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Explaining Bias Homicide Occurrences in the United States

Explaining Bias Homicide Occurrences in the United States

A thesis submitted in partial fulfillment
of the requirements for the degree of
Master of Arts in Sociology

by

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Indiana University
Bachelor or Arts in Music Supervision, 2010

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This thesis is approved for recommendation to the Graduate Council.

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Abstract

The purpose of this study is to examine the relationships between social-structural characteristics and bias homicide across counties in the United States between the years 1990 and 2014. While there have been several notable studies on this topic, most have been conducted in single cities or at the state level, thus overlooking variations across community types for the broader United States. Moreover, scholars have failed to distinguish violent from non-violent bias crimes in their research. Drawing from several ecological theories of crime, this study seeks to contribute to the literature by asking (1) what are the structural predictors of the likelihood of bias homicide occurrences? (2) do these same structural predictors affect the number of incidents across those counties that experience multiple bias homicides? To answer these questions, data on bias homicide are derived from the Extremist Crime Database (ECDB) and paired with social and structural variables from the U.S. Census Bureau. Results are discussed relative to the goals of understanding where fatal bias crimes are more likely to occur as a means of informing law enforcement and policymakers interested in preventing and responding to this form of crime.

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Table of Contents

I. Introduction…… 1

II. Theory and Prior Evidence…… 3

Measuring Bias Crime Within Prior Research…… 5

Prominent Sociological Theories and Bias Crime…… 6

Social Disorganization Theory and Bias Crime…… 6

Group Threat Theory…… 10

A Note On The Defended Neighborhood Perspective…… 11

III. Parameters of the Current Study…… 13

Sources of Data…… 14

Unit of Analysis…… 15

Dependent Variables…… 15

Independent Variables…… 16

Analytic Techniques…… 18

IV. Results…… 19

Bivariate Analysis…… 21

Multivariate Analysis: Predicting the Likelihood of Incident…… 24

Multivariate Analysis: Predicting the Number of Incidents…… 27

Supplemental Analyses…… 29

V. Discussion and Conclusion…… 30

Limitations and Directions for Future Research…… 32

VII. References…… 35

VIII. Appendices…… 39

List of Tables

Table 1.	Relationships Between Structural Variables and Racial Bias Violence/Attitudes in Prior Literature………………….	4
Table 2.	Dependent, Independent, and Control Variables……………………	17
Table 3.	Descriptive Statistics For Key Variables (N=9425)………………...	20
Table 4.	Correlations For All Key Variables (N=9425)……………………...	22
Table 5.	Penalized Maximum-Likelihood Logistic Regression of Overall Fatal Hate Crime Likelihood On Key Theoretical Predictors and Other Key Controls (N=9425)………….	25
Table 6.	Negative Binomial Regression of Overall Fatal Hate Crime Counts On Key Theoretical Predictors and Other Key Controls (N=235)………………………………………..	28
Table A1.	Indicators of Bias……………………………………………………	39
Table B1.	Supplemental Models Predicting Likelihood of Incidents and Number of Incidents………………………………	40
Table B2.	Supplemental Models Examining Other Specifications Of Key Predictors Net of Controls (1)………………	41
Table B3.	Supplemental Models Examining Other Specifications Of Key Predictors Net of Controls (2)………………	42

I. Introduction

Interest in lethal violence motivated by hate or bias has risen in recent years, largely spurred by sensational incidents (e.g., Matthew Shepard and James Byrd Jr. in 1998, James Craig Anderson in 2011) and the accompanying media and political discourse surrounding them. In turn, scholars have turned their attention to the individual and contextual factors associated with hate homicides. Regarding the latter, contradictory findings have emerged from a growing body of literature on the ecological correlates of hate or "bias" crime in the United States. For example, some research reveals poverty and other measures of social disorganization to be positively associated with state-level bias crime (Gale, Heath, & Ressler, 2002; Medoff, 1999), while other scholars have found no evidence that bias crime is more likely to occur in more impoverished communities (Green, Glaser, & Rich, 1998). In fact, some research has revealed that bias crime may be more likely to occur in organized and prosperous communities (Green, Strolovitch, & Wong, 1998; Lyons, 2007). Overall then, and despite significant contributions to bias crime research over the previous two decades, scholars have only begun to understand the ways in which important social-structural factors shape this particular form of violent crime across American communities.

The inconsistency of findings within prior literature (and, more generally, the overall shortage of empirical research) can largely be attributed to the paucity of bias crime data. In particular, underreporting by police continues to plague official bias crime data and, in an attempt to resolve this measurement issue, has resulted in a host of methodological issues that continue to plague bias crime research at the macro-level. In short, empirical research examining the ecological correlates of lethal bias crime is still emerging and, because of prominent measurement issues, findings are somewhat inconsistent.

The purpose of the proposed research is to utilize an alternative measurement strategy and database to examine some remaining key questions about the relationships between ecological conditions and bias violence across U.S. communities. Specifically, I ask two related questions: *(1) what are the structural predictors of the likelihood of bias homicide occurrences*? *(2) do these same structural predictors affect the number of incidents across those counties that experience multiple bias homicides?* To answer these questions, I draw on bias crime data from the Extremist Crime Database (ECDB) (see Freilich, Chermak, Belli, Gruenewald, & Parkin, 2014), an open-source database that includes information on violent crimes against social minorities, including those that were officially classified as bias crimes by police and those that were not. Additionally, the proposed study avoids making assumptions of homogeneity across bias crime types that have plagued previous research by focusing exclusively on bias homicides that occurred in the U.S. between 1990 and 2014. The use of homicide is noteworthy because it is the most serious form of crime and the most consistently reported by law enforcement and media sources (Chermak, 1995; Graber, 1980), thus avoiding some of the ambiguity in defining bias crime that has plagued much of research.

The study unfolds as follows. First, I review prior empirical research on bias crime, focusing in particular on the macro-level research and the persistent problems within this literature. Second, I draw on prominent sociological and criminological theories to discuss the expected relationships between key social-structural features of communities and the likelihood (and amount) of bias homicide. Third, I describe the parameters of the current study, including the sources of data, the methodology employed, and the results of the analytic models. Fourth, I discuss the implications of these findings relative to both prior research and theorizing, while simultaneously identifying some directions for future research.

II. Theory and Prior Evidence

Bias crime research to date has largely focused on an individual level of analysis as compared to broader geographic patterns of bias crime (Green, McFalls, & Smith, 2001). In particular, the individual-level research demonstrates that bias crimes are more likely to involve multiple offenders (Martin, 1996) and these offenders tend to be younger than those participating in parallel crimes (Martin, 1996; Maxwell & Maxwell, 1995; Messner, McHugh, & Felson, 2004).

Increasingly, however, some scholars have sought to examine the broader contextual factors associated with bias crime, including several relatively recent studies (Gale et al., 2002; Grattet, 2009; Green, Glaser, and Rich, 1998; Green, Strolovitch, and Wong, 1998; Lyons, 2007; Medoff, 1999; Pinderhughes, 2003). Generally, this body of research has explored how key structural features as derived from prominent macro-level theories (e.g., social disorganization, group threat) predict bias crime. Table 1 displays the findings from this body of work.

Upon examination, Table 1 reveals two persistent issues within research examining the macro-level covariates of bias crime. First, there is little consistency in the structural and demographic features of communities across studies. Of the ten studies listed in Table 1, unemployment is the most frequently included measure and appears in a little over half of the studies. In contrast, other predictors like concentrated disadvantage, poverty, and residential instability (which are staples within the broader macro-level criminological literature) are utilized in only one or two studies. Moreover, virtually absent are studies that examine a multitude of different measures in order to compare their effects (for an exception, see Grattet, 2009). Thus, it is difficult to conclude that any particular contextual feature is associated with bias crime because few studies comparatively examine them.

Table 1. Relationships Between Structural Variables and Racial and Bias Violence/Attitudes in Prior Literature[a,g]

	Poverty	Concentrated Disadv.	Unemploy.	Full-time hourly wage rate	Res. Instability	Ethnic Heterogeneity	Black Pop.	Minority in-migration	Educ.
Beck & Tolnay							+		
Corzine, Creech, & Huff-Corzine							+		
Corzine, Huff-Corzine, & Creech							+		
Gale, Heath, & Ressler	+		+				/		
Grattet		+			+	/		−,+[b]	
Green, Glaser, & Rich			/						
Green, Strolovitch, & Wong			/					+[c]	
King & Wheelock			+					+	
Lyons		/[d]	/		−,+[e]		+, /[f]		
Medoff			+	−					+

a. Table shows any significant effects at .10 or lower
b. Grattet: (-) relationship in mixed neighborhoods with an influx of minorities and a (+) relationship in predominantly white neighborhoods with an influx of minorities
c. Green, Strolovitch, & Wong: (+) in white dominated neighborhoods
d. Lyons: (/) in the final model
e. Lyons: (+) communities characterized by "residential instability" have an increased likelihood of anti-white crime, (-) communities with high levels of social control tend to "favor" anti-black crime
f. Lyons: (+) with anti-black hate crimes, (-) with anti-white hate crimes
g. (+) = a positive relationship, (-) = a negative relationship, (/) = a null relationship

Second, Table 1 also reveals inconsistency in the findings across previous studies. That is, even when the same measure is included in several studies (e.g., unemployment, percent Black), the results of analytic models do not reveal relationships that are consistently in the same direction or that register as statistically significant. In short, compounding the lack of uniformity in model construction is the relative inconsistency in key relationships even when specific measures are included across different studies. As a result, more research is needed examining the structural and demographic features of geographic units that are associated with the likelihood and overall prevalence of bias crime.

Measuring Bias Crime Within Prior Research

So why is macro-level bias crime research generally scarce and inconsistent in terms of key findings? One contributing factor may be the lack of suitable data for studying the phenomenon. The vast majority of prior research has constructed incident or prevalence indicators of bias crime using official criminal justice data. Unfortunately, these data suffer from consistency and reporting problems across jurisdictions (and, therefore, across geographic units). In particular, it is widely acknowledged that the police have limited resources and little in the way of training regarding bias crimes. As a result, official estimates of bias crime may lack accuracy and consistency in their coding at the same time that officer prejudices and a general reluctance to report these offenses further undermines their validity and reliability (Berk, Boyd, & Hamner, 1992; Green, McFalls, & Smith, 2001; Levin & McDevitt, 1993, 2002).

As a result of this issue, scholars have chosen to either (a) limit the geographic generalizability of studies by using localized data or (b) implement data aggregation techniques that ignore significant heterogeneity in bias crimes within geographic units. Regarding the former, some scholars have looked past using national-level bias crime statistics and have instead drawn statistics from single law enforcement jurisdictions (e.g., Chicago, New York City, and Sacramento) where recording problems are thought to be less severe (Grattet, 2009; Green, Glaser, & Rich, 1998; Green, Strolovitch, & Wong, 1998; Lyons, 2007; Pinderhughes, 1993). The sacrifice, of course, is an inability to generalize beyond the specific locale to other communities or areas where bias crimes may occur. Regarding the latter, others have aggregated data to even larger geographic levels (e.g., state-level) (Gale et al., 2002; Medoff, 1999), but in doing so have combined together a heterogeneous collection of both fatal and non-fatal (as well as violent and non-violent) bias crimes.

Prominent Sociological Theories And Bias Crime

Overall then, there is the need for additional empirical research that examines the structural characteristics associated with bias crime by extending prior research that has been hampered by data availability. As such, the current study draws from two sociological theories to better understand why bias crime is more prevalent in some communities than others. In particular, both social disorganization theory (Shaw & McKay, 1942) and group threat theory (Blumer, 1958) are the most common frameworks utilized in prior research to generate expectations regarding the link between community-level characteristics and bias crime. I turn now to a more thorough discussion of each theory.

Social Disorganization Theory And Bias Crime

Structural perspectives of crime causation are based on the premise that crime varies by how places (e.g., communities, neighborhoods, counties) are structured and change over time, regardless of who is residing in those places. Social disorganization theory has been the most prominent of the macro-level social theories used to explain how structural changes shape the "criminal careers" of communities. This theory draws from the consensus perspective by assuming that varying social groups hold shared or similar values and norms (Durkheim, 1893/1997), including shared sentiments about how society is to be organized and the rules for a functioning social order.

The origins of social disorganization theory can be traced back to the work of two theorists, Robert Park and Ernest Burgess (1925), both urban sociologists who suggested that cities, such as Chicago, evolve over time. Using the "concentric zone model," Park and Burgess maintained that cities grow naturally by expanding outward to form distinct zones. Of particular interest is the zone in transition, or "interstitial area," which is situated between city centers and inexpensive housing of the working class, but is characterized by rapid population growth, increased levels of population turnover, and racial and ethnic heterogeneity. Subsequent work by Clifford Shaw and Henry D. McKay (1942) suggested that transitional or "disorganized" communities (like the "zone in transition") produced fear, mistrust, and a failure to realize shared interests among residents (Bursik, 1988; Kornhauser, 1978), resulting in the breakdown of social institutions, other social control mechanisms and ensuing crime. Now a staple observation within criminological history, Shaw and McKay (1942) observed that disorganized communities had higher rates of delinquency regardless of the socio-demographic makeup of the population (often immigrant groups).

Since the early 1980s, research on the relationship between structural measures of disorganization and violent crime, especially homicide, in the United States has grown tremendously (Pridemore, 2002). For example, studies have found a positive relationship between homicide and ethnic heterogeneity (Hansmann & Quigley, 1982) and residential mobility (Crutchfield, Geerken, & Gove, 1982), as well as a consistently strong and positive relationship between poverty or concentrated disadvantage and homicide (see Bailey, 1984;

Hsieh & Pugh, 1993; Kposowa & Breault, 1993; Pratt & Cullen, 2005; Sampson, 1986; Sampson, Raudenbush, & Earls, 1997; Williams, 1984). In fact, Pridemore (2002) has suggested that the significant relationship between poverty and homicide is by far the most consistent finding in the criminological literature on homicide (see also Pratt & Cullen, 2005).

Though few studies have directly tested social disorganization theory in the context of bias crime, some have examined how deleterious economic conditions of communities shape bias crime outcomes. For example, Pinderhughes (1993) found that deteriorating economic conditions (among other structural variables) were associated with youth involvement in racial violence in New York City. Similarly, Medoff (1999) examined the effects of socioeconomic indicators on bias crime across several states for a single year and found that the unemployment rate (another indicator of economic disadvantage) was positively associated with the number of bias crimes (see also Gale et al., 2002 for similar findings across several states and years), while the full-time hourly wage rate was negatively associated with the number of bias crimes. Finally, assuming that routine and bias crime share similar traits, Grattet (2009) more directly examined the relationships between bias crime and key social disorganization concepts in Sacramento, California, between 1995 and 2002, finding that residential turnover, as well as concentrated disadvantage, significantly predicted the frequency of bias crime occurrences.

As noted above in discussing Table 1, other studies have observed contradictory findings, however. For example, Green, Glaser, and Rich (1998) examined possible links between unemployment and bias crime occurrences across New York City boroughs from 1987 to 1995, but found no relationship between bias crime occurrences and economic conditions. In a related study, Green, Strolovitch, and Wong (1998) examined the effects of several demographic and socioeconomic variables (e.g., unemployment) on racially motivated crimes across New York

City communities, but similarly found no relationship between bias crime and economic conditions.

An important point to note here is that some criminologists have suggested that the social disorganization experienced by specific racial and ethnic groups may uniquely predict crime and that capturing socioeconomic disadvantage, mobility, and other key indicators of disadvantage separately for Whites and Blacks provides greater leverage than measuring social disorganization overall. For example, Sampson and Wilson (1995) note that the impoverished community contexts of Blacks far exceed those of Whites, coinciding with social and physical isolation and stigma to a greater degree. Substantively, this means that Black socioeconomic disadvantage and other tenets of disorganization may drive bias crime to a greater degree than that of Whites. Methodologically, other scholars point to the necessity of disaggregating structural measures – like those derived from social disorganization theory – by race because of the qualitatively different levels of exposure to deleterious neighborhood conditions (McNulty, 2001 refers to this as the problem of "restricted distributions"). As such, social disorganization among Black residents may have a greater criminogenic effect on bias crime than disorganization experienced by the overall (or even White) population. Despite the apparent necessity of examining race-specific measures in relation to bias crime, only a handful of studies have done so (e.g., Gale et al., 2002; Green, Strolovitch, & Wong, 1998; Lyons, 2007). Even more, the studies on bias crime that have used race-specific measures generally only applied them to variables capturing unemployment and inequality, leaving out other important measures, such as disadvantage and residential stability that are central to social disorganization perspectives.

Overall then, social disorganization theory clearly generates expectations that bias crimes will be more likely to occur in disadvantaged and racially/ethnically heterogeneous communities where informal social controls have broken down, especially as it regards to social disorganization experienced by Blacks. Thus, the current study will contribute to the literature by testing the following hypotheses:

> **H1** *Based on social disorganization theory, socioeconomic disadvantage, mobility, and racial/ethnic heterogeneity will have significant and positive relationships with bias homicide.*

> **H2** *Based on social disorganization theory, Black socioeconomic disadvantage and mobility will have stronger relationships with bias homicide than White disadvantage and mobility.*

Group Threat Theory

Another structural perspective known as group threat theory (also referred to as racial threat or competition theory) has been applied to racial violence and other forms of crime, including bias crime. Group threat theory draws from the conflict perspective as it assumes that different social groups within society hold opposing values and norms (Sellin, 1938). This theory maintains that dominant groups who strive to maintain their social positions of status may feel threatened (e.g., economically, socially, culturally) by subordinate groups who are perceived as competing for opportunities, resources, and social space. For example, perceived economic threats may result in animus and inter-group hostility toward subordinate groups (Blalock, 1967; Blumer, 1958). In particular, dominant groups are more likely to perceive threats when racial and ethnic minority groups move into areas of limited resources, leading the dominant group to view minorities as disrupting long-standing social order (Blumer, 1958). Prejudiced views toward subordinate groups lead to feelings of hostility by members of the dominant group who may turn to discriminatory and reactionary forms of aggression in order to remove the perceived threat: the greater the threat is perceived to be, the more harshly the dominant group is likely to respond to outsiders (Quillian, 1995). Building on these themes, Blalock (1967) suggests that discriminatory violence increases in likelihood as racial and ethnic groups gain in their overall share of the population, especially under strained economic conditions (see also Quillian, 1995).

Empirical evidence regarding the relationship between group threat and bias crime is scant. The most applicable are a series of studies that have found a direct link between racial violence in the form of Black lynchings and the size of the Black population (Beck & Tolnay, 1990; Corzine, Corzine, & Creech, 1988; Corzine, Creech, & Huff-Corzine, 1983). Though not a study of bias crime, a more recent study by King and Wheelock (2007) examined the relationship between social conditions, perceived group threat, and punitive attitudes, concluding that attitudes tended to be more punitive in places experiencing high unemployment rates and an in-migration of Blacks.

Based on the previous literature and the specific tenets of group threat theory, it is clear that group threat, in some ways, offers differing expectations about the relationship between certain social-structural variables and bias crime. While social disorganization theory assumes that the main factors driving bias crime are poverty (or the concentration of socioeconomic disadvantage), residential instability, and racial/ethnic heterogeneity, group threat theory focuses more specifically on the perceived threat of minority groups by the dominate group, especially in disadvantaged communities, as viewed through the lens of minority population size. As such, I generate the following hypothesis drawing from group threat theory:

> **H_3** Based on group threat theory, racial/ethnic heterogeneity will have a significant and positive relationship with bias homicide.

A Note On The Defended Neighborhood Perspective

Viewed by some as an extension of group threat theory, the defended neighborhood perspective has similarly been applied to the study of bias crime. This perspective, which also draws from the conflict perspective, maintains unique assumptions concerning the ways in which racial violence and minority population representation (and migration) are related to each other. Compared to the wide array of environments in which group threat might play out, Green, Strolovitch, and Wong (1998) suggest that defended neighborhoods are those longstanding predominantly White communities who perceive their relatively homogenous neighborhoods as their "territory" that should be guarded against increased levels of residential ethnic transition (Suttles, 1972). Thus, as minorities move into these communities, bias crime increases as a means to "defend their neighborhood." In essence, defended neighborhoods applies primarily (or even only) to predominantly White neighborhoods.

Although there have been at least three studies that have found a relationship between bias crime occurrences and the defended neighborhood perspective (i.e., Grattet, 2009; Green, Strolovitch, & Wong, 1998; Lyons, 2007), ambiguity remains regarding how to operationalize defended neighborhoods. For example, Grattet (2009) refers to Suttles' (1972) ethnographic study to suggest that the defended neighborhood perspective involves a perceived threat to a community's identity and the need for residents to step in and defend it (which bias crime may serve to do). In contrast, Lyons (2007) suggests that another implication of the defended neighborhood perspective on bias crime is related to community economic resources and social capital. He proposes that racially motivated bias crimes are more likely to take place in White, organized communities that have the economic resources to be able to afford to keep racial minorities out. At the extreme level, residents from these communities may resort to bias crime as a defense mechanism in order to protect the racial homogeneity of the community.

Due to the definitional ambiguity, the difficulty in operationalizing key concepts, and the general overlap with the broader group threat perspective, the current study does not attempt to examine bias crime in relation to the defended neighborhood perspective. Moreover, as discussed below regarding the parameters of the current study, the dependent variable (bias homicides) examined in the current study may not provide an adequate test of the defended neighborhood perspective. Indeed, it is unlikely that affluent White communities would respond to (disadvantaged) minority populations with lethal violence and would instead likely turn to law enforcement or other resources to keep minorities out. Therefore, this perspective goes beyond the scope of this study and will not be examined, though I describe it here given its centrality in prior research.

Overall then, empirical research has begun to lay the groundwork for examining the relationships between social structural conditions and bias crime, but there remains much work to be done to fully untangle the socio-structural correlates of bias crime. Drawing from social disorganization theory and group threat theory, the current study builds on prior research by examining the theoretically relevant predictors of both the likelihood of bias homicide occurrences, as well as the total number of bias homicide incidents. I turn now to a description of the current study's data, methods, and key findings.

III. Parameters of the Current Study

To reiterate, the goal of the current study is to answer two closely related questions: *(1) what are the structural predictors of the likelihood of bias homicide occurrences*? *(2) do these same structural predictors affect the number of incidents across those counties that experience multiple bias homicides?* I turn now to the sources of data, codification of key dependent and independent variables, and the analytic techniques employed to answer these questions.

Sources Of Data

First, data on bias homicides over the 1990-2014 period is drawn from the United States Extremist Crime Database (ECDB), an open-source relational database on violent extremist crimes (see Freilich et al., 2014).[1] Bias homicides (or hate homicides) are defined as fatal attacks against social minorities due in whole or part because of their real or perceived race, ethnic origin, religion, sexual orientation, or gender identity and are identified from publicly available sources, including official criminal justice sources, watch group reports, scholarly reports and chronologies, and from systematic news media searches.[2]

All bias homicides included in the ECDB must meet one or more primary bias indicators (see appendix A) (Gruenewald, 2012). Primary indicators consist of observable homicide attributes indicating that offenders targeted victims as a result of real or perceived status, as well as bias indicators indicating one or more of the following: verbal harassment (e.g., the use of bigoted slurs), symbolic homicide location, specific modes of victim selection, official hate crime charges, offender admission of bias, prior bias motivated crimes perpetrated by the offender, and/or the symbolic manipulation of the victim's body. Additionally, the ECDB employs secondary indicators that, while alone cannot be used to determine motive, are useful for providing supportive information regarding the categorization of bias homicides. These indicators include a lack of ulterior motive (e.g., robbery), evidence of overkill, and victim attire (most applicable to transgender bias homicides).

[1] The ECDB includes data on bias homicides committed by domestic extremist groups (or "hate groups"), as well as offenders who have no known links to extremist groups.
[2] Although not yet considered a federally protected group, several states have adopted laws to protect homeless persons (e.g., Alaska, California, Florida, Maine, Maryland, Rhode Island, and Washington) from discriminatory violence. Therefore, anti-homeless homicides will also be included in the study.

The second source of data used is the U.S. Census summary files in 1990, 2000, and 2010. This source provides key measures of social and economic characteristics to be paired with the ECDB data in order to examine the structural predictors of bias homicide.

Unit of Analysis

The unit of analysis for the current study is the county year. The county was chosen for several substantive and methodological reasons. First, homicides are rare events and bias homicides even more so. As such, counties are large enough to ensure that there are enough units to conduct a meaningful statistical analysis, while still including a satisfactory number of covariates. Second, because the bias homicides are drawn from as far back as 1990, many smaller units of analysis cannot be utilized since race-specific information is unavailable for many of the key structural characteristics described below. Third, the theoretical frameworks employed above are not restricted to any specific unit of analysis (see Sampson, 2013 for a discussion). Finally, fourth, some previous research on the covariates of other rare events (e.g., bias homicides, terrorism) has utilized counties (Adamczyk, Gruenewald, Chermak, & Freilich, 2014; Chermak & Gruenewald, 2015; LaFree & Bersani, 2014).

Every county was used for each of the three time points: 1990, 2000, and 2010. Bias homicides from the years 1990 through 1995 were paired with Census data from 1990, while Census measures for 2000 and 2010 were used for homicides between 1996 and 2004 and 2005 and 2014, respectively. The final sample includes 9425 county years, constituting nearly complete coverage for the United States for each of the three time points.

Dependent Variables

The current study examines two dependent variables for bias homicide as drawn from the ECDB. The first is a dummy variable capturing *whether there was an occurrence of a bias* *homicide* in a U.S. county or not over the 1990-2014 period (see the data pairing strategy above). This variable directly taps into the first research question addressing the structural covariates of the likelihood of a county experiencing a bias homicide. Second, I measure the *total number of bias homicides* in each county using incident counts. This dependent variable bears on the second research question regarding the predictors of the number of bias homicide incidents across counties.

Independent Variables

To predict bias homicide likelihood and incidence, I draw on a host of macro-structural characteristics from the Census data (See Table 2). To account for the basic demographic composition of counties that has been shown to influence levels of aggregate crime, I include *population size* and *population density* (both are logged to induce normality), as well as dummy variables for the *South*, *West*, and *Midwest* regions (Northeast is the reference).

Drawing on social disorganization theory, I include several measures of disadvantage, which are disaggregated separately for the overall/total population and then for Whites and Blacks. Specifically, *poverty* is measured as the percentage of persons living below the poverty line; *unemployment* is operationalized as the percentage of the civilian labor force that is unemployed; *female headship* is measured as the percentage of families headed by a female with children under 18; *low education* is operationalized as the percentage of persons without a high school degree in a particular county. Because measures of disadvantage tend to be highly correlated in macro-level data (see the discussion of the correlation matrix below), I ran a principal component analysis in order to combine them into total, White, and Black disadvantage indexes (Land, McCall, & Cohen, 1990) (see the discussion on race-specific measures for methodological and substantive reasoning). As an added social disorganization measure, I also

Table 2: Dependent, Independent, and Control Variables

Dependent Variables	**Data Source**	**Measurement**	**Operationalization**
Bias Homicide Occurrence	ECDB	Dichotomous	Whether a U.S. county had a bias homicide or not
Number of Bias Homicides	ECDB	Continuous	Total number of bias homicides that took place in a county
Independent Variables			
Population Density	U.S. Census	Continuous	Persons per square mile
Population Size	U.S. Census	Continuous	Total population in a county
Poverty	U.S. Census	Continuous	Percentage of persons below poverty line
Unemployment	U.S. Census	Continuous	Percentage of civilian labor force that is unemployed.
Low Education	U.S. Census	Continuous	Percentage of persons without a high school degree
Female Headship	U.S. Census	Continuous	Percentage of families headed by female (no male present) with children under 18
Mobility	U.S. Census	Continuous	Percentage of persons living in a different county five years prior
Racial/Ethnic Population	U.S. Census	Continuous	Percentage of population that is Black and Hispanic
Control Variables			
Region	U.S. Census	Dichotomous	Northeast, South, West, Midwest
Percent Foreign Born	U.S. Census	Continuous	Percentage of foreign-born residents in a county
Percent Recent Foreign-Born	U.S. Census	Continuous	Percentage of foreign-born population that arrived between 1990 and 2000

included *mobility*, measured as the percentage of the population (total, White, Black) living in a different county five years prior, as well as measures of the relative representativeness of racial and ethnic groups in a particular area as *percent Black* and *percent Hispanic*. I note also that these latter two measures are similarly consistent with group threat perspectives as noted in my literature review above.

Dovetailing with the group threat perspective, I also include a measure of the *percent foreign born* (the percent of the total population who are foreign born) and *percent recent foreign born* (the percent of the total population that are foreign born and who arrived in the previous 5 years). While not as widely used as racial and ethnic composition within the group threat literature, these measures are intended to examine alternative dimensions of minority population size that might be also be associated with bias homicide as a result of encroachment and conflict.

Analytic Techniques

The analysis unfolds as follows. First, descriptive statistics are displayed in order to provide insight on the distribution of bias homicides across counties, as well as to describe variation in theoretically important macro-structural characteristics across racial/ethnic groups and across counties. Second, I estimate bivariate correlations that display the one-to-one relationships between bias homicide and key macro-level covariates. The goal here is to explore any initial relationships between the various theoretical measures and the likelihood and overall number of incidents of bias homicide before simultaneously controlling for a multitude of structural and demographic covariates.

Third, I construct a series of multivariate penalized maximum likelihood logistic regression models (to predict the likelihood of bias homicide) and negative binomial regression models (to predict the number of bias homicide incidents) to address the two central research questions. Regarding the former, the dummy dependent variable is dichotomous in nature, but the rarity of bias homicides introduces the potential for bias in the estimation of standard logistic regression models (King & Zeng, 2001). As a result, penalized models are more appropriate because they account for the disproportionate influence of a small number of rare events in a large sample of observations by generating lower variance estimates of logit coefficients and their variance-covariance matrix (see also Adamczyk et al., 2014). Regarding the latter models predicting the number of bias homicide incidents, the dependent variable is a count of bias homicides (i.e., whole integers) with evidence of over-dispersion (see the descriptive statistics below). As such, negative binomial models are more appropriate than standard least squares regression techniques (Osgood, 2000).

IV. Results

Beginning with the descriptive statistics, I note the following. First, as expected, there are large disparities in disadvantage across racial groups in the U.S. As shown in Table 3, nearly 27% of Black residents in the U.S. live below the poverty line compared with only 12% of White residents, while nearly 20% of Black homes have single females as head of households compared to only 7% of White homes. Similar disparities are observed for unemployment and low education (i.e., substantial Black-White disparities).

Second, not only are there significant disparities across racial groups for several of the structural variables, but there is variation across counties, as well. In particular, there are rather larger standard deviations for many of the key theoretical measures, including Black poverty and female headship. Indeed, many of the variables have standard deviations nearly as large as their

Table 3. Descriptive Statistics For Key Variables (N=9425)

	Mean	Std. Dev.	Min.	Max.
Dependent Variables:				
Total Incidents	.035	.264	0	8
Ever Incidents	.025	.156	0	1
Basic Demographic Variables:				
Population size	88498.36	288932.5	41	9758256
Population size (ln)	10.203	1.418	3.714	16.094
Population density	247.181	1681.183	0.04	69357.7
Population density (ln)	3.760	1.693	0	11.147
South	.453	.498	0	1
West	.132	.338	0	1
Midwest	.335	.472	0	1
Social Disorganization:				
Black Poverty	26.603	22.319	0	100
White Poverty	12.092	5.281	0	53.86
Black Unemployment	9.766	13.777	0	100
White Unemployment	4.689	2.314	0	44.18
Black Female Headship	20.041	18.199	0	100
White Female Headship	7.278	2.396	0	27.27
Black Low Education	27.141	22.992	0	100
White Low Education	20.360	10.047	0	64.87
Black Mobility	30.783	26.406	0	100
White Mobility	22.480	11.229	0	100
Defended Neighborhoods/Group Threat:				
Percent Black	8.709	14.448	0	86.136
Percent Hispanic	6.156	12.066	0	98.328

means (or, in some cases, standard deviations larger than their means), suggesting that counties vary considerably in their social and demographic composition in important ways.

Third, it is clear that bias homicides are rare events. Table 3 reveals that the average county experienced less than 1 bias homicide during the time period under examination (mean = .035) and, indeed, the likelihood of a county ever having a bias homicide was minimal, as well (mean = .025). In short, the descriptive statistics reveal that fatal bias crime is incredibly rare and that very few counties experience an incident (though several counties experienced more than one, as demonstrated by the maximum values).

Bivariate Analysis

The next step in the analysis is to examine the bivariate correlations between bias homicide incidence and each of the key independent variables (as well as between the key independent variables themselves) in order to identify the baseline relationships underlying the patterns described in Table 3. Table 4 provides the Pearson correlation coefficients and their significance levels for the entire group of dependent, independent, and control variables. Below, I focus on how the independent variables correlate with the two main dependent variables (i.e., the likelihood of a bias homicide, the number of bias homicides).

I note the following key findings. First, population size, population density, Black disadvantage, percent Black, and percent Hispanic are all significantly and positively associated with the likelihood of a bias homicide. This means that counties with larger populations, that are more densely populated, where the Black population is more disadvantaged, and where there is greater Black and Hispanic relative population representation are more likely to experience a bias homicide. I also find that the variables total disadvantage, White disadvantage, Black mobility, and percent White are all significantly and negatively associated with the likelihood of a bias homicide. In other words, counties with more total or White disadvantage, a greater percentage of the Black population that is residentially unstable, and where Whites represent a greater proportion of the overall population are relatively less likely to experience a bias homicide.

Table 4. Correlations For All Key Variables N=9425

	1	2	3	4	5	6	7	8	9	10	11	12	13
1). Total Incidents	1												
2). Ever Incidents	.823	1											
	(.000)												
3). Population Size (ln)	.292	.309	1										
	(.000)	(.000)											
4). Population Density (ln)	.187	.195	.689	1									
	(.000)	(.000)	(.000)										
5). Total Disadvantage	-.011	-.023	-.070	.005	1								
	(.277)	(.028)	(.000)	(.622)									
6). White Disadvantage	-.077	-.086	-.158	-.027	.700	1							
	(.000)	(.000)	(.000)	(.008)	(.000)								
7). Black Disadvantage	.017	.025	.222	.239	.381	.259	1						
	(.092)	(.015)	(.000)	(.000)	(.000)	(.000)							
8). Total Mobility	.003	.016	.098	.050	-.138	-.046	-.020	1					
	(.795)	(.130)	(.000)	(.000)	(.000)	(.000)	(.054)						
9). White Mobility	-.004	-.004	.054	.027	.193	.262	.069	.737	1				
	(.725)	(.735)	(.000)	(.009)	(.000)	(.000)	(.000)	(.000)					
10). Black Mobility	-.032	-.030	.051	-.025	-.106	.023	.036	.314	.278	1			
	(.002)	(.003)	(.000)	(.016)	(.000)	(.027)	(.001)	(.000)	(.000)				
11). Percent Black	.055	.058	.133	.220	.465	-.004	.355	-.066	-.008	-.221	1		
	(.000)	(.000)	(.000)	(.000)	(.000)	(.717)	(.000)	(.000)	(.454)	(.000)			
12). Percent White	-.129	-.123	-.149	-.067	-.523	.123	-.212	.024	-.001	.167	-.643	1	
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.020)	(.919)	(.000)	(.000)		
13). Percent Hispanic	.104	.091	.073	-.076	.171	-.101	-.011	.031	-.010	-.024	-.105	-.558	1
	(.000)	(.000)	(.000)	(.000)	(.000)	(.000)	(.302)	(.003)	(.320)	(.019)	(.000)	(.000)	

Of particular note, White disadvantage is negatively associated with the likelihood of a bias homicide, whereas Black disadvantage is positively associated with the likelihood of a bias homicide. That is to say that bias homicides are less likely to take place in counties with a greater amount of White disadvantage (poverty, unemployment, female headship, and educational deficits), but more likely to take place in counties with greater prevalence of these same features for Blacks. Thus, there appears to be a unique criminogenic relationship between Black disadvantage and bias homicide likelihood. As it relates to the theoretical frameworks described above, this provides mixed support for the social disorganization perspective, which predicts disadvantage to lead to an increased likelihood of bias homicide. The results displayed in Table 4 reveal this is true only for Black disadvantage. Additionally, the expectation from social disorganization theory that residential mobility is positively associated with bias homicide is not borne out: total mobility and White mobility are not significantly correlated with either the likelihood of a bias homicide or the number of bias homicides (discussed below), while Black mobility is negatively correlated with both dependent variables. Thus, the bivariate correlations provide partial support for hypothesis 2 predicting a specific criminogenic effect of Black (but not total or White) disadvantage on bias homicide as observed here.

Regarding percent Black and percent Hispanic, their correlations with bias homicides provide some support for my hypotheses given that they are key measures for both group threat and disorganization perspectives. That is, the positive and significant correlations for percent Black and percent Hispanic with bias homicide likelihood dovetail with both social disorganization and group threat theories in that the racial/ethnic heterogeneity of a county increases the likelihood of a bias homicide occurring.

Turning to the number of bias homicides, the variables population size, population density, Black disadvantage, percent Black, and percent Hispanic are all significantly and positively associated with the total number of bias homicides, while White disadvantage, Black mobility, and percent White are all significantly and negatively associated with the total number of bias homicides. Again, I find that while White disadvantage is negatively associated with the total number of bias homicides, Black disadvantage was positively associated with the total number of bias homicides. These patterns are consistent with those observed for the overall likelihood of an incident occurring and overlap with the theoretical frameworks as noted above.

As a final point of emphasis, Table 4 demonstrates the value of combining the individual variables that constitute the disadvantage index. Several of the race-specific disadvantage measures (e.g., poverty, female headship) are strongly correlated with each other and have the potential to introduce problematic multicollinearity in any subsequent multivariate models. As such, there appears to be statistical support for the construction of the disadvantage index using principal component methods as discussed above.

Multivariate Analysis: Predicting The Likelihood Of Incident

While instructive, the correlations discussed above do not take into account the degree to which many of the bivariate relationships are affected by other key independent and control variables (i.e., their shared variance). As such, Table 5 provides the findings from multivariate models simultaneously controlling for theoretically derived independent variables and demographic/structural controls. I start by utilizing penalized maximum-likelihood logistic regression analyses to predict the likelihood that a county will experience a bias homicide. Panel A shows the findings using a Black-specific disadvantage index and a Black mobility variable, while Panel B provides the findings in relation to the White disadvantage index and White

Table 5. Penalized Maximum-Likelihood Logistic Regression of Overall Fatal Bias Crime Likelihood On Key Theoretical Predictors and Other Key Controls (N=9425)

	(A) Black Specific Variables				(B) White Specific Variables			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Social Disorganization:								
Black Disadvantage Index	-	.297**	-	.273*	-	-	-	-
	-	(.114)	-	(.116)	-	-	-	-
White Disadvantage Index	-	-	-	-	-	.110	-	.101
	-	-	-	-	-	(.080)	-	(.083)
Black Mobility	-	-.003	-	-.002	-	-	-	-
	-	(.006)	-	(.006)	-	-	-	-
White Mobility	-	-	-	-	-	-.005	-	-.005
	-	-	-	-	-	(.008)	-	(.008)
Group Threat:								
Percent Black	-	-	.012†	.007	-	-	.012†	.011†
	-	-	(.006)	(.007)	-	-	(.006)	(.006)
Percent Hispanic	-	-	-.000	-.000	-	-	-.000	-.002
	-	-	(.006)	(.006)	-	-	(.006)	(.006)
Basic Demographic variables:								
Population size (ln)	1.372***	1.368***	1.350***	1.356***	1.372***	1.401***	1.350***	1.383***
	(.076)	(.076)	(.079)	(.080)	(.076)	(.079)	(.079)	(.085)
Population density (ln)	.004	.015	-.011	.007	.004	.011	-.011	-.003
	(.054)	(.056)	(.054)	(.056)	(.054)	(.059)	(.054)	(.059)
South	.327	.283	.175	.199	.327	.368†	.175	.237
	(.213)	(.256)	(.233)	(.234)	(.213)	(.218)	(.233)	(.241)
West	.508*	.649*	.556*	.666*	.508*	.564*	.556*	.621*
	(.249)	(.257)	(.260)	(.267)	(.249)	(.254)	(.260)	(.268)
Midwest	-.066	-.108	-.096	-.126	-.066	-.039	-.096	-.074
	(.248)	(.250)	(.250)	(.251)	(.248)	(.250)	(.250)	(.252)

† p<.10, * p<.05, ** p<.01, *** p<.001

mobility. For each panel, model 1 includes only the basic demographic variables, while model 2 introduces disadvantage and mobility (per social disorganization theory), model 3 examines the percent Black and Hispanic (per group threat perspectives), and model 4 includes all measures together in a saturated model.

I note three key findings. First, I find that population size and the West region are significantly related to overall bias homicide likelihood. Across all models in Table 5, counties with larger populations and those in the western region of the U.S. are more likely to have a bias homicide incident. In fact, the odds ratios in the final model (not shown) suggest that counties in the western region are 94 percent more likely to experience a bias homicide, while an increase in the log of the county population increases the likelihood of a bias homicide substantially, as well.

Second, structural disadvantage is a statistically significant predictor of bias homicide likelihood, but only as it regards to Black (but not White) disadvantage. That is, model 2 in Panel A indicates that Black disadvantage is a significant predictor of bias homicide likelihood, net the effects of all other variables, while model 2 in Panel B shows no statistically significant effect of White disadvantage on incidence at traditional significance levels. Indeed, the association between Black disadvantage and bias homicide likelihood remains even in the fully saturated model (model 4 in panel A). The odds ratio for Black disadvantage in the fully saturated model (not shown) indicates that a one unit increase in Black disadvantage increases the likelihood of a bias homicide incident by 31 percent.

Finally, percent Black is marginally significant ($p<.10$) in three out of the four models in which it is included, but Hispanic population composition does not appear to be associated with greater/lesser likelihood of bias homicide. Overall then, Table 5 reveals that counties with greater levels of Black disadvantage, a larger population size, and those located in the Western region are more likely to experience a bias homicide.

Multivariate Analysis: Predicting The Number Of Incidents

While the results above are helpful for shedding light on several key theoretical frameworks predicting the likelihood of a bias homicide occurring at the county-level, it is clear from the descriptive statistics that many counties experience more than one bias homicide incident. As such, I turn now to a series of models examining the same independent variables as predictors of the number of bias homicides across counties. Due to the larger number of units analyzed in predicting the number of bias homicides and the whole integer count nature of the dependent variable, I utilize negative binomial regression in order to examine whether counties with only one bias homicide differ from counties that experience multiple bias homicides (see Osgood, 2000 for a detailed discussion of the negative binomial procedure in aggregate crime data).

The results for the negative binomial regression of overall fatal bias crime counts are shown in Table 6. First, although both the race-specific variables were again analyzed separately, I found only population size to be a significant predictor across all four models. In other words, within those counties that have experienced a bias homicide, those with smaller population sizes are more likely to experience multiple bias homicides, a finding that contrasts with the results of the penalized maximum likelihood models in Table 5. It is important to note also that the negative binomial models include an exposure term for the total population that essentially converts the counts to rates, meaning that this finding is not simply a reflection of a relationship that exists in a few sparsely populated counties with two or three bias homicides.

Table 6. Negative Binomial Regression of Overall Fatal Bias Crime Counts On Key Theoretical Predictors and Other Key Controls (N=235)

	(A) Black Specific Variables				(B) White Specific Variables			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Social Disorganization:								
Black Disadvantage Index	-	.052	-	.048	-	-	-	-
	-	(.101)	-	(.103)	-	-	-	-
White Disadvantage Index	-	-	-	-	-	.075	-	.073
	-	-	-	-	-	(.072)	-	(.073)
Black Mobility	-	.001	-	.001	-	-	-	-
	-	(.005)	-	(.005)	-	-	-	-
White Mobility	-	-	-	-	-	.003	-	.003
	-	-	-	-	-	(.006)	-	(.006)
Group Threat:								
Percent Black	-	-	.002	.001	-	-	.002	.001
	-	-	(.005)	(.005)	-	-	(.005)	(.005)
Percent Hispanic	-	-	.001	.001	-	-	.001	.001
	-	-	(.005)	(.005)	-	-	(.005)	(.005)
Basic Demographic variables:								
Population size (ln)	-.785***	-.780***	-.791***	-.786***	-.785***	-.782***	-.791***	-.789***
	(.055)	(.057)	(.061)	(.062)	(.055)	(.055)	(.061)	(.062)
Population density (ln)	.024	.026	.021	.025	.024	.045	.021	.043
	(.036)	(.038)	(.037)	(.038)	(.036)	(.040)	(.037)	(.041)
South	.164	.168	.153	.159	.164	.195	.153	.185
	(.164)	(.165)	(.167)	(.168)	(.164)	(.176)	(.167)	(.181)
West	.258	.273	.267	.272	.258	.296	.267	.291
	(.182)	(.188)	(.191)	(.195)	(.182)	(.194)	(.191)	(.205)
Midwest	.024	.019	.032	.027	.024	.053	.032	.061
	(.195)	(.195)	(.199)	(.199)	(.195)	(.200)	(.199)	(.203)

† p<.10, * p<.05, ** p<.01, *** p<.001

Second, none of the other theoretically relevant independent or control variables reached statistical significance. Though this may be due to limited statistical power in such a small sample (N=235), it is noteworthy that where several key predictors had important effects on the likelihood of an incident occurring, none of these predictors are associated with the total number of bias homicides across counties. Taken together then, Tables 5 and 6 suggest that theoretically informed macro-structural covariates impact the likelihood, but not the number, of bias homicides.

Supplemental Analyses

In order to add to the robustness of findings, I constructed a battery of supplemental models that are available in the appendix. Because the primary models in this study focus on race-specific variables, I also examine non race-specific models (see appendix B, Table B1). These findings generally parallel those in the Black-specific and White-specific models, with a few exceptions. Although population size and the western region are significant predictors in the total (not race-specific) model, the total disadvantage index does not significantly predict the likelihood of a bias homicide or the number of bias homicide incidents. In some ways this lends credence to the assumption that it is Black disadvantage (and other race-specific predictors) that matters, rather than those for Whites or the overall population.

Additionally, I estimate White and Black models that included the discrete components of the disadvantage indexes (i.e., poverty, unemployment, female headship, low education) to see if there are any significant findings regarding variables related to disadvantage that might be overshadowed by the construction of the combined index (see appendix B, Tables B2 and B3). These models also examine alternative specifications of group threat by replacing the racial/ethnic composition measures with the relative size of the foreign born population and the recent foreign born population. Both sets of models revealed no significant findings, suggesting that it is the combined influence of all four measures together that are criminogenic (rather than their separate effects), as well as that group threat is racial/ethnic in nature rather than characterized by foreign born status.

V. Discussion and Conclusion

Identifying community factors that may increase the likelihood of bias crime is important as previous studies have shown that this form of crime is more harmful to communities, adversely affecting immediate victims and their respective communities (Green, McFalls, & Smith, 2001; Levin & McDevitt 1993, 2002). To date, there have been relatively few studies that have examined bias crime at the macro-level. Unfortunately, because of a lack of available bias crime data and the use of varying measures in testing specific theoretical frameworks, few studies have comparatively examined structural and demographic features of communities in relation to bias crime. Of the few studies that have made these comparisons, the results are inconsistent across studies and have led to uncertainty regarding the most important community-level correlates of bias crime.

Moreover, most prior studies examining bias crime at the aggregate level have tended to neglect race-specific contextual measures and focused on variations in bias crime occurrences in single cities or across multiple states, making it difficult to draw conclusions about specific community factors affecting bias crime outcomes. Also important, these studies have failed to distinguish between forms of fatal and non-fatal bias crimes, disputably assuming that social and economic factors affect both types of bias crime in the same ways. Therefore, the goal of the current study was to contribute to this emerging body of literature by examining the structural and demographic features of counties as predictors of bias homicide occurrences using data from the ECDB. Specifically, I asked (1) what are the structural predictors of the likelihood of bias homicide occurrences? and (2) do these same structural predictors affect the number of incidents across those counties that experience multiple bias homicides?

Overall, I noted three key findings. First, bias homicides are rare and tend to be geographically concentrated. It is important to note, however, that although bias homicides only took place in 235 counties, some counties experienced multiple bias homicides (as many as eight homicides in one time period) between 1990 and 2014. Second, the likelihood of a bias homicide is associated with population size, geographic location, and the concentration of Black disadvantage. Conversely, overall/White disadvantage did not appear to be an important predictor of the likelihood of bias homicide or the number of bias homicides, nor did racial/ethnic diversity. Third, the number of bias homicides was inversely related to the size of the population, suggesting that while the likelihood of a bias homicide is greater in counties with large populations, smaller counties were more likely to have multiple incidents, after accounting for other structural factors.

While it was beyond the scope of the current study to explicitly test any specific theoretical framework, the overall findings for the current study lend partial support for both social disorganization and group threat theory. Concerning the social disorganization hypotheses, hypothesis 1 was not supported in that overall disadvantage, overall mobility, and racial/ethnic heterogeneity were not significantly related to either the likelihood of a bias homicide or the number of bias homicides. However, hypothesis 2 was partially supported in that Black socioeconomic disadvantage had a stronger relationship with the likelihood of a bias homicide than White socioeconomic disadvantage, while neither Black mobility nor White mobility was significantly associated with either dependent variable. In regards to group threat theory, I found partial support for hypothesis 3, suggesting that racial/ethnic heterogeneity had a marginally significant and positive relationship with the likelihood of a bias homicide, but was not significantly associated with the number of bias homicides. As noted in the review of both the social disorganization and group threat perspectives, there is considerable overlap in the key structural characteristics of communities that are thought to predict crime and violence. As such, it should be unsurprising that the analytic models yielded partial support for both theories without much leverage to adjudicate between them.

Limitations and Directions for Future Research

There are several limitations to the current study that future research may be able to better address. While this study attempts to examine how two theoretical frameworks (i.e., social disorganization and group threat) affect the likelihood of a bias homicide, this study lacks certain variables that may allow for a more complete test of each theory. For example, while group threat focuses on the racial/ethnic heterogeneity of places, it also suggests that a key component of the racial threat is the influx of minority migration to areas with limited resources. Therefore, future research should not only examine the percent of population that is non-White, but also include a measure for the in-migration of minorities. Relatedly and in regards to the defended neighborhood thesis, Lyons (2007) suggests including a measure of community affluence in addition to racial/ethnic in-migration variables in order to examine the particular contexts where bias crime may be used to "defend" against cultural and economic encroachment. While this study lacks a measure of community affluence, future research examining the defended neighborhood perspective in relation to bias crime should attempt to also capture such a dimension. Third, it was beyond the scope of this study to distinguish between victim group types. While this may only be possible for some types of victim groups (anti-race and anti-LGBT homicides) due to their larger sample sizes, future research would do well to examine whether certain county-level characteristics are more likely to correlate with these forms of bias homicide, as well as examine non-fatal bias crimes.

A review of prior literature reveals that the study of bias crime is still emerging and much of the findings are inconsistent. Only after examining the social conditions affecting bias homicide occurrences in communities can research truly begin to move from asking *what* leads to bias homicides to examining *how* these types of violent crimes can be prevented. The current study is a step in this direction and, coupled with the handful of other studies in this area, can help provide policy-makers and others responsible for improving community health with preliminary directions for making changes that may reduce the likelihood of bias homicide. In addition, the current study may help to inform educational programs aimed at reducing the harm bias crime has on communities, as well as, the social causes of bias crime. If we know that certain social conditions affect the likelihood of bias homicide occurrences, then communities can work to change these conditions in order to reduce this form of crime. Much of the bias crime policies that have already been put in place (e.g., the Matthew Shepard and James Byrd Jr. Hate Crimes Prevention Act) are more of reactive laws that focus on harsher penalties of bias crime offenders. Better data and research on bias crimes can and should provide policy-makers with the knowledge they need to create more preventative laws in the future.

While this study is far from conclusive, it does suggest that integrating social theories is one useful approach to explaining variations in bias crime across communities. One theory alone is likely insufficient for explaining the varying social causes of bias crime. Instead, it is through the convergence of social, economic, cultural, and other macro-level measures stemming from multiple theoretical frameworks that we can advance our understanding of the social-structural factors most associated with bias homicide across U.S. communities.

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VII. Appendices

Appendix A

Table A1. Indicators of Bias

Primary Indicators[a]	**Description**
Verbal harassment prior, during, and following the homicide	Bigoted innuendo, slurs, or slang.
Location of homicide	Examples include symbolic sites, such as gay bars or cruising areas, black churches, homeless encampments, religious centers.
Official hate crime charge	Homicide offender officially charged and/or prosecuted for bias crime.
Offender admission	Offender admits that the homicide was motivated at least in part by animus toward social minority victims.
Prior violence toward social minorities	Similar offenses against social minority group committed without arrest prior to incident, or specific offender is charged and/or prosecuted for prior violent crimes against social minority victims (i.e., serial offenders).
Mode of victim identification or selection	Homicide victim was identified or selected through affiliation with social minority group, organization, or business (Ex. gay chatroom or gay singles service).
Symbolic manipulation of victim body	Most often includes the manipulation includes post-mortem posing of victim's body and mutilation of face and genitals.
Secondary Indicators[b]	
Lack of known or ulterior motive	Available evidence shows that animus toward social minority victim was the only motive.
Victim attire	Most often found in murders of transgender victims. Examples include males dressing as females and vice versa.
Overkill	Evidence that victim, in addition to fatal wounds, endured an Excessive amount of nonfatal wounds.

a. Only 1 primary indicator is needed for homicide inclusion, b. A secondary indicator must be paired with a primary indicator for homicide inclusion.

Appendix B

Appendix B1. Supplemental Models Predicting Likelihood of Incidents and Number of Incidents

	(A) Predicting Likelihood of Incident				(B) Predicting Number of Incidents			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Social Disorganization:								
(Total) Disadvantage Index	-	.102	-	.077	-	.038	-	.069
	-	(.067)	-	(.090)	-	(.055)	-	(.086)
(Total) Mobility	-	.010	-	.009	-	-.006	-	-.006
	-	(.012)	-	(.012)	-	(.011)	-	(.011)
Group Threat:								
Percent Black	-	-	.012†	.008	-	-	.002	-.003
	-	-	(.006)	(.008)	-	-	(.005)	(.007)
Percent Hispanic	-	-	-.000	-.003	-	-	.001	-.003
	-	-	(.006)	(.007)	-	-	(.005)	(.006)
Basic Demographic variables:								
Population size (ln)	1.377***	1.375***	1.355***	1.368***	-.785***	-.797***	-.791***	-.785***
	(.076)	(.075)	(.079)	(.082)	(.055)	(.056)	(.061)	(.063)
Population density (ln)	-.002	-.013	-.017	-.001	.024	.022	.021	.027
	(.053)	(.054)	(.054)	(.056)	(.036)	(.036)	(.037)	(.038)
South	.324	.221	.171	.143	.164	.196	.153	.224
	(.213)	(.228)	(.233)	(.246)	(.164)	(.171)	(.167)	(.182)
West	.499**	.431†	.547**	.505†	.258	.317†	.267	.332
	(.249)	(.261)	(.260)	(.273)	(.182)	(.196)	(.191)	(.207)
Midwest	-.069	-.081	-.099	-.116	.024	.059	.032	.054
	(.248)	(.250)	(.250)	(.251)	(.195)	(.199)	(.199)	(.200)
N	9425	9425	9425	9425	235	235	235	235

† p<.10, * p<.05, ** p<.01, *** p<.001

Appendix B Cont.

Appendix B2. Supplemental Models Examining Other Specifications Of Key Predictors Net Of Controls

	(A) Predicting Likelihood of Incident			(B) Predicting Number of Incidents		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Social Disorganization:						
Black Poverty	.005	-	-	.000	-	-
	(.006)	-	-	(.006)	-	-
Black Unemployment	.014	-	-	.004	-	-
	(.012)	-	-	(.010)	-	-
Black Low Education	.003	-	-	.004	-	-
	(.007)	-	-	(.006)	-	-
Black Female Headship	.012	-	-	-.004	-	-
	(.009)	-	-	(.010)	-	-
Black Mobility	-.001	-	-	.001	-	-
	(.006)	-	-	(.006)	-	-
Group Threat:						
Percent Foreign Born	-	.013	-	-	-.002	-
	-	(.011)	-	-	(.008)	-
Percent Recent Foreign Born	-	-	.050†	-	-	.004
	-	-	(.029)	-	-	(.019)
N	9425	9425	9425	235	235	235

Note: All models include a full set of demographic controls as listed in previous tables.
† p<.10, * p<.05, ** p<.01, *** p<.001

Appendix B Cont.

Appendix B3. Supplemental Models Examining Other Specifications Of Key Predictors Net Of Controls

	(A) Predicting Likelihood of Incident			(B) Predicting Number of Incidents		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Social Disorganization:						
White Poverty	.030	-	-	.006	-	-
	(.021)	-	-	(.017)	-	-
White Unemployment	.059	-	-	.003	-	-
	(.074)	-	-	(.057)	-	-
White Low Education	-.011	-	-	.011	-	-
	(.015)	-	-	(.011)	-	-
White Female Headship	-.003	-	-	-.042	-	-
	(.049)	-	-	(.039)	-	-
White Mobility	-.003	-	-	.000	-	-
	(.008)	-	-	(.006)	-	-
Group Threat:						
Percent Foreign Born	-	.008	-	-	-.001	-
	-	(.011)	-	-	(.008)	-
Percent Recent Foreign Born	-	-	.042	-	-	.006
	-	-	(.029)	-	-	(.018)
N	9425	9425	9425	235	235	235

Note: All models include a full set of demographic controls as listed in previous tables.
† p<.10, * p<.05, ** p<.01, *** p<.001