied almost exclusively on police assessments of their own work. On the one hand, this fact may bolster the study's findings regarding officer safety. If police were to provide inaccurate estimates of their victimizations, we would expect these numbers to be exaggerated because it would justify heavy-handed police responses, unchecked discretion, and the greater allocation of resources to enhance officer safety. Despite potentially inflated numbers, officer assaults and murders were either insignificant or negative predictors of BLM bills. Thus, even by their own metrics, police do not face safety concerns necessitating protected class status.

On the other hand, relying on police data is more problematic for other types of questions, like measuring the degree of repression in a jurisdiction. Police may underestimate their own wrongdoing. Quite significantly, studies have found more than half of police killings go undocumented (e.g., Feldman 2017; Bank et al 2015). Moreover, use of force estimates also suffer underreporting since many departments fail to collect such statistics and, when they do, they rely on records created by officers who were involved in the action and who have legal, reputational, and financial incentives to lie (e.g., Alpert and Dunham 2004). Further, we might infer those departments lacking integrity in their conduct on the street will likewise lack integrity in their documentation and reporting of said conduct. They have more to hide, and they have a greater propensity towards misconduct generally.

Another problem with federal police data is its omission of information pertaining to misconduct resulting in no arrest, use of force, or death. For instance, police may engage in *Terry* stops (stops and frisks), and jurisdictions vary in their documentation of these encounters. Almost uniformly, police can engage in "mere conversation" with civilians without record, even though those conversations can often be highly coercive or threatening. These interactions often breed community distrust, resentment, and conflict but, despite their significance, they go largely undetected in our existing data.

Therefore future research should refine methods for measuring police repression, incorporating data from impartial sources, and capturing information currently missing. For example, the Bureau of Justice Statistics recently redesigned its Arrest Related Death statistics program to incorporate information from news outlets and non-police agencies to supplement law enforcement and coroner data. Also of note, non-governmental entities have begun collecting data on police killings in the United States based on news accounts. The Guardian, the Washington Post, Vice News, and Mapping Police Violence have created their own databases using such information. Hopefully, these creative methods will not only improve our calculations of deaths but also spur other similar efforts in other police contexts, like use of force, stop and frisk, and less formal encounters.

Another limitation of this study is its lack of qualitative analysis. More historical context would greatly enrich the discussion. Similarly, deeper analyses of discussions around these issues – as depicted through legislative history, public meetings, and news stories – would further enhance our understanding of the social and political dynamics at play. Interviews with stakeholders could also provide a more direct view into the motives behind BLM laws. Another important contribution would be an exploration of the interest groups (other than police) supporting these laws, and their respective political agendas.

V. Conclusion

This dissertation set out to examine hate crime laws and their potentially perverse consequences for African Americans. Despite the palpable skepticism of the criminal justice system, it has recognized that hate crime laws likely have good intentions. They arose from a civil rights movement and attempt to address conduct that arguably hinders racial equality. But can the same be said for BLM proposals? These laws represent a significant departure from traditional hate crime legislation in their protection of a group that is (1) the government, (2) very powerful, and (3) has a history of perpetuating repressive acts that hate crime laws aim to prevent. What are we to make of BLM laws?

This study tested two possible explanations for why state legislators propose extending hate crime protections to police: officer safety or ongoing repression of African Americans. The results reject the officer safety rationale for hate crime protections. States in which lawmakers proposed BLM protections do not differ significantly from other states in terms of violence against police. In fact, they are more likely to have seen a decline in violence. Police in these states do not need enhanced protections.

However, the results are consistent with – though certainly do not prove – the state repression theory. States with more repressive police practices – as measured through arrests of African Americans – are significantly more likely to introduce legislation extending hate crime protections to law enforcement. The results indicate states proposing BLM laws are those in which police have historically exercised broad powers and wish to continue doing so. This evidence supports concerns that states may be using hate crime laws to protect the powerful, weaponizing civil rights laws to suppress movements for racial justice. Further research is needed to fully understand the social context of these laws and their future consequences for racial equality.

CHAPTER V

CONCLUDING THOUGHTS ON CRIMINALIZING OUR WAY TO RACIAL EQUALITY

I. Introduction

This dissertation set out with two goals. First, it highlighted the need for empirical research regarding whether regulating hate actually promotes racial equality. Second, it began chiseling away at this larger question by focusing on a particular aspect of hate regulation, its criminal penalties, and who bears the burden. Within this focus on criminalization, the lens of this dissertation zooms in further, looking at a particular phase in the criminal justice system, policing. This chapter synthesizes those findings, and situates them within the narrow and broad questions posed in Chapter 1.

II. What We Learned

Chapters 2, 3, and 4 began the analysis into whether hate crime laws have the unintended consequence of promoting racial inequality by contributing to the mass criminalization of African Americans. Chapter 2 looked at police-level decisions regarding who has committed a hate crime, examining whether any racial ethnic groups are overrepresented among hate crime offenders, and the extent to which disparities in hate crime enforcement resemble those throughout the criminal justice system. These preliminary findings suggest there is cause for concern. Police are less likely to designate an assault a hate crime for African American suspects than white, but African Americans are nonetheless significantly overrepresented among hate crime offenders, regardless of community-level enforcement patterns, though these disparities are significantly lower than those seen in non-hate contexts. Likewise, major disparities exist among American

Indians. The effects on Hispanics remain unknown. These results indicate hate crime enforcement may indeed be a double-edged sword that cuts against those it aims to protect.

Chapter 3 assessed whether offender race/ethnicity shapes how victims and police interpret and respond to a crime. Specifically, it asked whether victims are more or less likely to label an incident a hate crime or react punitively by calling police, and whether police are more likely to make an arrest, based on the perpetrator's demographic characteristics. Acts of African American offenders have the greatest odds of being labeled and punished as hate crimes. Meanwhile, offenses perpetrated against African Americans are least likely to be attributed to bias. Further, victim perceptions of crime appear to influence police enforcement. Victims are more likely to report crimes involving African American offenders, and police are more likely to arrest African Americans. If a victim believes bias drove the offender to target them, arrest disparities grow exponentially. Police are also more likely to arrest other non-white offenders, as well as those of Hispanic ethnicity. These results support the inference that victims have negative bias towards racial and ethnic minority offenders, and that these biases perpetuate systemic racial disparities.

Chapter 4 examined another hate crime context involving police, but where they were the purported victims. It tried to make sense of Blue Lives Matter laws extending hate crime protections to law enforcement, who are neither vulnerable nor historically oppressed. This study tested two possible explanations for why state lawmakers introduce this legislation: officer safety or ongoing repression of African Americans. The results appear to reject the former rationale. States in which lawmakers proposed BLM protections do not differ significantly from other states in terms of violence against police. In fact, they are more likely to have seen a decline in violence. Police in these states do not need enhanced protections. However, evidence supported the latter rationale: states with more repressive police practices – as measured through arrests of African Americans – are significantly more likely to introduce legislation extending hate crime protections to law enforcement. The results indicate states proposing BLM laws may do so in response to Black Lives Matter and to protect police from legitimate criticism. This suggests states are using hate crime laws to protect the powerful, and they are weaponizing civil rights laws to suppress movements for racial justice.

Collectively, these three chapters tell the following story. Police generally arrest African Americans at disproportionately high rates, even when controlling for type and severity of offense. When considering the most reliable and representative data available (NCVS), it appears these disparities grow steeply for hate crimes. Victims are much more likely to label a crime as hate driven when the offender is African American, and when they label it as such, the likelihood of arrest rises precipitously. Yet, when African Americans and allies critique these disparities and other repressive police practices, states respond by deploying hate crime laws to suppress democratic protest and inoculate police from oversight and accountability. All three studies suggest hate crime laws have the distorted effect of enabling police repression and undermining racial equality.

III. Unanswered Questions

a. *Does Enforcement Perpetuate the Mass Criminalization of African Americans?*

These findings only begin to answer the question of whether African Americans bear the burden of hate crime criminalization. More research is needed to understand these disparities throughout the criminal justice process. This dissertation only looks at policing. Prosecutors, judges, juries, and parole boards play significant roles in determining who is punished and to what extent. A complete answer of this question requires analyzing decisions around charging, plea bargaining, pretrial release, conviction, sentencing, and parole. This empirical work is necessary to understand how officials enforce hate crime laws, against whom, and the attendant burdens.

b. *What is the Value of Criminalization?*

We must proceed with even greater caution when drawing inferences regarding hate regulations and racial equality more broadly. Let us assume, without finding, criminalization is a burden that African Americans disproportionately bear, and that hate crime enforcement perpetuates their mass criminalization. The inquiry into whether regulating hate promotes or hinders racial equality does not stop there. We must assess whether the benefits are worth the costs.

i. <u>Deterrence, Rehabilitation, and Restitution</u>

Understanding the benefits of criminalization requires measuring its efficacy in addressing hateful expression and conduct. In other words, how do these laws and their enforcement fare in achieving criminal justice objectives – aside from immediate incapacitation or sheer retribution – such as restitution, deterrence, and rehabilitation? Do the processes empower victims and communities to find resolutions that are restorative and make them whole? Do the laws succeed in stopping or preventing people from engaging in hateful expression and/or conduct? Does involvement in the criminal justice system therapeutically address the underlying issues within the perpetrator such that they are able to function in a diverse society? Some research indicates otherwise: prosecution may increase resentment towards minorities because it plays into the offenders' perceptions that they were the victims of oppression by a more socially privileged and powerful group (Franklin 2002). Moreover, scholarship has revealed significant limitations of the retributive models in addressing the needs of either the victims or the offenders generally (see Zehr 1995). More empirical analysis is needed to conclusively determine whether anti-hate laws and their enforcement effectively address bigotry and violence.

In considering the efficacy of approaches to combating hate, we should also ask whether evidence-based alternatives exist that may be less socially or economically costly or more successful. In other words, we may face a false choice in deciding between criminalization and unencumbered hate. Less-restrictive policies, like education and anti-poverty campaigns, restorative justice, etc., may have more meaningful, longer-lasting, positive impacts, without the negative consequences. For instance, in other criminal justice contexts, therapeutic approaches have been shown to have outcomes superior to those seen with punitive models (see, e.g., Warren 2009). More research is needed to adequately evaluate the value of hate crime legislation and to identify the most empirically grounded ways forward.

ii. Norm-Setting Functions of Anti-Hate Laws

Traditional criminal justice objectives aside, anti-hate laws may have important symbolic value. Laws are imbued with social meaning that affects public attitudes and behavior. The law has the hegemonic effect of creating a social order that people widely accept as neutral, inevitable, and uncontroversial (Crenshaw 1988, discussing Gramsci). Legal consciousness therefore defines the boundaries of what people believe to be possible. Sometimes, this means the law induces people to accept the oppression of themselves or others. However, it can also convince the masses to pursue and support a more egalitarian society.

Considerable scholarship has shown lawmaking shapes public opinion and behavior. People care about, and are influenced by, decisions and actions of judges and legislators (Matsubayashi 2013; Hoekstra 2000; Hoekstra 1995). Even when it fails to directly change individual beliefs, the law affects norm *perception* (Tankard and Paluk 2017). People look to the law to gauge how others feel about issues, as a signpost for what opinions and actions are acceptable in the eyes of their peers. Sometimes these perceptions change individual attitudes, but even when not, they shape conduct because people wish to conform their behavior to avoid social rejection (see Tankard and Paluk 2017 for a review of the literature).

Significantly here, changes in policy can influence the public with regards to minority rights (Kreitzer, Hamilton, and Tolbert 2015). For instance, following the legalization of same-sex marriage in Iowa, and before *Obergefell*, Kreitzer, Hamilton, and Tolbert (2015) found the decision signaled new social norms that, in turn, compelled people to modify their expressed attitudes. Researchers have observed similar phenomena in other contexts, including affirmative action (Clawson, Kegler, and Waltenburg 2001). Conversely, anti-immigrant laws have been found to mobilize those already harboring anti-immigrant sentiment to become vocal about their prejudices (Flores 2017).

For this very reason, there has been considerable attention paid to the norm-setting power of government recently. Prominent civil rights advocates have warned of the grave dangers of having leaders acquiesce to, encourage, and provoke bigotry. For instance, the Southern Poverty Law Center stated:

> Welcome to Donald Trump's America. It's an America where the social norms that stitch our society together – the unwritten rules of common decency and civilized behavior that have been built up over generations – are unraveling before our very eyes. Trump's racially charged, xenophobic campaign, coupled with his attacks on so-called political correctness, not only energized the white supremacist movement but gave people a license to act on their worst instincts – their anger, their prejudices, their resentments.

(Cohen 2017). The National Association for the Advancement of Colored People (NAACP) articulated similar concerns (2018):

> As our nation fights to move forward, our President falls deeper and deeper into the rabbit hole of racism and xenophobia. The United States' position as a moral leader throughout the world has been thoroughly damaged by the continuous lowbrow, callous and unfiltered racism repeatedly espoused by President Trump. . . . This President's failure to grasp simple ideas of inclusion and maturity is an open sore on our democracy that continues to fester. It is clear that the President wants to return America to its ugly past of white supremacy . . . "

Both statements focus on the President's role as moral and normative leader. These advocates know, as research confirms, that government positions on civil rights issues matter, not only because they translate into policy, but also because they convey codes of civility, decency, and social acceptability. At a time when our most powerful officials espouse views of intolerance and dehumanization, having strong legal norms to communicate zero tolerance for bigotry and violence may be all the more important.

Anti-hate laws may be necessary in our current political climate as a means to counteract destructive messages.

Laws have a vital norm-setting function, establishing boundaries of socially acceptable conduct. Thus, anti-hate laws may help create an environment in which people are free from words and actions that are demeaning, threatening, or that undermine full and equal citizenship. They have the potential to promote egalitarian attitudes, beliefs, behaviors, and social structures. These considerations are necessary for one to assess the equality-promoting benefits of regulating hate.

c. Weighing the Burdens and Benefits of Criminalization

Finally, once we have answered the questions above and enumerated the benefits and burdens of criminalization, we must weigh them to determine what approach best promotes racial equality. This is an impossibly difficult task, in part because the harms of either mass criminalization and hateful rhetoric and conduct are severe and substantial. Both involve loss of security caused by harassment. Both can result in extreme limitations on liberty due to fear or actual confinement. Both can result in stigma and reputational harm. Both involve extreme forms of discrimination. Both limit the ability of individuals to participate in social and civic life. Either can be accompanied by violence and psychological or physical trauma, even death. These negative effects ripple throughout the communities, as well, who suffer the loss of members or contend with these members when they return traumatized and handicapped by the experience. Both mass criminalization and unfettered hate create an environment wherein the targets are relegated to second-class citizenship, and both are incredibly corrosive to individual and community well-being. How can we prioritize one form of suffering over the other? This dilemma is not one easily resolved. It has moral and ideological dimensions, and will require insights from multiple disciplines and stakeholders.

IV. Thinking Critically, Imaginatively, and Sociologically About Hate

Recognizing this empirical inquiry could be misconstrued as an effort to undermine advocacy to address and eradicate hate, I wish to end by unambiguously articulating the intent behind, as well as the implications of, this research. This section highlights the crucial need to address hate, but encourages doing so through creative evidence-based approaches that do not perpetuate the injustices of mass criminalization.

Why critique anti-hate enforcement? Perhaps every critical sociologist, at some point, faces reproach for critiquing institutions that enjoy broad unquestioning support. Whether the scrutiny focuses on gender, religion, capitalism, or the legal system, it is often met with strong resistance. Particularly during times of public panic and hysteria, there is great momentum towards taking action against perceived imminent dangers, and any criticism or concern raised is seen as a hindrance to those efforts and therefore a threat in and of itself.

Some of the fiercest opposition to critical empirical inquiry can come from those with whom researchers share common ideals and objectives, who feel betrayed by the seeming divergence. These individuals may infer the logical conclusion of any critique is total obstruction. In other words, they adopt a mindset of 'you're either with us or against us,' and assume that those who critique their efforts are naturally enemies.

However, it is the job of a sociologist to be curious about social processes and social structures widely taken for granted, and to empirically test the underlying assumptions justifying the status quo. Those institutions that are widely accepted and celebrated are, perhaps, those most needing critical examination, as they are least likely to be otherwise challenged, understood, and improved. Further, sociologists must situate phenomena within broader social and historical contexts to help the public see beyond the immediacy of current events and circumstances. These are fundamental premises of the sociological discipline, as articulated by canonical scholars like C. Wright Mills (1959).

In this sociological tradition, I proposed a systematic empirical examination of anti-hate laws. This project attempts to explore questions regarding how anti-hate laws actually operate in the real world, whether they function as expected, and the nature of their unintended consequences. I attempted to connect the current anti-hate regulatory policies to broader historical and contemporary patterns in the criminal justice system to provide a deeper understanding of the context in which these policies take place. The lack of sociological evidence or discussion was the impetus.

By problematizing anti-hate laws and their enforcement, I do not suggest abandoning the struggle to address hate. Rather, I encourage us to think outside of the box and consider alternatives that may meet those interests without the deleterious effects. It is completely uncontroversial that hate and violence are destructive forces within our society that must end. However, we simply must rethink traditional punitive criminal justice strategies to the extent they fail to address these issues, particularly when the social and economic costs are so high. In the United States, we tend to address social problems – from addiction to violence to homelessness to gangs to terrorism to hate – by throwing the book at them. We look to the criminal justice system as the universal solution. However, time and again, it has proven itself unworthy of this faith, failing to address the underlying causes of these issues and, indeed, exacerbating them. Less-restrictive, proactive policies – like education, community-building, anti-poverty campaigns, and restorative justice – may have more meaningful, longer-lasting, positive impacts, without the negative consequences. We may face a false choice in deciding between mass criminalization and unencumbered hate. Collectively, we can generate more options than this.

The ultimate goal of this project is to promote a theoretically and scientifically grounded approach to addressing hate. Accordingly, this research should not be construed as diminishing the severity or urgency of the threat and the need to act. In fact, it arises from a deep commitment to addressing the problem. Thus, this dissertation should be understood as a call for more curiosity, more research, more creativity, and more evidence-based policymaking. It is incumbent upon us as scholars, advocates, and citizens to end racial hierarchy, whether the culprits are private individuals or the government, hateful conduct or a flawed criminal justice system.

V. Conclusion

What is the role of government in addressing hateful expression or conduct? Does greater government intervention address racial subordination and persecution, thereby creating an environment in which equal citizenship can be realized? Alternatively, does invoking and empowering the government result in abuse of power and institutionalized racial repression? How can we effectively address hate and promote racial equality?

This dissertation began an empirical quest to answer some of these questions, focusing particularly on who bears the burden of hate criminalization. The findings provide an important but modest contribution to the discussion. African Americans are most likely to be seen as hate criminals and, while they generally suffer from disproportionately high arrest rates, the magnitude of this effect is significantly greater when police ascribe a hate motive. Further, there is reason to believe states may use hate crime protections to dominate and control African Americans advocating for social change and racial justice.

While an important first step, these findings are limited. More research is needed to understand how criminal laws around hate are executed and whether racial disparities permeate the system. We have very little evidence regarding the relative efficacy of anti-hate regulation in addressing bigotry and violence. Moreover, it is imperative we consider non-penal objectives, like establishing norms of inclusion and civility, when evaluating these efforts. Once all of the data is in, deeper analysis will be necessary to weigh the benefits and burdens of enforcement or the lack thereof, and to determine what best serves the interest of equality.

APPENDIX A

INEQUALITY RATIOS

1. Calculate income ratio:

$$\frac{\text{African Am. median income} - \text{white median income}}{\text{white median income}}$$

A higher positive number indicates a greater disparity, with whites farther behind in income.

2. Calculate the educational attainment ratio:

$$\frac{\text{proportion of African Am. population w/o bachelors} - \text{proportion of white population w/o bachelors}}{\text{proportion of white population without bachelors}}$$

A higher positive number indicates a greater disparity, with African Americans farther behind in educational attainment.

3. Calculate unemployment ratio

$$\frac{\text{proportion of African Am. population unemployed} - \text{proportion of white population unemployed}}{\text{proportion of white population unemployed}}$$

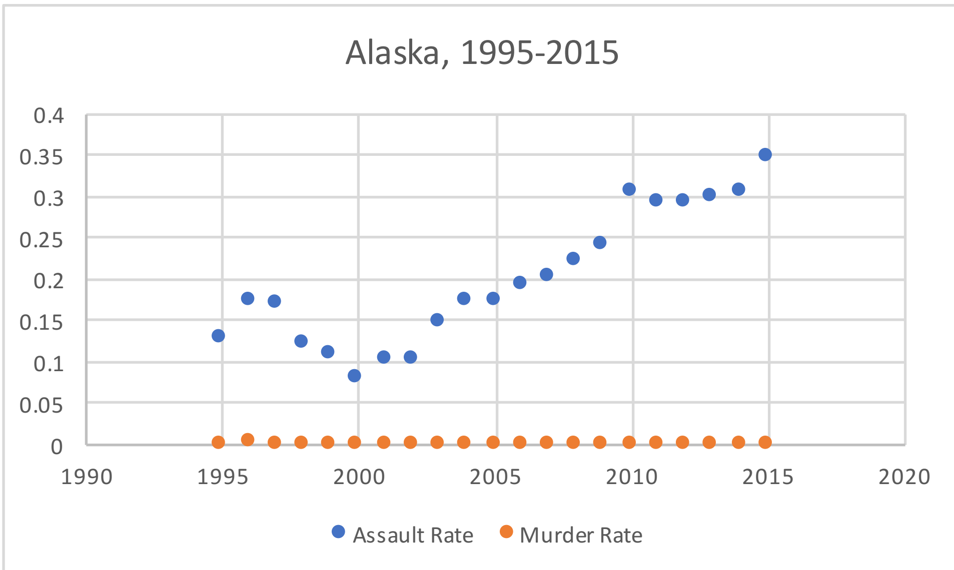
A higher number indicates a greater disparity, with African Americans experiencing higher unemployment.

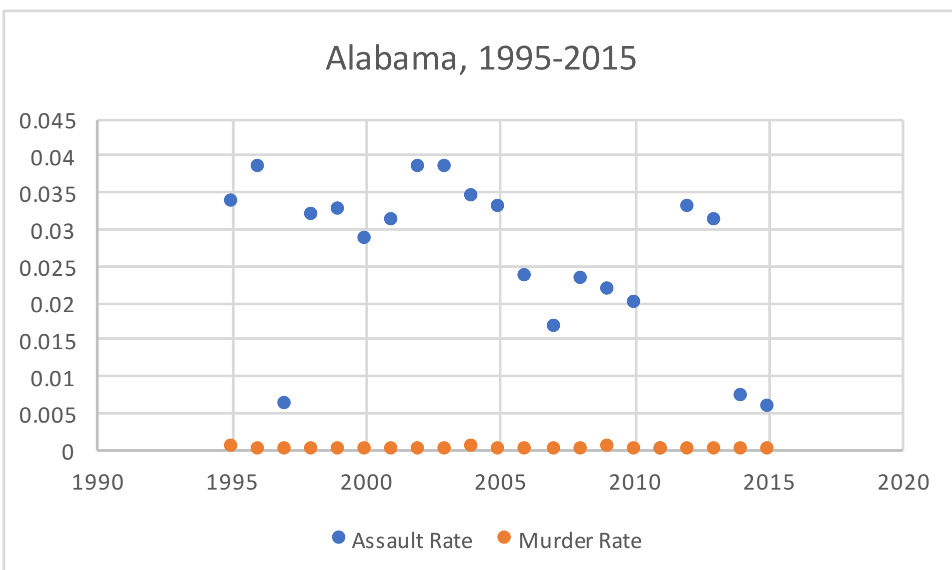
APPENDIX B

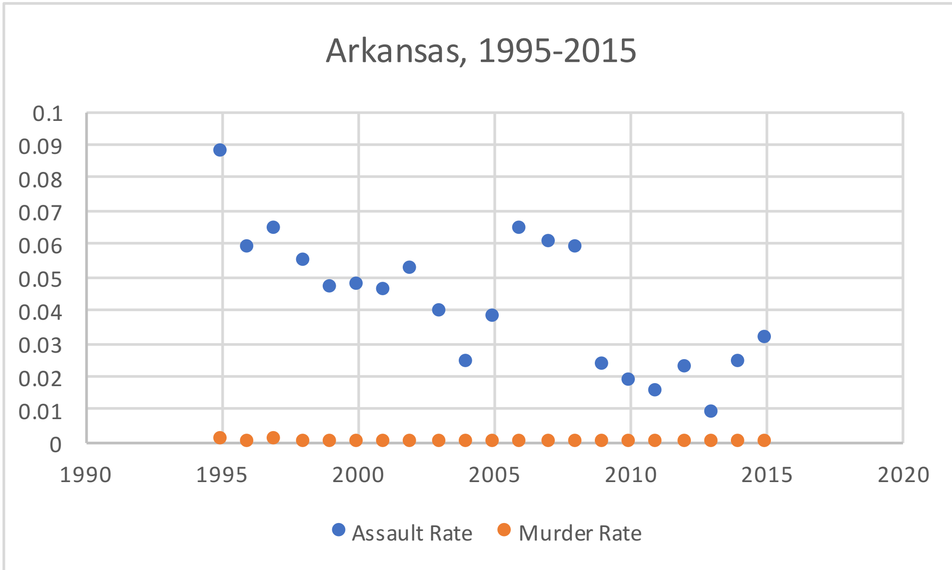
YEARLY RATES OF VIOLENCE AGAINST POLICE BY STATE

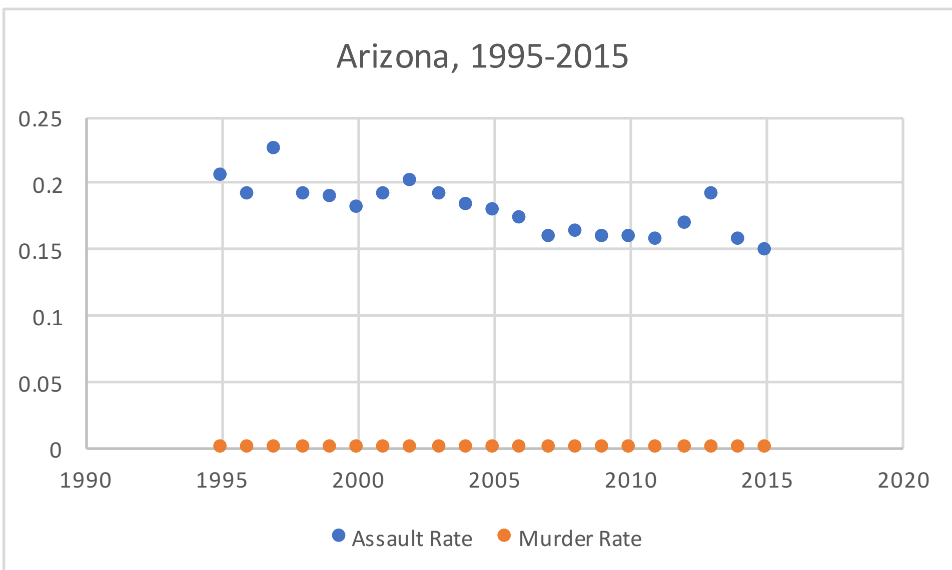
Calculated by taking the number of assaults or murders of officers divided by the number of officers serving.

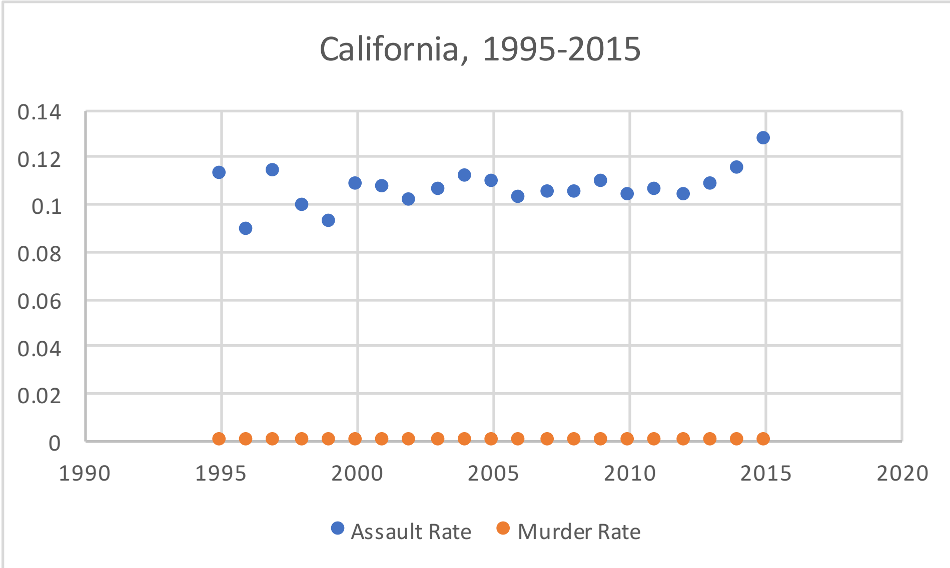
Note: Data is complete for all years in all states. If a chart appears to miss a data point for assault rates for a given year, it means the rate was zero.

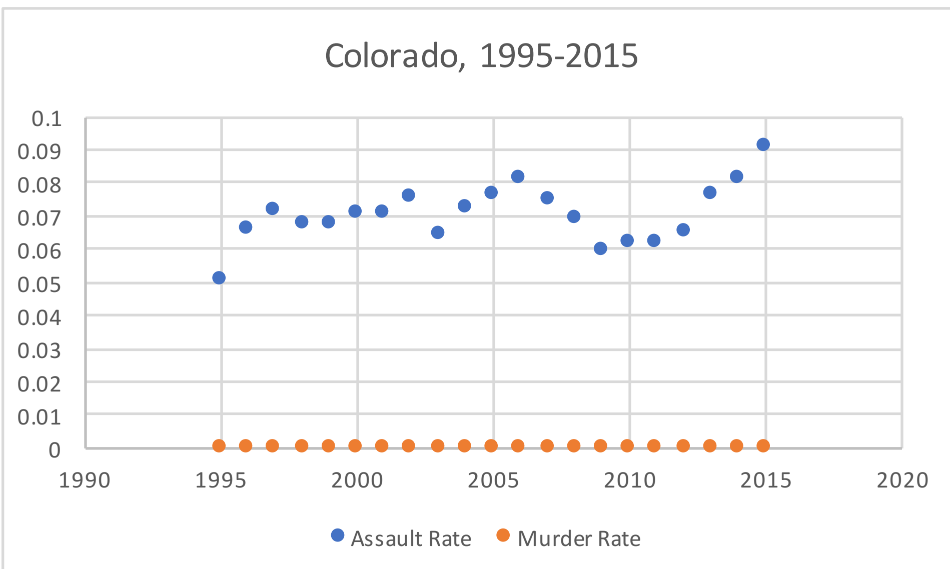


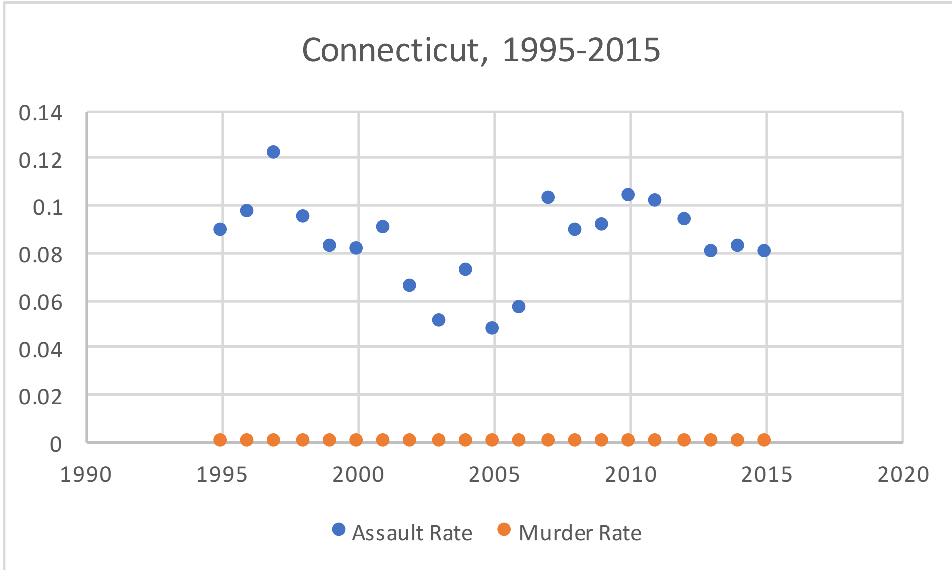


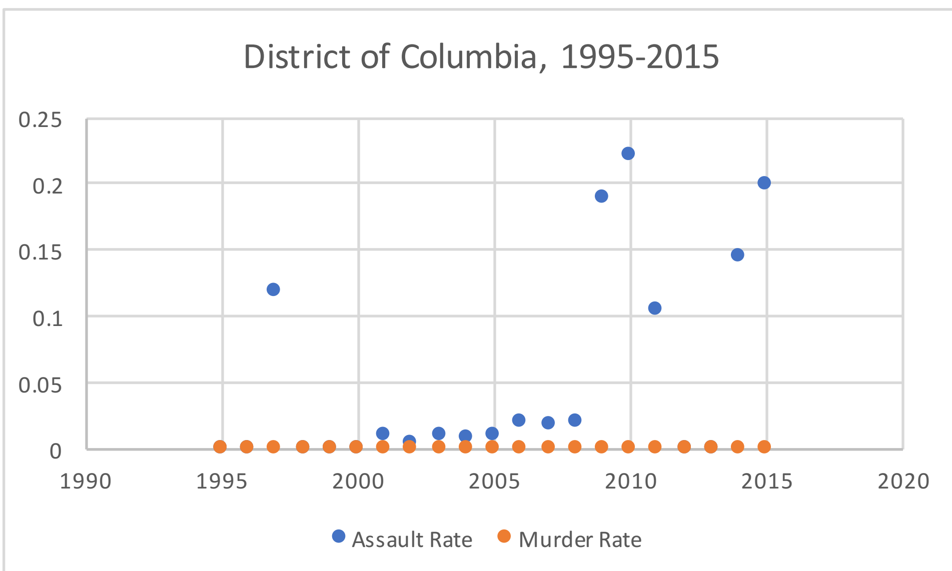

Arkansas, 1995-2015
0.1
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate

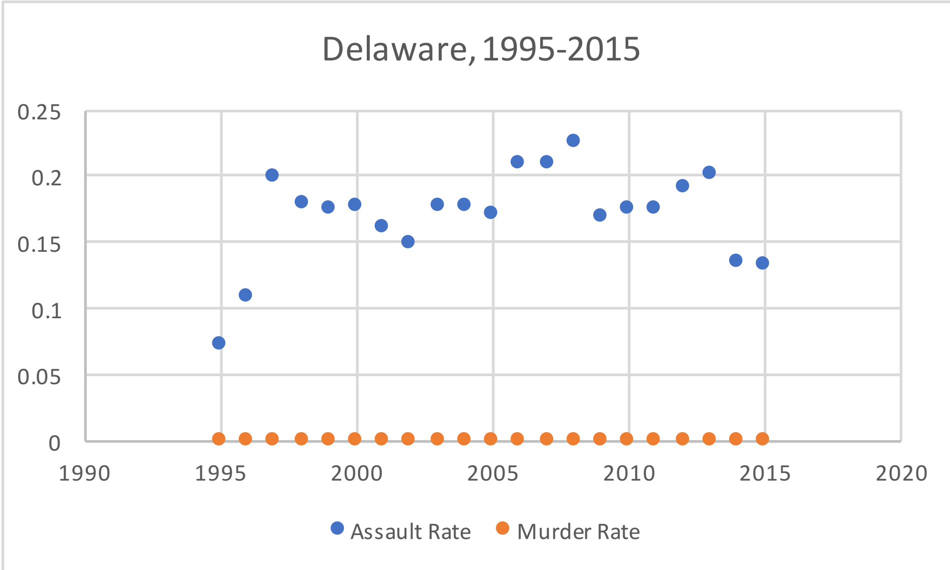

Arizona, 1995-2015
0.25
0.2
0.15
0.1
0.05
0
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate

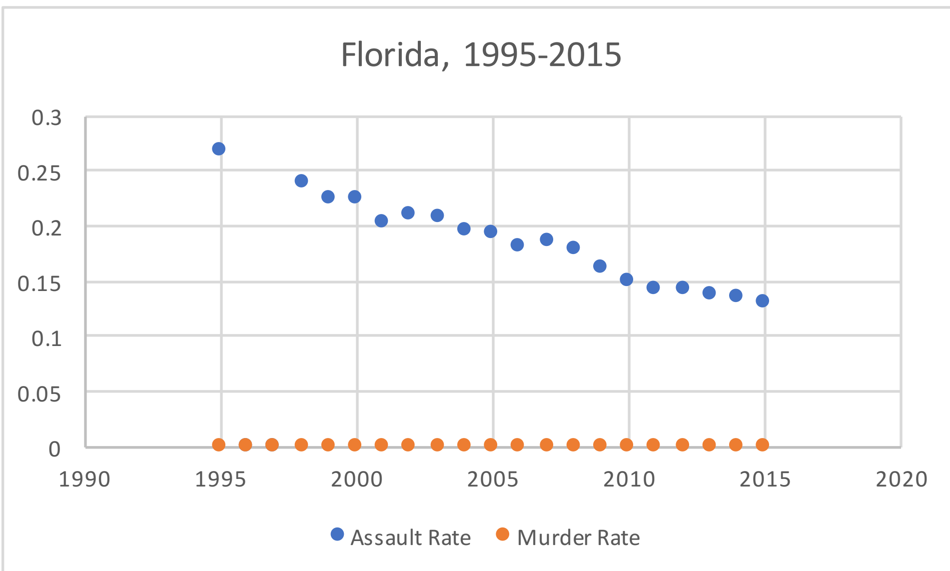

California, 1995-2015
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate

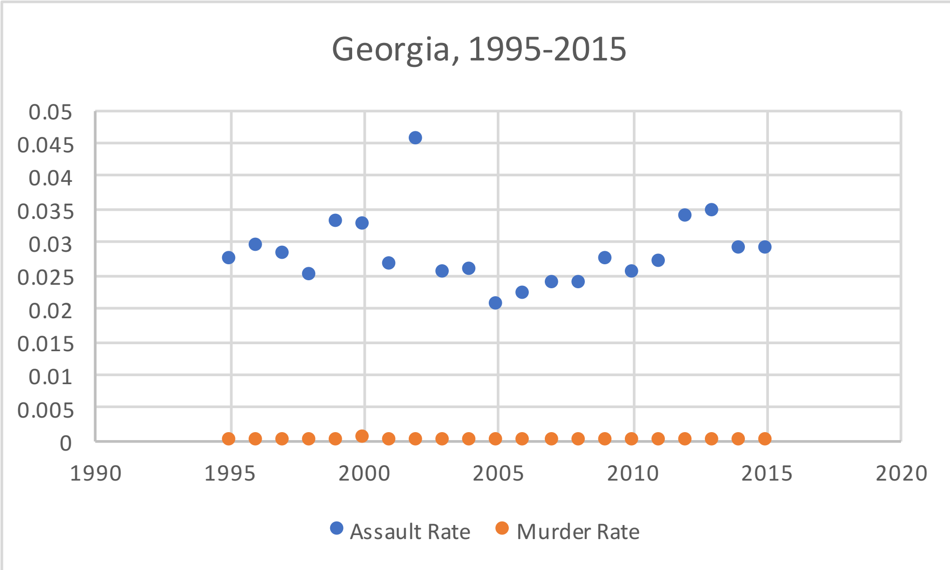

Colorado, 1995-2015
0.1
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate

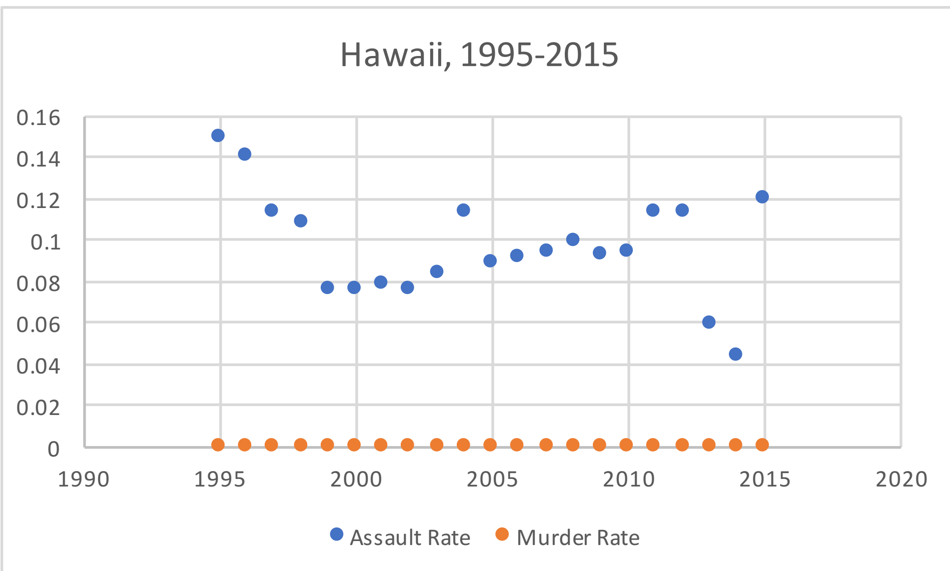

Connecticut, 1995-2015
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate

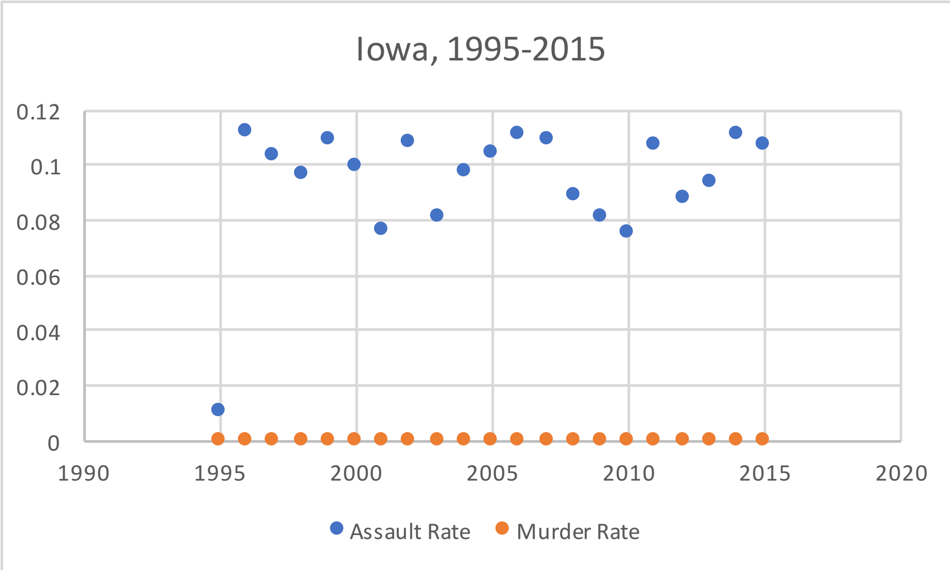

District of Columbia, 1995-2015
0.25
0.2
0.15
0.1
0.05
0
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate

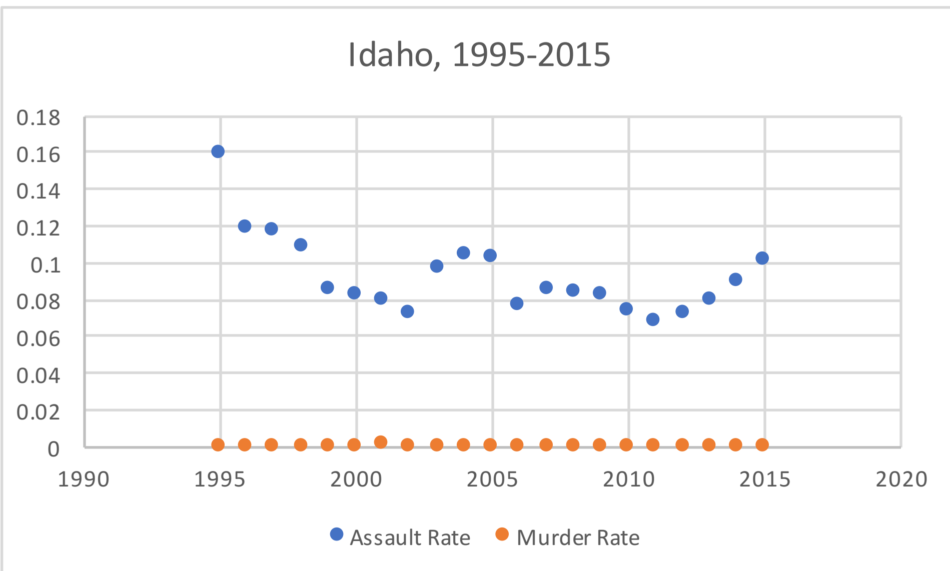

Delaware, 1995-2015
0.25
0.2
0.15
0.1
0.05
0
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate

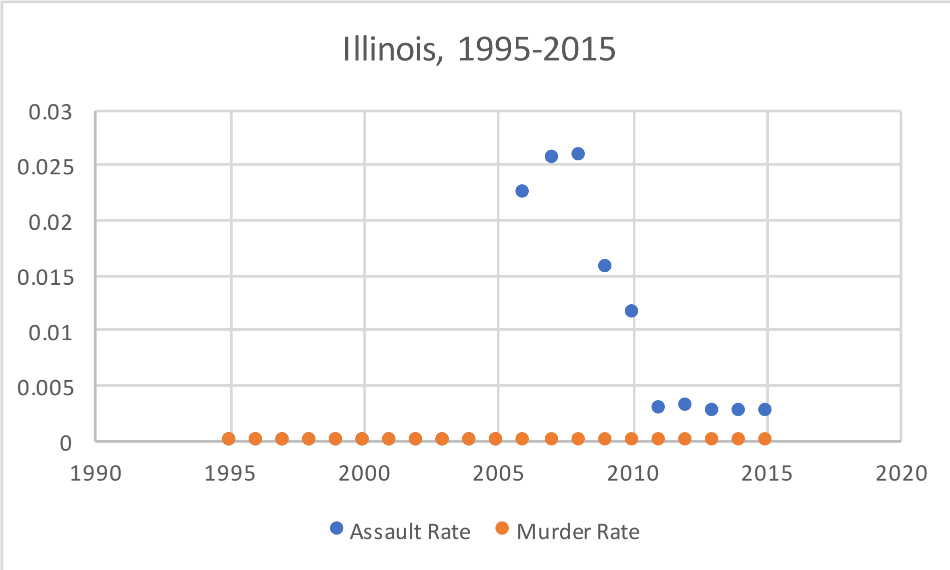

Florida, 1995-2015
0.3
0.25
0.2
0.15
0.1
0.05
0
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate

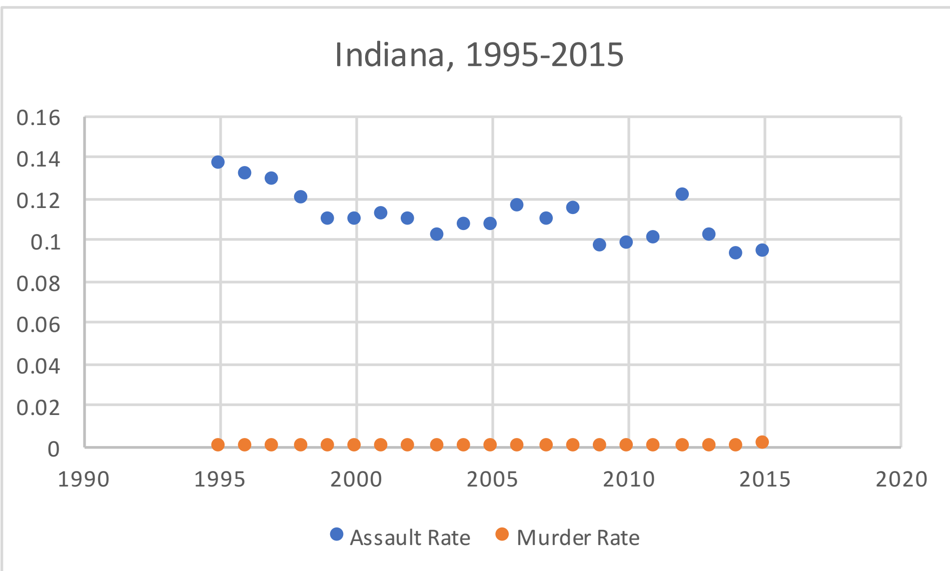

Georgia, 1995-2015
0.05
0.045
0.04
0.035
0.03
0.025
0.02
0.015
0.01
0.005
0
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate

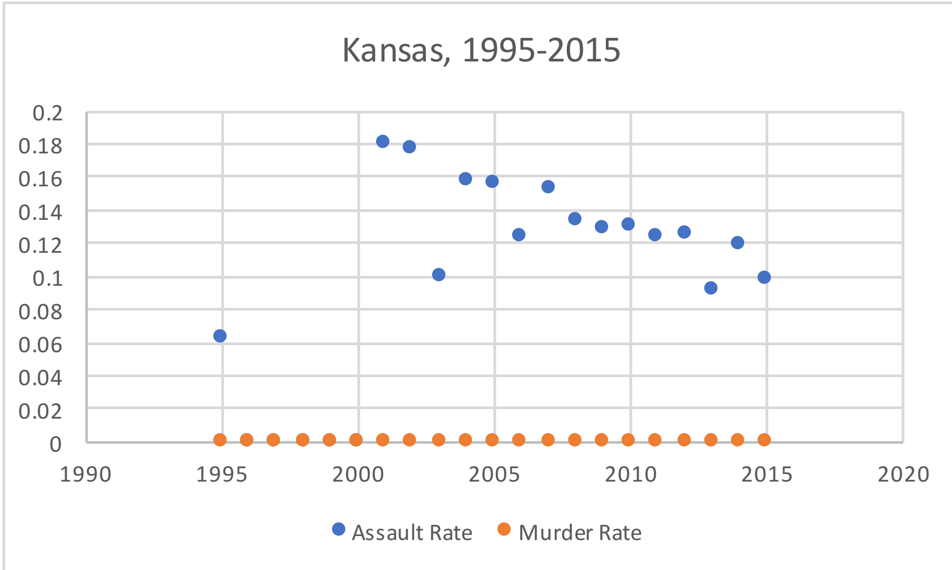

Hawaii, 1995-2015
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate


Iowa, 1995-2015
0.12
0.1
0.08
0.06
0.04
0.02
0
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate


Idaho, 1995-2015
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate


Illinois, 1995-2015
0.03
0.025
0.02
0.015
0.01
0.005
0
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate


Indiana, 1995-2015
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate


Kansas, 1995-2015
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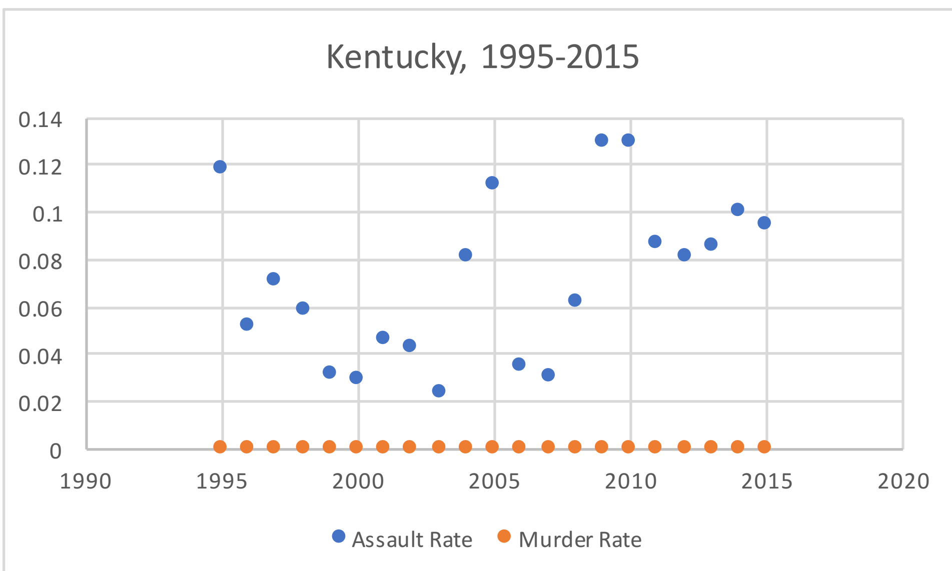
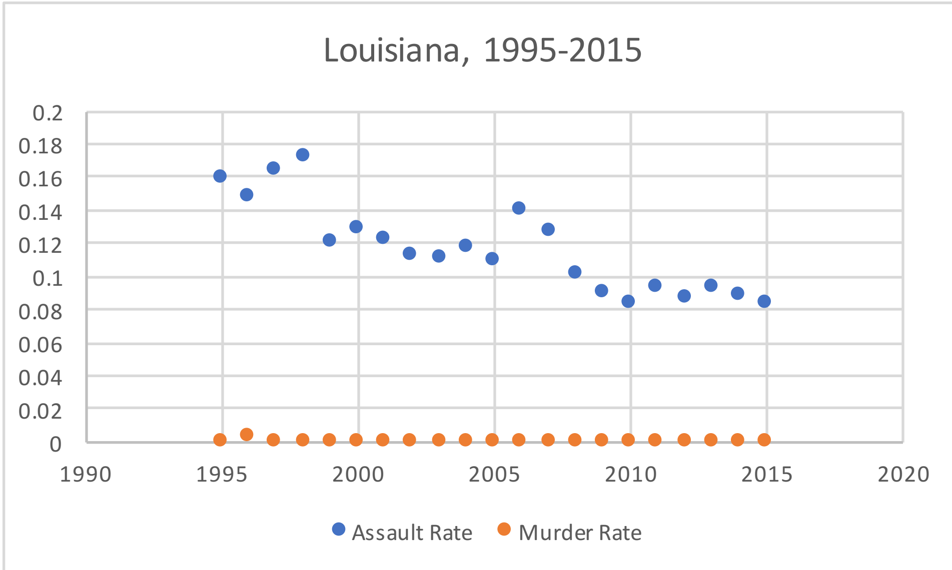
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate


Kentucky, 1995-2015
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate


Louisiana, 1995-2015
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0.18
0.16
0.14
0.12
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0.08
0.06
0.04
0.02
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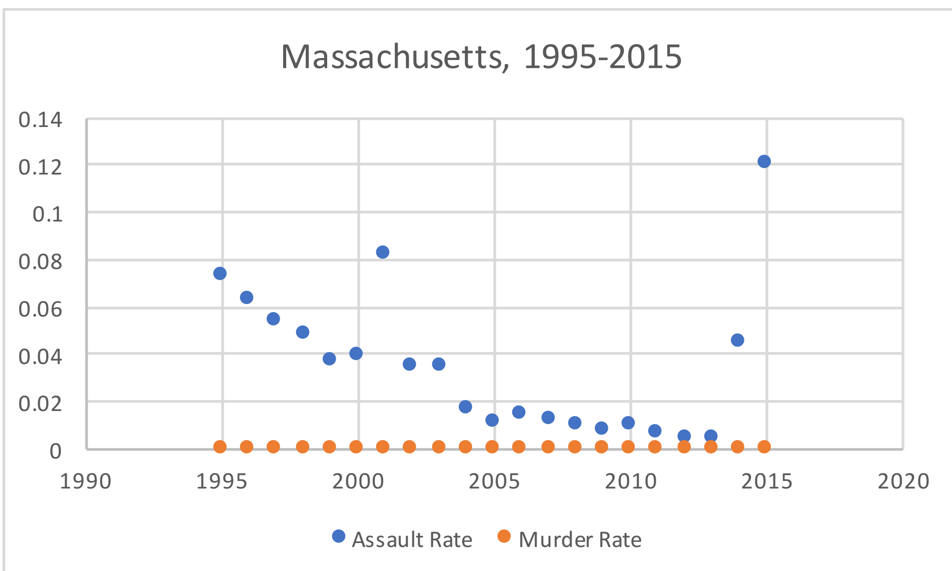
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate


Massachusetts, 1995-2015
0.14
0.12
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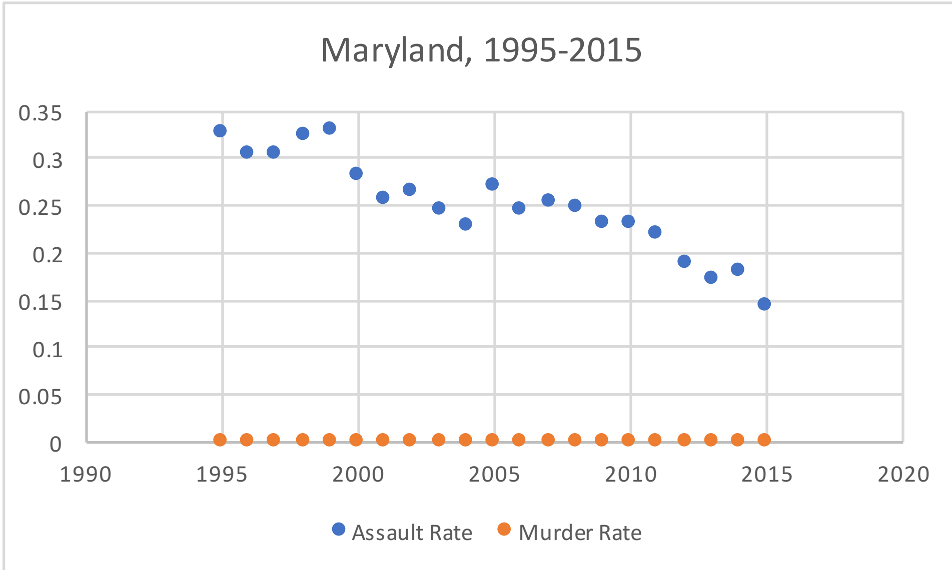
0.08
0.06
0.04
0.02
0
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate


Maryland, 1995-2015
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
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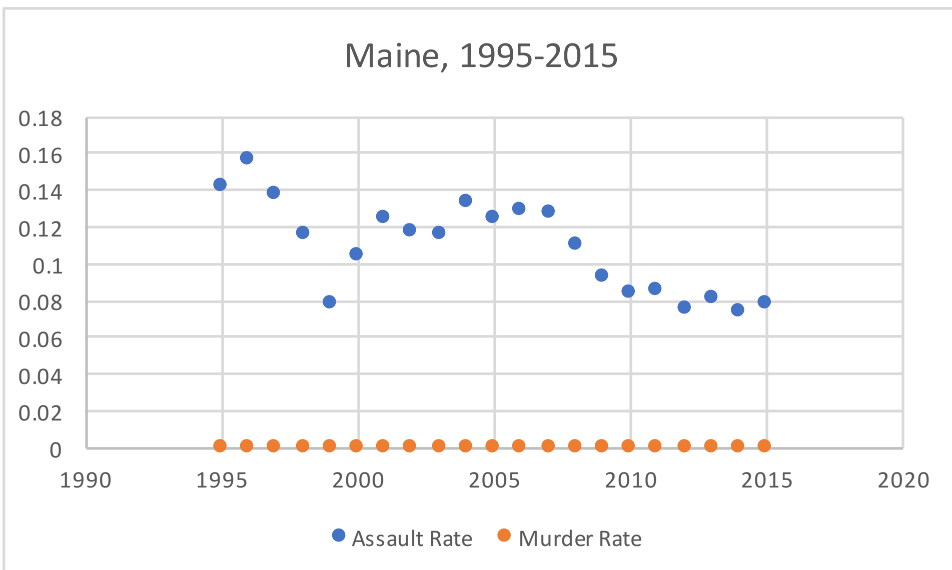
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate


Maine, 1995-2015
0.18
0.16
0.14
0.12
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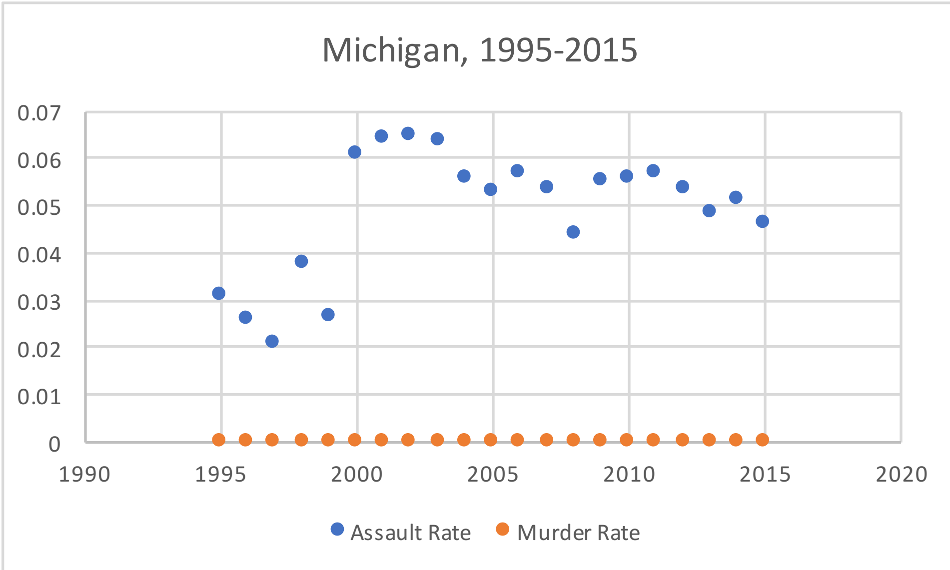
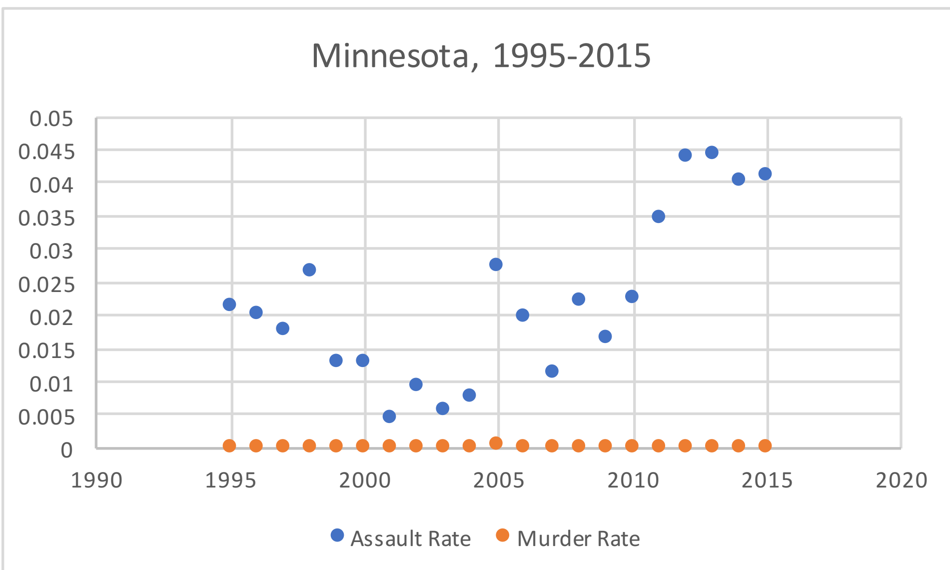
0.08
0.06
0.04
0.02
0
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate


Michigan, 1995-2015
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate


Minnesota, 1995-2015
0.05
0.045
0.04
0.035
0.03
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0.02
0.015
0.01
0.005
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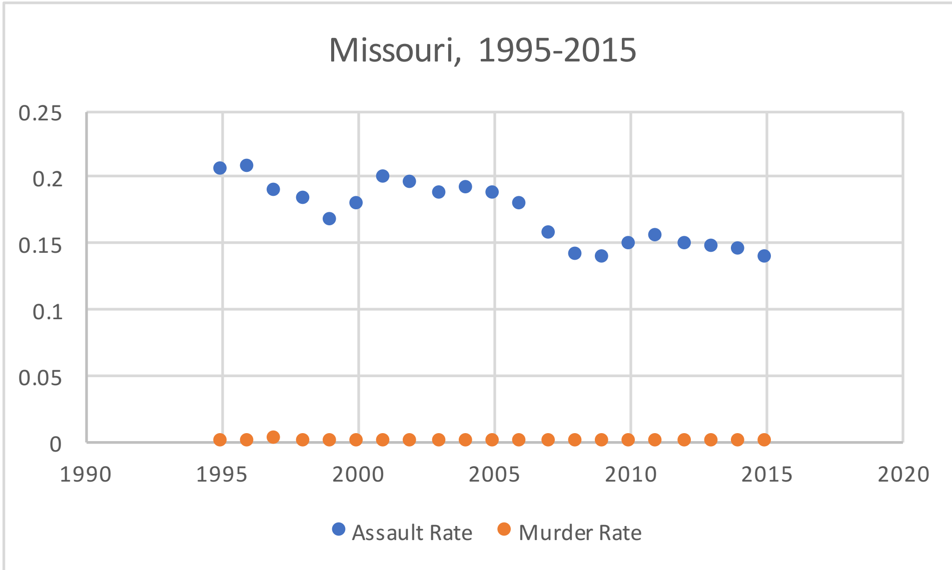
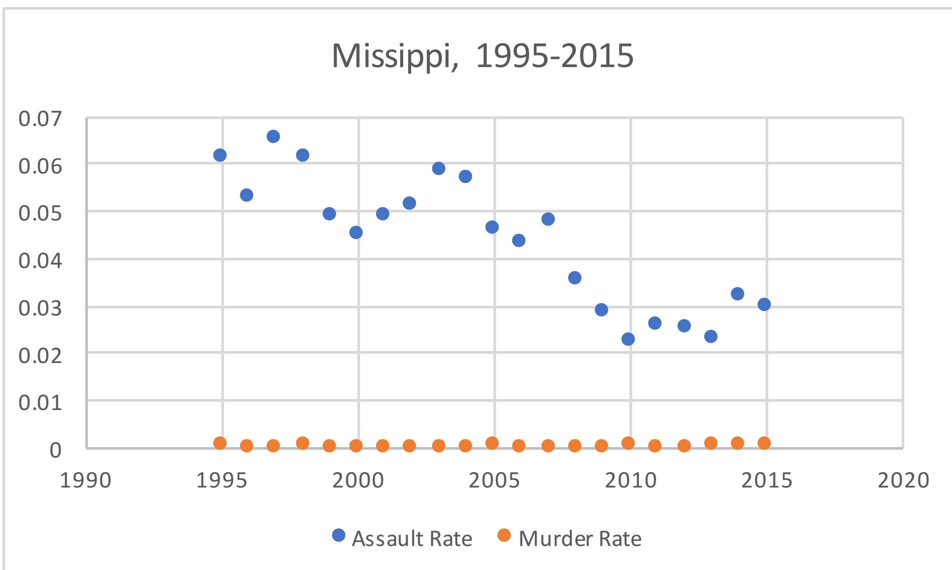
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate


Missouri, 1995-2015
0.25
0.2
0.15
0.1
0.05
0
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate


Missippi, 1995-2015
0.07
0.06
0.05
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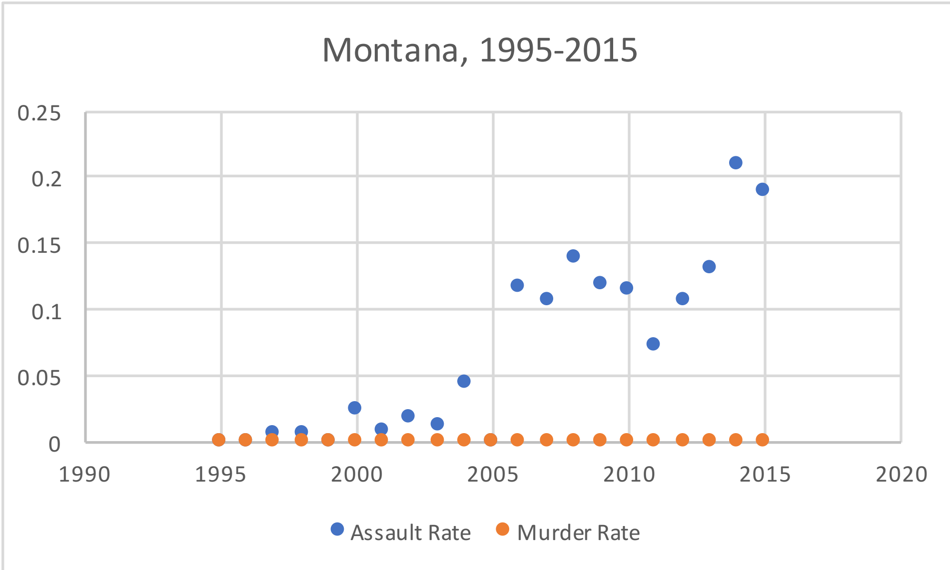
0.03
0.02
0.01
0
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate


Montana, 1995-2015
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0.2
0.15
0.1
0.05
0
1990
1995
2000
2005
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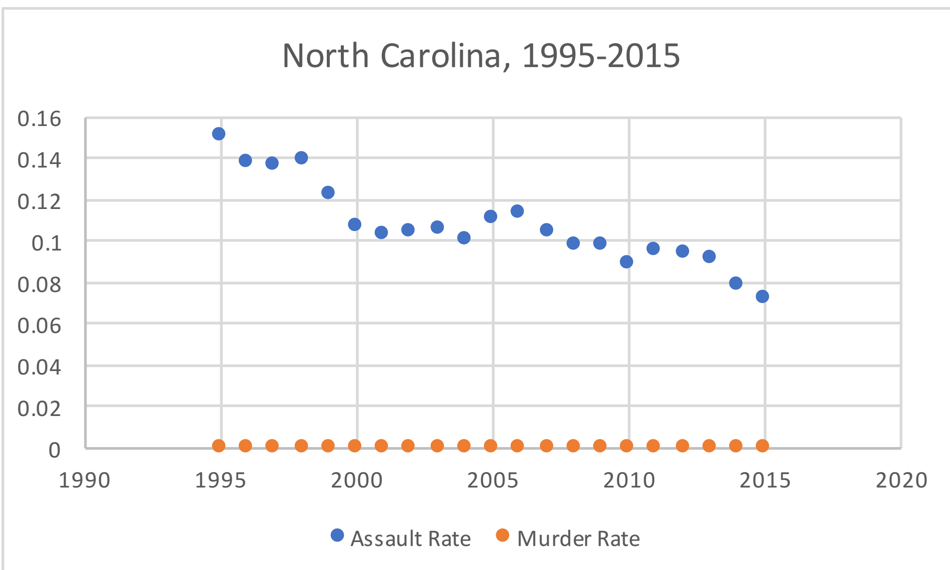
2015
2020
Assault Rate
Murder Rate


North Carolina, 1995-2015
0.16
0.14
0.12
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0.06
0.04
0.02
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1990
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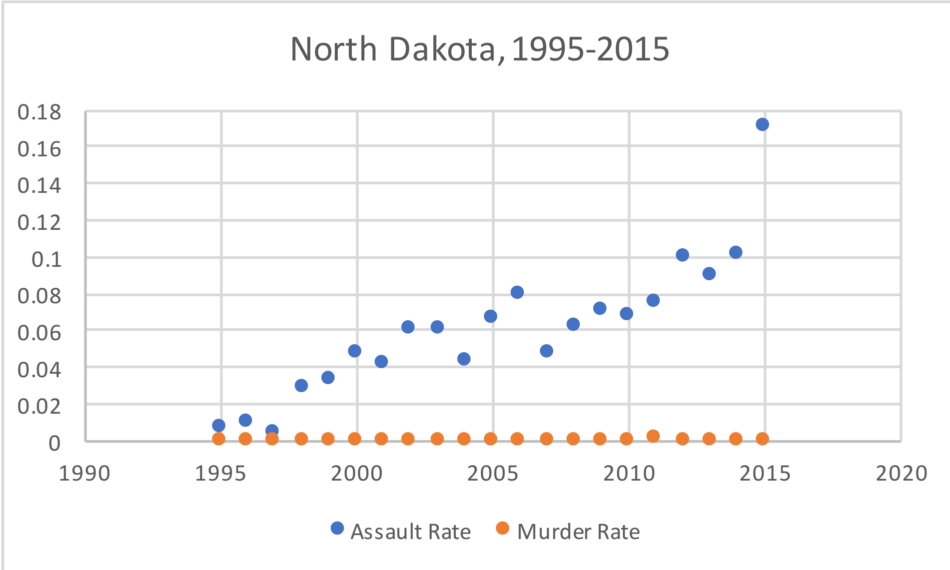
2000
2005
2010
2015
2020
Assault Rate
Murder Rate


North Dakota, 1995-2015
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0.16
0.14
0.12
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0.06
0.04
0.02
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1990
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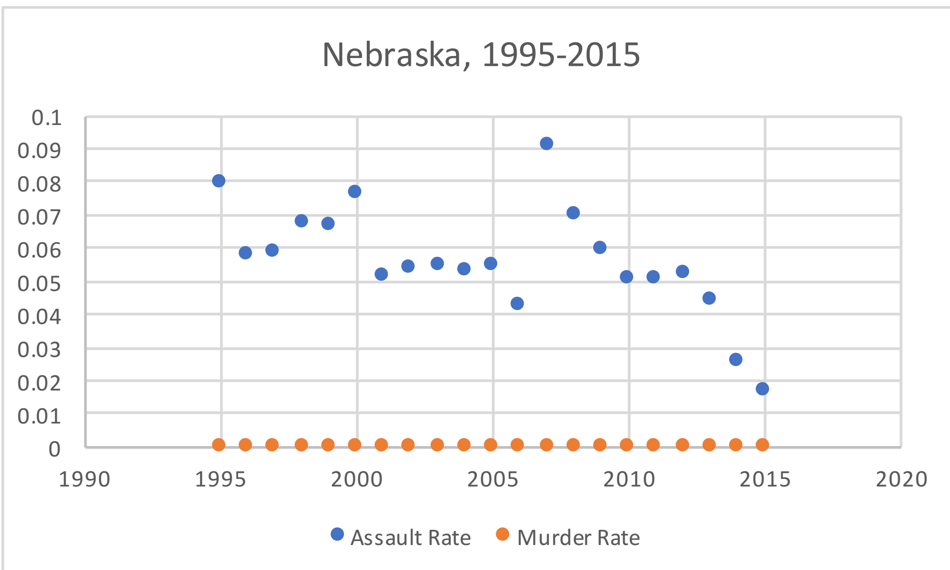
2000
2005
2010
2015
2020
Assault Rate
Murder Rate


Nebraska, 1995-2015
0.1
0.09
0.08
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0.06
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0.03
0.02
0.01
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1990
1995
2000
2005
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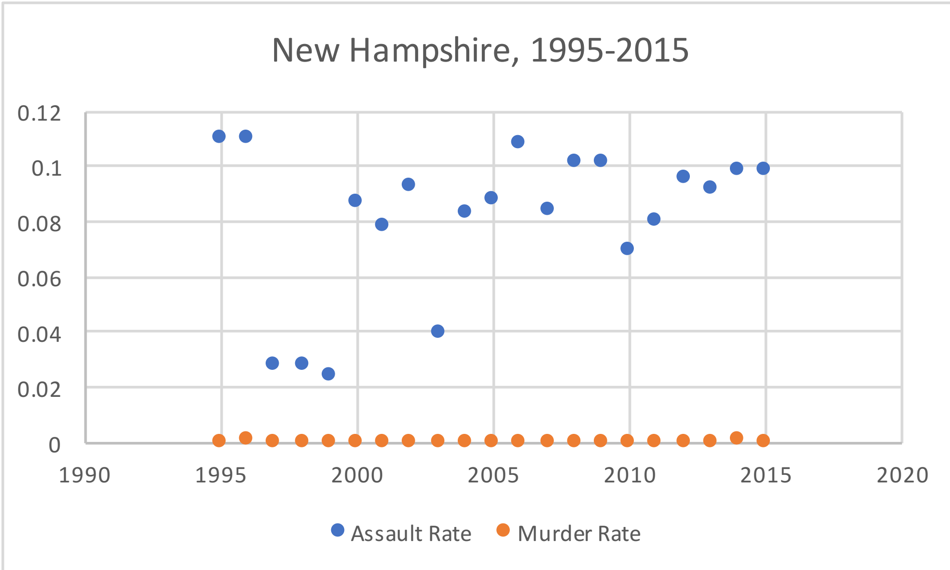
Assault Rate
Murder Rate


New Hampshire, 1995-2015
0.12
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0.04
0.02
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1990
1995
2000
2005
2010
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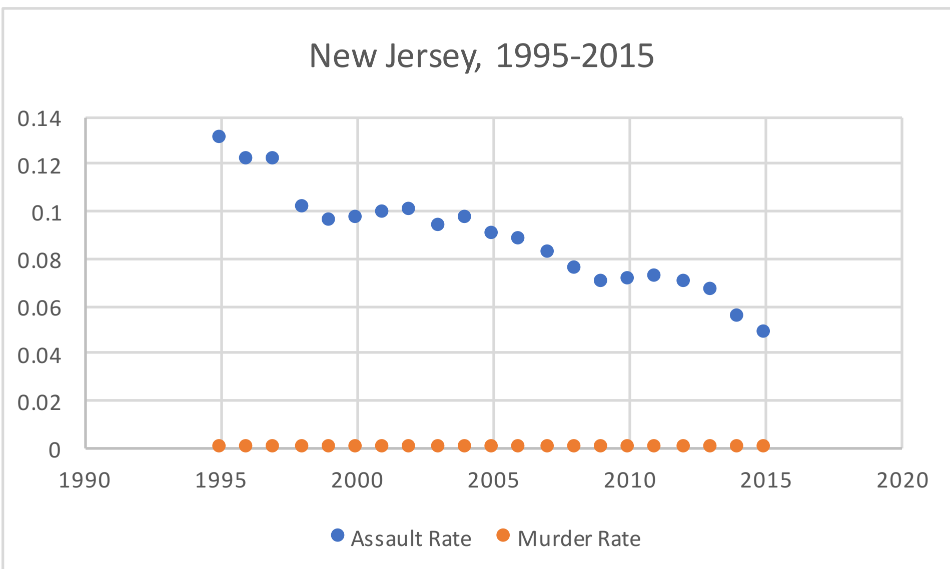
2020
Assault Rate
Murder Rate


New Jersey, 1995-2015
0.14
0.12
0.1
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0.06
0.04
0.02
0
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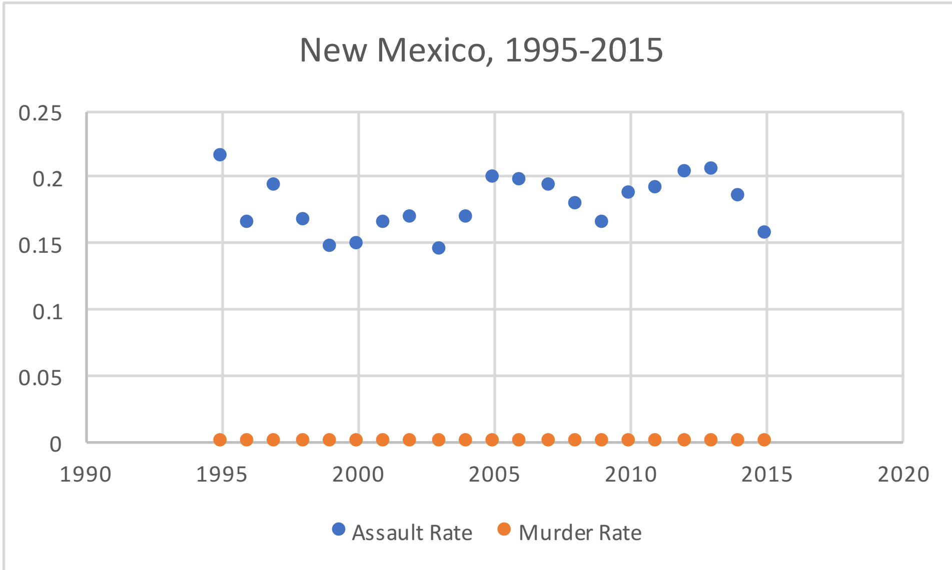
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate


New Mexico, 1995-2015
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0.1
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1990
1995
2000
2005
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2015
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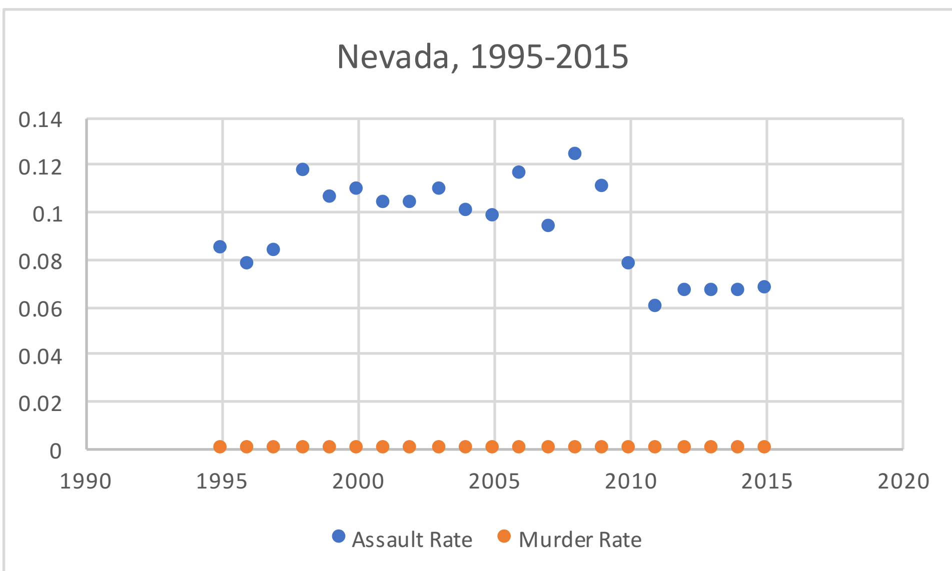
Assault Rate
Murder Rate


Nevada, 1995-2015
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0.12
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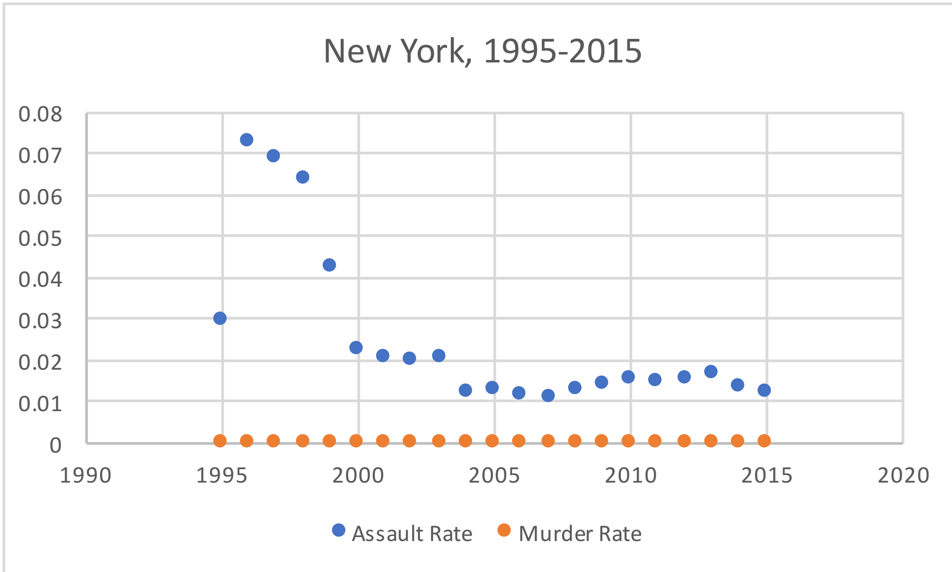
0.06
0.04
0.02
0
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate


New York, 1995-2015
0.08
0.07
0.06
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0.03
0.02
0.01
0
1990
1995
2000
2005
2010
2015
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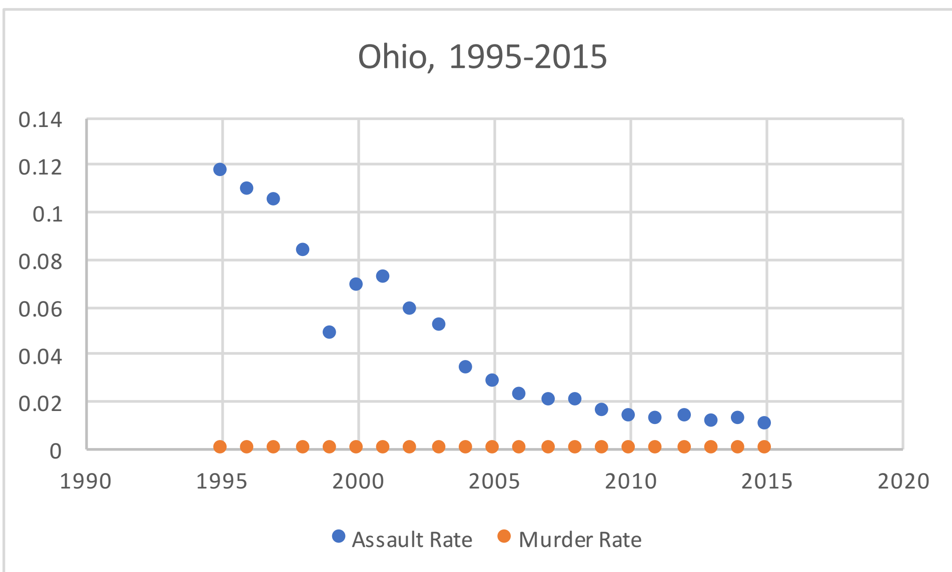
Assault Rate
Murder Rate


Ohio, 1995-2015
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0.12
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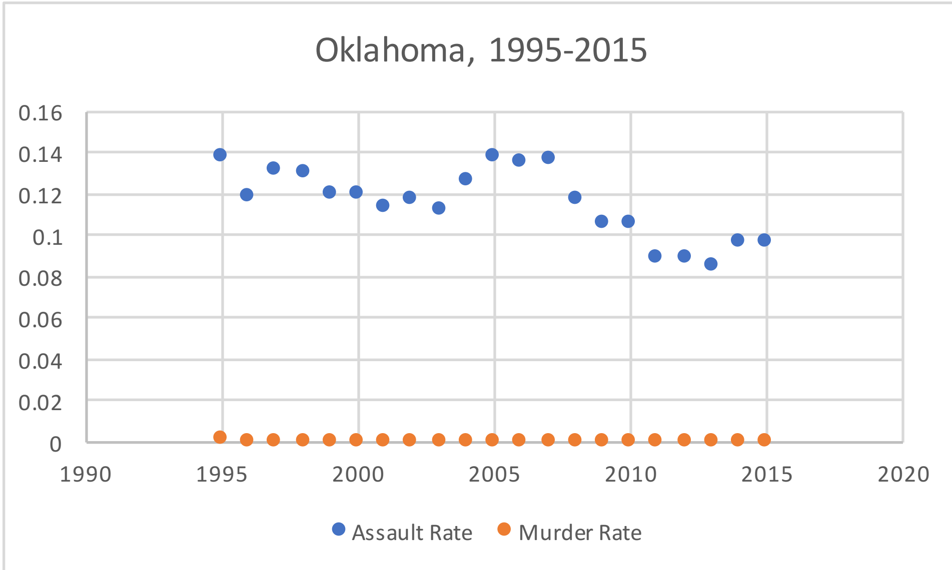
0.08
0.06
0.04
0.02
0
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate


Oklahoma, 1995-2015
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0.14
0.12
0.1
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0.04
0.02
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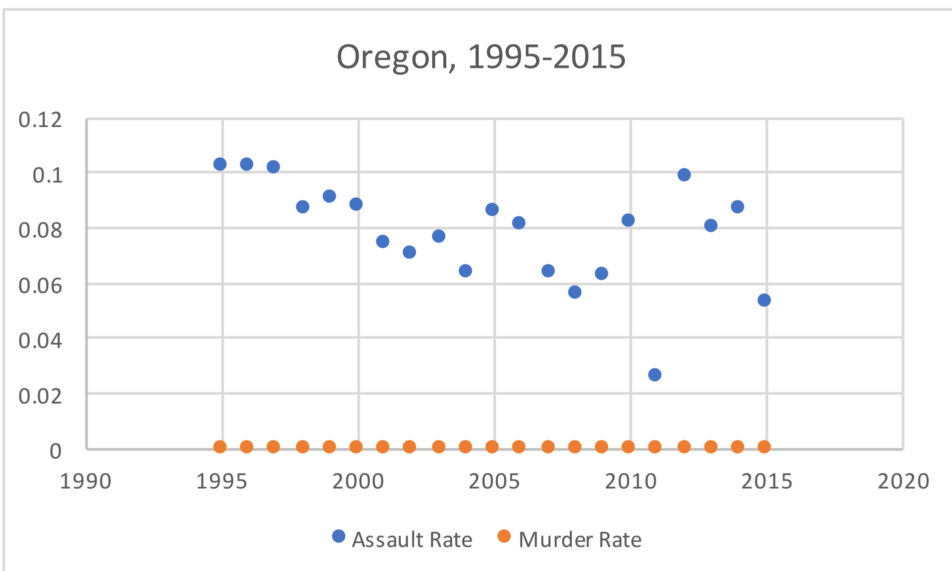
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate


Oregon, 1995-2015
0.12
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0.06
0.04
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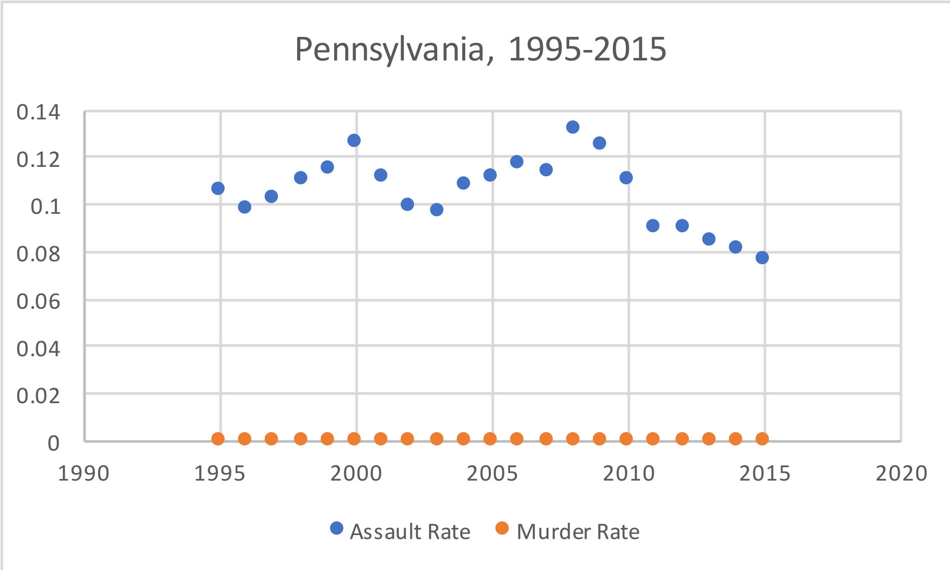
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate


Pennsylvania, 1995-2015
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0.12
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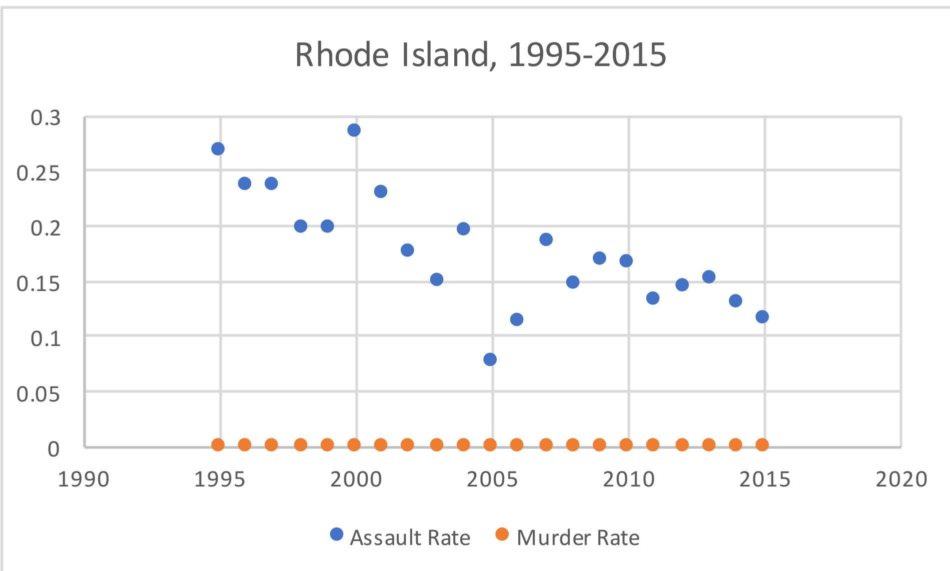
0.08
0.06
0.04
0.02
0
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate


Rhode Island, 1995-2015
0.3
0.25
0.2
0.15
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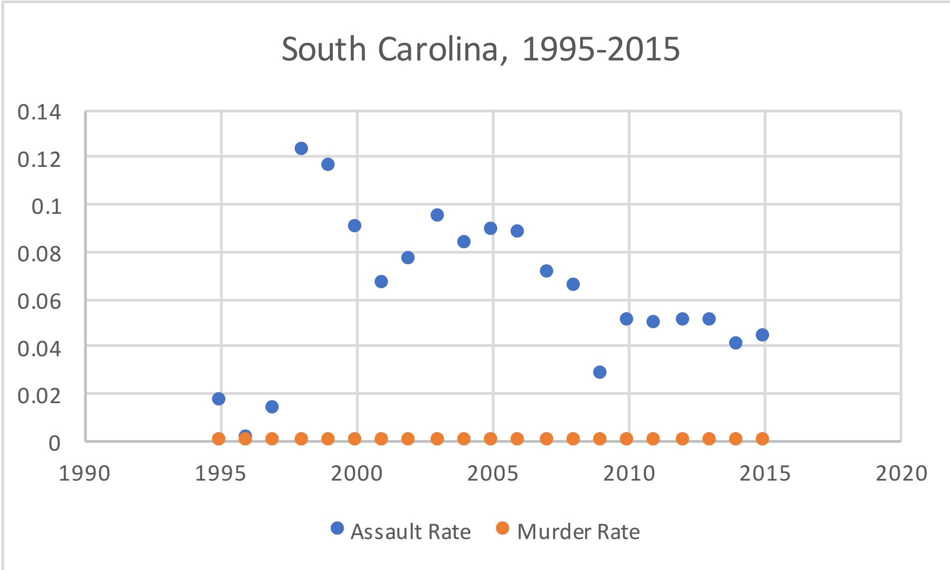
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate


South Carolina, 1995-2015
0.14
0.12
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0.04
0.02
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1990
1995
2000
2005
2010
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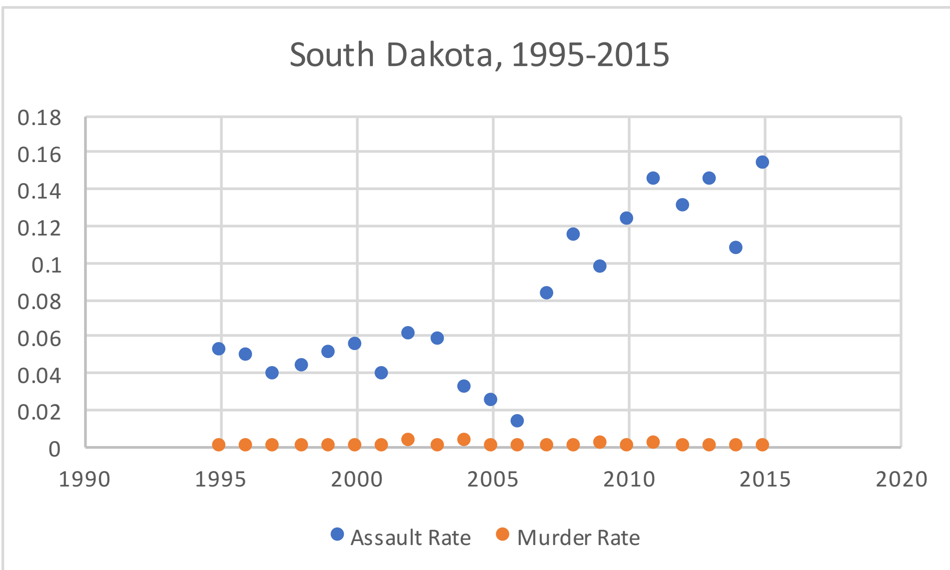
Assault Rate
Murder Rate


South Dakota, 1995-2015
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0.16
0.14
0.12
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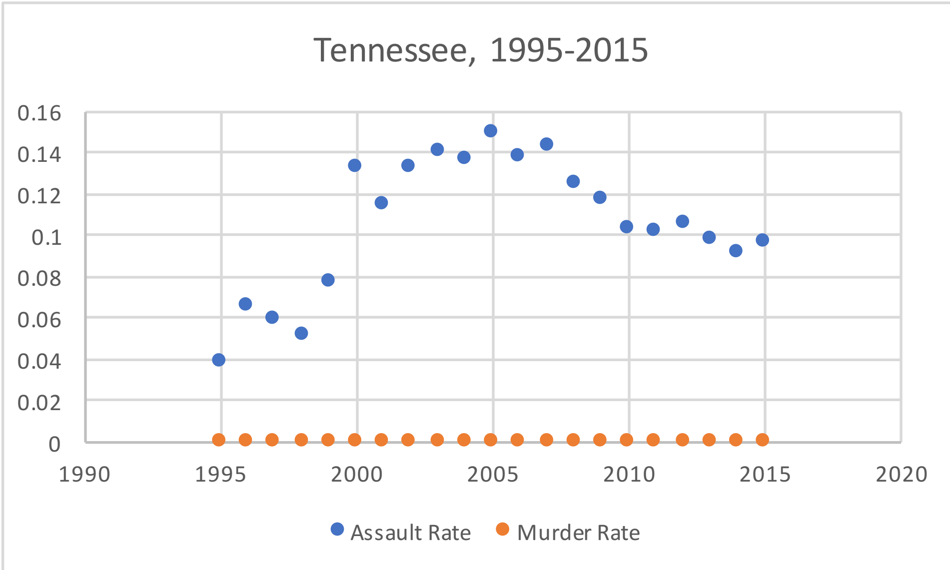
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate


Tennessee, 1995-2015
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0.14
0.12
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0.04
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1990
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2000
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2010
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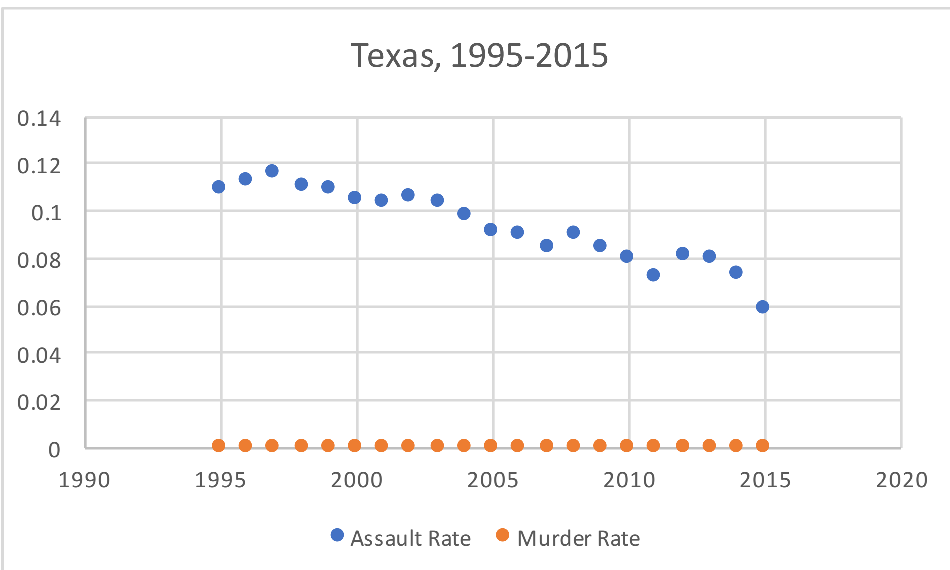
Assault Rate
Murder Rate


Texas, 1995-2015
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0.12
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0.04
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0
1990
1995
2000
2005
2010
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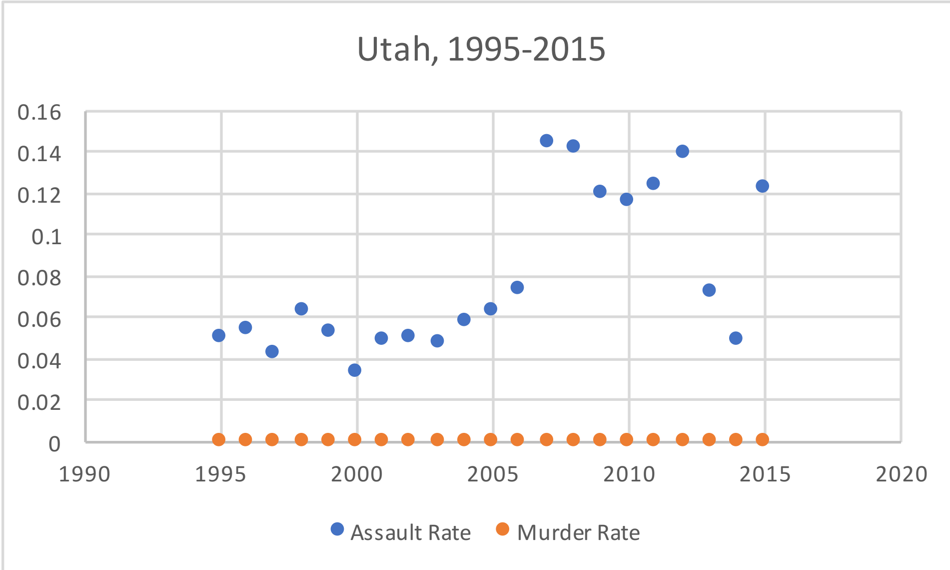
Assault Rate
Murder Rate


Utah, 1995-2015
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0.14
0.12
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0.06
0.04
0.02
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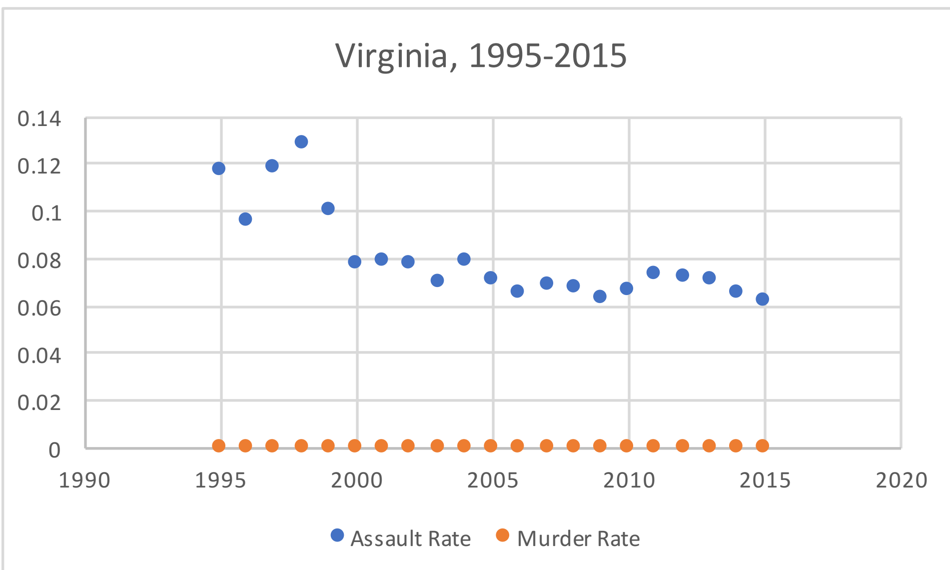
2000
2005
2010
2015
2020
Assault Rate
Murder Rate


Virginia, 1995-2015
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0.12
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0.06
0.04
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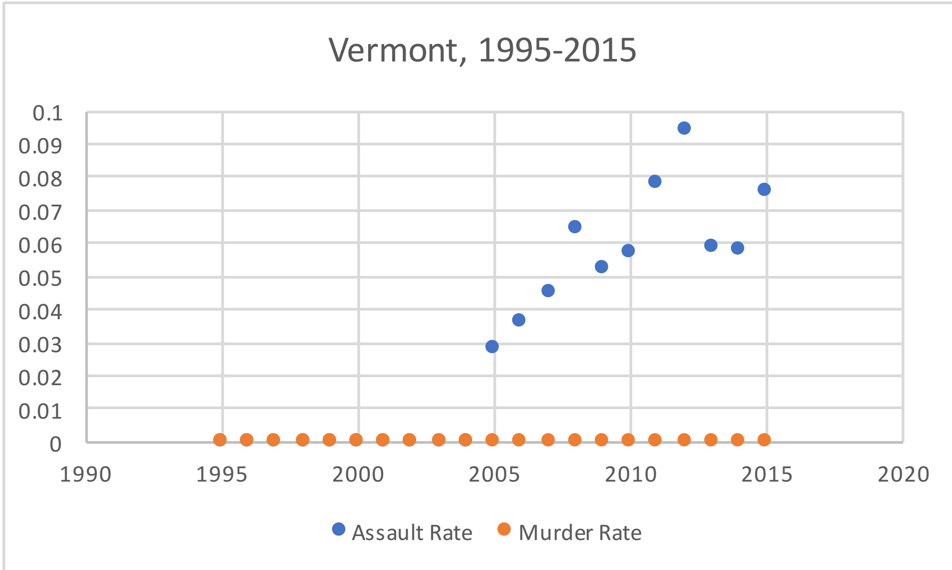
0
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate


Vermont, 1995-2015
0.1
0.09
0.08
0.07
0.06
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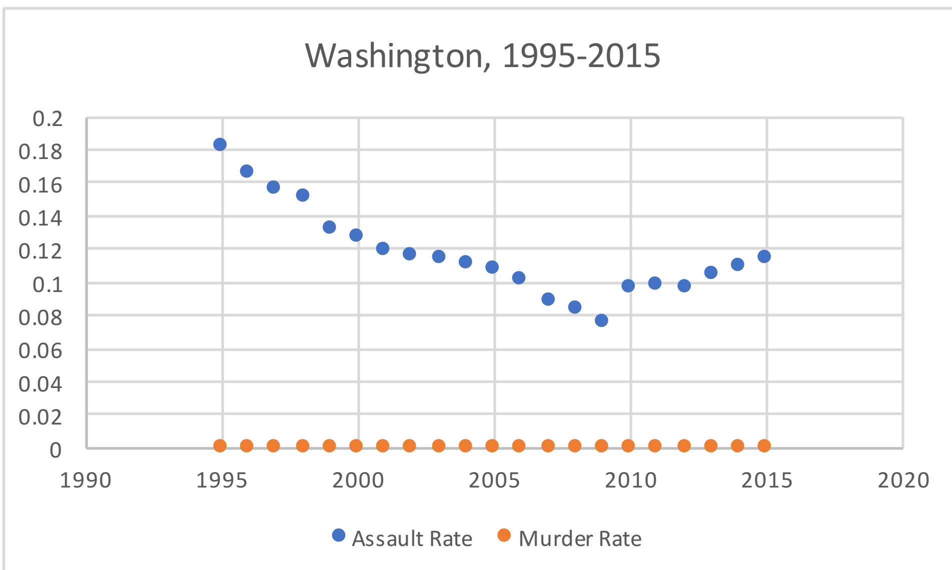
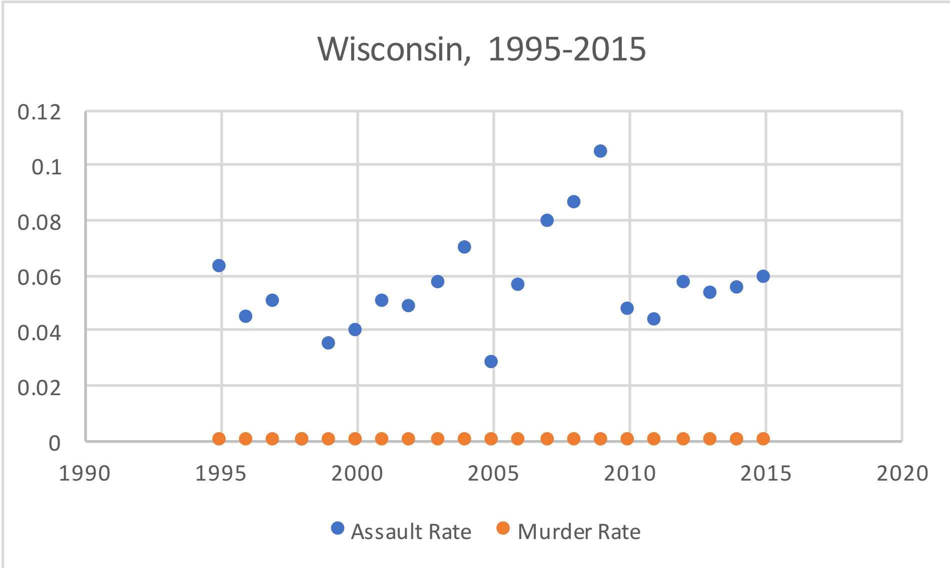
0.04
0.03
0.02
0.01
0
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate


Washington, 1995-2015
0.2
0.18
0.16
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate


Wisconsin, 1995-2015
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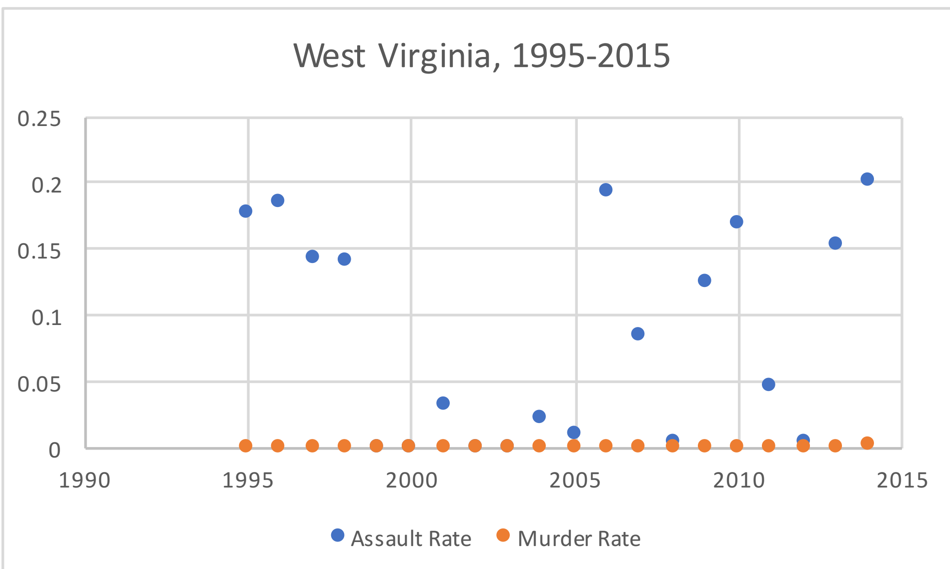
0.06
0.04
0.02
0
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate


West Virginia, 1995-2015
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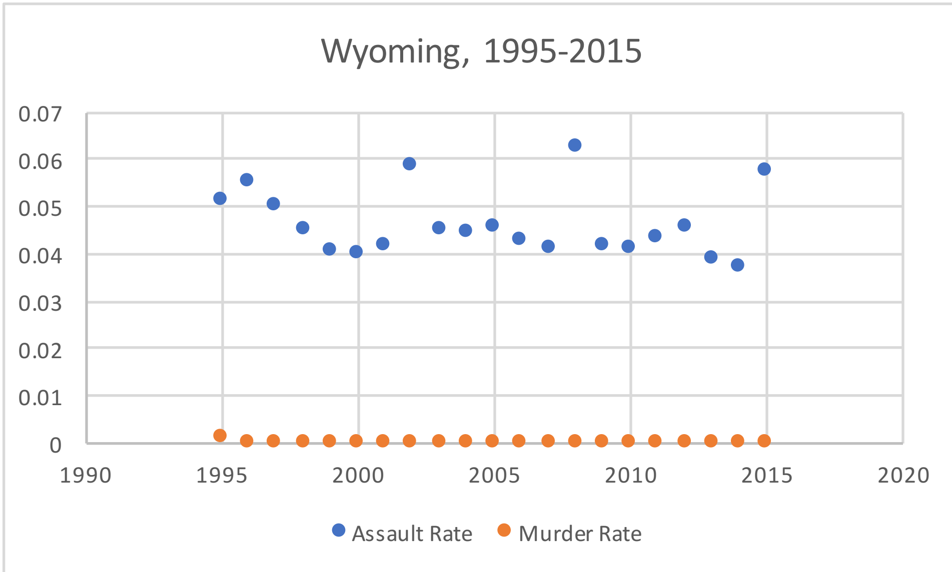
0.2
0.15
0.1
0.05
0
1990
1995
2000
2005
2010
2015
Assault Rate
Murder Rate


Wyoming, 1995-2015
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
1990
1995
2000
2005
2010
2015
2020
Assault Rate
Murder Rate

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