Hate Groups and Hate Crime[*]

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Abstract

This paper is the first to investigate the relationship between hate groups and hate crime empirically. We do so using panel data for the U.S. states between 2002 and 2008. Contrary to conventional wisdom, we find little evidence that hate groups are associated with hate crime in the United States. We find somewhat stronger evidence that economic hardship may be related to hate crime. However, evidence for the potential importance of economic factors remains weak. Further, we find that demographic variables aren't significantly related to hate crime in the United States. Our results leave the question of what factors may drive hate crime in America unresolved. But they cast doubt on the popular perception that hate groups are among them.

1 Introduction

Hate groups are organizations of individuals whose "beliefs or practices . . . attack or malign an entire class of people, typically for their immutable characteristics," such as race or sexual orientation, but sometimes for their mutable ones, such as religious beliefs (Southern Poverty Law Center 2010). They include organizations such as the Ku Klux Klan, neo-Nazi groups, white nationalist groups, neo-Confederate groups, and black separatist groups. Hate crimes are "crimes that manifest evidence of prejudice based on race, religion, disability, sexual orientation, or ethnicity" (DOJ and FBI 2004).

The potential connection between hate groups and hate crime is obvious. Yet no one has explored it empirically.[1] Indeed, very little work in economics has explored hate crime at all. Dharmapala and Garoupa (2004) examine various aspects of hate crime policy. But their analysis is theoretical and focuses on how the law influences hate crime. Medoff (1999) considers hate crime's determinants empirically.[2] But his study is based on a single cross-section meant to append a theory of hateful behavior and doesn't consider hate groups. Gale, Heath, and Ressler's (2002) work, which is closest to ours, takes a more serious empirical approach to investigating hate crime's determinants. But it, too, neglects the potentially important influence of hate groups.

Our paper is a first step toward filling this lacuna. It investigates the relationship between hate groups and hate crime empirically using panel data on the U.S. states between 2002 and 2008.

American hate groups grew significantly over the past decade. Between 2002 and 2008 the number of hate groups per capita increased 25 percent. But American hate crime didn't. Over the

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[1] Two papers consider the determinants of hate groups (Jefferson and Pryor 1999 and Mulholland 2010).

[2] Glaeser (2005) presents a more general theory of the political economy of hatred.

same period the number of hate crimes per capita *decreased* 1.3 percent. This stylized fact foreshadows the basic finding of our econometric study: contrary to conventional wisdom, we find little evidence that hate groups are connected to hate crime in the United States. There are lots of reasons to loath hate groups. But their influence on hate crime doesn't appear to be one of them.

This study considers two other types of factors that may be related to hate crime in America: economic factors, such as the extent of unemployment and poverty, and demographic ones, such as race and urbanism. In examining economic and demographic factors that may be related to hate crime, this paper follows the small existing literature that addresses hate crime empirically. That literature's focus on economic variables derives from Dollard et al.'s (1939) "frustration-aggregation thesis." According to that thesis, when people endure economic hardship they get frustrated. They take their frustration out on vulnerable social groups, such as racial, sexual, and religious minorities.

Existing empirical support for the frustration-aggregation thesis is mixed. In their paper that examined the American South in the late 19th and early 20th centuries, Hovland and Sears (1940) found a strong relationship between lynchings of blacks and poor economic conditions. However, subsequent work showed their results to be fragile (see Mintz 1946; Hepworth and West 1988; Beck and Tolnay 1990; Olzak 1990; Tolnay and Beck 1995; and Green, Glaser, and Rich 1998).

Krueger and Pischke (1997) find no relationship between economic conditions and racially motivated crime against foreigners in early 1990s Germany. However, Green, and Rich (1998) find weak links between unemployment and assorted hate crimes in North Carolina between 1987 and 1993. Green, Glaser, and Rich (1998) find no consistent relationship between the

unemployment rate and a range of racially motivated crimes in New York City between 1987 and 1995. But Gale, Heath, and Ressler (2002) find evidence of a relationship between economic factors and hate crime in the United States. Compared to hate groups, our analysis finds somewhat stronger evidence that economic hardship may be related to hate crime. However, evidence for the potential importance of economic factors remains weak.

The existing literature's focus on demographic factors that may be related to hate crime derives from the observation that crime tends to be higher in urban areas and that potential conflicts leading to, and opportunities for, hate crime are greater in areas that have a higher concentration of socially vulnerable groups, such as racial, sexual, and religious minorities. Gale, Heath, and Ressler (2002) find that demographic determinants aren't strong predictors of hate crime in America. Our study confirms the unimportance of demographic variables.

This paper's results leave the question of what factors may drive hate crime in America unresolved. But they cast doubt on the popular perception that hate groups are among them.

2   Data

We collect hate-crime data from the Federal Bureau of Investigation's *Hate Crime Statistics* (HCS). The Hate Crime Statistics Act of 1990 brought these data into existence.[3] That Act requires the Attorney General to collect annual data on "crimes that manifest evidence of prejudice based on race, religion, disability, sexual orientation, or ethnicity, including where appropriate the crimes of murder, non-negligent manslaughter; forcible rape; aggravated assault, simple assault, intimidation; arson; and destruction, damage or vandalism of property" (DOJ and

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[3] Hate Crime Statistics Act, 28 USC § 534, 1990.

FBI 2004). The Department of Justice made these data available at the state level beginning in 1995.

Hate-crime reporting to the HCS is voluntary. Within reporting states, local jurisdictional reporting is incomplete and varies by year. Because of this, hate-crime reporting is imperfect. Still, it's very good. In our sample, which covers forty-nine U.S. states (Hawaii didn't report hate crime activity) and the District of Columba from 2002 to 2008, the percentage of the American population covered by hate-crime reporting to the HCS ranges from 82.9 percent, in the lowest-covered year, to 88.6 percent, in the highest-covered year.[4] We return to the issue of imperfect hate-crime reporting and how we address this issue empirically below.

We collect data on the number of hate groups in each state between 2002 and 2008 from the Southern Poverty Law Center (SPLC). The SPLC provides these data in an annual report called "The Year in Hate." The SPLC separates hate groups into the following categories: Ku Klux Klan, Neo-Nazi, White Nationalist, Racist Skinhead, Christian Identity, Neo-Confederate, Black Separatist, and General Hate. They also report the number of patriot groups in each state.

A significant limitation of these data is their aggregate nature. We have no data on hate-group membership, which may or may not move in tandem with hate-group numbers. Further, our data are state level. We don't know in which particular counties hate groups are growing or declining. While our state-level hate-group data provide a basic sense of hate-group activity across states over time, it's important to keep the limitations that aggregation may impose in mind when interpreting our results.

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[4] Data are missing for five state-years in our sample: Alabama 2005; Arkansas 2002; Mississippi 2005, 2006, 2007.

Our empirical model uses three sets of key regressors. The first is our measure of hate crime, discussed above. This variable is unique to our analysis. It allows us to investigate the relationship between organizations such as the KKK, neo-Nazis, and so on, and hate crime.

The other two sets of regressors focus on potential contributors to hate crime that previous studies of hate crime have examined. One of these is a set of economic variables. These variables allow us to investigate the frustration-aggregation thesis. They include the state unemployment rate for persons 16 years old and older (*Unemployment*), the percentage of the state's population that lives in poverty as defined by the U.S. Census Bureau (*Poverty*), and gross state product per capita (*GSPpc*).

The reason we focus on these economic variables is straightforward. The frustration-aggregation thesis predicts that economically struggling persons are more likely to take their frustrations out on the members of weaker, minority groups. Economically struggling persons are more prevalent in states where citizens are poorer (e.g., states with lower GSPs per capita and higher poverty rates) and have more difficulty finding work (e.g., states with higher unemployment rates).

The other set of regressors we consider includes demographic variables. These regressors are same ones Gale, Heath, and Ressler (2002) use in their study of hate crime's determinants.[5] The first of these variables is the percentage of a state's population living in a metropolitan area (*Metro*). Crime is a predominantly urban phenomenon. Thus it's important to control for variation in urbanization across states and over time.

Our second and third demographic variables are the percentage of a state's population that's African-American (*Black*) and the percentage of its population that's Jewish (*Jewish*). The

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[5] We omit one of their controls—a constructed ratio between white and black income—because it's unavailable as a state-level annual metric.

prevalence of persons who hate crimes may be committed against is a potentially important determinant of hate crime. Where hate-crime targets are more numerous, so is the potential for hate crime. On the other hand, where hate-crime targets are more numerous, they may be more insulated from hate crime.

Our final demographic variable is the percentage of a state's children under 18 years old who are victims of abuse or neglect (*Abuse*). Previous research has linked child abuse to criminal activity. Persons who are abused as children are more likely to commit crime as adults. To account for the presence of such persons, we include our variable *Abuse*.

Though not a demographic variable, we also control for the percentage of state and local government spending devoted to police protection (*Police*) in each state. This variable accounts for potential differences in criminal activity across states and over time resulting from differences in citizens' protection against crime.

We collect data for these variables for each state and year in our sample. We get data for each of them from the *Statistical Abstract of the United States*. Table 1 provides summary statistics for all our variables.

To account for the measurement problem that imperfectly reported hate crime creates, our empirical model also includes a variable that controls for the percentage of the population covered by crime-reporting statistics in each state in each year (*Popshare*). We get these data from the HCS reports. Our sensitivity analysis considers an alternative approach for addressing the uneven population coverage of crime-reporting statistics. We discuss this approach in Section 4.3 where we perform robustness checks for our main results.

3 Empirical Approach

To identify potential relationships between hate groups, economic factors, demographic factors, and hate crime empirically, we estimate the following two-way fixed effects model with standard errors clustered by state:[6]

$$HateCrime_{i,t} = \alpha + \beta_1 HateGroups_{i,t} + \beta_2 \textbf{Economic}_{i,t} + \beta_3 \textbf{Demographic}_{i,t}$$

$$+ \beta_4 Popshare_{i,t} + \phi_i + \zeta_t + \varepsilon_{i,t} \tag{1}$$

$HateCrime_{i,t}$ is the number of hate crimes per capita in state i in year t. $HateGroups_{i,t}$ is the number of hate groups, including patriot groups, per capita in state i in year t.[7] $\textbf{Economic}_{i,t}$ is a matrix of economic variables discussed above. $\textbf{Demographic}_{i,t}$ is a matrix of demographic variables discussed above. $Popshare_{i,t}$ is the percentage of the population covered by HCS hate-crime reporting in state i in year t.

ϕ_i is a vector of comprehensive state-specific fixed effects. It controls for time-invariant differences across states that might affect hate crime, such as a long-standing culture of certain kinds of prejudices or tolerance. ζ_t is a vector of comprehensive year-specific fixed effects. It controls for features that are common across states but vary across time that might affect hate crime, such as the national population's changing attitudes toward various racial groups, religious groups, and changing views about homosexuality. $\varepsilon_{i,t}$ is a random error term.

One important limitation of our empirical approach is that hate groups may be endogenous. Hate groups may influence hate crime's prevalence. But hate crime's prevalence may also

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[6] The Hausman test confirms the superiority of a fixed-effects model over a random-effects one.
[7] Following Gale, Heath and Ressler (2002), the population figure we use to generate per capita measures is the population covered by hate-crime reporting.

influence the formation of hate groups. For example, hate groups may find it easier to form where hate crime is more common and thus there's a larger base of potential members to recruit.

Because of this potential, it's important to interpret our empirical results with caution. Our analysis precludes causal inference. Still, it allows us to see whether there might be any significant relationship between hate groups' and hate crime's prevalence. This is a critical first step in assessing hate groups' impact on hate crime and supplies suggestive evidence about hate groups' potential importance as a driver of hate crime in America.

4   Empirics

4.1   Hate Groups and Hate Crime at a Glance

We begin our investigation by examining the relationship between hate groups and hate crime in the raw data. Figure 1 depicts this relationship across the U.S. states for the years 2002 to 2008. Figure 1 displays a positive relationship—but an extremely weak one. This pattern anticipates the basic finding of our econometric analysis below. There's little evidence that hate groups have an important relationship to to hate crime in America.

4.2   Econometric Results

Table 2 presents our primary results. The first column in this table presents a stripped down specification that looks at the relationship between hate groups and hate crime including only fixed effects. When we include no economic, demographic, or other controls, hate groups exhibit a positive and statistically significant relationship to hate crime. The second column in Table 2 considers a second incomplete specification. Here we include economic and demographic

controls but exclude fixed effects. The result is similar to that in column 1. Hate groups are positively and significantly related to hate crime.

The estimates in columns 1 and 2 suggest that hate groups may be meaningfully related to hate crime after all. But the estimates in columns 3 and 4 disagree. Hate groups' relationship to hate crime doesn't survive the inclusion of basic control variables and fixed effects. Consider column 3. Here we present our fully specified, benchmark regression. This regression includes all of our economic and demographic controls and fixed effects. The sign on hate groups is positive. But hate groups' relationship to hate crime is statistically insignificant.

Column 4 considers the same specification as column 3 but restricts hate groups to non-patriot groups. The result is the same. Hate groups are statistically unrelated to hate crime.

Column 5 excludes our economic variables to see whether their inclusion might explain why hate groups are insignificant when we include basic controls and fixed effects. It doesn't. Excluding economic variables from the fully specified regression does nothing to improve hate groups' statistical importance. Hate groups remain insignificant.

The results in Table 2 provide at best weak evidence that hate groups are related to hate crime. It's possible to find a positive, significant relationship between hate groups and hate crime. But one must look to rather unreasonable specifications to find it.

One of the specifications in which hate groups are positive and statistically significant excludes all factors that vary across states and over time that might affect hate crime's prevalence. For example, this specification ignores how differences in average income and resources spent on law enforcement may affect hate crime.

The other specification in which hate groups are positive and significant excludes all permanent differences across states and all trends that are common across states over time that

might affect hate crime's prevalence. For example, this specification ignores deep-rooted differences in attitudes about race in southern states and northern ones. Similarly, it ignores changes in national attitudes about race and homosexuality over time. When these factors are considered, hate groups become unimportant.

Our (non-)result casts doubt on the conventional wisdom according to which hate groups are clearly an important contributor to hate crime. For example, Levin (2007) argues that hate groups provide the "situational facilitator" needed to translate a latent, widespread dislike of minority groups into violence. Jenness et al. (2000) postulate that white supremacist movements encourage people to commit hate crimes. Levin and McDevitt (1993: 103) claim that hate groups actively foster aggressive behavior towards innocents and that, even when their members don't themselves commit hate crimes, they persuade others to, who "are . . . *inspired* by the presence of such groups." Berrill (1992: 31) sees hate groups as playing a similar role, providing potential offenders with "encourage[ment] by . . . rhetoric."

These scholars may be right. Hate groups may be interested in committing hate crimes and encouraging others to commit them. But, if they are, they seem to be quite bad at doing so. Alternatively, hate groups, though populated by hateful people, may be a lot of hateful bluster. Hate-group members may say they're interested in harming the minorities. But, in practice, they may not actually commit hate crimes or convince others to.

Turning attention to our economic variables delivers a somewhat different picture. The results for these variables are presented in columns 2-4 in Table 2. In column 2, which excludes fixed effects, GSP per capita has a statistically significant relationship to hate crime. However, that relationship is a positive one. This would seem to cut against the frustration-aggregation thesis since presumably citizens are less frustrated in economically richer states than in poorer

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ones. Further, our poverty variable, while statistically insignificant, is negative in this specification.

However, in column 3, which includes fixed effects, we find some support for the frustration-aggregation thesis. Here, GSP per capita, though positive, becomes insignificant. Further, our poverty variable, while still insignificant, becomes positive. Most important, our unemployment variable exhibits a positive and statistically significant relationship to hate crime. States with higher unemployment rates have more hate crime.

We find the same pattern in column 4 when we consider only non-patriot hate groups. GSP per capita is positive but insignificant. *Poverty* is positive but insignificant. Most notably, *Unemployment* is again both positive and significant. The results in columns 3 and 4 lend some support to the frustration-aggregation thesis. Since these estimates are generated by fully specified models, we have greater confidence in them.

Finally, consider our results for demographic factors, also contained in columns 2-4 of Table 2. With a single exception—the African-American variable in the specification without fixed effects—demographic factors are statistically unrelated to hate crime. Greater urbanization is consistently associated with more hate crime. So is a higher percentage of Jewish persons. More African-Americans are consistently associated with less hate crime, as are more abused children. However, in each of these cases, save the single instance noted above, the estimated relationships aren't statistically different from zero.

Though not this study's variable of interest, it's worth noting that our measure of legal protection against crime is also a statistically unimportant correlate of hate crime in Table 2, regardless of the specification we consider. The coefficient on *Police* is consistently positive in the specifications that include fixed effects, but always insignificant. The positive coefficient on

Police likely reflects this variable's endogeneity. In states where crime, including hate crime, is higher, governments may spend more money attempting to combat it. We address the potential endogeneity of *Police* in our sensitivity analysis below.

4.3   Sensitivity Analysis

We take several steps to ensure the robustness of our (non-)results that consider the relationship between hate groups and hate crime. As noted above, because crime reporting to the HCS is voluntary, the populations covered by our crime-reporting statistics vary across states and years. While most states in most years have high rates of population coverage, some have much lower rates of population coverage.[8]

In the regressions in Table 2 we account for this unevenness by including the variable *Popshare*, which controls for the percentage of the population covered by crime reporting in each state-year. To ensure that this approach isn't responsible for the weak evidence we find that hate groups are related to hate crime, we try omitting our *Popshare* variable and instead splitting our sample into subsamples according to observations' percentage of population coverage.

We create three such subsamples: one that includes observations falling into the lowest third of our full sample in terms of percentage of population coverage; a second that includes observations falling into the middle third of our full sample in terms of percentage of population coverage; and a third that includes observations falling into the highest third of our full sample in terms of percentage of population coverage. The lowest third of our full sample contains state-years in which crime-reporting population coverage is less than 85 percent. The middle third

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[8] The ten observations in our sample with the lowest crime-reporting population coverage are: Alabama, 2003 (5.2%); Georgia, 2008 (5.7%); Alabama, 2002 (5.8%); Georgia, 2007 (7.1%); Alabama, 2005 (10.0%); Alabama, 2004 (11.7%); Georgia, 2006 (12.3%); Arkansas, 2002 (14.4%); Alabama, 2006 (15.1%); Oregon, 2003 (15.4%).

contains state-years in which crime-reporting population coverage is between 85 percent and 99.5 percent. The highest third contains state-years in which crime-reporting population coverage is greater than 99.5 percent.

Table 3 presents the results of our benchmark regression when we use this alternative approach for addressing the unevenness of crime-reporting population coverage. The first column in this table considers our full sample but excludes *Popshare*. The result is familiar: hate groups are insignificant.

Columns 2-4 look at each of our subsamples. Hate groups are significant in the subsamples that consider the lowest and highest third of observations in terms of crime-reporting population coverage. However, their sign is *negative* in the former subsample instead of positive. In the latter subsample, where hate groups have the "correct" sign, their significance is marginal. In the subsample that considers the middle third of our full sample in terms of crime-reporting population coverage, hate groups aren't even marginally significant.

As a final check, in column 5 of Table 3 we try estimating our benchmark regression, which controls for *Popshare*, but this time excluding observations for which crime-reporting population coverage isn't greater than 50 percent. The result is similar: hate groups remain insignificant. The results in Table 3 support the weak-to-nonexistent evidence that hate groups are meaningfully related to hate crime in Table 2.

We find somewhat stronger evidence for economic factors' potential importance for hate crime in the regressions in Table 3. GSP per capita is negative and significant once. *Unemployment* is positive and significant once. And *Poverty* is negative significant once. Each of these variables' signs is the one predicted by the frustration-aggregation thesis.

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One possibility is that hate groups are significantly related to hate crime, but it takes time for that relationship to appear. To see if this is the case we try lagging hate groups one, two, and three years. Perhaps giving hate groups additional time to affect hate crime will produce positive and strongly significant results.

It doesn't. Consider Table 4. Hate groups are never significant, regardless of the lag structure we use. Indeed, in the specification that considers a three-year lag, hate groups' coefficient is negative. The pattern is similar for the other variables we consider, none of which find more consistent relationships to, or more consistently significant relationships to, hate crime. In the specification that considers a three-year lag of hate groups, even our unemployment variable, which up to now has always been positive, if rarely significant, becomes significant but turns negative.

Another possibility is that our economic variables suffer from multicollinearity. Average income, unemployment, and poverty are closely related. Perhaps this is influencing our estimates. To check if this is the case we consider six combinations of our economic variables, first including each variable one at time and then including them in pairs but excluding the third economic variable. The results of these estimations are in Table 5.

Multicollinearity doesn't seem to be influencing our results for hate groups or our economic variables. Hate groups are statistically unrelated to hate crime in all six specifications. Among our economic variables, *Unemployment*, and only *Unemployment*, is significantly related to hate crime in any of these specifications. Indeed, each time *Unemployment* is included, it's significant. States with higher unemployment rates have more hate crime.

As a final robustness check, we try excluding our *Police* variable to see how this affects hate groups' relationship to hate crime. Among our control variables, *Police* is the most plausibly

endogenous. As noted above, government may spend more resources on police in response to higher crime. This potential endogeneity may be influencing our results.

It turns out that it's not. Excluding *Police* has no qualitative effect on our main result. Hate groups remain a statistically unimportant correlate of hate crime. Excluding *Police* in specifications that lag hate groups one, two, and three years delivers the same result. Because of their similarity to previous results, we don't report these regressions separately.

5   Concluding Remarks

This paper is first to explore the relationship between hate groups and hate crime empirically. Contrary to conventional wisdom, our analysis finds little evidence that hate groups are related to hate crime in the United States. We find somewhat stronger evidence that economic hardship may be related to hate crime. However, evidence for the potential importance of economic factors remains weak. Similarly, we find no evidence that demographic factors are important predictors of American hate crime.

Our findings leave the question of what factors may drive hate crime in America unresolved. But they cast doubt on the possibility that one of the popularly conceived leading candidates is responsible: hate groups. There are many reasons to loathe hate groups. But our analysis suggests that their contribution to hate crime isn't one of them.

We hasten to add that our study is limited in at least two important ways. First, as indicated above, our analysis relies on aggregated hate-group data provided by the Southern Poverty Law Center. These data measure the number of hate groups per state, but don't measure hate-group membership or hate-group numbers at more local levels. The aggregation inherent in our hate-group measure may mask a relationship between those groups and hate crime that our study is

unable to detect. Further, as we also indicated above, our analysis is unable to isolate causal effects. Future work that overcomes the potential for hate-group endogeneity may find different results. Our paper is a first attempt at addressing the potential connection between hate groups and hate crime. Further research that explores this issue should aim to overcome the limitations described above.

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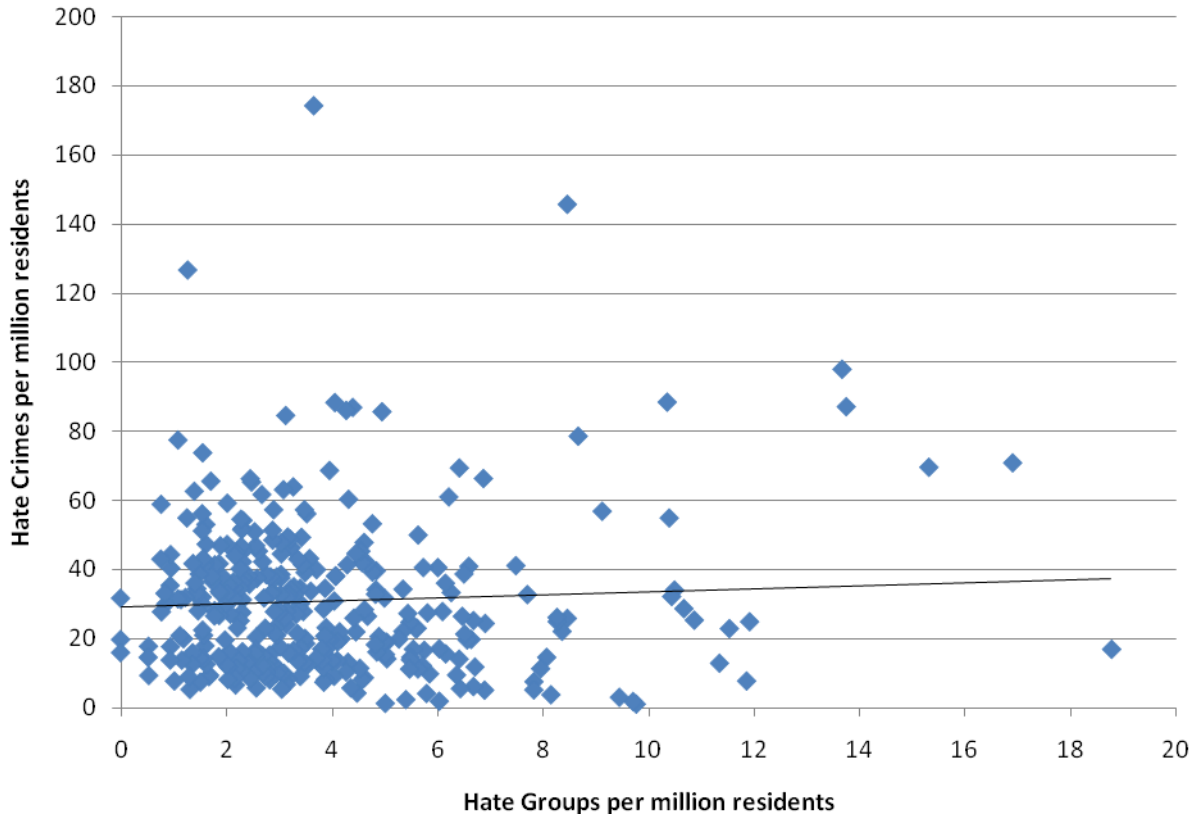# Figure 1. Hate Groups and Hate Crimes, 2002-2008

Table 1. Summary Statistics

Variable	Definition	Mean	S.D.
HateCrime	Total crimes attributed to all bias motivations per 1,000,000 covered population, by state	30.82	21.73
	Total crimes attributed to race bias per 1,000,000 covered population, by state	16.36	13.03
	Total crimes attributed to religion bias per 1,000,000 covered population, by state	4.74	5.17
	Total crimes attributed to sexual orientation bias per 1,000,000 covered population, by state	5.86	7.69
	Total crimes attributed to ethnicity bias per 1,000,000 covered population, by state	3.55	3.00
	Total crimes attributed to disability bias per 1,000,000 covered population, by state	0.32	0.90
HateGroups	Total number of hate groups, including patriot groups, per 1,000,000 residents, by state	3.89	2.76
	Total number of hate groups, excluding patriot groups, per 1,000,000 residents, by state	3.14	2.59
	Total number of Ku Klux Klan, Neo-Nazi, White Nationalist and Racist Skinhead groups per 1,000,000 residents, by state	1.80	1.42
GSPpc	Gross State Product per capita, in thousands of 2000 dollars	36.80	13.18
Unemployment	State unemployment rate for individuals 16 years and older	5.04	1.16
Poverty	Percentage of state population in poverty	12.58	3.24
Police	Percentage of state and local government expenditures on police protection	2.60	0.61
Popshare	Percentage of state population covered by HCS reporting	82.38	26.35
Metro	Percentage of state population residing within a metropolitan statistical area (MSA)	85.51	12.84
Abuse	Percentage of children under 18 years of age who were victims of abuse or neglect	1.17	0.67
Black	Black population as a percentage of state population	11.29	11.46
Jewish	Jewish population as a percentage of state population	1.37	1.70

Data sources: Hate Crime Statistics, Southern Poverty Law Center,
Statistical Abstract of the United States.

Table 2. Hate Groups, Economic Factors, Demographic Factors, and Hate Crime

	Fixed Effects Only	Excluding Fixed Effects	Benchmark	Excluding Patriot Groups	Excluding Econ Vars
	1	2	3	4	5
HateGroups	1.743*	1.719**	1.066	0.398	1.360
	(0.997)	(1.113)	(0.884)	(0.930)	(1.045)
GSPpc		0.673***	1.323	1.564	
		(0.153)	(1.554)	(1.634)	
Unemployment		2.346	4.108**	4.301**	
		(1.936)	(1.756)	(1.753)	
Poverty		-0.721	1.947	1.944	
		(0.674)	(1.836)	(1.870)	
Police		-1.961	1.472	2.047	2.089
		(3.656)	(5.268)	(5.440)	(5.426)
Popshare		-6.292	-64.431**	-64.588**	-65.787**
		(10.802)	(27.947)	(28.086)	(28.362)
Metro		0.002	0.315	0.331	0.261
		(0.143)	(4.680)	(0.288)	(0.316)
Abuse		-2.999	-0.315	-0.126	-1.110
		(2.820)	(4.680)	(4.854)	(5.143)
Black		-0.719**	-2.698	-2.810	-2.834
		(0.310)	(4.676)	(4.789)	(4.813)
Jewish		3.947	2.915	3.023	5.267
		(2.467)	(6.838)	(6.895)	(8.191)
Fixed effects (y/n)	y	n	y	y	y
Observations	345	292	292	292	292
R-squared	0.03	0.25	0.25	0.25	0.23

Notes: Robust standard errors, clustered by state, in parentheses. ***=1%; **=5%; *=10%.

Table 3. Splitting the Sample by Population Coverage

	Full Sample	Pop Cover < 85%	99.5% > Pop Cover > 85%	Pop Cover > 99.5%	Excluding Pop Cover ≤ 50%
	1	2	3	4	5
HateGroups	1.328	-2.563*	1.567	1.248*	0.533
	(0.968)	(1.295)	(1.418)	(0.633)	(0.853)
GSPpc	1.418	-3.330	-2.984*	2.353	2.001
	(1.555)	(3.361)	(1.540)	(1.477)	(1.472)
Unemployment	4.431*	4.441	0.617	1.473	2.093
	(2.243)	(5.916)	(2.699)	(1.777)	(1.361)
Poverty	2.490	-3.888	0.982	2.123	3.505**
	(1.933)	(3.367)	(0.929)	(1.943)	(1.554)
Police	0.045	17.281	-2.024	-6.427	-1.006
	(5.470)	(20.799)	(6.532)	(8.626)	(6.434)
Popshare					-32.819**
					(14.729)
Metro	0.083	0.366	-0.061	0.709*	0.466
	(0.318)	(0.999)	(0.253)	(0.407)	(0.283)
Abuse	-2.827	-2.958	-10.610**	7.368*	-4.388
	(5.559)	(8.666)	(3.934)	(3.899)	(5.384)
Black	-2.774	8.267	-24.932***	-1.589	-3.692
	(5.147)	(17.482)	(6.686)	(5.977)	(4.032)
Jewish	3.238	-65.264	10.006	-8.981	4.031
	(6.369)	(42.018)	(12.600)	(8.117)	(6.431)
Observations	292	94	96	102	259
R-squared	0.08	0.17	0.62	0.34	0.16

Notes: All regressions include state and year fixed effects. Robust standard errors, clustered by state, in parentheses. ***=1%; **=5%; *=10%.

Table 4. Lagged Hate Groups

	1-Year Lag	2-Year Lag	3-Year Lag
	1	2	3
HateGroups	1.135	0.772	-0.862
	(1.369)	(1.100)	(1.154)
GSPpc	-0.284	0.433	-2.286
	(1.806)	(1.898)	(4.643)
Unemployment	2.999	-1.497	-8.171**
	(2.482)	(1.760)	(3.843)
Poverty	1.602	2.307	-0.110
	(2.246)	(2.063)	(2.809)
Police	-1.348	-0.388	-8.290
	(6.007)	(8.316)	(10.395)
Popshare	-68.352**	-31.892*	-2.988
	(28.447)	(17.555)	(26.602)
Metro	0.116	0.158	-17.245**
	(0.484)	(0.711)	(8.091)
Abuse	1.552	4.274	2.544
	(5.677)	(3.881)	(4.174)
Black	-0.160	4.943	16.164***
	(5.337)	(3.875)	(6.060)
Jewish	3.501	24.403	20.314
	(7.790)	(16.836)	(28.011)
Observations	243	193	143
R-squared	0.24	0.08	0.13

Notes: All regressions include state and year fixed effects. Robust standard errors, clustered by state, in parentheses. ***=1%; **=5%; *=10%.

Table 5. Economic Factors, One at a Time

	GSPpc Only	Unemployment Only	Poverty Only	Excluding GSPpc	Excluding Unemployment	Excluding Poverty
	1	2	3	4	5	6
HateGroups	1.238	1.256	1.433	1.324	1.230	1.050
	(0.971)	(1.005)	(1.024)	(0.997)	(0.930)	(0.909)
GSPpc	0.618				1.065	1.008
	(1.744)				(1.661)	(1.595)
Unemployment		4.370**		3.847**		4.637**
		(2.002)		(1.702)		(2.031)
Poverty			2.195	1.293	2.456	
			(1.909)	(5.201)	(1.927)	
Police	2.216	1.589	1.626	1.293	1.788	1.765
	(5.549)	(5.494)	(4.998)	(5.201)	(5.057)	(5.632)
Popshare	-65.803***	-65.147**	-64.908**	-64.550**	-64.832**	-65.134**
	(28.638)	(27.494)	(28.148)	(27.497)	(28.575)	(27.853)
Metro	0.298	0.260	0.237	0.241	0.298	0.320
	(0.297)	(0.302)	(0.294)	(0.288)	(0.283)	(0.289)
Abuse	-1.203	-0.402	-0.746	-0.207	0.862	-0.509
	(5.155)	(4.782)	(4.967)	(4.713)	(4.969)	(4.762)
Black	-2.075	-3.711	-3.575	-4.174	-2.354	-2.525
	(5.185)	(4.626)	(4.867)	(4.707)	(4.992)	(4.840)
Jewish	5.358	2.801	5.013	2.901	5.140	2.798
	(8.190)	(7.212)	(7.792)	(7.044)	(7.600)	(7.089)
Observations	292	292	292	292	292	292
R-squared	0.23	0.24	0.24	0.25	0.24	0.24

Notes: All regressions include state and year fixed effects. Robust standard errors, clustered by state, in parentheses. ***=1%; **=5%; *=10%.