Hotbeds of Hate:
Analyzing Spatial and Temporal Disparities in Hate Crime Across U.S. Cities

Addison Larson
Dr. Patrick Brandt
PSCI 4399
May 6, 2016

In 1998, three known members of a white supremacist group tied James Byrd, Jr., a middle-aged black man from East Texas, behind the back of a pickup truck and dragged him for roughly three miles along an asphalt road. Byrd remained conscious for most of this journey, until his body struck a culvert, cutting off his head and right arm. His dismembered torso was later deposited at a local African-American cemetery. Though the media and the public viewed Byrd's tragic story as an evident hate crime, the crime was labeled as an aggravated homicide (Jenness and Grattet 2001: 4). Byrd's story exemplifies both the importance and the difficulty of explaining where and why hate crime occurs.

Crimes motivated by hatred have existed throughout human history, but the legal concept of hate crime arose in the United States only in the late 20th century. The civil rights movements of the 1960s elevated issues of diversity, identity, and equality before the law to national prominence, and in 1990 the U.S. Congress established federal guidelines for hate crime reporting through the Hate Crime Statistics Act (HCSA). Some argue that the HCSA arose organically out of the legislature's need to enforce the provisions of civil rights legislation (Hall 2013: 21). Others argue that civil rights legislation, especially the Civil Rights Act of 1968, created a destructive identity politics that would inevitably lead to a higher incidence of hate crime and a need for new enforcement provisions (Jacobs and Potter 1998: 5).

Regardless of the suspected causal forces behind hate crimes legislation, the aim of the HCSA was fourfold, seeking to build up the criminal justice system's monitoring of hate crimes, to make law enforcement more sensitive to hate incidents, to raise public awareness of hate crimes, and to signal that hate crimes are unacceptable across the nation (Jacobs and Potter 1998: 69-70). The legislation defines hate crimes briefly as "crimes that manifest evidence of prejudice based on race, religion, sexual orientation, or ethnicity" (Bureau of Justice Statistics, 2016), and mandates the FBI to collect nationwide hate crime data on an annual basis.

The HCSA's definition captures the type of crime that is committed and reported, but it fails to delve into the unique aspects of hate crime as opposed to other types of crime. Hate crime is different from other types of crime for its unique combinations of perpetrators and victims, its excessive violence, and its spillover effects. First, hate crime is "downward" crime, where in-groups persecute members of out-groups through acts of violence: "it is a mechanism of power and oppression, intended to reaffirm the precarious hierarchies that characterize a given social order" (Perry 2001: 10). Second, hate crimes are "more likely to involve excessive violence" (Levin 1999: 15) than other types of crime. Third, victims are targets primarily as a function of their characteristics and not of existing grievances or disputes. Because of the particular type of targeting associated with hate crime, society tends to view hate crimes not as isolated incidents but as a broader message to minority groups that share the victim's identity. Hate crime sends "waves of harm," provoking fear in the victim's group, other marginalized groups, and society as a whole (Iganski 2001: 629). Hate crimes are simultaneously more brutal, more anonymous, and more threatening than other types of crime, and this is the reason they warrant further study. In an environment where prejudice cannot be directly measured, hate crime is an important metric of the prejudice that continues to pervade the United States.

Hate crime reporting varies widely across space and time. A brief glance at the FBI's hate crime statistics reveals that cities such as New York and Los Angeles report hundreds of crimes per year, while most cities in the southern U.S. report zero crimes, or only a handful. Even when viewed in terms of crime rate, the disparity from city to city is equally stark. Reporting within cities also fluctuates in a seemingly unpredictable manner from year to year, masking an overall decrease. This analysis will seek to make sense of these confusing trends by identifying the structural and demographic factors that affect hate crime incidence in U.S. cities. Drawing upon theories employed by similar studies of prejudice, it finds that variations in demographic and economic characteristics have little bearing on hate crime rates.

The power approach is a theoretical framework used to conceptualize minority group relations. According to the power approach, interactions between the majority and the minority are “intergroup power contests,” where groups strive to gain numbers, resources, and organization among themselves to defeat the others (Blalock 1967: 109). This comprehensive framework considers demographic, economic, and social factors as vital components of a group’s ability to win the contest. The majority group relies on its power to translate prejudice into discrimination (Blalock 1967: 111). The power approach emphasizes environmental factors as causes of prejudiced behavior. It also lends itself to empirical analysis since demographic and economic records are meticulously maintained over time.

Many former studies rely on the power approach to study tensions between majority and minority groups. The power approach has served as the analytical framework for studies of interracial crime (D’Alessio, Stolzenberg, and Eitle 2002; Giles and Evans 1986; Grattet 2009; Green, Strolovitch and Wong 1998), anti-immigrant prejudice (Kunovich 2004), racial biases (Eitle, D’Alessio, and Stolzenberg 2002; Quillian 1996), and lynching (Corzine, Creech and Corzine 1983; Tolnay, Beck, and Massey 1989). However, applications of power theory to study hate crime, and empirical studies of hate crime in general, are rare (Giles and Evans 1986; Lyons 2008). The two studies that employ the power approach in hate crime analysis restrict their causal variables to measures of demographic change and unemployment, leaving a broad scope for further exploration of the power approach. All the literature is restricted to analyzing the power approach vis-à-vis racial minorities and racial bias hate crime, ignoring other types of bias.

According to the logic of the power approach, this paper employs measures of "numbers, resources, and organization" to assess whether demographic, economic, or organizational factors affect racial and religious bias crime rates in U.S. cities. Drawing upon nine years of data (2006-2014) across 72 U.S. Combined Statistical Areas (CSAs), it does not find support for the power approach, suggesting issues with the model, with the selected variables, with hate crime reporting practices, or with the definition of hate crime.

Expectations of the Model

The power approach has three major tenets: numbers, resources, and organization. The primary tenet of the power approach connects minority presence with prejudiced behavior. As minority groups grow in visibility, the majority group is more likely to discriminate in response to the perceived threat (Blalock 1967: 154). Previous power analyses of lynchings and hate crime have measured minority group numbers by percentage of minority residents or percent change in minority residents over time (Corzine, Creech and Corzine 1983; Lyons 2008; Tolnay, Beck, and Massey 1989). However, in the context of this study, which analyzes both racial and religious bias crime, only the numbers of racial minorities may be categorized in this way. There are no parallel data on the prevalence of religious minorities. Given the paucity of data on religious diversity at the local level, the population of each CSA under analysis is assumed to approximate both racial and religious diversity. One would expect hate crime to be higher in large, diverse cities, suggesting the following hypothesis with regard to population size:

H1. Hate crime incidence will be higher in more populous cities, as more populous cities tend to be more diverse.

The second major tenet of the power approach connects the availability of resources with prejudiced behavior. When the majority faces situations of labor surplus, economic instability, or limited resources to compete with the minority, it is expected to resent the minority more (Blalock 1967: 168-69). Previous power analyses have used measures of unemployment or household income to approximate economic resources (D'Alessio, Stolzenberg, and Eitle 2002; Rosenstein 2008). This analysis compares two parallel measures of economic resources: percentage of residents earning an income below the poverty line, and percentage of residents earning $150,000 or more annually. The first is expected to model a scarcity of economic resources at the local level, and the second models an abundance of economic resources at the local level. Therefore:

H2. Hate crime incidence will be higher in cities with higher poverty rates, as these cities tend to exhibit stiff competition for scarce employment or other types of economic distress.

H3. Hate crime incidence will be lower in cities with a large proportion of residents earning a high income ($150,000 or more); these places are often shielded from diversity and economic competition.

Another important aspect of resource availability is education. "Whenever certain goals (such as the success goal) become highly important for nearly all individuals, many of whom lack the resources to achieve them by 'legitimate' means, pressures will develop to redefine certain of the 'illegitimate' means (e.g., discrimination) as being legitimate" (Blalock 1967: 139-140). A power analysis of hate crime includes education as a control variable but appears not to adhere to the power hypothesis in analyzing the education variable, citing "the influence of education in reducing the psychological traits associated with prejudice and discrimination" (Giles and Evans 1986: 476). In the spirit of testing the power approach as directly as possible, this study maintains that a positive connection may exist between education and prejudice. Cities with higher education levels are thought to place a higher value upon this scarce resource than cities with low education levels. In an environment of fierce competition, discrimination may be employed more frequently to win the power contest, leading to the hypothesis:

H4. Hate crime incidence will be higher in cities where residents are better educated, as education is a major field in which groups compete for power.

Group mobilization "is a multiplicative function of the strength of one's goals and the perceived probability of achieving these goals" (Blalock 1967: 142). Groups band together only when there is a perceived need to do so, and only when it is believed that mobilization will lead to tangible change. Hate groups are a destructive form of group mobilization, as they "have beliefs or practices that attack or malign an entire class of people, typically for their immutable characteristics" (Southern Poverty Law Center 2015, "Hate Map"). In the context of this paper, hate groups are expected to serve as an important approximation of prejudice at the group level.

The link between the prevalence of hate groups and hate crime rates is empirically tenuous. One study found no relationship between the number of hate groups and hate crime incidence at the statewide level (Ryan and Leeson 2011), while another found that the presence of at least one white supremacist group, at the county level, raised that county's hate crime rates by 19.1% (Mulholland 2013: 102). Mulholland's study suggests that the statewide level of analysis may be too broad to capture local spillover effects. Locally, the presence of a white supremacist group may "signal to community members that a particular bias is acceptable" (Mulholland 2013: 110). It is expected that the presence of hate groups at the local level is an important indicator of prejudice and potentially of hate crime as an expression of this prejudice. Therefore:

H5. Hate crime incidence will be higher in cities where there are higher counts of KKK chapters, as these chapters signal that prejudice is acceptable at the local level.

The models for racial and religious bias crime are essentially identical. According to the power approach, the contest for power will be fought in the same spheres — in numbers, resources, and organization — regardless of the identity of the out-group. By keeping both explanatory models the same, one is able to see whether any of these factors is weighted more heavily in modeling hate crimes against racial versus religious minorities.

Data Collection

Crime Reporting

Since the passage of the 1990 Hate Crime Statistics Act, the FBI has collected data on racial and religious bias crime throughout the United States. This data is furnished by local and state law enforcement agencies and is issued annually as a part of the FBI's Uniform Crime Reporting (UCR) Program. As of 2014, law enforcement agencies in 49 states, encompassing 97.7 percent of the U.S. population, participated in the program (FBI Uniform Crime Reports, 2014). This study uses annual UCR data on raw counts of racial and religious bias hate crime reported in U.S. cities between the years 2006 and 2014. Data for each year can be found under Table 13 of UCR Hate Crime Statistics reports (FBI Uniform Crime Reports 2016). For the purpose of this analysis, the hate crime data from each city are spatially aggregated into CSAs, the spatial unit of this study. Reporting of racial and religious bias crime rates are calculated as rates per 100,000 individuals in each CSA.

Violent crime data serve as a benchmark of crime rates across the U.S. and come from the FBI's UCR Program. This study uses annual UCR data on raw counts of violent crime reported in U.S. metropolitan statistical areas (MSAs) between the years 2006 and 2014. Data for each year can be found under Table 6 of UCR Crime in the United States reports (FBI Uniform Crime Reports 2016). For the purpose of this analysis, the data from each MSA are spatially aggregated into CSAs. Reporting of violent crime rates are calculated as rates per 100,000 individuals in each CSA.

Demographic Measures

All demographic measures, including population, poverty rates, household income, and education level come from U.S. Census Bureau estimates; these data may be viewed on American FactFinder (United States Census Bureau 2016). All Census Bureau data between the years 2006 and 2014 was reported by CSA. The choice of CSAs as the unit of spatial analysis for this study was a compromise between data availability and geographic specificity. The Census Bureau collects a wide range of data, over a longer time span, at the CSA level. Slightly smaller units of analysis such as MSAs did not offer as much data. While one can aggregate given data into larger spatial units, it would be patently unwise to slice data into smaller spatial units.

Hate Groups

The Southern Poverty Law Center collects robust information on the locations of hate groups across U.S. cities, which are published in the organization’s annual *Intelligence Reports* (Southern Poverty Law Center 2007-2015). Most issues include information on the names and locations of seven types of hate groups, including: the Ku Klux Klan, neo-Nazi groups, white nationalist groups, racist skinhead groups, Christian identity groups, neo-Confederate groups, and black separatist groups. Only counts of active chapters of the Ku Klux Klan are included in this analysis. When the city and state was provided for these groups, they were spatially aggregated into the appropriate CSA. A handful of rare exceptions listed only the groups’ counties or states. These groups were reported and aggregated with locations in the groups’ county seats or state capitals according to the most specific level of information available. The final measure indicates counts of KKK chapters by CSA between the years 2006 and 2014.

Statistical Analysis and Results

Data on hate crime, violent crime, demographic characteristics and hate groups were arranged in a panel format with a total of 648 observations per variable, representing data collected across 9 years for 72 CSAs. This panel data set contains cross-sectional time series data in which each CSA's attributes, such as poverty rates in New York, may be analyzed over the time period from 2006 to 2014. Descriptions of variables may be found in Table 1. Summary statistics of the panel data may be interpreted as follows: rows labeled "between" indicate the variability of a variable between each of the CSAs. For example, violent crime rates exhibit a high variability between different CSAs. Rows labeled "within" indicate the variability of a variable over time within each CSA. For example, the standard deviation of year within each CSA is 2.6, reflecting the fact that a data for each CSA was collected from 2006 to 2014. Summary statistics may be found in Table 2.

It is expected that there is a high degree of correlation within each CSA over time. For this reason, it is inappropriate to run a multiple regression, as a multiple regression model would consider all observations to be independent, inflating correlations between variables when the similarities are the result of within-CSA correlations. Population-averaged generalized estimating equations (GEEs) are the preferred method of analysis, incorporating both time-based effects and other variable effects (Burton, Gurrin, and Sly 1998; Diggle, Liang, and Zeger 1994; Hardin and Hilbe 2003; Hanley et al. 2003; Liang and Zeger 1986). Individual CSAs are assumed to be independent of one another while still accounting for correlations within each CSA. This study includes GEE analysis of three dependent variables, including the rate of racial bias crime per 100,000 individuals in U.S. CSAs, the rate of religious bias crime per 100,000 individuals in U.S. CSAs, and the rate of violent crime per 100,000 individuals in U.S. CSAs. Complete data from 72 U.S. combined statistical areas are included for the years 2006-2014.

Table 1 Descriptions of data used in the study, 2006-2014

Variable	*Description*	*Overall Mean*	*Std. Dev.*
Population	Number of residents in each CSA, divided by 100,000	25.242	37.24
Black Poverty Rate	Percentage of black residents living below the poverty line by CSA	29.760	6.586
Overall Poverty Rate	Percentage of residents overall living below the poverty line by CSA	11.070	2.844
High Income	Percentage of residents overall earning $150,000 or more annually by CSA	7.416	3.463
High School	Percentage of residents who attained a high school diploma as highest degree	29.601	4.570
Associates'	Percentage of residents who attained an associate's diploma as highest degree	7.868	1.515
Bachelors'	Percentage of residents who attained a bachelor's diploma as highest degree	17.475	3.316
Masters'	Percentage of residents who attained a master's diploma as highest degree	6.770	2.227
Doctoral	Percentage of residents who attained a doctoral or professional degree	2.924	0.934
KKK	Number of active KKK chapters by CSA	0.971	1.405
Racial Crime	Rate of racial bias crime per 100,000 people by CSA	0.791	0.843
Religious Crime	Rate of religious bias crime per 100,000 people by CSA	0.182	0.266
Violent Crime	Rate of violent crime per 100,000 people by CSA	242.764	149.161

Since GEE analysis incorporates the effects of both explanatory variables and time, there are two critical components to each input. The first is the correlation structure underpinning the GEE analysis, which gives information on the effects of time on changing crime rates. Correlations may be found in Table 3 and Figure 4. The second is the GEE model, including the effects of explanatory variables on the observed crime rate between different CSAs. The GEE model may be found in Table 4.

The time-dependent correlation structure yielded unexpected results. Because the majority of factors in the model are demographic and environmental, one would expect little year-to-year change based on these factors. Cities themselves do not change dramatically in their characteristics from year to year. However, the correlations decrease rapidly over time.

Table 2 Summary of panel data used in the study, 2006-2014

Variable		*Mean*	*Std. Dev.*	*Min*	*Max*	*Observations**	
Year	Overall	10	2.6	6	14	*N* =	648
	Between		0	10	10	*n* =	72
	Within		2.6	6	14	*T* =	9
Population	Overall	25.2	37.2	2.0	236.3	*N* =	648
	Between		37.4	2.1	224.6	*n* =	72
	Within		1.74	8.9	37.0	*T* =	9
Black Poverty Rate	Overall	29.8	6.6	13.2	48.5	*N* =	648
	Between		5.9	15.2	42.6	*n* =	72
	Within		3.1	18.0	39.3	*T* =	9
Overall Poverty Rate	Overall	11.1	2.8	5.0	23.5	*N* =	648
	Between		2.6	6.0	19.7	*n* =	72
	Within		1.3	6.8	15.3	*T* =	9
High Income	Overall	7.4	3.5	2.5	23.1	*N* =	648
	Between		3.3	3.1	20.0	*n* =	72
	Within		1.0	3.5	10.7	*T* =	9
High School	Overall	29.6	4.6	16.9	45.0	*N* =	648
	Between		4.5	18.1	43.5	*n* =	72
	Within		1.1	25.8	33.7	*T* =	9
Associates'	Overall	7.9	1.5	3.9	12.4	*N* =	648
	Between		1.4	4.5	11.6	*n* =	72
	Within		0.5	6.1	10.6	*T* =	9
Bachelors'	Overall	17.5	3.3	10.8	26.0	*N* =	648
	Between		3.3	11.8	25.0	*n* =	72
	Within		0.7	15.7	22.4	*T* =	9
Masters'	Overall	6.8	2.2	2.0	14.5	*N* =	648
	Between		1.9	3.4	12.9	*n* =	72
	Within		1.2	0.7	8.6	*T* =	9
Doctoral	Overall	2.9	0.9	1.0	6.3	*N* =	648
	Between		0.9	1.3	6.2	*n* =	72
	Within		0.2	2.2	4.0	*T* =	9
KKK	Overall	1.0	1.4	0.0	8.0	*N* =	648
	Between		1.1	0.0	5.2	*n* =	72
	Within		-0.9	2.4	4.7	*T* =	9
Religious Crime	Overall	0.79	0.84	0.00	4.83	*N* =	648
	Between		0.67	0.00	2.66	*n* =	72
	Within		-0.52	1.01	3.38	*T* =	9
Racial Crime	Overall	0.18	0.27	0.00	1.88	*N* =	648
	Between		0.22	0.00	1.10	*n* =	72
	Within		-0.16	0.36	1.08	*T* =	9
Violent Crime	Overall	242.8	149.2	0.0	766.3	*N* =	648
	Between		120.6	37.7	652.6	*n* =	72
	Within		-88.8	313.3	488.9	*T* =	9

n = data collected for 72 CSAs;

T = data collected for 9 consecutive years (2006-2014) for each of these 72 CSAs;

N = 648 total observations per variable.

The decreasing correlation can primarily be explained by the unpredictability of hate crime reporting over time. A cursory glance at the time series data reveals that both racial religious bias crime rates rise and fall in indiscernible patters from year to year. Time series graphs may be found in Figure 2. While both racial and religious bias crime were at their highest levels in 2006 and have generally decreased over time, violent crime rates display the strongest and longest downward trend of any type of crime. This discrepancy explains the higher time-based correlation observed with violent crime rates.

Table 3 Year-to-year crime correlations

Years Between Measurements	*0*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
Racial Bias Crime	1	0.5901	0.3482	0.2055	0.1213	0.0715	0.0422	0.0249	0.0147
Religious Bias Crime	1	0.4865	0.2366	0.1151	0.0560	0.0272	0.0133	0.0064	0.0031
Violent Crime	1	0.6711	0.4504	0.3023	0.2029	0.1362	0.0914	0.0613	0.0412

Figure 1 Year-to-year crime correlations

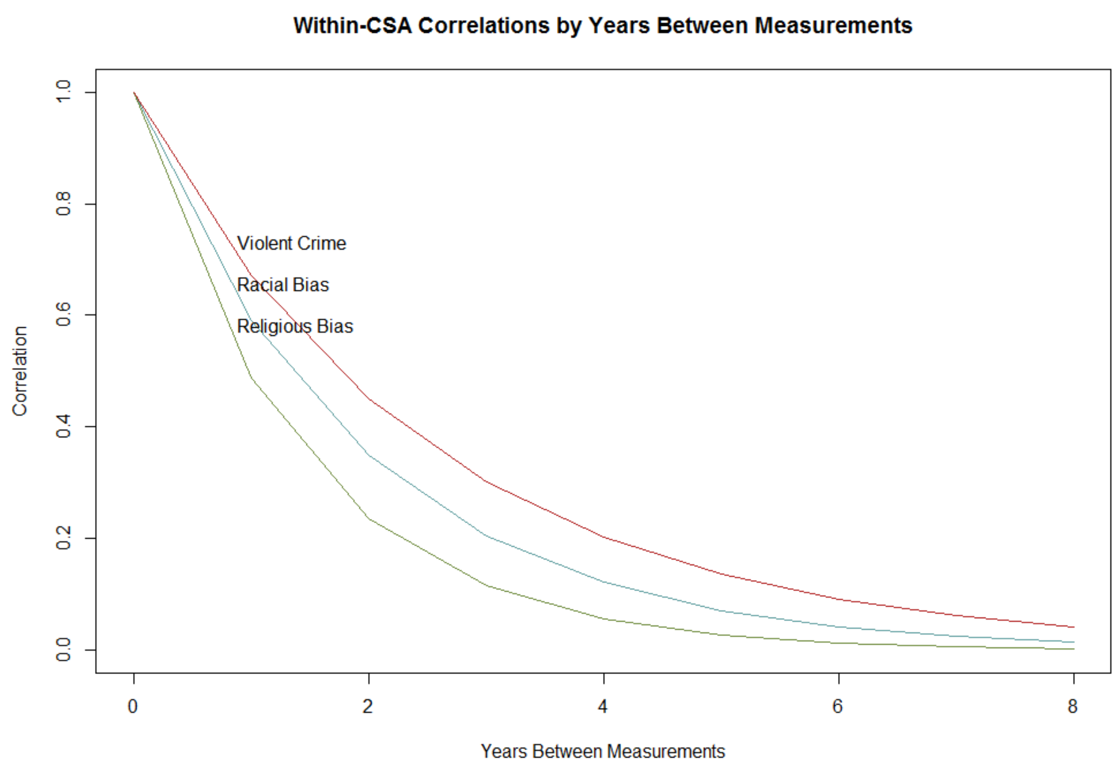


Figure 2 Average Bias Crime Rates, 2006-2014

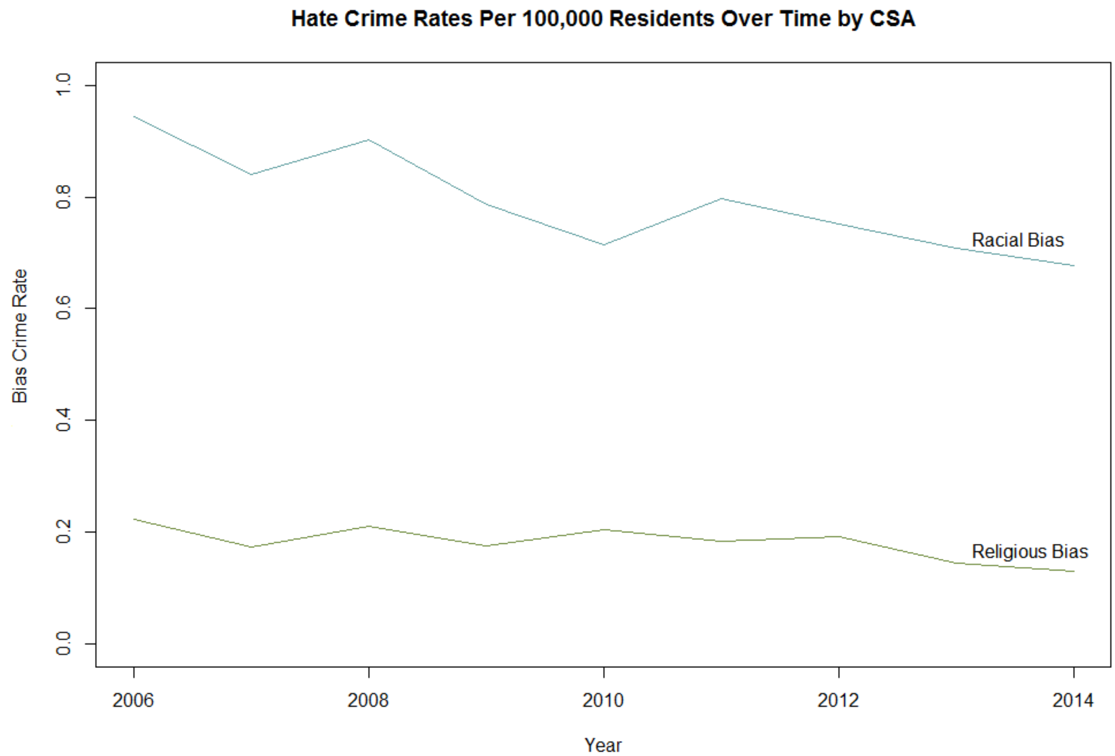


Table 4 GEE model for crime rates in U.S. CSAs, 2006-2014

	Racial Bias Crime Rates			***Religious Bias Crime Rates***			***Violent Crime Rates***		
	Coeff.	SE	*P*-value	Coeff.	SE	*P*-value	Coeff.	SE	*P*-value
Year	-0.0031	0.0201	0.88	-0.0222	0.0057	0.001***	-2.1406	3.9994	0.59
Population	-0.0010	0.0018	0.58	0.0018	0.0005	0.001***	-0.2179	0.3831	0.57
Black Poverty Rate	0.0188	0.0068	0.01***	-0.0043	0.0020	0.03**	1.3197	1.3055	0.31
White Poverty Rate	0.0229	0.0239	0.34	0.0120	0.0067	0.07*	5.6747	4.7784	0.24
Overall Poverty Rate	-0.0978	0.0259	0.001***	0.0086	0.0074	0.01***	-10.1224	5.2234	0.05**
High Income	-0.0250	0.0271	0.36	0.0196	0.0076	0.01***	-11.8690	5.3967	0.06
High School	-0.0049	0.0157	0.76	0.0098	0.0044	0.03**	-17.1366	3.1508	0.001
Associates'	-0.0059	0.0322	0.85	0.0143	0.0091	0.12	-7.6650	6.4076	0.007
Bachelors'	0.0294	0.233	0.21	0.0023	0.0066	0.73	4.1395	4.6173	0.097
Masters'	0.0148	0.0172	0.39	0.0136	0.0054	0.01***	10.9549	3.1673	0.191
Doctoral	-0.1237	0.0689	0.07*	0.0243	0.0197	0.22	0.2888	13.6516	0.422
KKK	0.0501	0.0218	0.02**	-0.0128	0.0066	0.052*	-2.8088	4.1297	0.944
Religious Crime	1.057	0.1215	0.001***	—	—	—	2.0328	7.5315	0.709
Racial Crime	—	—	—	0.1123	0.0111	0.71	914.3403	23.9899	0.932
Violent Crime	-0.0001	0.9953	0.90	0.0001	0.2868	0.04**	—	—	—

* Denotes significance at α = 0.10 level.

** Denotes significance at α = 0.05 level.

*** Denotes significance at α = 0.01 level.

Though both the racial and the religious bias crime models exhibit a few statistically significant variables, a closer look at the coefficients reveals that the effects of these variables on hate crime rates are negligible. Coefficient plots for racial bias crime rates, religious crime rates, and violent crime rates may be found in Figures 3, 4, and 5, respectively.

Figure 3 Plot of Racial Bias Crime Coefficients

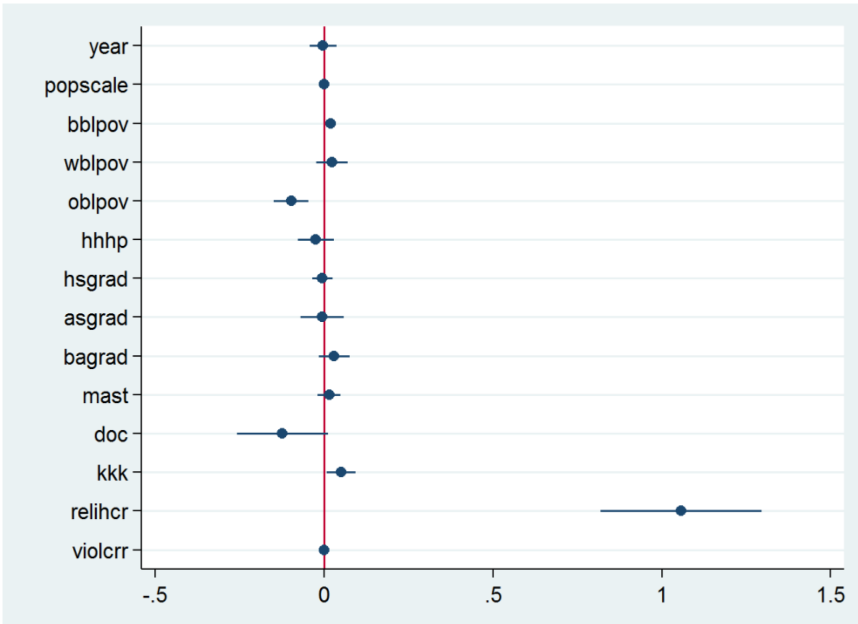


Figure 4 Plot of Religious Bias Crime Coefficients

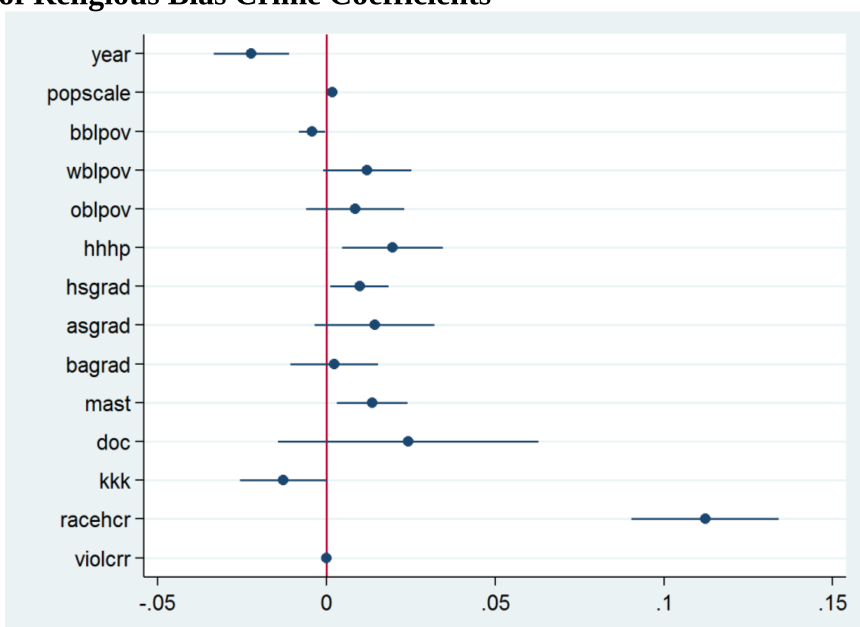
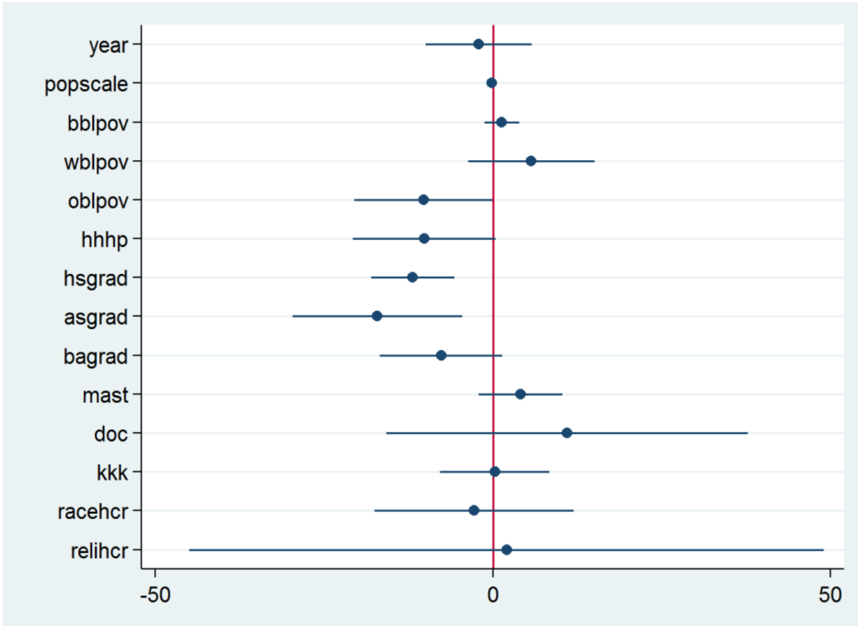


Figure 5 Plot of Violent Crime Coefficients



Crime Reporting

While cities that report higher levels of religious bias crime are more likely to report racial bias crime, the opposite does not hold; racial bias crime reporting is not a significant factor in religious bias crime reporting. This disparity can be attributed to the relative rarity of reported religious bias crime as opposed to racial bias crime. City police departments which emphasize the reporting and prosecution of religious bias crime — a rare type of crime — would be unlikely to ignore the more prevalent occurrence of racial bias crime.

Notably, violent crime reporting is a significant factor only in the reporting of religious bias crime. The data indicate that increasing violent crime rates tend to decrease the rate of religious bias crime reporting. This inverse relationship is clearer when looking at the aggregated time series data for religious bias crime and violent crime rates. While violent crime rates have been falling steadily since 2008, religious bias crime rates have fluctuated in an indiscernible pattern. The negative relationship between religious bias and violent crime rates may be seen as the contrast between religious bias and violent crime trends between the years 2006 and 2012, after which the crime rates move steadily downward.

Demographic Effects

There are only two shared explanatory demographic variables for racial bias crime rates and religious bias crime rates: the percentage of African-Americans living under the poverty line in each CSA, and the overall percentage of residents living under the poverty line in each CSA. As poverty rates of black residents rise in CSAs, the reporting of racial bias crime tends to rise and the reporting of religious bias crime tends to fall. As poverty rates of all individuals in CSAs rise, the reporting of racial bias crime tends to fall and the reporting of religious bias crime tends to rise. However, the strength of the coefficients is very small.

Other variables relevant only to the analysis of religious bias crime rates are education levels and the percentage of residents making a high income ($150,000 or more annually). With each of these variables, higher educational attainment and higher income are correlated with more religious bias crimes reported per capita.

Hate Groups

This analysis originally included counts of white nationalist, black separatist, and active KKK chapters across the nation’s CSAs; only counts of KKK chapters are found to be significant. As might be expected, higher counts of KKK chapters in CSAs is correlated with an increased prevalence of racial bias crime; but oddly, the opposite holds true for religious bias crime.

Evaluation of the Model

1. *Hate crime incidence will be higher in more populous cities, as more populous cities tend to be more diverse.*

   Population is a significant variable only in estimating religious bias crime rates. As expected, higher populations are correlated with more bias crime, though the strength of the coefficient is truly negligible in comparison with the crime rate.

2. *Hate crime incidence will be higher in cities with higher poverty rates, as these cities tend to exhibit stiff competition for scarce employment or other types of economic distress.*

   Rising poverty rates of black populations in CSAs are correlated with higher racial bias crime; rising poverty rates of the overall populations in CSAs are correlated with lower racial bias crime. The opposite trends hold for religious bias crime. All else equal, significant changes in poverty rates on the racial bias crime rates model might be expected to alter crime rates.

3. *Hate crime incidence will be lower in cities with a large proportion of residents earning a high income ($150,000 or more); these places are often shielded from diversity and economic competition.*

   High income is a significant variable only in estimating religious bias crime rates. Contrary to expectations, higher incomes are associated with higher religious bias crime rates. Compared to the coefficients of the poverty rates, the explanatory power of high incomes is weak.

4. *Hate crime incidence will be higher in cities where residents are better educated, as education is a major field in which groups compete for power.*

Education is a significant variable only in estimating religious bias crime rates. As expected, higher education levels are correlated with more bias crime.

5. *Hate crime incidence will be higher in cities where there are higher counts of KKK chapters, as these chapters signal that prejudice is acceptable at the local level.*

   While the presence of KKK chapters in CSAs appears to boost racial bias crime rates, KKK chapter counts are associated with lower levels of religious bias crime. Considering that the KKK variable is a count variable, each additional KKK chapter could have a small effect.

Discussion

This study assumes that hate crime is a clear and quantifiable metric; that hate crimes are a manifest sign of deeper cleavages within American society, not "a limited problem involving a small number of bigoted criminals" (Jacobs and Potter 1998: 8); and that structural and demographic factors can be used to explain and predict hate crime incidence in U.S. cities. However, the model explains little variation in hate crime across U.S. CSAs, and the directionality of variables run contrary to expectations. Perhaps the assumptions of this study are simply wrong. There are two possible explanations for the discrepancy between expectation and reality: first, that hate crime statistics are an unsuitable metric for analysis; and second, that there are too many confounding factors in terms of legal statutes and law enforcement practices to draw conclusions on the model used above.

First, researchers have criticized hate crime statistics on the count that the definition of "hate crime" is too ambiguous to quantify. Fundamentally, hate crime is defined as an expression of prejudiced attitudes, but Jacobs and Potter (1998) note that the concept of prejudice can be construed in any direction:

> "Prejudice" is an amorphous term. If prejudice is defined narrowly, to include only certain organized hate-based ideologies, there will be very little hate crime. If prejudice is defined broadly, a high percentage of intergroup crimes will qualify as hate crimes. […] If criminal conduct must be completely or predominantly caused by prejudice in order to be termed hate crime, there will be few hate crimes. If prejudice need only *in part* to have motivated the crime, hate crime will be plentiful. In other words, we can make the hate crime problem as small or large as we desire by manipulating the definition. (27-28)

When the definition of prejudice can be expanded and contracted at will, so follows the definition of hate crime. Perhaps the definition of hate crime is too elastic for analysis.

Second, institutional factors significantly affect hate crime reporting at the statewide, local, and individual levels. A cursory glance at statewide crime statutes reveals major collection differences between states: for example, while California collects data on a full range of bias crimes including race, religion, ethnicity, sexual orientation, and gender identity, among others; other states, such as Wyoming, have no laws about hate crime reporting at all (Perry 2001: 248-49). This analysis included only the two most common types of hate crime — racial and religious bias crime — but a glance at statewide statutes reveals that every state prioritizes different types of hate crime in their own way.

Statewide statutes do not tell the entire story. A glance at a map of hate crime counts shows that California reports many hate crimes in addition to having robust hate crime legislation. However, New York also reports many hate crimes even though its hate crime laws are not nearly as robust as California's. Washington State serves as a further example of the discrepancy between statewide statute and hate crime reporting; though its hate crime statutes are as robust as California's, it reports very few hate crimes. Hate crime cannot simply be a function of differences in statewide statutes.

Some research has been performed on differences in the bureaucracy of hate crime reporting between police divisions. In one study of two police divisions, the first division assigned one detective whose sole job was to determine hate motive based on officers' field reports, and to prepare reports of these hate-motivated crimes to send to the city or district attorney (Boyd, Berk and Hamner 1996). The detective was conservative in his estimation of which crimes were truly hate-motivated, reflecting the division's goal of reducing hate crime reporting and showing "the real rate of hate crimes" in the division's summary reports. The second division had no official detective to investigate hate crime. Here, the position was juggled around different departments. Detectives sought not to determine a perpetrator's hate motive, but to verify whether the details surrounding a crime, including "possible signs of provocation, prior encounters, and accompanying derogatory statements" (Boyd, Berk and Hamner 1996: 842), appeared to be hate-motivated. If the evidence lined up, all crimes marked as "motivated by hate or prejudice" ended up as hate crimes in the division's summary reports. All in all, the second division's summary contained far more hate crimes in its reports, even though the first division appeared more institutionally equipped to address hate crimes.

It is clear that institutional structures and pressures can force changes in hate crime reporting. In a future analysis, it may be feasible to control for department reporting practices to better isolate and analyze the demographic impacts of hate crime incidence.

Behind every reported hate crime is a web of individuals responsible for assessing and reporting that crime. Some individuals view hate crime as a waste of time; others view it is an important social issue. Police officers interviewed in one study expressed that the effort to sift through crimes to determine hate motivation was a cumbersome "bureaucratic imposition" (Boyd, Berk and Hamner 1996). In the words of one police officer: "'There are just two kinds of crime—dope and cars. The rest is just stupidity. I say dope and stolen cars are the only crimes worth my time. Not fruit bashing and not these domestic calls. That's just too bad.'" (Boyd, Berk and Hamner 1996: 827). Even for the well-intentioned, hate crimes are a challenge to detect at the finest grain of scrutiny. On a practical level, individual police personnel must "recognize, identify, and categorize certain crimes as hate motivated" (Boyd, Berk and Hamner 1996: 821). It is difficult for officers to sift through layers of evidence in the fast-paced environment of law enforcement, when a single officer may have to address multiple calls.

Variability in hate crime reporting can be attributed to definitional ambiguity, different hate crime legislation at the state level, bureaucratic practices, and individual constraints. In order to test for demographic effects on hate crime reporting, it may be necessary to control for differences in crime statutes and institutional structures from place to place.

Improving the Model: Future Recommendations

There are six potential ways to improve the model:

1. *Incorporate QIC to choose the appropriate correlation structure.*

   Our analysis assumed that an AR(1) model was the best correlation structure for the panel data set based on a presumed dependence on prior crime reporting. However, GEE analysis offers a multitude of correlation structures to choose from; even within the autoregressive correlation structures, one may choose between an AR(0), AR(1), or an AR(2) structure. The QIC (quasi-likelihood under the independence model criterion) would be a better way to select the best-fitting correlation structure for GEE analysis.

2. *Incorporate spatial correlation in the analysis.*

   While the GEE model allows for cross-sectional time series analysis, it assumes that the correlation between different areas is zero (Dormann et al. 2007: 615). However, the maps of racial and religious bias crime show that neighboring CSAs tend to exhibit similar crime reporting characteristics. It would be beneficial to test other spatial models for spatial correlation in addition to the existing GEE analysis. Maps of average racial and religious bias crime rates may be found in Figures 6 and 7, respectively.

Figure 6 Racial Bias Crime Rates by CSA

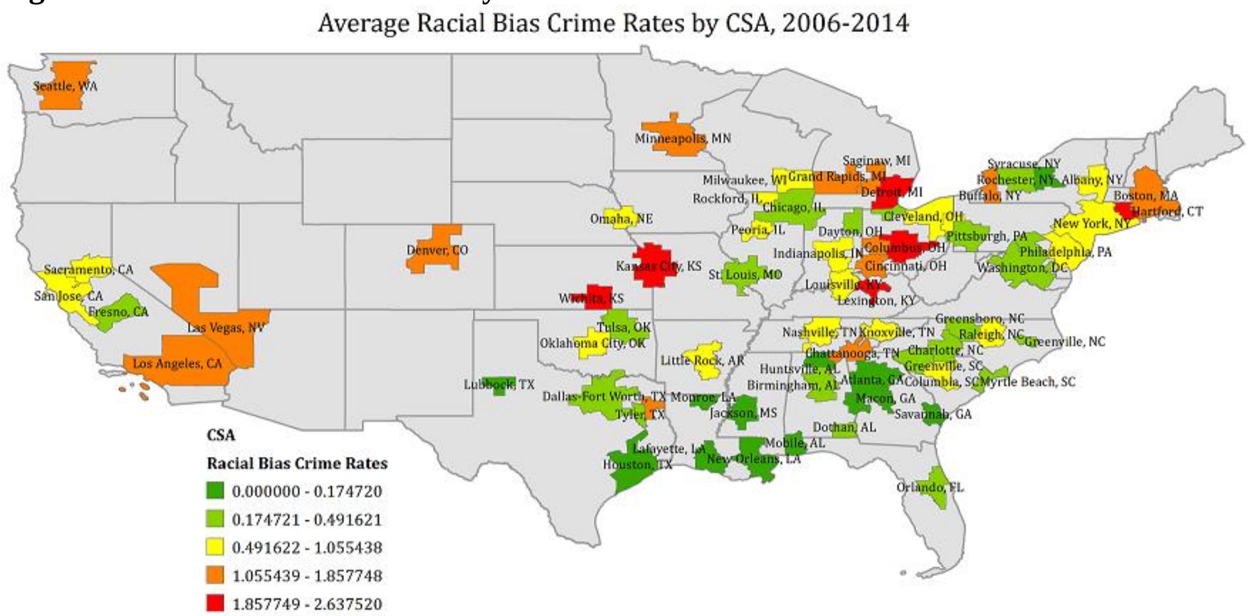
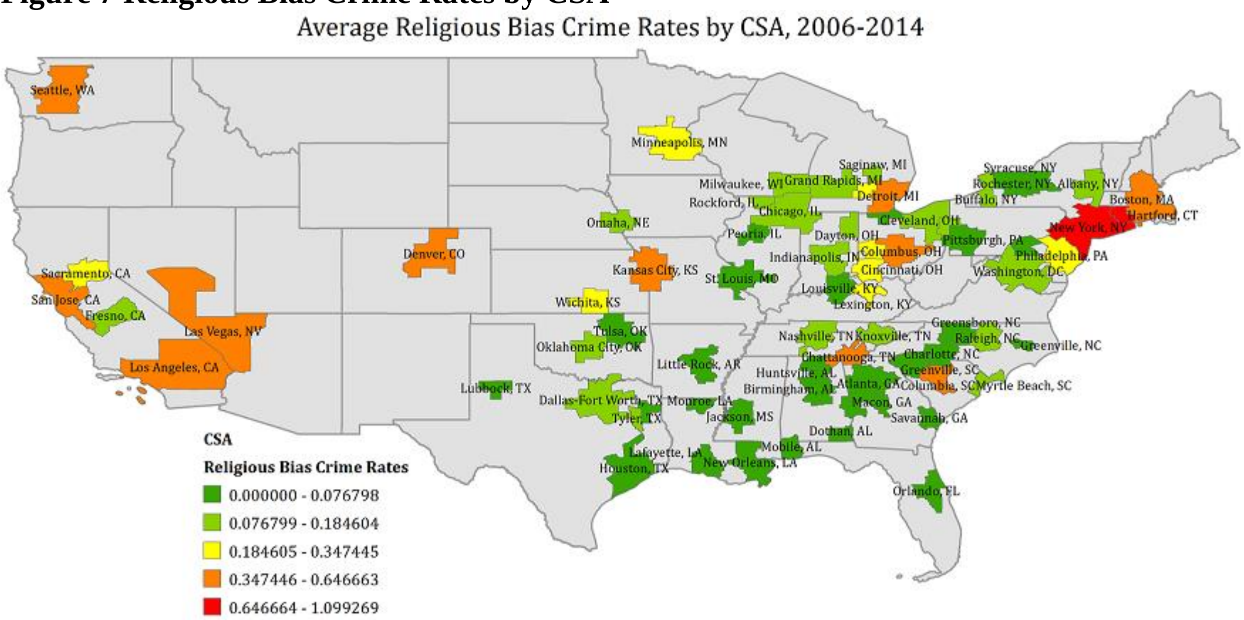


Figure 7 Religious Bias Crime Rates by CSA



3. *Incorporate differences in statewide hate crime reporting statutes and/or police division structures.*

Disparities in statewide statutes and police division structures are expected to affect hate crime reporting across time and space. It would be preferable to account for these disparities as control or explanatory variables in hate crime modeling.

4. *Incorporate NCVS data or other crime data.*

The National Crime Victimization Survey (NCVS) interviews roughly 90,000 households each year about their experiences as crime victims. Research on on hate crime reporting and crime victimization using NCVS and hate crime data has revealed that minority group members, and especially victims of racial bias crime, were less likely to report incidents than other victims or other types of crime (Zaykowski 2010: 389). If this effect is strongly correlated with hate crime trends, it may be feasible to weight different CSAs according to their demographic characteristics.

5. *Incorporate media or social media rhetoric over space and time.*

Mulholland suggested that the presence of white supremacist groups at the local level might indicate that certain types of prejudices are acceptable. However, the most recent edition of SPLC's Intelligence Report indicates that individuals may be shifting their presence from physical hate groups to online spaces of hate (*Intelligence Report*, 2015). Going into the future, social media rhetoric may provide a closer approximation of prejudiced attitudes between different CSAs.

6. *Incorporate voting patterns over space and time.*

Voting patterns may be an effective approximation of civic engagement and social solidarity within CSAs; however, because voting takes place more rarely, it may present a challenge to analysis over time.

References

Allport, Gordon. *The Nature of Prejudice*. Reading, MA: Addison-Wesley, 1954.

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

Boyd, Elizabeth, Richard Berk, and Karl Hamner. "'Motivated by Hatred or Prejudice': Categorization of Hate-motivated Crimes in Two Police Divisions." *Law & Society Review* 30, no. 4 (1996): 819-850. url: http://www.jstor.org/stable/3054119

Bureau of Justice Statistics. "Hate Crime." *Bureau of Justice Statistics*. February 11, 2016. http://www.bjs.gov/index.cfm?ty=tp&tid=37

Burton, Paul, Lyle Gurrin, and Peter Sly. "Extending the Simple Linear Regression Model to Account for Correlated Responses: An Introduction to Generalized Estimating Equations and Multi-Level Mixed Modelling." *Statistics in Medicine* 17 (1998): 1261-1291.

Corzine, Jay, James Creech, and Lin Corzine. "Black Concentration and Lynchings in the South: Testing Blalock's Power-Threat Hypothesis." *Social Forces* 61, no. 3 (1983): 774-796. url: http://www.jstor.org/stable/2578134

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

Diggle, Peter, Kung-Yee Liang, and Scott Zeger. *Analysis of Longitudinal Data*. New York : Oxford University Press, 1994.

Dormann, Carsten, et al. "Methods to Account for Spatial Autocorrelation in the Analysis of Species Distributional Data: a Review." *Ecography* 30 (2007): 609-628. doi: 10.1111/j.2007.0906-7590.05171.x

Eitle, David, Stewart D'Alessio, and Lisa Stolzenberg. "Racial Threat and Social Control: A Test of the Political, Economic, and Threat of Black Crime Hypotheses." *Social Forces* 81, no. 2 (2002): 557-576. url: http://www.jstor.org/stable/3086482

FBI Uniform Crime Reports. "Hate Crime Statistics Act." *Federal Bureau of Investigation*. 2012. https://www.fbi.gov/about-us/cjis/ucr/hate-crime/2012/resource-pages/hate-crime-statistics-act/hatecrimestatisticsact_final

FBI Uniform Crime Reports. "About UCR." *Federal Bureau of Investigation*. 2014. https://www.fbi.gov/about-us/cjis/ucr/hate-crime/2014/resource-pages/aboutucr_final

FBI Uniform Crime Reports. "UCR Publications." *Federal Bureau of Investigation*. 2016. https://www.fbi.gov/about-us/cjis/ucr/ucr-publications

Giles, Michael, and Arthur Evans. "The Power Approach to Intergroup Hostility." *Journal of Conflict Resolution* 30, no. 3 (1986): 469-486. url: http://www.jstor.org/stable/173964

Grattet, Ryken. "The Urban Ecology of Bias Crime: A Study of Disorganized and Defended Neighborhoods" *Social Problems* 56, no. 1 (2009): 132-150.

Green, Donald, Dara Strolovitch, and Janelle Wong. "Defended Neighborhoods, Integration, and Racially Motivated Crime." *American Journal of Sociology* 104, no. 2 (1998): 372-403. url: http://www.jstor.org/stable/10.1086/210042

Hall, Nathan. *Hate Crime*. New York: Routledge, 2013.

Hanley, James, et al. "Statistical Analysis of Correlated Data Using Generalized Estimating Equations: An Orientation." *American Journal of Epidemiology* 157, no. 4 (2003): 364-375. doi: 10.1093/aje/kwf215

Hardin, James, and Joseph Hilbe. *Generalized Estimating Equations*. Boca Raton, FL: Chapman and Hall/CRC, 2003.

Horton, Nicholas, and Stuart Lipsitz. "Review of Software to Fit Generalized Estimating Equation Regression Models." *The American Statistician* 53, no. 2 (1999) 160-169. url: http://www.jstor.org/stable/2685737

Horváth, Zsuzsanna, and Ryan Johnston. "AR (1) Time Series Process." n.d. http://www.math.utah.edu/~zhorvath/ar1.pdf

Iganski, Paul. "Hate Crimes Hurt More." *American Behavioral Scientist* 45, no. 4 (2001): 626-638.

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

Jacobs, James, and Kimberly Potter. *Hate Crimes: Criminal Law and Identity Politics*. New York: Oxford, 1998.

Jefferson, Philip, and Frederic Pryor. "On the Geography of Hate." *Economics Letters* 65 (1999): 389-395.

King, Ryan, and Darren Wheelock. "Group Threat and Social Control: Race, Perceptions of Minorities and the Desire to Punish." *Social Forces* 85, no. 3 (2007): 1255-1280. url: http://www.jstor.org/stable/4494972

Kunovich, Robert. "Social Structural Position and Prejudice: An Exploration of Cross-National Differences in Regression Slopes." *Social Science Research* 33 (2004): 20-44. doi:10.1016/S0049-089X(03)00037-1

Levin, Brian. "Hate Crimes: Worse by Definition." *Journal of Contemporary Criminal Justice* 15, no. 1 (1999): 6-21.

Liang, Kung-Yee, and Scott Zeger. "Longitudinal Data Analysis Using Generalized Linear Models." *Biometrika* 73, no. 1 (1986): 13-22. url: http://www.jstor.org/stable/2336267

Lyons, Christopher. “Defending Turf: Racial Demographics and Hate Crime Against Blacks and Whites.” *Social Forces* 87, no. 1 (2008): 357-385.

Medoff, Marshall. “Allocation of Time and Hateful Behavior: A Theoretical and Positive Analysis of Hate and Hate Crimes.” *American Journal of Economics and Sociology* 58, no. 4 (1999): 959-973.

Mulholland, Sean. “White Supremacist Groups and Hate Crime.” *Public Choice* 157 (2013): 91-113. doi: 10.1007/s11127-012-0045-7

Nolan, James, and Yoshio Akiyama. “An Analysis of Factors That Affect Law Enforcement Participation in Hate Crime Reporting.” *Journal of Contemporary Criminal Justice* 15, no. 1 (1999): 111-127.

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

Putnam, Robert. “*E Pluribus Unum*: Diversity and Community in the Twenty-First Century.” *Scandinavian Political Studies* 30, no. 2 (2007): 137-174.

Quillian, Lincoln. “Group Threat and Regional Change in Attitudes Toward African-Americans.” *American Journal of Sociology* 102, no. 3 (1996): 816-860. url: http://www.jstor.org/stable/2782464

Ryan, Matt, and Peter Leeson. “Hate Groups and Hate Crime.” *International Review of Law and Economics* 31 (2011): 256-262. doi: 10.1016/j.irle.2011.08.004

Rosenstein, Judith. “Individual Threat, Group Threat, and Racial Policy: Exploring the Relationship Between Threat and Racial Attitudes.” *Social Science Research* 37 (2008): 1130-1146. doi: 10.1016/j.ssresearch.2008.04.001

Southern Poverty Law Center. *Intelligence Report*. Montgomery, AL: Southern Poverty Law Center, 2007.

Southern Poverty Law Center. *Intelligence Report*. Montgomery, AL: Southern Poverty Law Center, 2008.

Southern Poverty Law Center. *Intelligence Report*. Montgomery, AL: Southern Poverty Law Center, 2009.

Southern Poverty Law Center. *Intelligence Report*. Montgomery, AL: Southern Poverty Law Center, 2010.

Southern Poverty Law Center. *Intelligence Report*. Montgomery, AL: Southern Poverty Law Center, 2011.

Southern Poverty Law Center. *Intelligence Report*. Montgomery, AL: Southern Poverty Law Center, 2012.

Southern Poverty Law Center. *Intelligence Report*. Montgomery, AL: Southern Poverty Law Center, 2013.

Southern Poverty Law Center. *Intelligence Report*. Montgomery, AL: Southern Poverty Law Center, 2014.

Southern Poverty Law Center. *Intelligence Report*. Montgomery, AL: Southern Poverty Law Center, 2015.

Southern Poverty Law Center. "Hate Map." *Southern Poverty Law Center*. 2015. https://www.splcenter.org/hate-map

Tolnay, Stewart, E. M. Beck, and James Massey. "Black Lynchings: The Power Threat Hypothesis Revisited." *Social Forces* 67, no. 3 (1989): 605-623. url: http://www.jstor.org/stable/2579531

United States Census Bureau. "American FactFinder." *United States Census Bureau*. 2016. http://factfinder.census.gov/faces/nav/jsf/pages/index.xhtml

Zaykowski, Heather. “Racial Disparities in Hate Crime Reporting.” *Violence and Victims* 25, no. 3 (2010): 378-394.