EXPLAINING SENTENCE SEVERITY IN LARGE URBAN COUNTIES: A MULTILEVEL ANALYSIS OF CONTEXTUAL AND CASE-LEVEL FACTORS

ROBERT R. WEIDNER
University of Minnesota Duluth

RICHARD FRASE
University of Minnesota Law School

IAIN PARDOE
University of Oregon

This study used hierarchical logistic modeling to examine the impact of legal, extralegal, and contextual variables on the decision to sentence felons to prison in a sample of large urban counties in 1996. None of the four contextual (county-level) variables—the level of crime, unemployment rate, racial composition, and region—increased the likelihood of a prison sentence, but 10 case-level factors, both legal and extralegal, and several macro-micro interaction terms were influential. These results demonstrate the importance of considering smaller geographic units (i.e., counties instead of states) and controlling for case-level factors in research on interjurisdictional differences in prison use.

Keywords: *contextual factors; county sentencing variations; hierarchical modeling; prison sentences*

This study sought to contribute to the body of research that explains interjurisdictional differences in prison use by determining the effect of contextual factors on the court processing of individual felony cases. This

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research used felony court case processing data from a sample of 30 urban counties located in 16 states to examine interjurisdictional differences in sentence severity, defined as the likelihood of a convicted felon receiving a prison sentence. It aimed to control for many case-based legal and extralegal factors underlying punishment severity, while accounting for contextual factors (i.e., crime rate, unemployment level, racial composition, and region of country) that have been found to be influential in research that has used states and counties as units of analysis.

BACKGROUND

The most commonly used gauge of interjurisdictional differences in punitiveness within the United States probably is states' rates of imprisonment. According to this measure, as of 2000, the United States imprisoned its citizens at a rate of 478 per 100,000 (Beck & Harrison, 2001, p. 3), a national rate that is 6 to 12 times as high as those of other Western countries (Tonry, 1999, p. 419). Yet this overall penal severity belies great variation in levels of imprisonment within the United States. For example, in 2000, Louisiana had a prison rate (801 per 100,000 residents) that was over 6 times as high as that of Minnesota (128 per 100,000) (Beck & Harrison, 2001, p. 3). Moreover, these differences are remarkably stable over time, despite the dramatic increases in state imprisonment rates in recent years—up 253% since 1978 (Beck, 2000, p. 3; Maguire & Pastore, 1999, p. 491). The rank-order correlation for states' rates of imprisonment for the years 1978 and 1999 is .77, with southern states tending to be ranked highly in both years. Louisiana, the 1st-ranked state in 1999, was ranked 8th in 1978; Minnesota, the 50th-ranked state in 1999, was ranked 48th in 1978.

RESEARCH ON INTERSTATE VARIATION IN PRISON USE

Many studies have used multivariate analyses to attempt to explain these marked, constant differences in prison use among the states.[1] There have been some consistent findings across these macro-level studies. For example, most have found violent crime rate to exert a positive influence on prison use (Carrroll & Doubet, 1983; Greenberg & West, 2001; McGarrell, 1993; Michalowski & Pearson, 1990; Taggart & Winn, 1993). A host of extralegal factors have been found to play key roles in explaining the severity of punishment as well. These include the percentage of the population that is African American (Arvanites, 1992; McGarrell, 1993), political conservatism (Greenberg & West, 2001; Taggart & Winn, 1993), and region (southern states punish more severely; Carroll & Doubet, 1983; Michalowski & Pearson, 1990).

RESEARCH ON INTERCOUNTY VARIATION IN CUSTODIAL SANCTIONS

A handful of macro-level studies have examined variations in punishment using counties as the unit of analysis. McCarthy (1990) examined 1981 case processing data for the 58 counties in California and found that violent crime and the percentage of the population who were poor were significantly related to prison use and that among urban counties, unemployment rate also had an effect. In the realm of juvenile justice, Sampson and Laub (1993, p. 285) used 1985 data from more than 200 counties to analyze how structural factors affect predisposition detention, formal petitioning, and the out-of-home placement of juveniles. They found that "underclass Blacks" were more likely to be subjected to increased control by the juvenile justice system. Finally, Weidner and Frase (2001) conducted a study to explain cross-county variation in prison use, operationalized as the percentage of convicted felons who were sentenced to prison. This research, which used 1994 data on felony sentencing from 203 counties in 42 states, examined the impact of several legal and extralegal factors. It found three legal variables and two extralegal variables, the percentage of the population who were Black and (southern) region, to have a significant impact on prison use.

RESEARCH ON CONTEXTUAL INFLUENCES ON SENTENCING DECISIONS

Although macro-level studies that use states and counties as their units of analysis are informative, they are limited in that they discount the role that individual court case characteristics, legal and extralegal,[2] might play in determining the level of punitiveness. In contrast to the two aforementioned macro approaches that use geographic areas as their unit of analysis, a substantial body of research has examined case-level sentencing decision making across jurisdictions to ascertain the effects of contextual factors on sentencing decisions (e.g., Eisenstein, Fleming, & Nardulli, 1999; Eisenstein & Jacob, 1977; Myers & Talarico, 1987; Ulmer, 1997; Ulmer & Kramer, 1996). Such research has been spurred by the recognition that sentencing may be influenced by the cultural, political, economic, and social contexts in which courts operate—that the effects of legal variables (e.g., criminal history) may vary according to contextual factors (Dixon, 1995). They represent an improvement over most studies of sentencing, which have focused exclusively on case-level data (Mears, 1998).

Prior research examining contextual impacts on sentencing decisions can be divided into two broad categories. Cross-jurisdictional studies compare sentencing decisions across a small number of jurisdictions (Britt, 2000). These studies typically involve within-jurisdiction analyses of case-level legal and extralegal factors, then consider how the effects of these factors vary according to the type of jurisdiction in which a court is located. For example, some cross-jurisdictional studies (e.g., Eisenstein et al., 1999; Eisenstein & Jacob, 1977) have examined the impact of the size of a jurisdiction on sentencing decisions; other studies (e.g., Ulmer, 1997; Ulmer & Kramer, 1996) have examined the differences in sentencing decisions across rural, suburban, and urban jurisdictions. Although the small numbers of jurisdictions considered in these studies are a strength in that they allow for more detailed comparisons of court communities, the consideration of only a handful of jurisdictions precludes the systematic study of macro-level factors on sentencing decisions. As is the case with studying a single jurisdiction, focusing on a small number of jurisdictions runs the risk of arriving at results that are the product of idiosyncratic features that may not be representative of other courts from similar jurisdictions, states, or regions.

The other category of studies examining the impact of contextual factors on sentencing decisions have typically used pooled statewide sentencing data to allow for the simultaneous study of numerous jurisdictions. Using this approach, researchers have examined the direct effects of jurisdictions' contextual characteristics on individual sentencing decisions (Britt, 2000, p. 709). For example, Dixon (1995) examined sentencing outcomes in 73 Minnesota counties; Myers and Talarico's (1987) study was based on a sample of felons from all of Georgia's counties; and Steffensmeier, Kramer, and Streifel's (1993) study was based on Pennsylvania Commission on Sentencing data from all of that state's 67 counties. Studies using this approach have found several contextual factors to have a direct effect on sentencing decisions, including crime rate (Huang, Finn, Ruback, & Friedmann, 1998; Myers & Talarico, 1987), racial composition (Crawford, Chiricos, & Kleck, 1998; Myers & Talarico, 1987; Steffensmeier et al., 1993), political conservatism (Huang et al., 1996; Steffensmeier et al., 1993), urbanization (Myers & Talarico, 1987; Steffensmeier et al., 1993) and the level of bureaucratization (Dixon, 1995).

Although this direct-effects approach allows for the analysis of multiple jurisdictions simultaneously, the ability of such studies to account for contextual factors is hindered by their use of conventional linear and logistic regression techniques to study sentence lengths and incarceration decisions, respectively. Even when they include interaction terms, these conventional statistical procedures are not ideal for addressing the multilayered quality of punishment decisions, because they cannot account for the possibility that the effects of legal variables at the individual level (e.g., criminal history) could vary according to jurisdictions' cultural contexts and/or organizational constraints (Mears, 1998).

HYPOTHESIZED IMPACT OF CONTEXTUAL FACTORS ON SENTENCING DECISIONS

This research was designed to assess the impact on sentencing decisions of contextual factors that have been found to be influential both in prior studies on sentencing and in macro-level studies of prison use. The impact of four contextual factors is assessed: the level of crime, the level of unemployment, racial composition, and region (i.e., southern jurisdiction). In addition to examining the direct effects of these contextual factors, this research was designed to also examine how each contextual factor interacts with legal and extralegal individual-level variables.

Level of crime. Research on the impact of the level of crime on sentencing decisions has yielded mixed results. For example, Britt (2000) found that crime rate had no effect on the decision to incarcerate and that violent crime rate did not affect mean sentence length. Myers and Talarico (1987) found that crime rate did not have an effect on the decision to incarcerate but was related to longer sentence lengths. Findings from macro-level studies are more consistent. With few exceptions, macro-level studies (e.g., McGarrell, 1993) have consistently found the level of crime to have a positive effect on prison use. We hypothesized that in jurisdictions with high levels of crime, courts would tend to punish more severely in an attempt to control it.

Level of unemployment. Many argue that the use of prison can be a response to contextual conditions other than crime. For example, it is possible that punishment could be more severe for those offenders perceived as posing a threat because of their economic circumstances (Mears & Field, 2000). Therefore, the size of economically subordinate populations, such as the unemployed, could have a positive impact on prison use (McCarthy, 1990). Alternatively, unemployment could increase sentence severity because judges may assess the unemployed as being more likely to reoffend (Greenberg & West, 2001; Spohn & Holleran, 2000).

Findings regarding the impact of unemployment level on states' rates of imprisonment have been inconclusive (Arvanites, 1992). Regarding research on the impact of contextual factors on sentencing decisions, Britt (2000) found that unemployment levels did not have an effect either on the decision to incarcerate or on sentence length. Myers and Talarico (1987) found that higher levels of unemployment increased the likelihood of incarceration. Given that findings with regard to the impact of unemployment are mixed, we believed that it would be worthwhile to examine this factor in the present study to determine whether there is support for the "economic threat" hypothesis.

Racial composition. This factor, which is typically defined as the percentage of the population that is African American, has commonly been considered in both macro-level studies (Weidner & Frase, 2001) and previous research on the contextual effects of sentencing decisions (Huang et al., 1996).[3] Macro-level studies (e.g., Arvanites, 1992; Sampson & Laub, 1993; Weidner & Frase, 2001) have found race to have a positive effect on punishment severity, arguably because of the "symbolic threat" that African Americans represent (Mears & Field, 2000, p. 992). As for sentencing studies that have considered contextual factors, some have found that all offenders were at greater risk for incarceration in counties with proportionately larger African American populations but that sentences in these counties tended to be shorter (Britt, 2000; Myers & Talarico, 1987). Others have found that racial composition had no effect on sentence severity (Steffensmeier et al., 1993; Ulmer & Kramer, 1996). Given these findings, along with attitudinal research that has found prejudice among Whites to increase as the African American population expands (Taylor, 1998), we hypothesized that jurisdictions with higher percentages of African Americans would sentence more severely.

Region (i.e., the South). The strong relationship between the southern region of the country and imprisonment is widely documented (Chiricos & Crawford, 1995). Moreover, given the South's greater use of the death penalty (Snell, 2000), it is plausible to conclude that southern culture is more punitive. The southern region is commonly accounted for and found to have an effect in macro-level studies explaining differences in prison use (e.g., Carroll & Doubet, 1983; Michalowski & Pearson, 1990). To our knowledge, previous research that has considered contextual factors' effects on micro-level sentencing decisions has been based on data from either a very small number of jurisdictions or multiple jurisdictions within a single state. Therefore, no studies using individual-level state sentencing data have had the capacity to test the effect of region as a contextual factor. Because the data for this study were sampled from counties throughout the country, they allowed us to control for the impact of region on individual sentencing decisions. We hypothesized that southern jurisdictions would sentence more severely, independent of the level of crime, the level of unemployment, and racial composition.

To examine the effect of these contextual factors on sentencing decisions, we used hierarchical modeling. Blumstein et al. (1983, cited in Mears, 1998) encouraged the use of hierarchical modeling, as opposed to simple linear models, to identify better the factors whose effects on sentencing decisions depend on the presence of other factors. Hierarchical modeling allows for a richer understanding of the punishment process with regard to the context in which it functions (Britt, 2000).

DATA AND METHODS

DATA

We used 1996 individual-level data from the State Court Processing Statistics (SCPS) program of the Bureau of Justice Statistics (BJS), a biennial collection of data on felony defendants in state courts in 40 of the nation's 75 most populous counties.[4] Information collected for this program includes the demographic characteristics, criminal histories, pretrial processing, and disposition and sentencing of felony defendants. In 1996, the SCPS program collected data for 15,474 felony cases filed during May 1996, 9,110 of which resulted in convictions. We linked these individual-level data to county-level variables using an identifier that is commonly included as a data element in federally collected data, the Federal Information Processing Standards code. After excluding counties with missing information, 4,358 convicted individuals from 30 counties remained.

INDIVIDUAL-LEVEL MEASUREMENT

Sentencing outcome. Given that the majority of studies that address cross-jurisdictional differences in punitiveness focus on prison use, this study's primary outcome measure was the likelihood of receiving a prison sentence. PRISON was coded 1 if an offender received a prison sentence and 0 if an offender was sentenced to jail or received a noncustodial sentence.[5]

Demographic characteristics. AGE was an offender's age in years. MALE was coded 1 for offenders who were men and 0 for those who were women. BLACK was coded 1 if an offender was African American and 0 otherwise.[6]

Criminal history. PFELON was coded 1 if an offender had one or more prior felony convictions and 0 otherwise. PMISDM was coded 1 if an offender had one or more prior misdemeanor convictions and 0 otherwise.

Case characteristics. Case disposition was measured by TRIAL, which was coded 1 if an offender was convicted by trial and 0 if an offender was convicted by any type of plea. CJSTAT was coded 1 if an offender's criminal justice status was active (i.e., he or she was on probation, parole, or presentence release or in custody) at the time of the offense and 0 otherwise. DETAIN was coded 1 if an offender was detained after being charged and 0 if he or she was released. REVOKD was coded 1 if an offender's pretrial release was revoked and 0 otherwise. BADREL was coded 1 if an offender was arrested while on pretrial release but the release was not revoked.

The type of offense was measured with five dummy variables coded 1 if an offender's most serious conviction charge was for a "more severe" violent offense (murder, rape, or robbery; CHVIOS), a "less severe" violent offense (assault or other violent crime; CHVIOM),[7] a drug trafficking offense (CHTRAF), a drug possession offense (CHDRUG), or a property offense (burglary or theft; CHPROP). The reference category for these dummy variables included weapons offenses, driving-related offenses, other public order offenses, and felony cases that resulted in misdemeanor convictions.

COUNTY-LEVEL MEASUREMENT

To examine how contextual factors influence sentencing decisions, we considered four county-level factors. ARRATE was a jurisdiction's adult arrest rate per 10,000 residents in 1996; this variable served as a proxy measure for a county's level of crime.[8] UNEM was a jurisdiction's unemployment rate for 1996. BLACKPCT was a census estimate of the percentage of a jurisdiction's population who were African American in 1996. SOUTH was coded 1 if a county was located in a southern state and 0 otherwise.

DESCRIPTIVE STATISTICS

Table 1 gives descriptive statistics for these model variables. Note that descriptive statistics for the four contextual factors were calculated on the

TABLE 1: Descriptive Statistics for Model Variables

Variable	M	SD	*Minimum*	*Maximum*
Individual level[a]				
AGE	29.98	9.35	14	80
MALE	0.83	0.37	0	1
BLACK	0.55	0.50	0	1
CHVIOS	0.06	0.23	0	1
CHVIOM	0.08	0.27	0	1
CHTRAF	0.18	0.38	0	1
CHDRUG	0.17	0.38	0	1
CHPROP	0.28	0.45	0	1
CJSTAT	0.44	0.50	0	1
PFELON	0.42	0.49	0	1
PMISDM	0.51	0.50	0	1
DETAIN	0.45	0.50	0	1
REVOKD	0.12	0.32	0	1
BADREL	0.04	0.20	0	1
TRIAL	0.06	0.24	0	1
PRISON	0.30	0.46	0	1
County level[b]				
ARRATE	582.83	228.04	293	1349
UNEM	5.62	1.96	3.5	10.6
BLACKPCT	21.85	16.15	1.9	64.8
SOUTH	0.20	0.41	0	1

a. Statistics based on a sample of 4,358 cases.
b. Statistics based on a 30-county sample.

basis of the 30-county (as opposed to 4,358-individual) sample. It is also worthy of note that there was great cross-county variation (from 7% to 45%) in the percentage of convicted individuals receiving prison sentences.

ANALYTICAL STRATEGY

To analyze these data, we used a hierarchical logistic regression model, also referred to as a multilevel model. In contrast to the conventional logistic regression model, this methodology is able to account for the lack of independence across levels of nested data (i.e., individuals nested within counties). When data are nested, dependence among individual responses from the same county is likely, which can lead to biased parameter estimates and unrealistic notions of precision.[9] The conventional logistic regression model assumes that all experimental units are independent in the sense that any factors affecting prison sentencing prevalence are the same in all counties. To relax this assumption and allow these factors' effects to vary across counties, a hierarchical modeling approach is required. Because hierarchical models permit this variation, they more accurately estimate model parameters, with more realistic standard errors.

In recent years, there has been an emergence in criminal justice research of hierarchical modeling procedures, which have been applied to a wide range of areas, from a study on intracity neighborhood differences in victimization risk (Rountree, Land, & Miethe, 1994) to research examining the impact of prison inmate–level and prison-level characteristics on the likelihood of inmate misconduct (Wooldredge, Griffin, & Pratt, 2001). A study by Britt (2000) demonstrated hierarchical modeling's utility as it relates to the present research. He used 1991 to 1994 data from the Pennsylvania Commission on Sentencing for all 67 of Pennsylvania's counties to examine the link between social context and racial disparities in punishment decisions. In his hierarchical models, Britt controlled for four contextual factors—urbanization, racial threat, economic threat, and crime control—and found "convincing evidence" of variation in punishment severity by race across jurisdictions, but measures of social context explained little of this variation (p. 707). As in Britt's study, the methodology used in this research allowed for the consideration of the influence of individual case factors while examining the interplay between individual and contextual influences.

Hierarchical logistic regression modeling can be approached in a number of alternative ways. One approach is based on Bayesian statistics.[10] For an introductory overview of Bayesian statistics, see Bernardo (2001).

FINDINGS

MULTIVARIATE PRISON-USE MODEL

The Bayesian hierarchical logistic regression model we used is that of Wong and Mason (1985). It can be described as a series of stages; in this research, we dealt with just two such stages.[11] First, the usual logistic regression model was fit to n_j micro units (individuals) within each of $j = 30$ macro units or contexts (counties). The number of individuals in each county ranged from 39 to 371. For the ith individual in the jth context, we observed a dichotomous response:

$$Y_{ij} = 1$$

for a prison sentence, and

$$Y_{ij} = 0$$

for a nonprison (jail or noncustodial) sentence. Then,

$$Y_{ij} \mid p_{ij} \sim \text{Bernouilli}(p_{ij}),$$

where $p_{ij} = Pr(Y_{ij} = 1)$ and

$$\text{logit}(p_{ij}) = \log[p_{ij}/(1 - p_{ij})] = X_{ij}^{T}\beta_j, \tag{1}$$

where X_{ij} represents measurements on K micro variables and β_j consists of K unknown micro coefficients (specific to the jth context).

Next, because each of the K micro coefficients was likely to be related across contexts, we assumed that each micro coefficient could be explained by L macro variables at the contextual level:

$$\beta_j = G_j\eta + \alpha_j, \tag{2}$$

where G_j is a $K \times KL$ block-diagonal matrix representing measurements on L macro variables, η consists of KL unknown macro coefficients, and α_j is a $K \times 1$ vector of macro errors.

For example, suppose that we consider just one micro variable (CHVIOS) and one macro variable (ARRATE), as well as a micro intercept and a macro intercept. Then, $K = L = 2$, and Equation 1 becomes

$$\text{logit}(p_{ij}) = \beta_{j1} + \beta_{j2}\ \text{CHVIOS}_{ij},$$

while Equation 2 becomes

$$(\beta_{j1}) = (\eta_1 + \eta_2\ \text{ARRATE}_j) + (\alpha_{j1})$$

$$(\beta_{j2}) = (\eta_3 + \eta_4\ \text{ARRATE}_j) + (\alpha_{j2}).$$

Combining the micro and macro parts leads to

$$\begin{aligned}\text{logit}(p_{ij}) = {} & \eta_1 + \eta_2\ \text{ARRATE}_j + \eta_3\ \text{CHVIOS}_{ij} + \eta_4\ \text{ARRATE}_j\text{CHVIOS}_{ij} \\ & + \alpha_{j1} + \alpha_{j2}\ \text{CHVIOS}_{ij}.\end{aligned} \tag{3}$$

The η parameters have no j subscripts and so represent the same effect over all counties.[12] In conventional statistical models, the η parameters are called fixed effects, and the α parameters are called random effects. The presence of both types of effects makes Equation 3 a mixed model, and such models cannot be fit using standard logistic regression software. Suppressing the macro errors so that Equation 3 becomes a fixed-effects model and amenable to standard logistic regression requires the assumption that the micro-level effects are the same across counties, an assumption that is unlikely to be satisfied in practice.

Mixed models can be fit using specialized computer software such as MLwiN (Rasbash et al., 2000) and HLM (Raudenbush, Byrk, Cheong, & Congdon, 2001). However, by putting a mixed model into a Bayesian framework, the distinction between fixed and random effects disappears, because all effects are considered random in Bayesian statistics. To fit the model, we used a software package, WinBUGS (Bayesian inference using Gibbs sampling; Spiegelhalter, Thomas, & Best, 1999), that is designed to perform the Bayesian analysis of complex statistical models using Markov-chain Monte Carlo methods.[13] Vague prior distributions were specified for the model parameters to let the data "speak for themselves." (Further details about the specification of prior distributions can be obtained by contacting the corresponding author.)

Using a Bayesian framework, mixed models explaining the likelihood of an individual receiving a prison sentence were specified in a stepwise fashion, whereby the number of model terms was pared from 75 to 30 (including an intercept term). We began the analysis with $K = 15$ micro variables (including an intercept term) and $L = 5$ macro variables (including an intercept term). The first model considered included $15 \times 5 = 75$ η coefficients. One other micro variable, AGE, was considered initially, but preliminary analyses indicated that, given the presence of the other variables, it had no effect on whether or not a prison sentence was meted out.[14]

After seven iterations, to simplify the model and remove unimportant terms, we arrived at a final model that included 30 η coefficients.[15] (More detailed information on the modeling process is available from the corresponding author.) We judged this model to provide a good compromise between, on one hand, parsimoniously describing the dependence of sentence type on 14 micro variables and 4 macro variables and, on the other hand, inadvertently excluding potentially important terms. In generating posterior samples for the η coefficients in WinBUGS, the variables were centered at their sample means. Summary statistics for this model, on the basis of 40,000 posterior samples,[16] are presented in Table 2.

Table 2 shows that in the final prison-use model, 10 individual-level factors and 8 macro-micro interaction terms had 95% highest posterior density (HPD) intervals that excluded zero. These intervals provide an indication of the factors' effects along with the precision with which we could estimate these effects. Those 95% HPD intervals that excluded zero were roughly equivalent to conventional statistical significance at the $p < .05$ level; we call such terms "influential" in the following discussion. The means of the poste-

TABLE 2: Hierarchical Logistic Model Explaining the Likelihood of Receiving a Prison Sentence

Term	M	SD	*95% HPD Interval*[a]		*Exp(*M*)*
MALE	0.523	0.160	0.206	0.837[b]	1.687
CHVIOS	1.974	0.684	0.654	3.334[b]	7.199
CHVIOM	2.236	0.276	1.705	2.796[b]	9.356
CHTRAF	1.038	0.417	0.191	1.859[b]	2.824
CHDRUG	0.722	0.334	0.077	1.408[b]	2.059
CHPROP	1.260	0.253	0.772	1.770[b]	3.525
CJSTAT	0.529	0.131	0.281	0.797[b]	1.697
PFELON	0.638	0.382	–0.128	1.375	1.892
PMISDM	0.363	0.214	–0.050	0.783	1.437
DETAIN	2.250	0.167	1.915	2.573[b]	9.488
REVOKD	1.706	0.199	1.312	2.092[b]	5.507
BADREL	0.483	0.892	–1.313	2.202	1.620
TRIAL	1.342	0.288	0.786	1.915[b]	3.827
ARRATE	0.001	0.001	0.000	0.002	1.001
UNEM	–0.050	0.082	–0.208	0.113	0.951
BLACKPCT	0.004	0.011	–0.020	0.025	1.004
SOUTH	0.837	0.446	–0.055	1.690	2.308
ARRATE × CHTRAF	0.002	0.001	0.001	0.003[b]	1.002
ARRATE × BADREL	0.003	0.001	0.000	0.005[b]	1.003
UNEM × CHVIOS	0.168	0.105	–0.035	0.377	1.183
UNEM × PFELON	0.250	0.067	0.120	0.382[b]	1.284
BLACKPCT × PFELON	–0.019	0.009	–0.037	–0.002[b]	0.981
BLACKPCT × PMISDM	–0.020	0.009	–0.037	–0.004[b]	0.980
BLACKPCT × BADREL	–0.063	0.026	–0.115	–0.013[b]	0.939
SOUTH × PFELON	–0.642	0.354	–1.333	0.055	0.526
SOUTH × PMISDM	0.557	0.327	–0.104	1.180	1.746
SOUTH × DETAIN	–0.862	0.387	–1.638	–0.114[b]	0.422
SOUTH × REVOKD	–1.320	0.598	–2.478	–0.127[b]	0.267
SOUTH × TRIAL	–1.168	0.658	–2.477	0.102	0.311

a. Highest posterior density interval.
b. Excludes zero (roughly equivalent to a level of significance at $p < .05$).

rior samples provide reasonable point estimates for the η coefficients, while the standard deviations provide measures of precision; these are equivalent to standard errors in a conventional regression analysis.

Regarding the individual-level factors, according to this model, DETAIN was the most influential model term; convicted offenders who were detained before trial had odds of receiving prison sentences nearly 9.5 times as high as defendants who were not detained before trial, all other factors being equal (refer to the column headed "Exp[M]": this indicates the multiplicative impact on the odds of receiving a prison sentence, commonly referred to as the "odds ratio"). Five other individual-level factors were associated with at least a tripled increase in the odds of receiving a prison sentence, all other factors held constant: defendants whose pretrial releases were revoked (REVOKD), defendants convicted by trial (TRIAL), and three charge variables: the two violent offense categories (CHVIOS and CHVIOM) and property offenses (CHPROP). The effect size for drug trafficking (CHTRAF) was almost as large, and although CHDRUG's effect size was smaller, this other charge variable also positively affected the odds of receiving a prison sentence. Being male (MALE) and having an active criminal justice status (CJSTAT) also increased offenders' chances of receiving prison sentences. Although both of the criminal history variables (PFELON and PMISDM) had strong bivariate relationships with prison use (output not presented here), neither was influential in the hierarchical model. This result could have been the product of multicollinearity between the criminal history variables and active criminal justice status (CJSTAT). It stands to reason that the criminal history variables would be strongly related to CJSTAT, given that most offenders with active criminal justice status had prior felony and/or misdemeanor convictions, the reason their status is active.[17]

The eight key interaction terms collectively involved all four macro-level variables. The two interaction terms involving SOUTH both had negative coefficients, which was antithetical to the hypothesis that southern jurisdictions tend to be more punitive. For example, being detained before trial (DETAIN) had a lesser effect on the odds of receiving a prison sentence in the South; the effect was a multiplicative factor of $0.422 \times 9.488 = 4.008$ in the South but 9.488 elsewhere.

All three of the interaction terms involving percentage Black (BLACKPCT) had negative effects on the odds of receiving a prison sentence. For example, each 1% increase in percentage Black reduced the prior misdemeanor (PMISDM) effect on the odds of receiving a prison sentence by 2%. The PMISDM effect for 2% Black was estimated to be $1.437 \times 0.980^2 = 1.379$; with each 1% increase in percentage Black, this effect was further reduced by a factor of 0.980.[18]

By contrast, the interaction term involving UNEM and PFELON was positively related to prison use, and the two interaction terms that included ARRATE also had positive coefficients. For example, the PFELON effect became more pronounced as the percentage unemployed in a county increased.[19] Also, the effects of CHTRAF and BADREL became slightly more pronounced as the county arrest rate increased, by multiplicative factors of 1.002 and 1.003, respectively, for each one unit increase per 10,000 residents.

Finally, these results show that none of the four contextual factors by itself influenced the decision to sentence to prison. Although the signs of the means were in the expected direction for three of the four contextual factors (with the exception of UNEM), none of these macro factors could be estimated with the precision required to deem it influential.[20]

COMPARISON OF HIERARCHICAL TO CONVENTIONAL LOGISTIC REGRESSION

We compared the results of the hierarchical model with a conventional logistic regression model (output not presented here). The results were somewhat similar to those obtained via hierarchical logistic regression. For example, the same three factors—CHVIOS, CHVIOM, and DETAIN—had the highest odds ratios according to both models. However, there were some crucial differences in the two models' results. Two factors that were influential according to the hierarchical procedure, BLACKPCT × PFELON and ARRATE × BADREL, were not significant according to the conventional procedure. Also, three factors that were significant in the conventional model—PFELON, ARRATE, and SOUTH—were not influential according to the hierarchical procedure. Irrespective of the differences in findings, it is important to be aware that using standard statistical approaches such as conventional logistic regression with multilevel data is not advisable because such approaches do not account for the implicit hierarchy involved between individuals and the jurisdictions in which they are sentenced. Many problems can result, including increased Type I errors (Rountree et al., 1994) and unequal error variances at the macro level (heteroscedasticity) (Wooldredge et al. 2001).

DISCUSSION

CONTEXTUAL FACTORS

Findings based on the analyses herein do not support the proposition that any of the four contextual variables by itself increases the likelihood that a court will impose a prison sentence. Although arrest rate, racial composition, and southern region had coefficients with positive posterior means, their effects could not be estimated with enough precision to indicate that they were influential. Although percentage unemployed had a coefficient with a negative posterior mean, it did not have a substantial impact either.

The finding that arrest rate (ARRATE) by itself does not have an impact on the decision to sentence to prison is consistent with prior studies on the impact of the level of crime on the decision to incarcerate (Britt, 2000; Myers & Talarico, 1987).[21] On the other hand, this finding is inconsistent with macro-level studies, which consistently have found violent crime rate to have a positive effect on states' imprisonment rates (e.g., McGarrell, 1993). These divergent findings could very well be the product of distinct operationalizations of prison use. Macro-level studies typically define prison use as inmate population per capita (e.g., prison inmates per 100,000 state residents). Such a measure is directly influenced by the volume and seriousness of crime: More crime or arrests per capita, especially more violent crime, tend to result in more felony convictions, which in turn yield more inmates in prison. In other words, the level of crime and the prison population are both measures of case volume, so it is not surprising that macro-level studies consistently have revealed a positive relationship between the two. In contrast, micro-level sentencing studies such as ours define prison use in terms of an individual defendant's likelihood of receiving a prison or custodial sentence. In such a model, crime or arrest rates would be expected to have only an indirect effect on prison use: Higher crime rates cause judges to sentence more offenders to prison in an effort to lower crime rates. However, the crime rate could have the opposite effect: Higher crime rates "swamp" the system, overloading its resources and increasing the need to grant leniency to persuade defendants to waive their legal rights and plead guilty. These opposing effects may explain why ARRATE is not influential.

The only other influential macro-micro interaction term that is associated with an increased likelihood of an individual receiving a prison sentence is UNEM × PFELON, indicating that individuals with prior felony convictions were more likely to receive prison sentences in jurisdictions with higher unemployment rates. Although SCPS data do not contain information on individual offenders' employment status, it is probably safe to assume that unemployment is more common among samples of offenders than the general population (Sullivan, 1989) and that the higher a jurisdiction's general level of unemployment, the more likely that any given offender will be unemployed. On the basis of this assumption, the apparent influence of this interaction term makes sense, because judges may assess offenders who are both unemployed and have serious criminal records as being more likely to reoffend (Spohn & Holleran, 2000). Conversely, judges may be reluctant to imprison an offender, especially one with no serious prior record, if this would result in the loss of the offender's job.

Aside from this one interaction term involving UNEM, there is no other evidence of the influence of unemployment rate on sentencing severity. This is not surprising, in light of the mixed findings from prior sentencing studies that considered contextual factors: Although Myers and Talarico (1987) found that higher unemployment increased the likelihood of incarceration, Britt (2000) did not.

More surprising is the finding that racial composition (BLACKPCT) does not positively influence sentence severity. We hypothesized that BLACKPCT would have a positive impact on sentence severity, on the basis of findings from contextual sentencing studies (Britt, 2000; Myers & Talarico, 1987), macro-level studies of punishment severity (e.g., Arvanites, 1992), and research on the relationship between racial composition and prejudice (Taylor, 1998). Yet not only is it not influential, but all three of the influential interaction terms involving BLACKPCT are associated with decreased sentence severity.

When considered in conjunction with the finding regarding the individual race variable—the influence of BLACK was so weak that it was the only micro-level factor excluded from the final 30-term hierarchical model—the findings regarding BLACKPCT are especially remarkable. That neither the contextual nor the individual race variable has a positive influence on sentence severity indicates that there is no evidence that African Americans are punished more severely because of the "symbolic threat" they pose, as prior sentencing research (e.g., Crawford et al., 1998; Steffensmeier et al., 1993) has found. Perhaps there is something about the type of jurisdiction on which this analysis was based (i.e., very large urban counties) that serves to reduce racial bias or perceived threat. For instance, higher percentages of African Americans in these jurisdictions might function to increase African Americans' political power, making racial bias less likely (Greenberg & West, 2001).

Like BLACKPCT, the macro-level variable SOUTH was not found to be influential either, although it did result in a coefficient with a positive posterior mean. And also like BLACKPCT, each of the influential macro-micro interaction terms involving SOUTH had a negative impact on sentence severity. Although this result does not support our hypothesis that southern jurisdictions will sentence more severely, it is consistent with the bivariate relationship between SOUTH and PRISON: Whereas 31% of convicted offenders from nonsouthern jurisdictions received prison sentences, only 24% of convicted offenders from southern jurisdictions received prison sentences.

These findings regarding SOUTH could also be a product of the type of jurisdiction on which this analysis was based. Analysis of another BJS-sponsored data set, the National Judicial Reporting Program (NJRP), suggests that large southern jurisdictions are quite different from medium-sized and small ones in terms of sentencing practices. The NJRP program reports sentences imposed on convicted felons in 341 counties, of all sizes, selected to be nationally representative (Brown, Langan, & Levin, 1999, p. 2). For

1996, NJRP data show that 37.6% of convicted felons received prison sentences, with southern counties slightly more likely to use prison (38.5% compared with 36.9%). However, of the NJRP sampled counties that were among the 75 most populous (in other words, "SCPS" counties), southern counties were actually less likely to sentence to prison than nonsouthern counties (34.0% compared with 40.8%). Conversely, among medium-sized and small counties, those in the South had higher prison sentence percentages (38.9% in the South compared with 36.1% in the rest of the country). These comparisons, along with our multivariate findings, suggest that the "South effect" found in previous research could be caused by smaller jurisdictions in that region.

In one sense, then, the fact that our analysis includes only the most populous (and therefore atypical) counties can be viewed as a limitation. On the other hand, this finding is informative in that it sheds light on the issue of overaggregation. Because it contradicts the findings of several state-level studies (e.g., Carroll & Doubet, 1983) that SOUTH has a positive impact on punishment severity, it suggests that there could be differences in sentence severity within states and that these differences could be influenced by the sizes of counties' populations, irrespective of the regions in which they are located. This points to the utility of considering smaller geographic units when studying contextual factors' effects on punishment severity.

MICRO-LEVEL FACTORS

Although defendant's prior record (PFELON, PMISDM) did not strongly affect the sentencing decision, a host of other legal factors and one extralegal factor did. These results are largely consistent with findings from prior studies on sentencing severity. For example, the two violent offense variables (CHVIOM and CHVIOS) were both influential and had the highest odds ratios of all the charge variables, increasing the likelihood that an offender would receive a prison sentence by 9.4 and 7.2 times, respectively. As another example, TRIAL had an odds ratio of 3.8, indicating that individuals convicted by trial were almost 4 times as likely to receive prison sentences as those whose cases were disposed by plea agreements, perhaps because nonprison sentences were components of many plea deals (Frase, 1993; Dixon, 1995). The one individual-level extralegal factor in the final model, MALE, was influential too; its odds ratio indicates that male offenders were about 70% more likely to receive prison sentences than female offenders, a finding that is consistent with prior research (e.g., Spohn & Holleran, 2000; Steffensmeier et al., 1993). Finally, the finding that DETAIN had a very strong influence on the decision to imprison is not surprising, given the empirical support for the idea that previous decisions in the justice process (i.e., whether to detain) affect sentencing outcomes (Mears, 1998).

CONCLUSION

This study was undertaken to help advance the understanding of how contextual factors, in combination with case-level factors, affect punishment severity. This study demonstrates the utility of multilevel modeling using Bayesian statistics, applied to BJS-collected sentencing data from large urban counties in 16 states. None of the four contextual factors considered here by itself had an impact on the decision to sentence to prison. Instead, the results of this research suggest that sentencing decisions in these counties are determined primarily by case-level factors. However, these findings do not prompt us to conclude that contextual factors cannot be key determinants of sentencing decisions. To do so would be to discount a growing body of literature in this area (e.g., Mears, 1998).

It is important to reiterate that this study's findings are based on cases sampled from 30 of the 75 most populous counties—clearly a distinct group, especially in light of the fact that there are more than 3,100 counties in the United States. Because all of the sampled counties were urban, we were unable to control for the effect of urbanization on sentencing decisions, as others have done (e.g., Myers & Talarico, 1987). However the inclusion of only the most populous jurisdictions can be seen as advantageous, in that these jurisdictions have a disproportionate impact on both the use of criminal justice system resources (e.g., prison and jail bed space) and the numbers of individual offenders affected.[22]

Aside from urbanization, there are several other contextual factors whose effects on sentencing decisions merit further study, including applicable laws (e.g., mandatory prison terms), political conservatism (Huang et al., 1996; Steffensmeier et al., 1993) and case processing styles (e.g., percentage of the caseload disposed by trial). This line of research also could be enhanced by considering alternative outcome measures, such as sentence length (or actual time served), and by modeling procedures that allow for examination of the use of prison sentences relative to jail sentences, a distinction that is obscured when these two types of custodial sentence are collapsed into one category. Replication of this methodology using data from different sources and for different years also would be worthwhile.

It is our hope that this area of research will ultimately help pinpoint the (combination of) contextual characteristics possessed by jurisdictions with relatively moderate punishment practices. Put another way, an overarching goal of this line of inquiry is to identify the key organizational contextual determinants that keep punishment in check. For example, could it be that the existence of sentencing guidelines and/or the availability of a wide array of alternative sanctions, which provide judges with feasible sentencing options that fall "between prison and probation" (Morris & Tonry, 1990), are crucial? To the extent that future research in this area provides tangible answers to questions such as this, it would have great policy relevance.

NOTES

1. Most of these studies used states' per capita imprisonment rates as their outcome measure. Foremost among the limitations of this dependent variable is that it confounds the frequency and duration of prison sentences and thus cannot be used as a gauge of either.

2. Extralegal variables generally include those factors that either are proscribed (e.g., race) or are neither prescribed nor proscribed (e.g., court caseload) (Mears, 1998, p. 697).

3. Also, the effect of individuals' race has been studied extensively in sentencing research based on a single jurisdiction (for a review, see Chiricos & Crawford, 1995). Individuals' race was also considered in this study, facilitating an examination of the interaction between it and the racial compositions of jurisdictions' populations.

4. These data are available electronically from the Inter-University Consortium for Political and Social Research in Ann Arbor, Michigan.

5. A subsidiary reason for using PRISON as the outcome measure was the fact that the outcome measure "incarceration" lumps jail sentences with prison sentences (i.e., both are coded 1), when in fact it is highly likely that the factors influencing a decision to sentence to jail are markedly different from those affecting a decision to sentence to prison.

6. Missing data precluded more precise racial and ethnic breakdowns (e.g., between Hispanic and non-Hispanic offenders).

7. We included this second violent offense category because assaults are much more prevalent than more serious violent offenses, and because they are less severe, there is a tendency by the criminal justice system to treat them less harshly. For example, in the 75 most populous counties in 1996, whereas 100% of defendants convicted of murder, 56% convicted of rape, and 71% convicted of robbery received prison sentences, only 40% of defendants convicted of felony assault received prison sentences, a lower percentage than for those convicted of burglary (43%) (Hart & Reaves, 1999, p. 30).

8. To control for the level of crime, we used arrests rather than Uniform Crime Report Index offenses because arrests are a better measure of overall crime rates, given the high volume of drug and other non-Index offenses.

9. For example, suppose that we are considering the size of the average DETAIN effect across all counties (i.e., the average increase in prison sentence prevalence for individuals who have been detained before trial). Statistical analysis that ignores the county structure will be based on the variation over all individuals across counties. If the size of the DETAIN effect varies between different counties, this can lead to an estimate of the average DETAIN effect that is both inaccurate and stated with an exaggerated claim of precision.

10. Bayesian statistical analysis is based on Bayes's theorem, a mathematical formula that uses probability theory as a means of quantifying uncertainty. The theorem defines a rule for

refining hypotheses about model parameters by factoring in additional evidence and background information and leads to an updated understanding of the probability that these hypotheses are true. Bayes's theorem begins with a statement of belief about the situation in question prior to performing the experiment. This prior belief may reflect expert opinion about the relationships among the variables relevant to the situation or alternatively may incorporate only very vague notions of those relationships. Both the prior and the experimental results are modeled with a joint probability distribution, because they are both different views of reality. Bayes's theorem then states that the posterior probability distribution (after the experiment has been conducted) is based on the product of the conditional probability of the experiment, given the influence of the parameters being investigated, and the prior probability of those parameters. Inference about the model parameters is then based on this posterior distribution.

11. There was a third level within these data (i.e., counties are nested within states). However, 11 of the 16 states represented in this sample included only one county, meaning that for more than two thirds of macro-level units, there was no within-unit variation. The use of counties as the sole macro-level unit of analysis minimized the risk that observed results would be affected by similarities within state-level units (Silver, 2000; Wooldredge et al., 2001).

12. For example, in Equation 3, η_2 represents the effect of the arrest rate within the county, while η_3 represents the likelihood of a prison sentence if the offense is "more severe" violent. Also, the micro and macro variables combine in an interaction term; η_4 represents any change in the effect of the arrest rate for offenses classified as "more severe" violent (if η_4 were positive, the arrest rate effect would be greater for offenses classified as "more severe" violent than those in the reference category). The α parameters have *j* subscripts, representing different effects across counties. For example, in Equation 3, α_{j2} represents the likelihood of a prison sentence if the offense is classified as "more severe" violent in county *j*. So, the overall "more severe" violent offense effect in county *j* would be $\eta_3 + \alpha_{j2}$.

13. Markov-chain Monte Carlo methods are computer-intensive techniques that can be used to generate samples from posterior distributions in complex Bayesian analyses when closed-form solutions are not available (Gilks, Richardson, & Spiegelhalter, 1996).

14. Initially, we ran within-county logistic regression models using only the individual-level factors (30 separate runs). AGE was excluded from the hierarchical model because it was the only factor that was not significant ($p < .10$) in any of the 30 county-level models.

15. Although this final model contained only 40% of the initial 75 terms, it still contained all 4 macro terms and excluded only 1 micro term, BLACK.

16. A very large number of samples was required to obtain a reliable estimation of the posterior distribution because there was a fairly high degree of autocorrelation in the Markov chains.

17. A diagnostic rule suggests that when a relationship between independent variables is stronger than it is between independent and dependent variables, multicollinearity problems are more likely. An examination of a correlation table revealed that on the basis of this diagnostic rule, multicollinearity could indeed have been an issue with regard to these variables: both PFELON and PMISDM were more highly correlated with CJSTAT than with PRISON.

18. Note, however, that the PMISDM effect was estimated with a fairly high level of imprecision; the mean of the posterior samples was 0.363, and the standard deviation was 0.214. The interpretation of prior misdemeanor effects and their interactions must take this into account.

19. Again note, however, that the PFELON effect was estimated with a fairly high level of imprecision; the interpretation of prior felony effects and their interactions must take this into account.

20. Arrest rate (ARRATE) was on the cusp of being influential; the lower bound of this coefficient's 95% HPD interval was a very small negative value (–0.0001).

21. This conclusion is not merely a product of different model outcome measures (prison and incarceration). In an alternative hierarchical model with incarceration as its outcome measure (output not presented here), ARRATE also had a positive effect that was too small to be estimated accurately. Also, two interaction terms containing ARRATE were influential: Defendants convicted of drug trafficking or whose pretrial releases were not revoked despite rearrest were more likely to be sentenced to prison in jurisdictions with high crime rates.

22. In 1996, the 75 populous counties that this sample represents accounted for 37% of the U.S. population, 50% of all reported serious violent crime in the United States, 40% of all reported serious property crime, and 43% of all felony convictions (Hart & Reaves, 1999, p. 1).

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Robert R. Weidner is an assistant professor in the Department of Sociology-Anthropology at the University of Minnesota Duluth. He has published in the areas of sentencing, policy evaluation, community justice, and criminological theory. He received his Ph.D. in 1999 from the Rutgers School of Criminal Justice.

Richard Frase is the Benjamin N. Berger Professor of Criminal Law at the University of Minnesota Law School. He has published extensively in the area of sentencing, with particular emphasis on sentencing guidelines. He received his J.D. in 1970 from the University of Chicago Law School, where he was comment editor of the University of Chicago Law Review.

Iain Pardoe is an assistant professor of decision sciences in the Charles H. Lundquist College of Business at the University of Oregon. His research interests focus on applied statistics, including Bayesian approaches to regression, graphical methods, statistical computing, and nonparametrics. He received his Ph.D. in 2001 from the School of Statistics at the University of Minnesota.