Hate Managers and Where They Target: An Analysis of Hate Crime as Hate Group Self-Help

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Abstract

I explore the relationships between hate group activity, community factors, and the likelihood of hate crime occurrence within a county area. I integrate considerations raised by Routine Activity and Social Control theorists as well as current hate crime literature to frame my concept of the hate manager, an agent of social control that utilizes hate crimes as a means of enacting extralegal self-help for hate groups. I explore the relationship between hate managers and hate crime by testing a model relating hate group activity and hate crime occurrences by location. Next, I correlate hate crime occurrences with hate group activity at the county level for the state of Virginia using public data. I find that a hate group's presence holds greater predictive power than nearly any other factor for hate crime likelihood. My findings illustrate the nature of hate crime as a means of social control; whereby hate groups act as a parochial order and maintain hierarchical relations between offenders and victims through means of disciplinary crimes. I conclude by outlining suggestions for future research into the role of the hate manager.

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General Audience Abstract

In my thesis, I ask the question of how hate groups methodically encourage where hate crimes occur. I do this by creating the concept of the hate manager. Hate managers are figures which influence would-be criminals into their illegal acts. They do this by stoking the fears necessary for them to act outside legal boundaries in reaction to some feeling of threat, an act known as self-help. Hate crimes, I argue, are a form of self-help where the feeling of threat is directed towards individuals belonging to some marginalized group. By looking at data collected by various agencies in the state of Virginia, I discover that the presence of a hate group in a county is a stronger predictor for such acts than any other factor for hate crime likelihood. By doing so, I demonstrate that hate crimes are a form of social control. That is, I argue that hate groups maintain a sense of order or ranking by means of illegal and disciplinary self-help in the form of hate crimes. I conclude my thesis by outlining suggestions for future exploration of the hate manager's role.

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Chapter One: Overview, Literature Review, and Theoretical Foundations

Overview

Historical evidence demonstrates that hate group attention or presence can have a serious effect on the occurrence of hate crime and influence said groups' locales. Recent events likewise give reason to suspect that certain hate crime would not be committed without access to necessary information that routine visits of websites provide. To illustrate, consider that the harassment campaign or "troll storm" that Andrew Anglin ran against Jewish real estate agent Tanya Gersh would not have been possible without the resources that Anglin's Neo-Nazi website, the Daily Stormer, provided (Strickland and Gottbrath 2017). Likewise, the events surrounding the "Unite the Right" rally in Charlottesville, Virginia, where, among other violent occurrences, a 20-year-old man named James Alex Fields Jr. rammed a car into anti-racist protestors, killing thirty-two-year-old Heather Heyer, are intimately linked to the massive prior attention the rally had received in online circles (Al Jazeera News 2017; Strickland 2017). In short, these events demonstrate a need to explore the relationship between the hate group's online presence and the actual offenses, such as those committed by Anglin and Fields.

Hate Crime Literature

To begin, I integrate Barbara Perry's definition of hate crime into my thesis. Perry (2001) defines hate crime as "a mechanism [or mechanisms] of power intended to sustain somewhat precarious hierarchies, through violence and threats of violence (verbal or physical). [This violence] is generally directed toward those whom our society has traditionally stigmatized and

marginalized" (p. 3). This definition is in sharp contrast with the more succinct definition offered by the Federal Bureau of Investigation, that is, a hate crime is a "…criminal offense committed against a person or property which is motivated, in whole or in part, by the offender's bias against a race, religion, disability, sexual orientation, or ethnicity/national origin" (ICPSR 2009:84).

However, the FBI's definition reduces the social implications of the act to a matter of legality that depends on the subjective decisions of policymakers and law enforcement, ignoring the fact that laws change, are applied differentially, and are enforced differentially. Because of such differentiation, actions that one might reasonably call hate crime today have served to benefit powerful parties and the state in the past, such as killing and stealing from Native Americans (Perry 2001). Furthermore, as Woolf and Hulsizer note, "hate groups have operated in many areas around the United States with relative impunity as some government officials have turned a blind eye to hate group activities…[because] [l]ocal elected officials and law enforcement officials are not exempt from holding belief systems grounded in hate" (2004: 57). In keeping with Perry's definition of hate crime, Woolf and Hulsizer (2004:41) define a hate group as "any organized group whose beliefs and actions are rooted in enmity towards an entire class of people based on ethnicity, perceived race, sexual orientation, religion, or other inherent characteristic."

With this information in mind, it is important to also remember that there is neither a single type of hate crime nor a single type of hate crime perpetrator (Walters, Brown, and Wiedlitzka 2016:8). Rather, "in order to fully understand the nature of hate crime, practitioners

need to appreciate that situational factors (that is, location and victim-perpetrator relationships) may differ depending on the type of offence (for example, verbal abuse, harassment etc.) and the type of hate-motivation." (Walters et al. 2016:8). This line of thinking couples with the fact that most hate crime is not committed by hate groups, but rather by "groups of thrill-seeking youth who lack firm ideological beliefs or hate group affiliation" (Mills, Freilich, and Chermak 2017:6).

In fact, in the early 1990s, researchers Levin and McDevitt (1993) developed a typology of hate crime offender motivations which categorizes offenses as thrill based, reactionary, or mission based. To explain, recent work shows that "more than half of all hate crime [is] categorized as *thrill-motivated,* that is, as attacks on people who are different in some social significant way to gain a sense of power and dominance as well as peer acceptance" (Levin and Reichelmann 2015:1547). To explain, in their updated typology of hate crime motivations, McDevitt, Levin, and Bennett (2002) note that there can be four different categories of hate offenders. "In *thrill* crimes…the offender is set off by a desire for excitement and power; *defensive* hate crime offenders are provoked by feeling a need to protect their resources under conditions they consider to be threatening; [and] *retaliatory* offenders are inspired by a desire to avenge a perceived degradation or assault on their group" (McDevitt et al. 2002: 306). The fourth, and thankfully rarest group, "*mission* offenders," are those who are totally committed to their crimes, viewing themselves as crusaders against evil (McDevitt et al. 2002:309).

Despite this noted rarity, researchers have indicated a notable rise in hate crime committed by persons affiliated with hate groups through the years (Turpin-Petrosino 2004). To

contextualize this finding, Adamczyk, Gruenewald, Chermak, and Freilich (2014: 323) found

that of the counties in the United States that experienced a far-right ideologically motivated

homicide in the 1990s and 2000s, counties with at least one hate group experienced 6.15% of all

1990s incidents and 3.96% of all 2000s incidents, while counties with no hate groups only

experienced 0.64% of all 1990s incidents and 0.56% of all 2000s incidents.

Likewise, Mills, Freilich, and Chermak (2017: 12) find that "[o]ffenders who subscribe to

extremist right-wing ideology…prove more likely to resort to both ideologically motivated hate

crime and terrorist acts than non-ideological offenders."[1] Furthermore, and true to Perry's

conceptualization, Walters argues that hate crime typically results from fear or belief that said

stigmatized people will "encroach upon the offender's group identity, cultural norms and/or

socio-economic security" (Walters 2011:.315). Such arguments are supported by D'Alessio,

Stolzenberg, and Eitle's (2002: 403) findings that "as the ratio of black-to- white unemployment

decreases and the perceived threat of blacks taking jobs away from whites grows, whites are

more likely to criminally victimize blacks." As such, certain historical developments can cause

(and have caused) the popular motivations of hate crime to change.

While initially researchers characterized thrill as the prevalent motivation for hate crime,

there has been a noticeable increase in defensive hate-motivated assaults in the United States

since September 11, 2001 (Levin and Reichelmann 2015). Levin and Reichelmann note that

while thrill-motivated crimes still tend to be perpetrated by groups of teenagers and young

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[1] This is historically contextual, however, as left-wing extremism or armed struggle as popularized by Mao Zedong, Che Guvara, Tupamaros, and the Sendero Luminoso in the 1960's and 1970's greatly exceeded efforts of right-wing counterparts (see Malkki 2019).

adults, there was also an increase of both single-offender incidents as well as those perpetrated by those over the age of thirty with a simultaneous decline of offenders in their 20s (2002:1552). Likewise, they also note that as hate crime against Muslims and Arabs dramatically increased immediately following 9/11, so did an increase of immigrants and a rise in the national unemployment rate coincide with anti-Latino assaults, and the candidacy, campaign, and victory of Barack Obama in the 2008 presidential race coincide with hate crime against Black Americans.

In short, the literature suggests that, true to Perry's conception, hate crime holds a much stronger societal and structural component than the psychological, legalistic, and motive-based conceptualizations imply. The constant appearance of fear as an implied theme behind the shifts and demographics leads to curiosity about what exactly causes and influences such fear? To summarize, the literature leads me to believe that some social component or components might serve as a link or influence for the motivational and demographic shifts.

Social Control Theory

Although they discuss and document motivational and demographic shifts, few researchers attempt to examine hate crime in a structurally-based theoretical framework. As Hopkins, Burke and Pollock note, "[t]here is invariably an assumption that the perpetrators of such offenses are in some way psychologically troubled individuals or groups of such like-minded individuals" (2004: 6). With such little theoretical framing, researchers have a large task ahead of them to properly address the issues and complexities surrounding hate crime. As a means of remedy, I begin my theoretical considerations by addressing specific hate crime

locations, an area currently marked by scant theoretical consideration, much less empirical research.

However, the considerations of hate crime as being primarily a fear-based reaction as well as the defensive and retaliatory motivations described above synergize with the conceptualization of hate crime as a social control. In this context, social control refers to "how people define and respond to deviant behavior…It thus includes punishment of every kind—such as the destruction or seizure of property, banishment, humiliation, beating, and execution" (Black 1993c: 4). The conceptualizations offered lend themselves to the view of hate crime, especially when defensive or retaliatory in motive, as being primarily a means of addressing a grievance, or a form of self-help (Black 1993b:41).

In particular, defensive motivated hate crime can be conceptualized as forms of discipline or rebellion. To clarify, defensive motivated crimes require the presence of a threat great enough to warrant extralegal action. Self-help, being a one-way and aggressive form of handling grievances, includes such action (Black 1993a). Likewise, discipline and rebellion refer to forms of self-help whereby the applicants attempt to address a grievance in relation to inequality in an authoritarian and penal style, with discipline being downward self-help and penalizing those lower in a hierarchical society and vice-versa for rebellion. As Black (1993a:78) notes, a parasitical hierarchy type society is the most conducive to this form of self-help. Consequently, the social structure of discipline and rebellion typically has five characteristics:

1. *Inequality*: The greater the inequality, the more severe the self-help.
2. *Vertical segmentation:* Discipline and rebellion will usually occur between classes rather than within them.

3. *Social distance*: The greater the social distance, the more discipline. The same goes for cultural distance.
4. *Functional unity*: The greater the functional unity, the more likelihood a group will participate in discipline or rebellion.
5. *Immobility:* For discipline or rebellion to occur, the parties must share a social space and lack the ability to easily leave it[2].

With this in mind, I turn attention to relating hate crime as social control to the places where such crimes occur.

To begin, I briefly outline the nature of social orders in order to contextualize the theoretical elements I am applying. In short, as Hunter (1985) explains in his analysis of social control in urban neighborhoods, social order can be classified into three different levels. The *civil* or *public* order, the *sacred* or *parochial* order, and the *private* or *personal* order[3]. Each order carries with it a spatial domain, with the personal being found in network relations linking the household to the greater metropolitan environment and defined by intimates and friends.

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[2] These five characteristics can be defined as such:
Inequality: *Significant socioeconomic disparity between groups in a community.*
Vertical Segmentation: *Hierarchical class distinctions between groups in a community.*
Functional Unity: *Group effort towards some end or goal, usually in a workplace setting.*
Social Immobility: *Shared social space without easy escape.*
Social Distance: *Significant amounts of hierarchical heterogeneity.*

[3] Hunter (1985) defines the orders in relation to their social bond, institutional locus, and spatial domain, the last of which I discuss in the main text. The civil social order holds a neutral, universal, formal, and ritualized nature, neutral social affectation, and an institutional base in the formal and bureaucratic state agencies (Hunter 1985: 232-234).

Likewise, Hunter (1985) explains that the parochial order holds an intermediate social affectation and uniformity. It's institutional base in local interpersonal networks and local/residential institutions. The parochial order holds two values: "providing mutual aid and sustenance support" and differential community power arrangements. (p. 233-234).

Finally, participants negotiating their social bonds uniquely construct and see the emergence of the private social order (Hunter 1985:232). As such, the private order's institutional basis resides in informal and formal groups alike, "…where the values of sentiment, social support, and esteem are the essential resources of the social order and the basis of social control" (Hunter 1985:232).

Likewise, the parochial order's domain is typically found in the neighborhood and defined by "neigh-dwellers, co-habitants of a common area sharing a common fate" (Hunter 1985:235). Lastly, the public order's domain is found in "those locations where people are most likely to be interacting solely as citizens" (Hunter 1985:235).

These three spheres of social order often intersect and interpenetrate one another. Indeed, Carr (2003) makes a compelling argument for the *new parochialism,* an informal social control which relies upon interplay between the parochial and public spheres. Furthermore, Hunter finds that disruptions may emerge from any social order but resulting attempts at control often emerge from all three spheres. As hate groups, being primarily status-based task groups, fit best into the parochial definition and given the considerations of spatial domain, the question remains regarding how hate groups' spatial domains relate to hate crime occurrences. To begin to answer that question, I must address the role of places within that domain in a hate crime occurrence.

Routine Activity Theory

Fortunately, the principles of Routine Activity Theory (RAT) offer a way to successfully address places' role in hate crime occurrence. In general, Routine Activity Theory explains structural changes in routine activity patterns as the primary influence in direct-contact, predatory crime rates. In this context, routine activities are "any recurrent and prevalent activities which provide for basic population and individual needs, whatever their biological or cultural origin" (Cohen and Felson 1979:593.) Such influence, Cohen and Felson argue, is evidenced by any one of the three required elements for a criminal offense, "...an *offender* with both criminal

inclinations and the ability to carry out those inclinations, a person or object providing a suitable *target* for the offender, and absence of *guardians* capable of preventing violations" (1979: 590).

In his 1994 dissertation, John Eck combined RAT with the rational choice perspective to stress the importance of individual places in crime theory. To Eck (1994), *places* are defined as "(a) having known geographic locations, (b) having boundaries, (c) a dominant function or purpose, [and] (d) someone or something with legal control over how the place is used [called a manager]" (1994:10-12).

In integrating places and managers to Routine Activity Theory, Eck created the "Crime Triangle." This idea is best represented by Figure 1: a recreated model of two nested triangles, the outer triangle (black) represented the *facilitators* for crime, with the inner triangle (red) representing the *controllers*. As Eck describes, "[c]rime is more likely when the elements in the outer triangle converge and all the elements in the inner triangle are missing than when any one of the inner triangle elements are present" (1994:29).
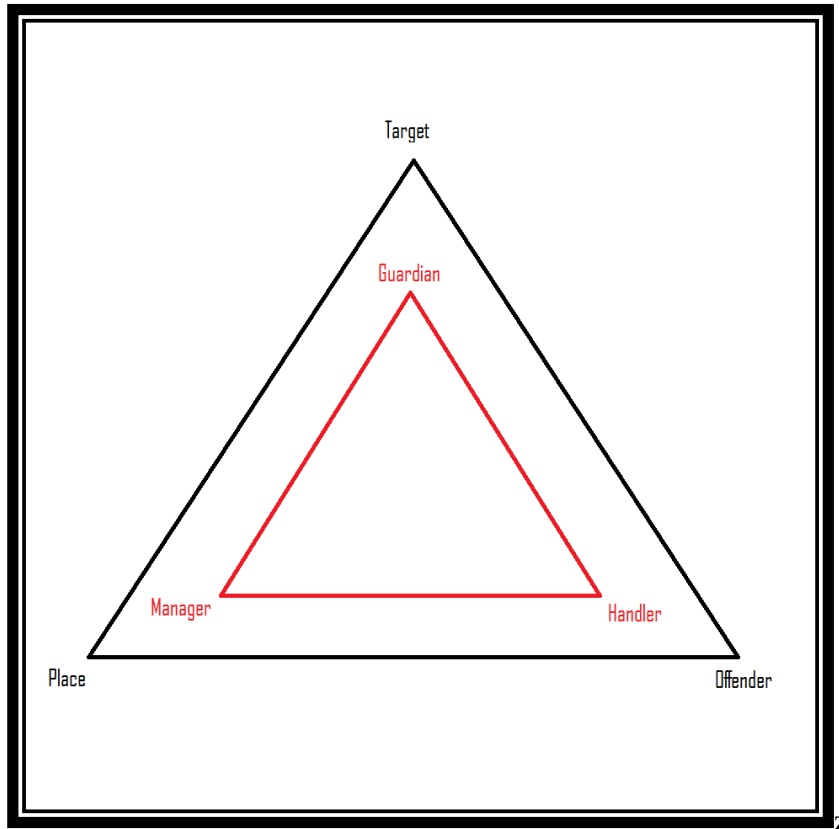
Figure 1: The Crime Triangle

To clarify, in the context of RAT, while *facilitators* refers to the offenders, targets, and places present during an individual crime, controllers consist of *guardians*, *handlers*, and *managers*. In this context, *guardians* are simply those groups that protect people and/or property from harm. They are seen in the public sphere as local police or security forces as well as the parochial sphere as neighbors. *Handlers*, though similar to guardians in their function, are distinguished primarily by their relation to the would-be offender serving as a deterrent from criminal activity. As Felson (1986:121) explains, "[s]ociety gains a *handle* on individuals to prevent rulebreaking by forming the social bond. People have something to lose if others dislike

their behavior, if their future is impaired, if their friends and families are upset with them, [and so on]." Accordingly, handlers can include parole officers or family members, among others. Finally, *managers*, as explained by Eck (1994), are those who have authority over places. These can include landlords, homeowners, apartment maintenance, flight attendants, park rangers, traffic cops, school resource officers, and so on.

In a later article, Sampson, Eck, and Dunham (2010: 40) expand on the controller idea to create the concept of a *super-controller:* "the people, organizations and institutions that create the incentives for controllers to prevent or facilitate crime." Such choices apply influence by making choices about how to manipulate "effort, risk, reward, [and excuses] and [how to reduce] provocations" (Sampson et al. 2010:45).

Super-controllers are usually categorized as formal, diffuse, or personal. To explain, *formal* supercontrollers consist of those who rely on some sort of authority to influence a controllers' behavior. For a parental guardian figure, a family court might serve as a super-controller the same way that a corporate structure serves as a super-controller for the manager of a grocery store. *Diffuse* supercontrollers are collections that influence controllers whose power "…rests on their ability to alter a broad set of circumstances around a somewhat amorphous set of controllers" (Sampson et al. 2010:43). As such, they also can influence each other as well as formal or personal super-controllers. Political institutions, market pressures, and publicity are all examples of diffuse super-controllers. Finally, *personal* super-controllers are those that rely on those domains and connections present in the personal and parochial social orders to exert influence. A parent's peer groups or other family members might act as super-controllers in how

they guard or handle their own children. The understanding of these elements will help to frame my methodology.

Theory Integration: Hate Groups, Spatial Domain, & The Internet

To adapt these principles to digital environments, I turn to Futrell and Simi's (2004) finding that free spaces, or "environments where participants nurture oppositional identities that challenge prevailing social arrangements and cultural codes…are critical for cultivating the social networks that anchor oppositional subcultures [such as hate groups]" (p. 20). In this respect, the Internet functions as one such "free space" for hate groups to act.

Prior work in relation to hate groups and their online activity has been extensive. Numerous researchers have found that hate groups have made heavy use of the internet as a vehicle to spread their messages. As Grizzle and Toreno (2016: 181) note, "Most governments and international stakeholders involved in countering hate, radicalization and extremism identify social media and online spaces as primary tools being used by radical and extremist groups" (also see Costello et al. 2016:311). McNamee, Peterson, and Peña (2010) find four overarching themes in such messages: education and spreading of information, participation and promoting association with the group, invocation of natural superiority and authority, and indictment of other groups. In doing so, McNamee et al. (2010:273) also found that such themes may work together to "(a) reinforce hate group identity; (b) reduce external threats; and (c) recruit new members." Interestingly, Caiani and Parenti (2013:98) find that, among extreme-right groups "…it is common to find on extreme right websites launches of threats and offences between

them and their antagonists (such as other civil society organizations from the left, the police, etc.), which subsequently develop into offline clashes; or the other way around."

In addition, Hawdon, Oksanen, and Räsänen (2015) find that amongst adolescent and young adult survey respondents in Finland, the United States, Germany, and the United Kingdom, exposure to hateful material online was relatively common, with approximately 53 percent of American respondents reporting such exposure. Hawdon (2012) also finds that personalized information and communication technology-based experiences results in an environment whereby one who has a hate-oriented worldview can enter a community of like-minded people, access hate material, develop online connections with other hateful individuals and groups, and in the process, find their ideology reaffirmed and at worst, see their violent aspirations praised and encouraged. In this respect, the internet functions similarly to a neighborhood for the parochial order or hate group to exert control over, providing the fear necessary to foster the status relations and parochial bonds necessary for effective social control in the form of hate crime.

While neither hate groups nor their sites always advocate for violence, the link between their presence and hate crime remains unexplored. As Eck and Weisburd (2015: 6) note, "how targets come to the attention of offenders influences the distribution of crime events over time, space and among target.... While a few offenders may aggressively seek out uncharted areas, most will conduct their searches within the areas they become familiar with through non-criminal activities." It is therefore reasonable to assume that hate crime offenders will generally act in areas with which they are already familiar. It is also reasonable to assume that online hate

groups, by highlighting certain content to their visitors, influence both the offenders' selection of target as well as noting ideal locations for the offender to act.

In this context, hate groups which maintain a web presence, which I refer to as hate managers, influence both place managers and offenders through their online environments. In other words, online hate managers act as supercontrollers, while local hate managers act as place managers. The influence of one manifests through the actions of the other. By utilizing the hate manager concept, one achieves a deeper understanding of location's role in relation to hate crime. To explain, in other circumstances, manager evaluation builds off the amount of activities they prevent. As opposed to a poor place manager, who may simply not care to exert control, an effective hate manager only stands to gain from criminal activity. A hate managers' efficiency, therefore, lies in the amount of crime they encourage or permit. In other words, hate managers act as corrupted controllers, rather than facilitators.

To clarify, researchers often explain bias violence as a consequence of group threat, whereby "certain prerogatives believed to belong to the dominant racial group are under threat by members of the subordinate group" (Quillan 1996:820). While group threat helps to understand the motivations of the perpetrators themselves, it lacks in addressing the greater deliberate institutional practices which influence hate crime occurrence. To illustrate, Green, Strolovitch, and Wong (1998) find that at the neighborhood-level, racially motivated crimes stem more from a desire to preserve a racial homogeneity of that neighborhood rather than any objective economic vulnerabilities. However, Green et al. (1998) also conceptualizes these crimes as mainly uncoordinated spontaneous actions, in effect leaving a gap between the

personal and structural level operations of racially motivated crim es. I argue that such a conceptualization accounts for the weakness of association between their measures of hate crime and the direct economic vulnerability of its perpetrators and that by conceiving of hate crime as a means of social control, one can account for the apparent gap in reasoning.

To alleviate this gap, I submit my social control-based conceptualization of the hate manager. In short, I argue that hate managers who call their attention to certain areas use hate crime as a form of discipline or rebellion to exert social control over that area.

Chapter Two: Hypotheses and Methodology

Hypotheses

       I fill gaps in the literature by addressing the relationship between online hate groups and the places where hate crime occurs. With the relevant literature in mind, I hypothesize that:

    H1.Hate crime is more likely to occur in places favorable to discipline or rebellion self-help.

        1a. Hate crime is more likely to occur in places with higher rates of inequality.

        1b. Hate crime is more likely to occur in places with higher rates of vertical segmentation.

        1c. Hate crime is more likely to occur in places with higher rates of social distance.

        1d. Hate crime is more likely to occur in places with higher rates of functional unity.

        1e. Hate crime is more likely to occur in places with higher rates of immobility.

    H2. Hate crime is more likely to occur in places with hate groups present.

    H3.Hate crime is more likely to occur in places discussed by hate managers.

       In this respect, the independent variables are inequality, vertical segmentation, social distance, functional unity, and immobility, online hate discussion of place, and hate group presence at the county level. The dependent variable is hate crime occurrence. The unit of analysis is the county. I examine hate crime occurrence and hate group presence by county using datasets obtained from the UCR and the SPLC, while constructing the measures of social control from census data. For ease of reference, I have included a chart of the variables, their theoretical and operational definitions, and the data sources used for their measurement in Figure 3.

CONCEPT	THEORETICAL DEFINITION	OPERATIONAL DEFINITION/MEASURE	DATA SOURCE FOR MEASURE
HATE CRIME	A MECHANISM OF POWER INTENDED TO SUSTAIN HIERARCHIES "THROUGH VIOLENCE AND THREATS OF VIOLENCE (VERBAL OR PHYSICAL)" (PERRY 2001:3).	THE NUMBER OF CRIMINAL INCIDENTS THAT WERE REPORTED AS HATE CRIME.	2015 FBI HATE CRIME DATA
HATE GROUP	AN ORGANIZATION WITHIN THE PAROCHIAL SOCIAL ORDER "WHOSE BELIEFS AND ACTIONS ARE ROOTED IN ENMITY TOWARDS AN ENTIRE CLASS OF PEOPLE BASED ON ETHNICITY, PERCEIVED RACE, SEXUAL ORIENTATION, RELIGION, OR OTHER INHERENT CHARACTERISTIC" (HULSIZER 2004:41).	THE PRESENCE OF A RECOGNIZED HATE GROUP OR GROUPS IN A GIVEN COUNTY. 0=NOT PRESENT 1= PRESENT	SPLC HATE MAP
ONLINE HATE DISCUSSION OF A PLACE	PLACE TARGETED OR OTHERWISE OCCUPIED BY HATE GROUP MEMBERS.	THE NOTATION OF A GIVEN COUNTY IN ASSOCIATED ONLINE LITERATURE OF A HATE GROUP. 0= NOT NOTED 1= NOTED	ONLINE HATE LITERATURE
INEQUALITY	A COMPONENT OF DISCIPLINE OR REBELLION; SIGNIFICANT SOCIOECONOMIC DISPARITY BETWEEN GROUPS IN A COMMUNITY.	THE PERCENTAGE OF HOUSEHOLDS WITH AN INCOME OVER \$150,000 AND THOSE WITH LESS THAN \$10,000 WITHIN A GIVEN COUNTY. $1 - \sum P_i^2$ WHERE P_i REPRESENTS THE PERCENTAGE OF PERSONS IN EACH GROUP. HIGHER NUMBERS INDICATE GREATER INEQUALITY.	UNITED STATES CENSUS
VERTICAL SEGMENTATION	A COMPONENT OF DISCIPLINE OR REBELLION; HIERARCHICAL CLASS DISTINCTIONS BETWEEN GROUPS IN A COMMUNITY	THE NUMBER OF PEOPLE AGED EIGHTEEN (18) OR OVER IN A GIVEN COUNTY WITH AN ADVANCED DEGREE (BA, MS, PH.D, ETC.) VS THOSE WITH ONLY A HIGH SCHOOL DIPLOMA/GED OR LOWER. $1 - \sum X_i^2 / (\sum X_i)2$ WHERE X_i REPRESENTS THE NUMBER OF PERSONS IN EACH GROUP.	UNITED STATES CENSUS
FUNCTIONAL UNITY	A COMPONENT OF DISCIPLINE OR REBELLION; GROUP EFFORT TOWARDS SOME END OR GOAL, USUALLY IN A WORKPLACE SETTING.	THE NUMBER OF CIVILIANS AGED SIXTEEN (16) OR OVER IN A GIVEN COUNTY WITH ONE OR MORE MEMBERS WORKING IN THE PROFESSIONAL, TECHNICAL, OR MANUFACTURING FIELDS (UNIFIED JOBS) VS. NON-UNIFIED JOBS.	UNITED STATES CENSUS
SOCIAL IMMOBILITY	A COMPONENT OF DISCIPLINE OR REBELLION; SHARED SOCIAL SPACE WITHOUT EASY ESCAPE.	1 – (THE NET MIGRATION OF PEOPLE WHO HAVE MOVED OUT OF A COUNTY WITHIN THE PAST FIVE (5) YEARS/TOTAL COUNTY POPULATION).	UNITED STATES CENSUS
SOCIAL DISTANCE	A COMPONENT OF DISCIPLINE OR REBELLION; SIGNIFICANTAMOUNTS OF HIERARCHICAL HETEROGENEITY	THE DIFFERENCE BETWEEN GROUPS IN TERMS OF ETHNICITY AND NATIONAL ORIGIN. $1 - \sum X_i^2 / (\sum X_i)2$ WHERE X_i REPRESENTS THE NUMBER OF PERSONS IN EACH GROUP AND THE SUM IS TAKEN OVER ALL GROUPS MEASURED.	UNITED STATES CENSUS

Figure 2: Key Concepts, Measures, and Data Sources
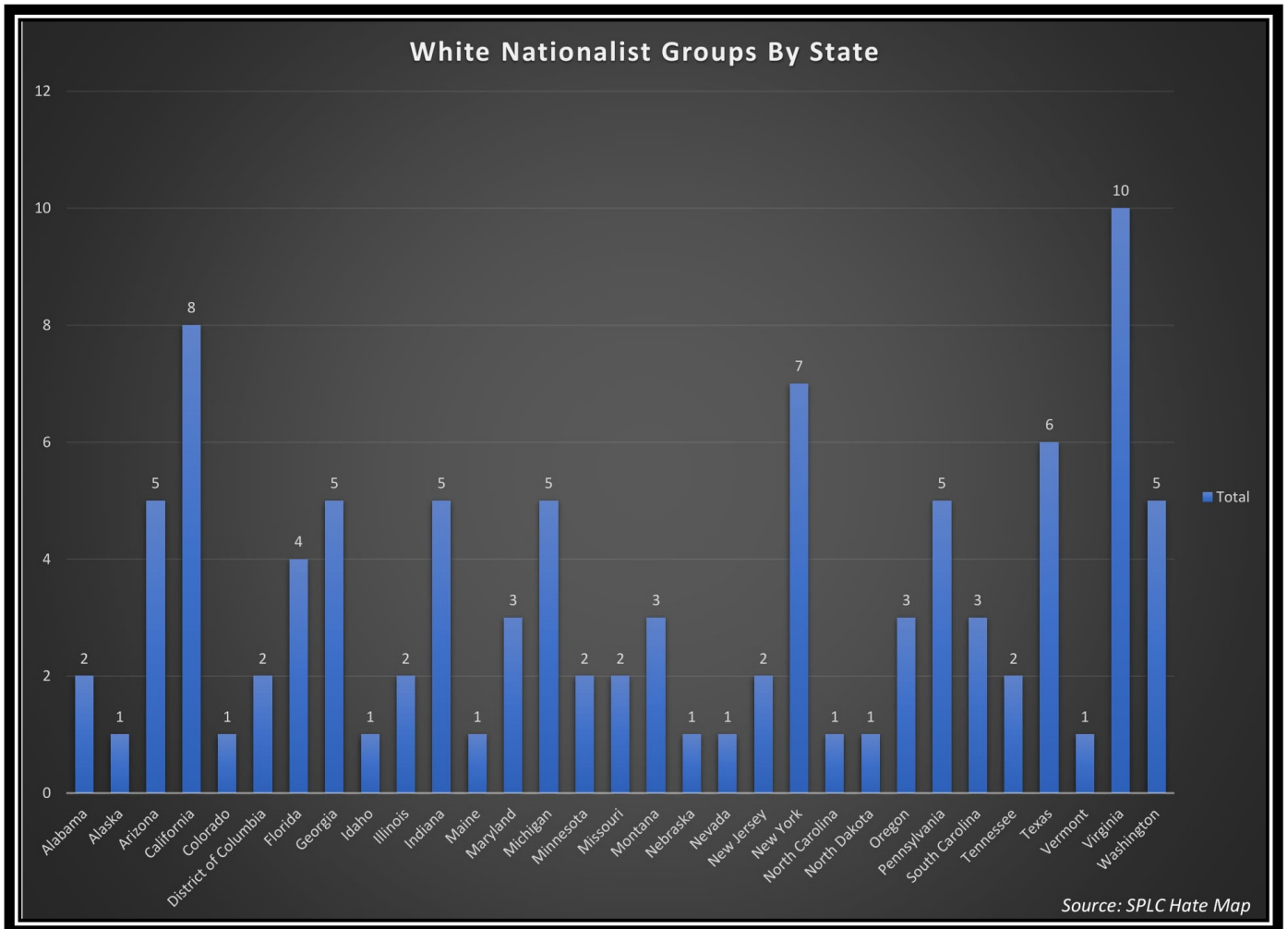
Figure 3: White Nationalist Groups by State

I choose to limit the scope of my study to Virginia because, although, Virginia does not

have the highest number of hate groups, it does carry the greatest amount of White Nationalist

groups (see Figure 4). While California carries the highest number of hate groups, the influence

of state size and population density overshadows other explanations of hate group

accommodation, making California a less than ideal unit of analysis. Furthermore, while many of

the group types listed trace back to some combination of formal religious orders, political organizations, or reactions against one of these, I argue that white supremacist hate groups best serve as a parochial social order exemplar due to their observable foci on integrating local networks and local cultural aspects into the wider white supremacist culture as well as their propensity for violence (Hamm 1993; Futrell and Simi 2004). Consequently, the area with the highest amount of such hate groups provides the ideal sampling frame. Due to time constraints, I limited analysis to the white nationalist group. Thus, I come to Virginia as my focal area.

Variable Construction

I begin by using secondary data sources to construct the independent and dependent variables. In Appendix C, I provide a list of all the specific data sources and tables used for variable extraction. For the dependent variables, I treat hate crime occurrence as a scale variable, taken from the FBI's 2015 Hate Crime Data. I re-coded the offense code of the first listed offense for each recorded incident, into a dichotomous variable called **VIOLENT OFFENSES**, where 0 represents non-violent offenses and 1 represents violent offenses.

For consistency's sake, I used the FBI's definition of what constitutes a violent crime to code the values of murder or non-negligent manslaughter, forcible rape, forcible sodomy, sex assault with an object, forcible fondling, robbery, and aggravated assault as 1, with all other offenses being coded as 0. This occurred after I ran a crosstabulation of the offense codes of the second listed offense by the offense code of the first and found that the only time any non-violent offense appeared for the second, it followed a violent offense in the first. Likewise, all violent

offenses recorded in the second followed a violent offense in the first. No other offense variables within the UCR dataset contained any relevant data.

I used **VIOLENT OFFENSES** to code two variables within my dataset: the number of violent hate crime occurring within a given county or **VIOLENT HATE CRIME** and the number of non-violent hate crime occurring within a given county or **NON-VIOLENT HATE CRIME**[4]. When combined, these variables constitute the **TOTAL NUMBER OF HATE CRIME** for each county. The **TOTAL NUMBER OF HATE CRIME** served as the singular dependent variable in my model due to sample size issues, which I discuss below. I then recoded the total into a dummy variable for simple notation of any **HATE CRIME OCCURRENCE**.

Next, I used the Southern Poverty Law Center's Hate Map to create a dichotomous variable representing whether a recognized hate group holds presence within a given county, or **HATE GROUP PRESENT**, and a continuous variable representing the number of hate groups (if any) present within a given county, or **HATE GROUP AMOUNT**. I should note here that I omitted coding for thirteen (13) groups, as though the Hate Map lists them as present within the state of Virginia, the groups are either too itinerant or have too informal membership procedures to be adequately classified as being based in a county. Furthermore, this map was used to run a search for online hate group websites.

Next, I visited websites associated with groups from the Hate Map. From there, I would search each website for mentions of the areas where hate crime occurred within the same year. I

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[4] The non-violent offenses that were recorded were Simple Assault, Intimidation, Arson, Burglary, Breaking & Entering, Pocket-Picking, Purse-Snatching, Shoplifting, Theft from Building, Theft from Motor Vehicle, All Other Larceny, False Pretenses, Swindling, Confidence Gaming, Credit Card Fraud, Destruction, Vandalism, and Weapon Law Violations.

did this by using the Google Site Search feature, typing in the term "Virginia", and filtering

results to display only those generated in 2015. For each mention of an area, I would code to the

county level. The **HATE GROUP DISCUSSION** variable records whether or not a county was

mentioned in any of these results[5]. Both **HATE GROUP PRESENT** and **HATE GROUP**

DISCUSSION serve as indicators of a hate group's influence, the former by physical location

and the latter by digital.

Next, to code for Black's (1993a) components of discipline and rebellion, I derived

variables from the 2015 United States Census. I measure **INEQUALITY**[6] as the percentage of

households in a given county with an income over \$150,000 **(RICH)** and those classified as

having income less than \$10,000 (**POOR**) within the same county[7]. For the sake of consistency

and further testing, this variable is represented by Blau's (1977) simplified measure of

heterogeneity $(1 - \sum p_i{}^2)$ where p_i represents the percentage of persons in each group and the

sum is taken over all groups. The higher the result of this equation, the greater the inequality.

This is because, as Blau (1977:9) noted, "[w]hen a few people are very rich and most are equally

poor…inequality is more pronounced than when wealth or power is more widely distributed".

By the same reasoning, I operationalized vertical segmentation through an educational

proxy. In this respect, the variable **VERTICAL SEGMENTATION** was measured as the

number of people aged eighteen or older in each county who have or are in the process of

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[6] Though this variable is called **INEQUALITY**, data represented in tables and figures might more accurately be called "Homogeneity". To avoid confusion, I have represented the variable as Heterogeneity in my tables and figures and explain the inverse principles in further reference to the terms.

[7] In SPSS syntax, **INEQUALITY** = 1 - SUM((**RICH** * **RICH**),(**POOR** * **POOR**)).

acquiring some postsecondary degree (**ADVANCED DEGREE**), and those with only a high-school diploma or GED or lower (**HS OR GED**). To calculate this variable, I use Blau's (1977) standard measure of heterogeneity ($1 - \frac{\Sigma x_i{}^2}{(\Sigma x_i)^2}$), where X_i represents the number of persons in each group and the sum is taken over all groups[8].

However, as **VERTICAL SEGMENTATION** resulted in an uninterpretable odds ratio in several models, I decided to recode it into a dichotomous variable, with heterogeneity measures of .45 and above being coded as 2, to represent high levels of vertical segmentation, and with measures of .49 and below being coded as 1, to represent low levels of vertical segmentation. This variable is referred to as **VERTICAL SEGMENTATION DICHOTOMIZED**.

Likewise, I used a proxy measure for functional unity, called **FUNCTIONAL UNITY,** which consists of the number of civilians aged sixteen (16) or older within a given county employed in fields classified by the census as being professional, technical, or manufacturing (**UNIFIED FIELDS)** against those working in other fields (**INDEPENDENT FIELDS**)[9]. This measure was chosen because the former fields tend to stress teamwork toward common and measurable goals and so are more likely to generate the familiarity needed for significant functional unity.

Social immobility is measured as 1 – the net migration of those who have moved out of a county between April 1, 2010 and July 1, 2015 (**MOVED IN PAST FIVE YEARS)** divided by

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[8] **VERTICAL SEGMENTATION** = 1- (SUM ((**ADVANCED DEGREE*ADVANCED DEGREE**), (**HS OR GED*HS OR GED**))/ (SUM (**ADVANCED DEGREE,HS OR GED**)* SUM (**ADV DEGREE,HS OR GED**))).
[9] **FUNCTIONAL UNITY = UNIFIEDFIELDS/(UNIFIED FIELDS+INDEPENDENT FIELDS)**

the total 2015 county population (**TOTAL POPULATION**) The subtracted figure (**SOCIAL IMMOBILITY**) represents mobility or the relative ease of escape from a community[10]..

Mobility and self-help are inversely related as communities with high degrees of mobility will rarely use discipline or rebellion, as both targets and offenders can simply leave if their grievances cannot be dealt with formally. It follows then that communities with high degrees of immobility will more likely have a greater reliance on self-help. Finally, I measured social distance (**SOCIAL DISTANCE**) through an ethnic/racial proxy, using total population estimates of the "Race and Hispanic Origin" categories of the census. Said Race and Hispanic Origin Categories were categorized and coded as follows: White alone (**RHO: WHITE),** Black or African American alone (**RHO: BLACK),** American Indian and/or Alaska Native alone: (**RHO: AMERICAN INDIAN OR ALASKAN NATIVE),** Asian alone (**RHO: ASIAN),** Native Hawaiian and/or Other Pacific Islander alone: (**RHO: HAWAIIAN OR PACIFIC ISLANDER),** Some Other Race alone: (**RHO: OTHER**), Two or More Races: (**RHO: TWO OR MORE),** and Hispanic or Latino with any race (**RHO: HISPANIC OR LATINO**). The categories were then constructed through Blau's (1977) measure of heterogeneity[11].

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[10] **SOCCIAL IMMOBILITY = 1-(MOVED IN PAST FIVE YEARS/TOTAL POPULATION)**.
[11] **SOCIAL DISTANCE = 1- (SUM ((RHO: WHITE*RHO: WHITE), (RHO: BLACK*RHO: BLACK),(RHO: AMERICAN INDIAN OR ALASKAN NATIVE * RHO: AMERICAN INDIAN OR ALASKAN NATIVE), (RHO: ASIAN*RHO: ASIAN), (RHO: HAWAIIAN OR PACIFIC ISLANDER * RHO: HAWAIIAN OR PACIFIC ISLANDER), (RHO: OTHER*RHO: OTHER),(RHO: TWO OR MORE*RHO TWO OR MORE), (RHO: HISPANIC OR LATINO * RHO: HISPANIC OR LATINO))/ (SUM (RHO: WHITE, RHO: BLACK, (RHO: AMERICAN INDIAN OR ALASKAN NATIVE,RHO: ASIAN, RHO: HAWAIIAN OR PACIFIC ISLANDER,RHO: OTHER,RHO: TWO OR MORE, RHO: HISPANIC OR LATINO)* SUM (RHO: WHITE,RHO: BLACK, RHO: AMERICAN INDIAN OR ALASKAN NATIVE,RHO: ASIAN, RHO: HAWAIIAN OR PACIFIC ISLANDER ,RHO: OTHER,RHO: TWO OR MORE, RHO: HISPANIC OR LATINO))).**

Following data collection, I coded the variables into SPSS and used them to test the first

two hypotheses via a negative binomial regression due to overdispersed data.

Variable	Range	Mean	Minimum	Maximum	Std Dev
VIOLENT HATE CRIMES BY COUNTY	3.00	0.12	0.00	3.00	0.46
NON-VIOLENT HATE CRIMES BY COUNTY	26.00	0.46	0.00	26.00	3.14
TOTAL NUMBER OF HATE CRIMES RECORDED IN 2015 BY COUNTY	29.00	1.26	0.00	29.00	3.44
HATE CRIME OCCURRENCE	----	0.35	----	----	0.48
HATE GROUP PRESENT IN COUNTY	----	0.14	----	----	0.35
HATE GROUP AMOUNT IN COUNTY	4.00	0.18	0.00	4.00	0.56
HATE GROUP DISCUSSION OF COUNTY	----	0.22	----	----	0.41
HOMOGENEITY	0.16	0.98	0.84	1.00	0.03
-RICH	0.40	0.08	0.00	0.40	0.08
-POOR	0.22	0.08	0.02	0.24	0.04
VERTICAL SEGMENTATION	0.25	0.45	0.25	0.50	0.04
-ADVANCED DEGREE	1121240.00	46675.83	1261	1122501	114874.80
-HS OR GED	896614.00	54753.42	2557	899171	99274.17
VERTICAL SEGMENTATION DICHOTOMIZED	----	1.57	----	----	0.50
FUNCTIONAL UNITY	0.39	0.27	0.13	0.52	0.06
-UNIFIED FIELDS	240473.00	9339.95	154	240627	24268.69
-INDEPENDENT FIELDS	362487.00	20666.24	852	363339	40779.56
SOCIAL IMMOBILITY	0.18	0.99	0.88	1.06	0.03
-MOVED IN PAST FIVE YEARS	37238.95	1240.46	-6061.00	42007.00	4768.05
-TOTAL POPULATION	1126478.00	62079.92	2244.00	1128722.00	122652.02
SOCIAL DISTANCE	0.69	0.38	1.01	0.70	0.18
-RHO: WHITE	591634.00	39380.44	2222.00	593856.00	66386.36
-RHO:BLACK	103367.00	11731.70	0.00	103367.00	22583.25
-RHO:AMERICAN INDIAN OR ALASKAN NATIVE	1461.00	128.16	0.00	1461.00	240.49
-RHO:ASIAN	206641.00	3681.28	0.00	206641.00	18998.95
-RHO: HAWAIIAN OR PACIFIC ISLANDER	632.00	37.35	0.00	632.00	97.11
-RHO: OTHER	3176.00	135.74	0.00	3176.00	367.89
-RHO: TWO OR MORE	38858.00	1651.59	3.00	38861.00	4268.26
-RHO: HISPANIC OR LATINO	181901.00	5332.00	0.00	181901.00	18675.65

Table 1: Descriptive Statistics

In each model, both heterogeneity/inequality and vertical segmentation bear an uninterpretable odds ratio. This stems from the nature of the secondary data sources. As such, negative binomial regression with such variables would appear to be inappropriate for these analyses. However, due to uninterpretable odds ratios in said regression, I found binary logistic regression more interpretable. As such, I used differing measures of the same concept until an adequate model could be created. The same regression was used to test the remaining hypotheses.

For the binary logistic regression model, I substituted **HATE GROUP AMOUNT** with **HATE GROUP PRESENT** since the range of the former variable was extremely low, rendering it inappropriate. Likewise, I substituted **VERTICAL SEGMENTATION** with **VERTICAL SEGMENTATION DICHOTOMIZED**, and integrated the **HATE GROUP DISCUSSION** variable. In addition, upon further review it was decided that the number of both violent and non-violent hate crime was too skewed at the county level for any meaningful analysis, therefore I substituted **VIOLENT HATE CRIME** and **NON-VIOLENT HATE CRIME** with the **HATE CRIME OCCURRENCE** dummy variable. The original dichotomy and coding structure remains in case future studies use sampling methods which might not share the skewness issue. Though this method provides a convenient way to measure hate crime occurrences, it does so at the cost of differentiating between motivations between hate crime. As such, I am not measuring *defensive* hate crime so much as hate crime in general. However, given the implied relationship between a defensive mentality likelihood and the likelihood of engaging in self-help as detailed

above, I submit that results which demonstrate correlation between self-help measures and hate crime occurrence ought to be attributed to perpetrator's defensive motivations.

Moving on, Pearson correlations, which can be found in Appendix A, informed my interpretations of the overall results. To summarize, I found that **HETEROGENEITY** shares a moderate negative relationship with **FUNCTIONAL UNITY** (-.514) and a moderate positive relationship (.426) with **SOCIAL IMMOBILITY**. **SOCIAL IMMOBILITY** also shares a moderate negative relationship (-.488) with **VERTICAL SEGMENTATION.** All three correlations hold a p-value equal to or below .01.

Chapter Three: Results

Binary Logistic Regression

Overall, my dataset contained 133 cases (N=133), one for each county and independent city (IC) within the state of Virginia, with no missing values. For each case of hate crime occurrence (**HATE CRIME OCCURRENCE**), identified hate group (**HATE GROUP PRESENT**), or discussion on a hate group website (**HATE GROUP DISCUSSION**) that was originally cross-referenced by city, town, or political district, the reference was up-coded to the county level. Special care was taken to ensure that these up-codes reflected the state of counties as they were in 2015 by consulting county maps from the relevant time.

Through binary logistic regression, I constructed a model of predicting hate crime that was both statistically significant (chi square=38.776, df=7, p<.000) and with an improved ability to predict (76.7%) over the baseline model (65.4%). In this regard, I treated the Hate Crime Occurrences (**HATE CRIME OCCURRENCE)** variable as a dependent variable, with "No" being the reference category. Furthermore, the Nagelkerke R-Square (see Table 2) shows that the predictive model explains about 35% of the variance.

Variable Explanatory Power & Significance

In order to identify potential sources of multicollinearity, I use a correlation matrix which I have provided in Appendix B. Fortunately, no variables are correlated above .434, leaving little cause for concern. In relation to H1, the regression model coefficients results show that while most of the self-help variables are related to higher likelihoods of hate crime occurrence, only

two of these can be explained at the county level with any sort of significance. Table 2 contains every coefficient relationship within this model.

To begin, counties with higher heterogeneity appear nearly twice as likely to experience hate crime as those without (OR=2.074), a finding that appears to contradict H1a. However, this relation bears no statistical significance (p=.949). However, vertical segmentation is associated with a higher likelihood of hate crime occurrence (OR= 2.881), and this relationship holds statistical significance (p=.044). In other words, vertical segmentations increases the odds of hate crime occurrence by nearly 200%. Therefore, H1b is supported. Likewise, higher social distance counties are nearly twenty-six times as likely to experience hate crime (OR=25.785). This relationship also occurs at a statistically significant level (p=.021). Therefore, H1c is also supported.

However, H1d appears to be contradicted by the result showing functional unity's increase as associative with a near 200% decrease in hate crime likelihood (OR=-2.772). As with H1a, this relationship fails to achieve statistical significance (p=.527). By the same token, though H1e appears supported by social immobility's association with a much higher likelihood of hate crime occurrence (OR=5700.309), the relationship holds no statistical significance (p=.313).

Overall, H1 stands unsupported, as only two out of its five propositions are supported with any statistical significance. The lack of support for this hypothesis might reasonably be

traced to the proxy measurments I utilized. I discuss the potential complications of these proxies in the findings and limitations sections of the next chapter.

Regarding H2, the hypothesis stands fully supported. The model shows that hate group presence results in a nearly 900% increase in hate crime likelihood (OR=9.934), a statistically significant relationship (p=.001). Aside from the social distance variable, hate group presence

Variable	Model 1		Model 2	
	OR	SE	OR	SE
HATE GROUP PRESENT	--	--	9.934**	
HATE GROUP DISCUSSION	--	--	2.428	.523
HETEROGENEITY	--	--	2.074	11.424
FUNCTIONAL UNITY	--	--	-2.772	4.380
VERTICAL SEGMENTATION DICHOTOMIZED	--	--	2.881*	.525
SOCIAL DISTANCE	--	--	25.785*	1.405
SOCIAL IMMOBILITY	--	--	5700.309	8.571
CONSTANT	.529**	.182	.000	12.608

N	133
-2 Log Likelihood	132.754
Cox & Snell R^2	.253
Nagelkerke R^2	.349

Table 2: Logistic Regression Model

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

holds the greatest predictive power observed for hate crime in a county. This lends support to the argument that hate crime functions as a form of social control. If hate group presence is an

indicator of hate manager influence, then it also supports the argument for the corrupted

controller's role.

In contrast, though discussion of counties by hate managers does appear to be associated

with higher likelihood of hate crime occurrence (OR=2.428), this relationship doesn't bear any

statistical significance (p=.090) which leaves H3 unsupported. The evidence supporting H2

demonstrates the basis for conceiving of hate crime as a means of social control as well as a

baseline for hate manager influence. However, the question of how hate managers control where

these crimes occur remains vague. This vagueness might result either from a lack of frequent

communications specifically referencing any of the counties recorded, difficulty in interpreting

online hate discussions, or the size of the sample. I discuss these possibilities in my limitations

section.

Chapter Four: Discussion

Findings

To summarize, I have expanded upon the relationship between hate groups and the places

where hate crime occurs. By integrating the principles found within Routine Activity Theory,

Social Control Theory as well as hate crime literature, I have constructed hypotheses generated

from each literature to test the value of their contribution towards explaining why hate crime

occurs in some places, but not others.

First, I tested the hypothesis that hate crime, as a means of self-help, likely occur in places conducive to discipline or rebellion. In the case of vertical segmentation and social distance, the hypotheses were supported. However, inequality and social immobility, while associated with an increased likelihood of hate crime occurrence, remain statistically insignificant. Statistical insignificance probably results from the scale of the sampling the sample size, or the unit of analysis. Replication of my study with a variety of samples and/or a different means of measuring self-help would provide more clear evidence of the relationship. Like inequality and social immobility, statistical insignificance as well as the contradictory findings might rectify itself with increased sampling. Alternatively, the presence of persons under the age of eighteen (18) or the civilian-only nature of the proxy might act as a mediator between the functional unity and hate crime occurrence. Again, further sampling or use of alternate proxy variables might rectify this issue. In the current context, though, the data suggests that while self-help influences the likelihood of hate crime occurrence, some factors hold greater influence than others.

Next, I tested the hypothesis that hate crime likely occurs in places with hate groups present. The data showed that hate groups hold extreme predictive significance, with odds holding that counties with a hate group are over 900% more likely to experience hate crime than those without one. That said, the data supporting the hypotheses so far clearly suggests a significant relationship between hate groups and hate crime occurrences, lending credence to the arguments that hate groups act as social orders that enact illegal self-help to address their grievances. From a RAT perspective, the diffusion of the hate groups likely affects where they

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are able to perform routine activities and thus directly influences where they are likely to commit offenses. However, the question remains of just how much control a hate group enacts over hate crime.

Accordingly, I tested the final hypothesis that hate crime likely occur in places discussed by hate managers, the primary agents of social control within their parochial orders. However, while the data showed a finding consistent with the hypothesis, that finding did not reach statistical significance. Again, sampling across a greater area or at a higher unit of analysis alone could determine whether the finding generally holds true or not. Furthermore, it might be the case that there is some unexplored interaction between the presence of a hate group and a hate group's discussion of a location which affects hate crime occurrence.

Likewise, my measurement of hate group discussion leaves open the possibility that numerous areas might have been left out. To illustrate, a hate group discussion might surround perceived victimization via a government agency and the suggestion might be raised to target local post offices, which is then read by Virginians associated with the hate group who then attack local postal workers. While such a suggestion would demonstrate the hate manager's influence in action, the lack of a specific county being mentioned would mean that the discussion would go unaccounted for in my dataset. In any event, the data suggests that while hate group activities are related to hate crime occurrences, the role of the hate manager involves more than simple discussion of a place to facilitate social control there.

In short, my findings lend credibility to the theoretical considerations raised by Black (1993b) in relation to the idea of crime as a means of social control. However, the results may

also highlight some of the limits within Black's theoretical framework, namely its applicability to differing types of criminal activity. In addressing said deficiencies through use of other theoretical components, I demonstrate that while the hate group as a social order partially predicts hate crime occurrences by virtue of their mere presence, the exact relationship remains unclear.

Limitations and Future Research

As noted, every piece of data in my analysis remains publicly available at the time of this writing for researchers to utilize and replicate the model I have presented. Easy replication, multiple indicators, and methodological flexibility are just a few of the benefits of utilizing such data, especially for exploratory and theoretically-driven efforts such as my own. Fortunately, public sources offer a wealth of potential information on hate crime places. The American-Arab Anti-Discrimination Committee, the Anti-Defamation League, and the FBI all offer data regarding this subject. In contrast, difficulties in pinning down the recorded hate groups to specific counties indicate that findings from sources such as these might not hold true at the state level or for counties outside of Virginia.

With that in mind, few researchers choose to focus on hate crime in the context of *where* they occur. Exceptions to the lack of focus include a study regarding hate crime on college campuses (Van Dyke and Tester 2014) as well as mentions in other work noting the potential for synagogues and mosques to be targets (as opposed to any specific person within) of a hate crime (Perry 2003; Adamczyk et al. 2014, Cheng, Ickles, and Kenworthy 2013).

Yet these examples all either fail to specify what kinds of hate offenses are likely to occur or who/what group is the most likely target. Fortunately, scholarship on location in relation to hate crime which has focused primarily on neighborhood contexts has found that hate crime against international students in Australia is related to socioeconomic conditions with those at the lower end of the housing and/or job market being more vulnerable to hate crime offenses due to lack of parochial bonds (Forbes-Mewett and Wickes 2017). These findings appear to contradict earlier research on racially motivated crimes at the neighborhood level that found that "racially motivated crime emanates not from macroeconomic conditions but rather from threats to turf guarded by a homogenous group" (Green et al. 1998: 398). However, several explanations including national and cultural differences between Australia and the United States might explain this difference. Furthermore, location-based hate crime research is still in a relatively early stage. For these reasons, these findings hold inconclusive on the exact relationship and require more research before a definite relationship can be established.

The difficulties in gathering comprehensive and representative statistics on hate crime exacerbate the literature paucity. The reasons for such difficulty range from issues with conceptualization (Perry 2003:7) to states' selective recognition and invocation of criminal legislation (Perry 2003:44), police's failure to recognize a hate crime (McDevitt, et al. 2002: 304-305), and reporting errors (Nolan, Haas, Ruley, Stump, and LaValle 2015). To address these issues, Nolan et al. (2015: 1584) suggests that "[s]eeking additional data from victims, and if possible, perpetrators of hate crime would enhance efforts for determining the role of bias."

Consequently, future versions of this work might benefit from augmenting official statistics with victim testimonies and reports gathered by advocacy groups and institutions such as the Anti-Defamation League. While my current means of analysis makes additional data acquisition difficult, its limitations towards explaining the hate group-hate crime location relationship make a variety of data sources essential to future research. As such, I suggest that the next step on explaining the hate group-hate crime relationship calls for integrating the remaining actors not covered here, that is, the actual perpetrators of hate crime, their victims, and the victim's guardians. What role each plays in the likelihood of hate crime occurrence remain unexplored.

Furthermore, while my efforts have provided a method for acquiring information on the "hate managers", the scope of my work limits my discussion. Social scientists, activists, and other interested parties who continue the work I've started here must expand sampling techniques beyond the county level of one American state. While my use of proxy measures provides an adequate preliminary measure towards linking the concepts of self-help and hate crime, it comes at the cost of accurately reflecting Black's (1993a) measures of discipline or rebellion.

Specifically, my proxy measure for functional unity proves particularly troublesome. When Black (1993a) outlines functional unity in relation to self-help, he does so to note that those who functionally similar are bound by mutual participation in some enterprise. High functional unity, Black (1993a) argues, might therefore be best exemplified by servitude, imprisonment, warfare or production. As a result of the limits of my proxy measure, I observe

only the mildest form of productive functional unity, which fails to fully operationalize the concept. One remedy for this might be to triangulate the concept with other records, including prisoner and juvenile populations as well as more detailed industrial or occupational job descriptions.

Finally, my work speculates on the importance of acknowledging and including locations both physical and virtual within theoretical considerations of hate crime. Yet my findings do not support the conclusion that hate crime is more likely to occur in places discussed by hate groups online. Likewise, while it makes theoretical sense for the hate group to precede hate crime, my analytical method remains incapable of establishing a time order. Still, the explanatory power of the hate manager's influence through presence merits further research. As hate crime continues to attract public attention (Cochrane Times 2018; Hauslohner 2018; Malveaux 2018; Mitros 2018; Morris 2018), informing the public regarding hate crime, dispelling any misconceptions regarding their causes, and revealing unexplored avenues to explaining those same causes grows ever more important.

Chapter Five: Conclusion

Hate groups and hate crime share an intimate relationship. The findings in this paper show that the presence of a hate group holds greater predictive power than most of the proxy measures used for criminal self-help. Yet self-help itself plays no small role in explaining hate crime. To illustrate, I began this paper by conceptualizing of hate crime as a form of self-help. My findings fail to dismiss that conceptualization. Instead, I argue that hate crime differs from

other forms of self-help, as while there is an established relationship between the group and the offender, the exact role of the hate-manager remains a mystery. The hate manager's influence can be felt at the county level, with its mere presence resulting in a greater likelihood of hate crime occurrence than nearly any other factor. Furthermore, even though the statistical significance of hate group discussion was minimal, the fact that it still held a positive relationship with hate crime likelihood indicates the potential of the hate manager to influence via online environments. The hate manager's abilities must be identified if they are to be countered, and while I have provided a glimpse into their presence and their expressions of power, questions remain regarding the relationship between the two.

Exploration must therefore continue. Those with the ability must explore the relationship and reveal the roles of those involved in hate crime, be they the actors, their controllers, and the super-controllers. In this regard, I advise we begin by focusing our attention on addressing the missing factors within the hate crime-hate group relationship: namely, the victims, the perpetrators, and the guardians. Regarding the measurement of self-help, testing via structural equation modeling should allow for better determination of what data appropriately constitutes a model of discipline or rebellion more than the approximations I have used in this thesis. With that done, a constructed theoretical model of the hate group-hate crime relationship can then reveal further avenues towards understanding and confronting both phenomena.

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Appendix A: PEARSON CORRELATIONS

	1	2	3	4	5	6	7
HATE GROUP PRESENT	1.00						
HATE GROUP DISCUSSION	.149	1.00					
HETEROGENEITY	-.279**	-.126	1.00				
FUNCTIONAL UNITY	.161	-.142	-.514**	1.00			
VERTICAL SEGMENTATION DICHOTOMIZED	.223**	.237**	-.315**	.246	1.00		
SOCIAL DISTANCE	.263**	.107	-.292**	.215*	.236**	1.00	
SOCIAL IMMOBILITY	-.074	-.297**	.426**	-.195*	-.488**	-.163	1.00

*p ≤ .05, **p ≤ .01

Appendix B: CORRELATION MATRIX

	1	2	3	4	5	6	7
HATE GROUP PRESENT	1.00						
HATE GROUP DISCUSSION	.001	1.00					
HETEROGENEITY	.220	.068	1.00				
FUNCTIONAL UNITY	-.058	.191	.426	1.00			
VERTICAL SEGMENTATION DICHOTOMIZED	-.032	-.014	.044	.004	1.00		
SOCIAL DISTANCE	-.009	.056	.111	-.174	..016	1.00	
SOCIAL IMMOBILITY	-.062	.240	-.326	-.010	.434	.039	1.00

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Appendix C: DATA SOURCES USED FOR VARIABLE CONSTRUCTION

SOCIAL CONTROL VARIABLES

- *Homogeneity/Inequality*: U.S. Census Bureau, American Community Survey, 2011-2015 American Community Survey Five Year Estimates, Table DP03-SELECTED ECONOMIC CHARACTERISTICS; generated by Jonathan A. LLoyd; using American FactFinder <http://factfinder.census.gov>; (7 April 2018)

- *Vertical Segmentation:* U.S. Census Bureau, American Community Survey, 2011-2015 American Community Survey Five Year Estimates, Table S1501-EDUCATIONAL ATTAINMENT; generated by Jonathan A. LLoyd; using American FactFinder <http://factfinder.census.gov>; (11 June 2018)

- *Functional Unity:* U.S. Census Bureau, American Community Survey, 2011-2015 American Community Survey Five Year Estimates, Table S2405-INDUSTRY BY OCCUPATION FOR THE CIVILIAN EMPLOYED POPULATION 16 YEARS AND OVER; generated by Jonathan A. LLoyd; using American FactFinder <http://factfinder.census.gov>; (16 April 2018)

- *Social Immobility (1):* U.S. Census Bureau, American Community Survey, 2011-2015 American Community Survey Selected Population Tables, Table B01003-TOTAL POPULATION; generated by Jonathan A. LLoyd; using American FactFinder <http://factfinder.census.gov>; (14 June 2018)

- *Social Immobility (2):* U.S. Census Bureau, Population Estimates, 2015 Population Estimates, Table PEPTCOMP- Estimates of the Components of Resident Population Change: April 1, 2010 to July 1, 2015; generated by Jonathan A. LLoyd; using American FactFinder <http://factfinder.census.gov>; (7 April 2018)

- *Social Distance:* U.S. Census Bureau, American Community Survey, 2011-2015 American Community Survey Five Year Estimates, Table B03002 - HISPANIC OR LATINO ORIGIN BY RACE ; generated by Jonathan A. LLoyd; using American FactFinder <http://factfinder.census.gov>; (12 June 2018)

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SOURCE FOR DETERMINING 2015 CONGRESSIONAL DISTRICTS

- U.S. Census Bureau, Geography Division. 2015. Congressional Districts of the 114th Congress of the United States, January 2015-2017/U.S. Department of Commerce, Economics and Statistics Administration, U.S. Census Bureau; prepared by the Geography Division. Washington, D.C.: United States Census Bureau.