AN ECONOMIC ANALYSIS OF HATE CRIME

Lewis R. Gale
University of Louisiana at Lafayette

Will Carrington Heath
University of Louisiana at Lafayette

and

Rand W. Ressler
University of Louisiana at Lafayette

INTRODUCTION

Most everyone agrees that "hate" crimes are especially vile offenses, and some claim that the problem has gotten worse in recent years [Lawrence, 1994]. Hate crimes differ fundamentally from other types of crime in that the defining characteristic of hate crime lies within the utility function of the perpetrator—specifically, the presence of *ill will or hatred towards the victim*.[1] To distinguish hate crimes from all other crimes, most states have adopted so-called "anti-bias" statutes and penalties. For example, Florida, New Hampshire, Pennsylvania, New Jersey, Connecticut, and Maryland employ a "racial animus" criterion: hate crime is differentiated by the perpetrator's ill will, hate or bias due to race. California provides for the enhancement of penalties for certain crimes if the offender commits the crime because of the victim's race, color, ancestry, national origin, or sexual orientation.

While the "because of" criterion clearly suggests discriminatory selection, it does not necessarily identify true racial or other group-related animus. Some states (for example, Idaho) augment this criterion with the element of "maliciousness." Similarly, the FBI has instituted new regulations that use only those indicators of discriminatory selection that allow for the inference of animus relating to race, religion, ethnicity/national origin, or sexual orientation.[2] In other words, the discriminatory selection of a victim is relevant only if that selection suggests an underlying animus.

While economists have theoretically and empirically explored criminal activity [Becker, 1968; Ehrlich, 1973; 1977; Sjoquist, 1973; Zhang, 1997], they have developed precious little economic foundation to address the special nature of hate crimes. Yet, an economic analysis of hate crime may, in fact, be found in theory developed in a different context. If those who commit hate crimes are presumed to be motivated by malevolent ill will, then it seems reasonable to characterize them as "envious" in much the same way as Gary Becker [1981] uses the term in his model of altruism and envy within the family. The following paper is, in part, a modest attempt to glean

insights from Becker's analysis of envy, and incorporate them into an empirical model of hate crime. Becker himself may not have intended this application of his theory, but it is plausible and potentially quite useful.

In this paper, we make use of hate crime data compiled by the FBI to estimate the determinants of hate crimes across states using random-effects and fixed-effects approaches. We also investigate whether there are regional differences in hate crime determinants given the painful history of racial prejudice in the South. While significant limitations inhere in the use of bias-motivation data in empirical analysis, we find statistical significance between the incidence of hate crime and several economic and socioeconomic variables. Particularly among the non-South states, a higher hate crime rate is associated with (a) higher abuse rates, (b) higher unemployment rates, and (c) lower law enforcement expenditure shares. Our most interesting result is that greater parity of black and white incomes is associated with higher hate crime rates.

HATE CRIMES

Hate Crime as Envious Behavior

Perpetrators of most parallel crimes do what they do for personal gain or profit and are indifferent with respect to the welfare of their victims. "Carjackers," "drug dealers," "pickpockets," and even muggers and robbers who assault their victims physically, are not motivated primarily by the desire to reduce the welfare of their victims. The perpetrator of a hate crime, however, is motivated *precisely* by the desire to make the victim worse off, and is willing to expend resources and incur costs to do so.

Such behavior is entirely consistent with what Gary Becker describes as "envious" behavior. Consider first what it means to be altruistic. Suppose a person, h, is altruistic toward some member of his family, w. Altruism, as Becker defines it, means simply that h's utility function depends positively on the well-being of w. Formally put,

$$U_h = U[Z_j,... Z_{mh}, U_w]$$

and

$$\partial U_h / \partial U_w > 0$$

where U_h and U_w are the utilities of the altruist and his beneficiary respectively, and Z_{jh} represents the jth commodity consumed by h. Thus in maximizing utility the altruist allocates resources to the procurement of goods for his own consumption (Z-commodities) *and* to the well-being of w. The equilibrium condition for allocating resources within the family would be

$$\partial U / \partial Z_h = \partial U / \partial Z_w.$$

We may think of envy as roughly the opposite of altruism.[3] More precisely, the envier's utility function depends *negatively* on the well-being (income or consumption opportunities) of those persons whom he envies *relative to his own well-being*. An

envious person is willing to expend resources and reduce his own consumption if the consumption of his victims is lowered even more. As discussed above, a number of states and the FBI recognize racial (or other) animus as the defining characteristic of bias-motivated crime. Becker's definition of envy clearly would encompass racial animus (the latter being a subset of the former, actually). Becker's analysis yields interesting implications for social policy designed to deal with envious behavior and we mention some of them briefly at the conclusion of this essay. But here we focus primarily on several determinants of hate crime—one explicitly economic determinant, and others more sociological and, unfortunately, more difficult to quantify.

Assume that, as is the case in the United States, the white majority enjoys greater income relative to the non-white minority. Because relative status matters in Becker's framework, it is intuitively plausible that if the minority were to narrow the income gap, this would incite envious members of the majority to reduce the well-being (economically and possibly otherwise) of minority members. Thus, as the income gap decreases, the number of hate crimes committed by majority members targeted towards minorities would increase. Likewise, an income-gap widening might lead to a greater incidence of hate crime committed by minority group members who may have animus towards members of the majority, especially if they feel the income gap is the result of deliberate discrimination.

Becker explores the implications for the family when the head of the household is altruistic. He concludes that an altruistic head of household induces even non-altruistic members of the family to behave as though they were altruistic, thus strengthening the family as a cohesive unit. Suppose Tom, who is inclined to be hateful towards his sister Jane, takes some action which makes himself better off at her expense—he destroys Jane's expensive bicycle, for instance. The altruistic parent might replace the bike, thereby lowering the allocation of family resources to Tom (assuming the family budget is limited). Thus the altruistic head of household responds in a way that ultimately reallocates some resources from Tom to Jane. These actions are not necessarily a matter of reward or punishment as such. The altruist is simply reallocating family resources in a manner consistent with maximizing his own utility, given finite family resources. The upshot is that Tom is made worse off from the actions of his altruistic parent, and would be discouraged from taking an action he would otherwise find attractive.

Whereas altruism on the part of the family head induces cooperative behavior and helps to keep the family intact, selfishness or envy on the part of the parent would fail to check the envious impulses among rival siblings. In the absence of an altruistic "household manager," the family structure is strained or even fractured. Thus envious behavior is not merely tolerated by the non-altruistic head, it is caused to flourish (perhaps more than the head would wish) as the family structure disintegrates.

Theoretically, a government controlled by an envious majority might operate in much the same way as an envious head of household in that many of its policies and institutions would be deliberately inequitable towards a disfavored minority group. Such a regime would not merely tolerate envious actions by individuals in the majority, but would actually (and perhaps unintentionally) encourage it, just as the non-

altruistic head of household would encourage envious behavior among siblings. The southern region of the United States has a painful history of racial discrimination, and the popular perception, rightly or wrongly, seems to be that "envious" behavior is tolerated more in the South than elsewhere. We examine the possibility that the South might experience relatively greater rates of hate crime than other regions, due to relatively more discriminatory—at least less altruistic—policy regarding the status and treatment of minorities.

We might expect persons who have been raised by a selfish or envious parent to be more likely to commit a hate crime, insofar as their upbringing did not enforce strictures against envious behavior. Such an upbringing might be measured in terms of reported child abuse; if so, we then should find a positive correlation between abuse and crimes of racial or group animus. A related point is that altruistic parents invest in the "quality" of their children since the utility of altruistic parents is raised by investment returns that enhance the children's well-being [Baumol, 1986, 197]. Consequently, children with altruistic parents tend to be better endowed for success, at least in terms of the child's health, education, and other determinable qualities that could be related empirically to the incidence of hate crime.

Hate Crime Data

In 1990, Congress passed the Hate Crime Statistics Act, which provided the impetus for the FBI's Uniform Crime Reporting Program to collect data on hate crimes. Subsequently, *Hate Crime Statistics* has been published annually since 1992. This study employs data from four of the hate crime reports: 1992-1995. It should be noted that participation (in gathering and providing hate crime data to the FBI) on the part of each state is essentially voluntary.[4] Furthermore, even in a participating state, the "(state) population covered" is typically less than the total population in the observed state. In other words, less than one hundred percent of a state's law enforcement officials are actively trying to distinguish between bias-motivated crime and parallel crime. For example, in 1992, the population covered in Maine was 197,527 people or 19.1 percent of total state population.

The situation seems to be changing, however. By 1995, these numbers (again, for Maine) were 1,234,660 or 99.5 percent. The dramatic increase in state population coverage undertaken in Maine is not unusual. As hate crime becomes more newsworthy, and as law enforcement educates more of its officers in how to identify such crime, increases in state coverage should be expected. In 1992, 45 states plus the District of Columbia participated and the mean population covered (as a percentage of total population) was 55.3 percent.[5] In 1995, the number of participating states remained constant, but the population covered increased to 81 percent.

Along with this increase in coverage, data characteristics seem to indicate that law enforcement officers have, since 1992, gotten a better handle on when a crime should be classified as being bias motivated. One could reason that as a variable becomes more clearly defined to data collectors, the distribution of the data should

"tighten." That is, the standard deviation of the hate crime rate should be at its largest value in 1992 and decrease in subsequent years as law enforcement becomes more skilled in hate crime data collection. The standard deviation of the hate crime rate (defined below and in Table 1) in 1992 is 4.5, and the corresponding values for 1993, 1994, and 1995 are 5.5, 3.1, and 2.8, respectively. This downward trend is consistent with the presumption that hate crimes have become more clearly defined through time.

Even with the improved documentation of hate crime, DiIulio [1996] correctly identifies two potentially severe measurement problems characteristic of most crime data: underreporting by victims and underreporting/hierarchical reporting by law enforcement agencies. Both measurement problems are likely to be present in our hate crime data because Uniform Crime Reports only capture voluntary reporting. Furthermore, there exists a wide range of participation of law enforcement within states. State differences in law enforcement participation can be controlled.

Voluntary reporting is an issue as well in that the source of our hate crime data is the Uniform Crime Reports. Besci [1999] notes that wide variation exists when comparing crime rates from different data sources to those from the Uniform Crime Reports. He argues that inferences from *reported* crime using Uniform Crime Reporting data are not necessarily the same as those that can be derived from *true* crime. Indeed, bias-motivated crime poses a problem in terms of accurate collection since it is inevitably based on the judgement of law enforcement officers involved. Grove, Hughes, and Geerken [1985] conclude that crimes more closely approximating true crime rates are those that are unambiguous to both victims and law enforcement (for example, theft, robbery, homicide). They also find that Uniform Crime Reporting data of crimes considered more ambiguous between victims and law enforcement (for example, aggravated assault) are less accurate and will likely overstate the actual crime rate.

By definition, hate crime is motivated by a personal bias on the part of the perpetrator regarding the victim. But how, as a practical matter, does one identify the *motivation* of a crime? In some cases it is clear, such as the defamation of a synagogue, for instance. However, in many, indeed perhaps most, cases ambiguity surrounds this question of motivation. For example, suppose a white man mugs an African-American. Law enforcement would likely assume that this crime was motivated by greed. In other words, the perpetrator commits the crime to make himself better off, *not* to make the victim worse off. But now suppose that in the course of committing this crime, the perpetrator utters a racial slur. Is this a hate crime? It may be clear that the offender is a racist, yet personal prejudice and hatred is a necessary *but not a sufficient* condition for a crime to be classified as a hate crime. Even if the person who commits a crime feels hatred towards the victim, this does not mean that the crime was motivated by this hatred. Greed may still be the primary motivation of the perpetrator. Thus, a degree of ambiguity and subjectivity characterizes the data on bias-motivated crimes. Accordingly, any empirical results derived from this data must be interpreted with caution.

TABLE 1
Definition of Variables and Summary Statistics, 1992-95

Variable	Definition	1995 Mean(S.D.)	1992 Mean(S.D.)
HateCrime	State bias motivation crime incidents reported to participating agencies per 100,000 covered population	3.86 (2.84)	5.48 (4.49)
Income	State per capita income in 1992 dollars	20696 (3218)	19554 (3216)
BWIncome	The ratio of state i to sample state mean of black household income relative to white household income in 1990 dollar times U.S. black household income relative to white household income in 1990 dollars	0.5932 (0.0916)	0.5527 (0.0854)
Unemploy	State unemployment rate for population 16 years and older	0.0533 (0.0115)	0.0695 (0.0121)
Poverty	Persons in poverty as a percentage of state population	0.1327 (0.0391)	0.1441 (0.0444)
Lawpop	State law enforcement expenditure share in 1992 dollars relative to state population share	0.953 (0.589)	0.952 (0.588)
Popshare	Population covered as a percentage of state population	0.810 (0.280)	0.553 (0.400)
Metro	Metropolitan population as a percentage of state population	0.733 (0.199)	0.724 (0.204)
Abuse	Number of children subject to child abuse and neglect in the observed state per 100,000 people	1222.8 (462.9)	1181.8 (406.2)
Black	Black population as a percentage of state population	0.1476 (0.1589)	0.1255 (0.1277)
Jewish	Jewish population as a percentage of state population	0.0156 (0.0192)	0.0159 (0.1277)

Data sources were *Hate Crime Statistics*, 1992-1995, the *Statistical Abstract of the United States*, 1992-1996, and the *American Jewish Year Book*, 1996.

MODEL SPECIFICATION AND EMPIRICAL FRAMEWORK

We specify the following equation of hate crime occurrence:

$$(1) \quad HateCrime_{it} = \beta_1 + \beta_2 Income_{it} + \beta_3 BWIncome_{it} + \beta_4 Unemploy_{it} + \beta_5 Poverty_{it}$$

$$+ \beta_6 Abuse_{it} + \beta_7 Black_{it} + \beta_8 Jewish_{it} + \beta_9 Popshare_{it} + \beta_{10} Metro_{it}$$

$$+ \beta_{11} Lawpop_{it} + \varepsilon_{it}.$$

Table 1 gives the variable definitions and summary statistics. Utilizing the FBI's *Hate Crime Statistics*, we include only those states in which hate crimes were reported in a consistent manner; hence our panel of data includes 37 states from 1992 to 1995.[6] Our dependent variable, $HateCrime_{it}$, is the number of hate crime incidents per 100,000 population covered in state i during time t. A hate crime rate is calculated so as to obtain a comparable value for all states regardless of population covered. It is

interesting to note that while both the number of hate crime incidents and the population covered increased during the time period analyzed, the rate of hate crime has declined.

With panel data, estimation by ordinary least squares may generate inconsistent estimates of coefficients because of heteroskedasticity, autocorrelation, and contemporaneous covariance, and thus be inappropriate [Fomby, Hill, and Johnson, 1988]. For equation (1), we estimated both a fixed-effects and a random-effects model. Using these estimation techniques, the error term in equation (1) is written as

$$\varepsilon_{it} = \mu_i + \omega_{it}$$

where ω_{it} is the standard mean zero error and μ_i is the state-specific effect. In general, the difference between the two estimators is whether or not μ_i is assumed to be fixed or random across individual states. If the participating agencies in the individual states appearing in our sample are randomly chosen and taken to be representative of a larger population, then the random effects model would be more appropriate. Since we cannot say, *a priori*, which method is more appropriate, we choose to use both methods.

As we discussed above, a narrowing of the income gap between majority and minority racial groups might encourage hate crime on the part of envious members of the *majority* population. A widening of the gap, on the other hand, would be expected to incite acts of envious behavior on the part of the *minority*. Ideally, state-specific data would indicate the race (or other demographic characteristics) of both the perpetrators and victims of hate crime. Unfortunately, data in *Hate Crime Statistics* have been aggregated so that such distinctions are not possible. Inasmuch as the majority accounts for a greater absolute number of hate crime offenders, we expect the response of the majority to be the predominant effect. To capture the effects on income differentials, we include *BWIncome* in equation (1) and expect the coefficient to be positive. The variable, in its fixed 1990 form, is unusable in the fixed-effects specification since it is constant across time. Therefore, we proxied a time-series for *BWIncome* during the sample's four years to maintain consistency when using this variable between specifications.[7]

Unemployed individuals or persons in poverty may also feel victimized by inequitable policies and institutions. Furthermore, the unemployed may find themselves with ample time in which to engage in criminal behavior. To control for both of these effects, we include the state's unemployment rate (*Unemploy*) and poverty rate (*Poverty*) and expect both of these variables to have positive effects on the hate crime rate.

We also include state per capita income as an explanatory variable of hate crimes. Based on the empirical literature, per capita income is highly correlated with educational attainment. One would assume that a person's level of schooling would be inversely correlated with his propensity to commit a hate crime, inasmuch as these are the persons in whose "quality" altruistic parents have "invested." Since we do not include an education variable in the present model, we may capture the effect of education with real state per capita income (*Income*), especially if the altruistic and their offspring are more successful, as Becker suggests.[8] On the other hand, higher

state per capita income may indicate a larger gap between the poor and the affluent in a particular state. If high-income states have a more unequal distribution of income, this pattern could result in higher rates of bias-motivated crimes on the part of the relatively less wealthy. Even though there is reason to remain ambiguous with respect to the effects of per capita income, we anticipate that it will be inversely related to hate crime.[9]

Envious parents may not create envious children, but surely they fall short in demonstrating the virtues of altruistic behavior. Indeed, as DiIulio notes, "75 percent of violent juvenile offenders have suffered abuse by a family member" [1996, 15]. Child abuse and neglect are characteristics of envious, not altruistic, parental behavior. Furthermore, it seems plausible that those who are willing to abuse their children are generally more envious than others, and more likely to commit bias-motivated crimes outside the family as well. For these reasons, we expect the rate of child abuse (*Abuse*) to have a positive impact upon the hate crime rate in the observed state.

For non-envy variables, states with relatively large numbers of residents under the scrutiny of law enforcement agencies that report hate crimes will have larger numbers of crimes reported, *ceteris paribus*. Incidents of hate crimes are collected for a segment of the population covered. The size of the population covered as a percentage of the state population (*popshare*) is included to control for the possible bias found among the participating states. In some states, for example, participating law enforcement agencies only "cover" 25 percent of the state's population (and there is no indication that the 25 percent is a random sample). This is not an issue when analyzing parallel crimes that are reported for 100 percent of the state's population. Therefore, it is possible that the hate crime rate (defined as hate crimes per 100,000) may vary depending on the percentage of the population covered in the participating state. Law enforcement coverage is expected to impact the observed hate crime rate positively.

Metropolitan areas tend to have higher overall crime rates and may have higher hate crime rates. To control for this, we also include the percentage of a state's population living in metropolitan areas (*Metro*) and we expect the coefficient on this variable to be positive. A variable reflecting law enforcement expenditures (*Lawpop*) is included to proxy the risk of being caught and punished for committing bias-motivated crimes. Assuming greater levels of law enforcement funding increases the probability of apprehension and punishment (and that punishment is, in fact, an effective deterrent of criminal behavior), we expect it to impact reported hate crimes negatively. Finally, we include variables to control for the size of a state's ethnic minority populations. In 1992, more than 63 percent of all reported hate crimes were motivated by race. The larger the percentage of the population of a particular ethnicity, the greater are the opportunities to commit crimes of hate against them, hence we expect the coefficients of *Black* and *Jewish* to be positive.[10]

RESULTS AND ANALYSIS

Table 2, columns 1-2 present the random-effects and fixed-effects results of equation (1). To be consistent with previous empirical studies of criminal behavior [Ehrlich,

TABLE 2
Estimation Results on the Determinants of Hate Crimes, 1992-95

	Random Effects	Fixed Effects	Southern States Random Effects	Fixed Effects	Non-Southern States Random Effects	Fixed Effects
Income	1.127	11.430	0.954	19.161	1.410	8.508
	(0.621)	(1.595)	(0.104)	(0.985)	(0.931)	(1.147)
BWIncome	4.397[a]	−5.493	5.703	−8.939	3.169[a]	−1.110
	(3.433)	(−0.770)	(1.619)	(−0.493)	(2.784)	(−0.153)
Unemploy	1.548[a]	2.092	2.063	4.398	1.939[a]	1.886
	(2.416)	(1.548)	(1.040)	(1.448)	(3.340)	(1.303)
Poverty	−3.87E-02	0.929	−1.129	−0.146	0.418	1.564[b]
	(−0.069)	(1.163)	(−0.797)	(−0.081)	(0.724)	(1.728)
Lawpop	−0.565	15.353	2.256	142.15	−1.298[a]	−11.557
	(−0.876)	(0.324)	(0.504)	(0.116)	(−2.660)	(−0.400)
Popshare	9.32E-02	0.252[b]	−1.69E-02	−7.02E-03	0.196	0.208
	(0.879)	(1.727)	(−0.082)	(−0.023)	(1.628)	(1.238)
Metro	0.844	1.038	0.506	270.96[a]	0.631	0.858
	(1.295)	(0.517)	(0.140)	(2.543)	(1.167)	(0.496)
Abuse	0.318	−0.406	−0.198	0.127	0.526[a]	−0.560
	(1.010)	(−0.626)	(−0.192)	(0.101)	(2.042)	(−0.754)
Black	2.73E-03	5.26E-02	−0.269	−4.79E-02	−8.40E-02	0.185
	(0.017)	(0.157)	(−0.580)	(−0.071)	(−0.498)	(0.489)
Jewish	0.292	−1.061	−0.281	−3.658	0.350[b]	−0.346
	(1.231)	(−0.819)	(−0.310)	(−1.203)	(1.662)	(−0.260)
Likelihood ratio	——	87.621	——	36.958	——	38.546
σ_μ^2	0.414	——	3.626	——	0.129	——
σ_ε^2	0.989	——	1.839	——	0.727	——
Adj. R^2	0.420	0.540	0.469	0.572	0.447	0.436
Observations	148	148	52	52	96	96

Estimates are based on log-log linear equation. t-statistics are in parentheses. σ_μ^2 is the estimated variance of the common-to-state component of the residuals, and σ_ε^2 is the estimated variance of the idiosyncratic component of the residual. The Likelihood ratio test is a test of the individual state effects being the same. The null hypothesis is rejected at the 0.01 level of significance indicating that individual state effects differ across states. We fail to reject the null hypothesis of no correlation between regressors and errors (Hausman test) at the 0.05 level of significance, thus the random effects model is efficient.
a. Significant at 5 percent level.
b. Significant at 10 percent level.

1973; 1977; Sjoquist, 1973; Zhang, 1997], the results are in log linear form. The random-effects model performs reasonably well with respect to coefficient sign but not in terms of significance. As hypothesized, *Unemploy* and *BWIncome* are both positive and statistically significant explanatory variables, which lends support to the role of envy in the determination of hate crimes. *Abuse*, *Metro*, and *Lawpop* all have the expected signs but none are statistically significant. The positive coefficient on *Income* indicates that states with higher per capita incomes also have higher hate crime rates, although it too is statistically insignificant.

As an alternative specification, the fixed effects model is an especially stringent test of the relationship between hate crime rates and the regressors inasmuch as it ignores all information contained in the cross-state variation in hate crime rates. Of

course, only time-varying regressors and dummy variables for each state can be included for this specification. These results are less encouraging in that several signs are reversed and only significant variable is *Popshare*; increases in population covered will generate a higher hate crime rate. Likelihood ratio tests indicate that the null hypothesis that individual state effects are the same is rejected in favor of the fixed-effects model. A Hausman procedure was performed to test whether the regressors were correlated with the error terms. If correlation exists, then a random-effects estimator is not consistent and should not be used. If correlation is not present, then the random-effects model is more efficient than the fixed-effects model. It is important to note that given either hypothesis, the fixed-effects estimator is consistent. Our test statistic indicates that the random-effects model is systematically different and more appropriate for the overall sample.

Given the results in Table 2, columns 1-2, we sought additional information to determine if there is any apparent regional stratification of hate crimes. The South, as a region, has a painful history of racial prejudice and violence, and indeed some still perceive the region to be more tolerant of bias-motivated crime. We partitioned our data into South and non-South states, and, as expected, there are general differences across regions.[11] Southern states consistently cover a lower percentage of their population than non-South states in corresponding years. Specifically, the percentage (on average) of population covered in the South is 41.9, 42.7, 61.9, and 66.8 percent for the years 1992, 1993, 1994, and 1995, respectively. While coverage is improving over time, these coverage ratios are much lower than those found in the non-South states: 60.4, 75.9, 77.3, and 88.7 percent for the same years. This discrepancy does not necessarily imply that the South does not take the issue of hate crime as seriously as the non-South.

Perhaps law enforcement agencies in southern states do not have access to the same level of resources as in the non-South; the mean of *Lawpop*, for example, in the South is less than in the non-South. It could also be the case that the FBI concentrated its initial training of law enforcement (in how to recognize hate crime) outside of the South. Finally, coverage often begins in metropolitan areas where crime rates are typically higher. Because the non-South contains more metropolitan areas than the South, it is possible that mere demographics are determining the South/non-South discrepancy in population covered. Beyond coverage, the distribution of the hate crime rate is distinctly different in the two regions. The standard deviation of the hate crime rate in the non-South in each of the four years is as follows: 4.2, 4.9, 2.9, and 2.4. The corresponding figures for the South are 5.1, 6.6, 3.4, and 3.5. Again, this tighter data distribution in the non-South may result from greater clarity in recognizing and reporting bias-motivated crime.

We present our results for South and non-South states in Table 2, columns 3-4 and 5-6, respectively. For only the Southern states, *Metro* is statistically significant and positive, yet the performance for all other variables is similar to that of the full sample for the fixed-effects model. The Hausman test indicates that the random effects model is more efficient than the fixed effects model for the South; however, the performance of the regressors is worse than that of the full sample. For the non-South states, the fixed-effects model reveals only *Poverty* to be statistically significant and

TABLE 3
Fixed Effects Estimation Results on the Determinants of
All Crimes excluding Hate Crimes, 1992-95

	All States	South	NonSouth
Income	1.148[a]	0.967	1.182[a]
	(3.477)	(1.302)	(2.710)
BWIncome	−1.108[a]	−0.712	−1.088[a]
	(−3.406)	(−0.944)	(−2.742)
Unemploy	5.94E-02	5.59E-2	5.74E-02
	(0.949)	(0.452)	(0.677)
Poverty	3.11E-02	1.00E-02	5.70E-02
	(0.790)	(0.135)	(1.128)
Lawpop	3.721[b]	10.854	3.837[a]
	(1.728)	(0.212)	(2.372)
Metro	−2.87E-02	1.447	−3.40E-02
	(−0.308)	(0.330)	(−0.348)
Abuse	1.60E-02	2.01E-02	1.96E-02
	(0.528)	(0.386)	(0.468)
Black	−1.22E-02	−1.54E-02	6.67E-04
	(−0.364)	(−0.569)	(0.003)
Jewish	−0.137	−0.131	3.62E-02
	(−2.267)	(−1.044)	(0.493)
Likelihood Ratio	413.1	117.5	240.1
Observations	148	52	96
Adj. R^2	0.974	0.955	0.975

Estimates are based on log-log linear equation. There are 148 observations and t-statistics are in parentheses. The Likelihood Ratio Test is a test of the individual state effects being the same. The null hypothesis is rejected at the 1% level of significance indicating that individual state effects differ across states.
a. Significant at 5 percent level.
b. Significant at 10 percent level.

of hypothesized sign. Again, the Hausman test indicates that the random-effects model is more efficient than the fixed-effects model. Consistent with our expectations, the coefficients on *Unemploy* and *Jewish* are positive and significant, while the coefficient on *Lawpop* is negative and significant.

The most striking results from the random-effects model for the non-South states are the coefficients on *BWIncome* and *Abuse*; both coefficients are positive and statistically significant. An increase in *BWIncome* represents an increase in black household incomes relative to that of white households, which leads to a higher white-on-black hate crime rate. As for *Abuse*, states with higher abuse rates also have higher hate crime rates, which is consistent with our expectations.

Weaknesses identified in the reported hate crime statistics for the South may explain why the empirical performance of the separate equations is different. Given the inferior nature of the South data, we are not prepared to make the claim that hate crimes in the South are fundamentally different from those in the non-South. The only distinguishable characteristic between the two regions, at this point, is the percentage of the population covered (agency participation) in southern states. Even

with the measurement problems inherent with hate crime data, we concluded that the general pattern of our results is encouraging and robust with respect to *BWIncome* and *Unemploy*. Specific variable performance is not what we had hoped; yet the pattern of performance is not unusual when compared to previous empirical studies of parallel crime.

The central theme of this paper is that bias-motivated crimes differ fundamentally from parallel crimes. For purposes of comparison, we regress our explanatory variables on the crime rate less the hate crime rate (net crime rate) for each state. If the determinants of hate crimes and other crimes are indeed different, then our model should provide some indication. Table 3 presents the estimates of the fixed-effects model with the net crime rate for all states in the sample, as well as the net crime rate for southern states and non-southern states.[12] Several of the regressors are statistically significant and some are of opposite sign when compared to our results for hate crimes.

The most striking is the negative and statistically significant coefficient estimate for *BWIncome*. The parallel (all other crimes) crime rate is lower when black household income increases relative to that of whites, yet this same increase is associated with a higher hate crime rate. In addition to this result, *Income* is positive and now significant while *Lawpop* is positive and significant—a result consistent with the literature.[13] While we were not able to obtain random effects results for parallel crimes, it is interesting to note that *Abuse* is not significant in any regression. For the southern sample, no variables are statistically significant although the likelihood ratio tests of state effects being the same across states is rejected for all three regressions. These results do suggest that the determinants of hate crimes are likely to be fundamentally different from determinants of other, parallel, crimes.

CONCLUDING REMARKS

Given the particular nature of bias-motivated crime, it is necessary to go beyond the standard economic model of crime based on purely selfish behavior. A model incorporating altruism and envy, such as Becker has developed, warrants further consideration. This paper represents the first tentative steps in applying such a model to the phenomenon of bias-motivated crime. Utilizing recent FBI data, we find that while there are differences among regions that cloud the empirics, proxies for envy, such as relative income, have a significant effect on the hate crime rate.

Given the implications of Becker's analysis regarding altruism and envious behavior within the family, further research into the effects of public policies—from criminal statutes to "welfare" of various types—should be fruitful. The really interesting thesis, in the context of public policy, is that altruistic governments reduce envious behavior just as the altruistic head of household does so within the family.

The data problems are enormous but manageable, and part of the research effort should focus on developing more reliable empirical measures of both the nature and incidence of hate crime. Despite the inherent empirical difficulties, we feel that our results justify further research along the lines developed here, especially during an age in which people remain highly concerned about racial and ethnic bias.

NOTES

We would like to thank Seung C. Min Ahn, T. Randolph Beard, R. Carter Hill, Melissa S. Waters, and John Keith Watson, for valuable comments, and Christiane Teuber for her assistance in data collection. All caveats apply. The authors' names appear alphabetically.

1. Hate crimes are more likely to involve physical assault than are parallel crimes. Perpetrators of hate crimes are more likely to be strangers to their victims and hate crimes are more likely to be committed by groups and not individuals. Hate crimes may give rise to a heightened sense of vulnerability, inasmuch as the potential victim cannot change the characteristic that would make him/her a victim. See Lawrence [1994, 342-3].
2. See Lawrence [1994, 335] for more discussion of FBI regulations.
3. Becker develops a somewhat more formal definition of envy. See Becker [1981, 185]. It is important to note that there are other definitions of envy. As a referee points out, Baumol [1986] treats envy as the desire to trade places. We do not define envy in this way. In this paper, "envy" describes a scenario in which a person gains utility from another's disutility.
4. See Hate Crime Statistics for a more detailed discussion of the FBI's hate crime methodology.
5. The mean is based on 37 participating states. As explained in our empirical section, several states were omitted due to inconsistent reporting across years.
6. Several states during the 1992 to 1995 time period reported hate crimes during some years yet did not report for all years. It is likely that agencies within those states, which periodically participated in the reporting of hate crime incidents, may be more prone to changing the interpretation of hate crimes, thus generating an inconsistent reporting pattern. Thus our choice to use a balanced data set (36 states plus the District of Columbia, 148 observations) rather than an unbalanced data set (44 states plus the District of Columbia, 175 observations) with more observations was to keep any inconsistencies in reporting to a minimum.
7. *BWIncome* is the product of a state component and a national component. First, the ratio of state i's median income of black households (b_i) to that of white households (w_i) in 1990 relative to the sample mean of the ratio of median income of black households (b) to that of white households (w) is calculated in 1990. This value is then multiplied by the ratio of U.S. median income of black households (b_{us}) to that of white households (w_{us}) from 1992-1995. In formulaic terms, BWIncome = $[(b_i / w_i)^* (w/b)][b_{us}/w_{us}]$. Only the state measure for 1990 is available making the first component fixed for each state. However, we make the assumption that any changes in the state value will be linked to changes in the national value to arrive at a time varying variable.
8. Aside from the econometric issues associated with including highly correlated variables, educational attainment data is only intermittently available in relation to the time period of this study. As a result, explaining intertemporal variation of hate crimes using education variables is considered an inferior approach for this study.
9. In addition to the above explanation, it may be that higher income victims are more likely to report crimes and characterize those crimes as being bias motivated.
10. But, as discussed above, it is possible that a greater minority population might be more empowered to rectify inequitable policies and practices, thus reducing envy and encouraging more cooperative behavior among its members. Therefore, we cautiously expect positive coefficient signs on the minority population variables.
11. The U.S. Bureau of the Census includes the following as southern states: Alabama, Arkansas, Delaware, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia, and West Virginia. Our data set excludes Alabama, North Carolina, and West Virginia, for intermittent reporting.
12. As specified, we could not estimate a random-effects model because the estimated variance was not positive. For this reason as well as the fact that all other crimes for all states represent the full sample, we are only able to provide fixed effects results.
13. Some studies, for example, indicate a consistently significant and positive relationship between income and total crime [Besci, 1999] while others find a consistently positive but insignificant relationship [Zhang, 1996]. These two studies also found a positive relationship between unemployment and total crime, but Zhang's results were significant in only one out of four regressions. Besci [1999]

separated crime by type and found unemployment to have a significantly negative relationship with violent crime and murder. Given the similarities of the results found in Table V with those of previous studies, it is possible that a hate crime rate might be symptomatic of the overall crime rate. We thank an anonymous referee for identifying this reasonable interpretation.

REFERENCES

Baumol, W. J. *Superfairness: Applications and Theory.* Cambridge, MA: MIT Press, 1986.

Becker, G. S. Crime and Punishment: An Economic Approach. *Journal of Political Economy*, March/April 1968, 169-217.

_____. *A Treatise on the Family*. Cambridge, MA: Harvard University Press, 1981.

Besci, Z. Economics and Crime in the State. Federal Reserve Bank of Atlanta *Economic Review*, Winter 1999, 38-56.

DiIulio, J. J., Jr. Help Wanted: Economists, Crime and Public Policy. *The Journal of Economic Perspectives*. Winter 1996, 3-24.

Ehrlich, I. Participation in Illegitimate Activities: A Theoretical and Empirical Investigation. *Journal of Political Economy*, May/June 1973, 521-65.

_____. Capital Punishment and Deterrence: Some Further Thoughts and Additional Evidence. *Journal of Political Economy*, August 1977, 741-88.

Fomby, T. B., Hill, R. C., and Johnson, S. R. *Advanced Econometric Methods*. New York: Springer-Verlag, 1988.

Grove, W. R., Hughes, M., and Geerken, M. Are Uniform Crime Reports a Valid Indicator of Index Crimes? An Affirmative Answer with Minor Qualifications. *Criminology* May 1985, 451-501.

Lawrence, F. M. The Punishment of Hate: Toward a Normative Theory of Bias-Motivated Crimes. *Michigan Law Review*, November1994, 320-81.

Sjoquist, D. L. Property Crime and Economic Behavior: Some Empirical Results. *American Economic Review*, June 1973, 439-46.

U.S. Department of Justice. Federal Bureau of Investigation. *Hate Crime Statistics.* 1992-1995. Washington, D.C.: U.S. Government Printing Office, 1994-1997.

Zhang, J. The Effect of Welfare Programs on Criminal Behavior: A Theoretical and Empirical Analysis. *Economic Inquiry*. January 1997, 120-37.