Sentencing Convicted Felons in the United States: A Bayesian Analysis Using Multilevel Covariates

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Abstract

Imprisonment levels vary widely across the United States, with some state imprisonment rates six times higher than others. Imposition of prison sentences also varies between counties within states, with previous research suggesting that covariates such as crime rate, unemployment level, racial composition, political conservatism, geographic region, and sentencing policies account for some of this variation. Other studies, using court data on individual felons, demonstrate how type of offense, demographics, criminal history, and case characteristics affect sentence severity. This article considers the effects of both county-level and individual-level covariates on whether a convicted felon receives a prison sentence rather than a jail or non-custodial sentence. We analyze felony court case processing data from May 1998 for 39 of the nation's most populous urban counties using a Bayesian hierarchical logistic regression model. By adopting a Bayesian approach, we are able to overcome a number of challenges. The model allows individual-level effects to vary by county, but relates these effects across counties using county-level covariates. We account for missing data using imputation via additional Gibbs sampling steps when estimating the model. Finally, we use posterior samples to construct novel predictor effect plots to aid communication of results to criminal justice policy-makers.

Key words: Gibbs sampling, Hierarchical model, Logistic regression, Missing data, Predictor effect plot, Random effect

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1 Introduction

In 2001, the imprisonment rate in the United States was 470 per 100,000 residents, six to twelve times higher than in other western countries. Furthermore, among the states, variation in imprisonment rates per 100,000 residents is considerable, ranging from 127 in Maine to 800 in Louisiana (Harrison and Beck, 2002, p.4). Studies looking at differences in prison use between states have identified a number of factors associated with increased imprisonment rates, for example: higher levels of crime (McGarrell, 1993; Sorensen and Stemen, 2002), in particular violent crime (Greenberg and West, 2001); percent of the population that is African American (McGarrell, 1993; Sorensen and Stemen, 2002); political conservatism (Steffensmeier, Kramer, and Streifel, 1993; Taggart and Winn, 1993; Greenberg and West, 2001); and whether the state is in the South (Michalowski and Pearson, 1990). There is also empirical evidence of a relationship between state sentencing policies (for example, presumptive sentencing guidelines, mandatory sentencing) and levels of incarceration, since such policies often dictate which types of offense warrant prison time (Sorensen and Stemen, 2002; Wooldredge, 1996).

Another group of criminal justice studies has examined aggregate punishment variation using a county as the unit of analysis. McCarthy (1990) found violent crime to be significantly related to prison use, and that, among urban counties, unemployment also appeared to have an effect. Sampson and Laub (1993, p.285) found that “underclass blacks” appeared more likely to be subjected to increased control by the juvenile justice system, while Weidner and Frase (2001, 2003) found percent of the population that is African American, Southern region, and political conservatism to show a significant impact on prison use.

A limitation of the aforementioned studies is that they cannot model how individual court case characteristics, both legal and extralegal, affect aggregate levels of punitiveness. In contrast to these analyses, most sentencing studies focus

on individuals, whereby effects of case characteristics, criminal history, and demographics are determined. A conviction for a violent crime such as murder tends to result in a harsher sentence than a conviction for a property crime such as burglary. Likewise, controlling for other factors, defendants with longer criminal histories typically receive more severe sentences. Prior research has also shown that those convicted by trial are more likely to receive a prison sentence than those whose cases are disposed by plea agreement, perhaps because a more lenient sentence is a component of many plea deals (Frase, 1993). Moreover, the conjecture that previous decisions in the justice process affect sentencing outcomes (Mears, 1998) suggests that cases in which a defendant is detained before trial (rather than being released) will be associated with more severe sentences. In regard to demographics, much criminal justice research has documented that African Americans (see Chiricos and Crawford, 1995) and males (see Spohn and Holleran, 2000) face more severe punishment after controlling for the aforementioned legally-relevant case-level factors.

However, effects of individual-level covariates on sentencing may also be influenced by the cultural, political, economic, and social contexts in which courts operate (Dixon, 1995). Studies using pooled statewide sentencing data to examine effects of jurisdiction characteristics on individual sentencing decisions have found several contextual covariates to be important. For example, Myers and Talarico (1987) found higher unemployment levels to increase the chance of incarceration, while other covariates found to have a positive influence include crime rate (Myers and Talarico, 1987), racial composition (Steffensmeier et al., 1993), political conservatism (Huang, Finn, Ruback, and Friedmann, 1996), and Southern region (Chiricos and Crawford, 1995).

The ability of such studies to account for contextual covariates has been hindered by use of conventional logistic regression techniques. Such techniques are unsuitable for addressing the multi-layered quality of punishment decisions because they do not correctly account for effects of individual-level covariates that

vary according to a jurisdiction's cultural context and organizational constraints (Mears, 1998; Britt, 2000). To properly account for covariates having a multilevel nature such as this, hierarchical modeling is more appropriate (for examples in criminal justice research see Kautt, 2002; Lee and Ulmer, 2000; Rountree and Land, 1996; Sampson, Raudenbush, and Earls, 1997; Wooldredge, Griffin, and Pratt, 2001). Of most relevance to this article, Britt (2000) examined the link between social context and racial disparities in punishment decisions for Pennsylvania counties from 1991 to 1994. Controlling for urbanization, racial threat, economic threat, and crime control, he found "convincing evidence" of variation in punishment severity by race across jurisdictions, but that measures of social context explain little of this variation (Britt, 2000, p.707).

In contrast to Britt's frequentist modeling approach for a single state, we take a Bayesian approach and consider sentencing across the whole of the U.S. In particular, we consider the impact on sentencing decisions of individual-level covariates and county-level contextual covariates that have been found to be influential in prior studies on sentencing. Section 2 describes the data, while Section 3 outlines the hierarchical logistic regression model used. Section 4 provides details of model estimation, including missing data imputation, and Section 5 concerns model assessment. Section 6 summarizes results, emphasizing predictor effect plots, while Section 7 contains a discussion.

2 Data

We use individual-level data for May 1998 from the Bureau of Justice Statistics' (BJS) State Court Processing Statistics (SCPS) program, a biennial collection of data on felony defendants in state courts in a representative sample of 39 of the nation's 75 most populous counties. [These data are available electronically from the Inter-university Consortium for Political and Social Research (ICPSR) in Ann Arbor, Michigan. Neither BJS nor ICPSR bear responsibility for the data analyses

and interpretations presented here.] The data for 8,446 felony convictions with sentencing information (out of 15,909 total felony cases, of which 9,653 resulted in convictions) include demographic characteristics, criminal history, and information on pretrial processing, disposition, and sentencing.

Studies of cross-jurisdictional differences in punitiveness usually focus on prison use, so this article's response variable, Y, is coded 1 if the offender received a prison sentence, 0 for a jail or non-custodial sentence. Within counties, the proportion of convicted offenders receiving prison sentences varies from 0% to 50%, averaging 22%. Of those convicted offenders who were not sentenced to prison, 46% were sentenced to jail and 54% received non-custodial sentences. Figure 1 provides details of 12 binary individual-level covariates conjectured to affect sentencing severity, including missing data rates for each covariate. There are 3,876 cases with some missing data; accounting for missing data using regression imputation is discussed in Section 4.

[FIGURE 1 ABOUT HERE]

An offender's most serious conviction charge places them in one of six categories; we include indicator variables for the five most likely to result in a prison sentence. To measure the perceived seriousness of prior criminal history, we use an indicator of whether an offender has had a prior term of incarceration in a state prison (see Wooldredge, 1998). We treat case disposition according to whether conviction was by trial or by any type of plea.

We include two demographic characteristics, gender and an indicator for African American. Missing data precluded more precise racial/ethnic breakdowns such as differentiating between Hispanic and non-Hispanic. Finally, we consider three indicators related to treatment and behavior of offenders before sentencing: offenders have an active criminal justice status if they are on probation, parole, pre-sentence release, or in custody at the time of offense; offenders can either be detained or released after being charged; and, even if released, offenders can have

that release revoked if, for example, they are subsequently rearrested. We also investigated age in preliminary analysis of the data, but found this to have very little impact on the type of sentence imposed once other case and individual characteristics are controlled for.

We linked individual-level data to county-level covariates using the Federal Information Processing Standards code. We consider six county-level covariates, summarized in Table 1.

[TABLE 1 ABOUT HERE]

We chose these six covariates based on findings from previous research, as discussed in Section 1, and data availability. In particular, we include crime and unemployment rates for 1998, as well as percentage of the county population that is African American, a common measure of racial composition in criminal justice research. Several studies assessing contextual factor effects on individual felony sentence length have also found political conservatism (defined as the proportion of residents who voted for the Republican candidate in presidential elections) to have a positive impact (for example, Huang et al., 1996; Nardulli, Fleming, and Eisenstein, 1988). Thus, we use share of the vote for George W. Bush in the 2000 presidential election (see Leip, 2001) as a proxy for political conservatism.

We consider region of the country using an indicator for whether the county is located in a Southern state (as defined by the Census Bureau). Finally, we also attempt to partially control for the sentencing policies under which a county's judicial system operates. In general, guidelines can take into account current offense as well as criminal history (measured in widely varying ways across states). However, practically speaking, it is not possible to control for a guideline effect on a case-by-case basis. We therefore chose to control for state sentencing guidelines at a very broad level, by including an indicator for the nine counties operating under some form of state guidelines, five of them voluntary and four mandatory (Rottman, Flango, Cantrell, Hansen, and LaFountain, 2000). The

limited number of such counties proved insufficient to distinguish between voluntary and mandatory guideline effects.

3 Hierarchical Logistic Regression Model

To analyze these data, we use a hierarchical logistic regression model, also referred to in the literature as a multilevel model. In contrast to conventional logistic regression, this methodology can account for the lack of independence across levels of nested data (i.e. individuals nested within counties). Conventional logistic regression requires that the intercept and any covariates affecting prison sentencing prevalence have the same effect in all counties. To relax this assumption and allow these covariate effects to vary across counties, a hierarchical modeling approach is required. Hierarchical modeling permits researchers to avoid several technical and conceptual obstacles (for example, poorly estimated standard errors, aggregation bias) that have hampered previous analyses of multilevel data in the area of criminal justice (Lee and Ulmer, 2000).

With individuals nested within counties, dependence among individual responses from the same county is likely, which in generalized linear models can lead to biased parameter estimates and unrealistic notions of precision. Consider the size of the average IDETAIN effect across all counties (i.e. the average increase in prison sentence prevalence for individuals detained pretrial). Analysis that ignores the county structure will be based on the variation over all individuals across counties. If the size of the IDETAIN effect varies between different counties, this can lead to an estimate of the average IDETAIN effect that is both inaccurate and stated with an exaggerated claim of precision. Hierarchical models correct for this problem by allowing effects to vary by county. This, in turn, leads to more accurate estimation of model parameters with more realistic standard errors.

In particular, we take a Bayesian approach and use a generalization of the model

of Wong and Mason (1985) to consider sentencing across the whole of the U.S. in 1998. Weidner, Frase, and Pardoe (2004) discuss policy implications of applying a variant of this model to 1996 SCPS data. There are between 23 and 905 individuals in each county, giving a total of $I = \sum_{j=1}^{39} n_j =$ 8,446. For the ith individual in county j, consider the binary response variable

$$\mathrm{Y}_{ij} = \begin{cases} 1 & \text{for a prison sentence} \\ 0 & \text{for a jail or non-custodial sentence} \end{cases}$$

Then $\mathrm{Y}_{ij}|p_{ij} \sim$ Bernouilli(p_{ij}), where $p_{ij} = \Pr(\mathrm{Y}_{ij} = 1)$, and

$$\mathrm{logit}(p_{ij}) = \log\left(\frac{p_{ij}}{1-p_{ij}}\right) = \boldsymbol{X}_i^T \boldsymbol{\beta}_j \tag{1}$$

where $\boldsymbol{X}_i$ represents measurements on K individual-level covariates and $\boldsymbol{\beta}_j$ consists of K regression parameters (specific to the jth county). Next, since each β-parameter is likely to be related across counties, we assume that each one can be explained by up to L county-level covariates,

$$\boldsymbol{\beta}_j = \boldsymbol{G}_j \boldsymbol{\eta} + \boldsymbol{\alpha}_j \tag{2}$$

where $\boldsymbol{G}_j$ is a $K \times M$ block-diagonal matrix of measurements on L county-level covariates, $\boldsymbol{\eta}$ consists of M regression parameters, and $\boldsymbol{\alpha}_j$ is a $K \times 1$ vector of county-level errors. In particular, the kth row of $\boldsymbol{G}_j$ contains a non-zero block with a one for an intercept, together with the county-level covariates needed to explain the kth β-parameter. Thus, M would be $K \times L$ if all county-level covariates are used to explain each β-parameter, or less than this otherwise.

Combining (1) and (2) leads to

$$\mathrm{logit}(p_{ij}) = \boldsymbol{X}_i^T \boldsymbol{G}_j \boldsymbol{\eta} + \boldsymbol{X}_i^T \boldsymbol{\alpha}_j \tag{3}$$

$\boldsymbol{X}_i^T \boldsymbol{G}_j$ contains each of the K individual-level covariates and L county-level covariates, as well as up to $(K-1)(L-1)$ interaction terms. Conventionally, the η-parameters in (3) are fixed effects while the α-parameters are random effects.

The presence of both types of effect makes (3) a mixed model; such models cannot be fit using standard logistic regression software. Suppressing the county-level errors so that (3) becomes a fixed effects model and amenable to standard regression assumes that individual-level effects are the same across counties, an assumption unlikely to be satisfied in practice. Mixed models can be fit from a frequentist perspective with specialized computer software such as "MLwiN" (Rasbash et al., 2000) and "HLM" (Raudenbush, Bryk, Cheong, and Congdon, 2001). An alternative approach is to put the mixed model into a Bayesian framework which explicitly models the hierarchical structure.

4 Estimation

To aid computation, CCRIME, CUNEMP, CPCTAA, and CCONS were standardized using sample means and variances. There are 18 main effects (12 individual, 6 county-level) and up to 72 interactions. We exclude 5 interactions involving CGUIDE from consideration however: those with IMALE, IBLACK, IACTCJS, IDETAIN, and IREVOKE. State guidelines do not take into account gender or race, while these last three individual-level covariates relate more to treatment and behavior of the defendant before sentencing rather than sentence structure itself.

To estimate the model, we need to specify prior distributions for $\boldsymbol{\eta}$ and $\boldsymbol{\alpha}_j$. With small samples this choice can be critical, but with larger samples (such as in this application) the choice is less crucial, since information in the data heavily outweighs information in the prior. We give $\boldsymbol{\eta}$ independent, zero-mean, normal priors, with variances that seem plausible in the context of this particular application. Exponentiating the $\boldsymbol{\eta}$-parameters gives odds ratios which indicate the multiplicative impact on the odds of receiving a prison sentence, where the odds are defined as the probability of receiving a prison sentence divided by the probability of receiving a jail or non-custodial sentence. Thus a change in odds of one order of magnitude corresponds to log(10) = 2.3 in the $\boldsymbol{\eta}$-scale, while two

orders of magnitude corresponds to log(100) = 4.6, and so on. It seems reasonable to expect that interaction effects will generally be of smaller magnitude than main effects, so we assume prior variances of 10 for the interactions (corresponding to a change in odds of between one and two magnitudes) and 100 for the main effects (corresponding to a change in odds of between four and five magnitudes).

We specify an exchangeable prior for the county-level errors, $\boldsymbol{\alpha}_j \sim \mathrm{N}(\mathbf{0}, \boldsymbol{\Gamma}^{-1})$, where $\mathbf{0}$ is a K-vector of zeros and $\boldsymbol{\Gamma}^{-1}$ is a $K \times K$ covariance matrix. Wong and Mason (1985) proposed an empirical Bayes estimation procedure for $\boldsymbol{\Gamma}^{-1}$. We use a fully Bayesian approach instead by specifying a hyper-prior distribution for the inverse covariance matrix, $\boldsymbol{\Gamma} \sim \text{Wishart}(\boldsymbol{R}, K)$, where $\boldsymbol{R}$ can be considered a prior estimate of $\boldsymbol{\Gamma}^{-1}$ based on K observations, and, to represent vague prior knowledge, degrees of freedom for the Wishart distribution is set as small as possible at K (the rank of $\boldsymbol{\Gamma}$). We give $\boldsymbol{R}$ values of ten along the diagonal and zero elsewhere. Sensitivity analysis, discussed in Section 5, confirms that our choice of prior constants for $\boldsymbol{R}$ and for the $\boldsymbol{\eta}$ variances has little effect on the results.

We used WinBUGS (Spiegelhalter, Thomas, Best, and Lunn, 2003) software to generate posterior samples for $\boldsymbol{\eta}$ and $\boldsymbol{\alpha}_j$. WinBUGS facilitates Bayesian analysis of complex statistical models using Gibbs sampling, a Markov chain Monte Carlo (MCMC) technique. To account for missing data, which, based on the patterns of missingness, it seems reasonable to assume is missing at random (see Little and Rubin, 1987), additional Gibbs steps were used to impute missing values for IMALE, IBLACK, IACTCJS, IPPRIS, and IDETAIN. In particular, from separate analyses of missing-data covariates regressed on complete-data covariates, the following missing-data distributions were identified and used for imputation:

$$\begin{aligned}
\textsc{Imale} \sim \text{Bernoulli}(p_1),\ \text{logit}(p_1) &= \theta_1 + \theta_2\, \textsc{Icviol1} + \theta_3\, \textsc{Icdrug} + \theta_4\, \textsc{Icprop} \\
&\quad + \theta_5\, \textsc{Itrial} \\
\textsc{Iblack} \sim \text{Bernoulli}(p_2),\ \text{logit}(p_2) &= \theta_6 + \theta_7\, \textsc{Icviol1} + \theta_8\, \textsc{Ictraf} + \theta_9\, \textsc{Icprop} \\
&\quad + \theta_{10}\, \textsc{Irevoke} + \theta_{11}\, \textsc{Itrial}
\end{aligned}$$

$$\begin{aligned}
\textsc{Iactcjs} \sim \text{Bernoulli}(p_3),\ \text{logit}(p_3) &= \theta_{12} + \theta_{13}\,\textsc{Icviol2} + \theta_{14}\,\textsc{Icdrug} + \theta_{15}\,\textsc{Icprop} \\
&\quad + \theta_{16}\,\textsc{Itrial} \\
\textsc{Ippris} \sim \text{Bernoulli}(p_4),\ \text{logit}(p_4) &= \theta_{17} + \theta_{18}\,\textsc{Icviol2} + \theta_{19}\,\textsc{Irevoke} \\
\textsc{Idetain} \sim \text{Bernoulli}(p_5),\ \text{logit}(p_5) &= \theta_{20} + \theta_{21}\,\textsc{Icviol1} + \theta_{22}\,\textsc{Icviol2} + \theta_{23}\,\textsc{Ictraf} \\
&\quad + \theta_{24}\,\textsc{Icdrug} + \theta_{25}\,\textsc{Icprop} + \theta_{26}\,\textsc{Itrial}
\end{aligned}$$

along with independent, zero-mean, normal priors with variances of 10 for θ_j $(j = 1, \ldots, 26)$.

We used WinBUGS to perform simultaneous missing data imputation and estimation of the model. Three chains of 10,000 iterations each produced trace plots with a good degree of mixing, and various MCMC convergence diagnostics indicated convergence. In particular, after discarding 5,000 burn-in samples and thinning to retain every tenth sample to reduce autocorrelation (leaving a total of 1,500 posterior samples), the 0.975 quantiles of the corrected scale reduction factor (Brooks and Gelman, 1998, p.438) for the η-parameters were each 1.2 or less. Posterior distributions were all unimodal.

5 Model Assessment

Before using results from the model estimation, we assessed some underlying assumptions. Posterior samples of the county-level errors, $\boldsymbol{\alpha}_j$, can be thought of as residuals, and so lend themselves to the usual kinds of model diagnostics. The fact that they averaged very close to zero across counties is reassuring, but unsurprising. More open to doubt are the normality and exchangeability assumptions. However, normal probability plots revealed no strong abnormalities, and plotting posterior means of the $\boldsymbol{\alpha}_j$ against county-level covariates also revealed no worrisome patterns (plots not shown).

We also checked the fit of the model using a generalization of the “Bayes marginal

model plot" (BMMP) of Pardoe (2001). Here, the response variable, Y, is plotted against selected functions of the covariates, $h(\boldsymbol{X}, \boldsymbol{G})$. A nonparametric smooth of the data provides a model-free estimate of the mean function in the plot, while a nonparametric smooth of the model fitted values provides a comparable model-based estimate. Smooths that match closely for any function h provide support for the model; otherwise model inadequacy is indicated. Adding model-based smooths using posterior samples allows this assessment to be made more easily. For example, Figure 2 is a BMMP with $h = \boldsymbol{X}_i^T \boldsymbol{G}_j \hat{\boldsymbol{\eta}} + \boldsymbol{X}_i^T \hat{\boldsymbol{\alpha}}_j$, where $\hat{\boldsymbol{\eta}}$ and $\hat{\boldsymbol{\alpha}}_j$ are posterior means.

[FIGURE 2 ABOUT HERE]

The black smooth of the data follows the pattern of the gray band of model-based smooths of the fitted values, $\text{logit}^{-1}(\boldsymbol{X}_i^T \boldsymbol{G}_j \boldsymbol{\eta}^* + \boldsymbol{X}_i^T \boldsymbol{\alpha}_j^*)$, where $\boldsymbol{\eta}^*$ and $\boldsymbol{\alpha}_j^*$ are 100 posterior samples, and $\text{logit}^{-1}(.)$ is the inverse logit function defined as $\exp(.)/(1 + \exp(.))$. So, there is no indication of lack-of-fit from this plot, or indeed from similar plots with other h-functions (see Pardoe, 2004).

Finally, we carried out a small sensitivity analysis for the elements of $\boldsymbol{R}$, the prior estimate of the covariance matrix for the random effects, and for the $\boldsymbol{\eta}$ variances. Decreasing or increasing these prior constants by a factor of 10 lead to changes in η-parameter posterior means averaging 0.1 in absolute value.

6 Results

Summary statistics for the posterior samples of $\boldsymbol{\eta}$ are presented in Table 2. The means of the posterior samples provide point estimates for the η-parameters, while the standard deviations in parentheses provide measures of precision.

[TABLE 2 ABOUT HERE]

ICVIOL1 has the largest individual-level main effect (ignoring interactions with county-level covariates for the moment). Offenders convicted of murder, rape or robbery appear to have odds of receiving a prison sentence exp(2.6) or 12.9 times higher than those convicted of a reference category felony or misdemeanor offense, all other covariates being equal. Six other individual-level covariates show at least a three-fold increase in odds of receiving a prison sentence: offenders detained pretrial (IDETAIN), or with a prior stay in state prison (IPPRIS), or whose pretrial release was revoked (IREVOKE), and three other charge categories: less severe violent offenses (ICVIOL2), drug trafficking (ICTRAF), and property offenses (ICPROP).

As demonstrated so effectively in Gelman, Pasarica, and Dodhia (2002), graphs can be a more effective tool for presenting statistical results than tables. In addition, carefully constructed graphs enable insights that are nearly impossible to glean from a table. For example, it is difficult to appreciate exactly how individual-county interactions affect the substantive conclusions above, or how precisely such effects have been estimated. Also, Table 2 contains no information on the magnitude of the county-level errors, α_j, from (2). To address these concerns, we summarize model results using "predictor effect plots" such as those in Figure 3.

[FIGURE 3 ABOUT HERE]

Figure 3 contains a 4×3 grid of scatterplots with odds ratio estimates on the vertical axes and the four continuous county-level covariates on the horizontal axes (one for each row of the grid). The columns of the grid represent different types of county: non-Southern counties without state sentencing guidelines (of which there are 21) on the left, Southern counties without guidelines in the center (9), and non-Southern counties with guidelines on the right (7). We exclude Southern counties with guidelines from the plots since there are just two of these in our sample. Within each plot, we display information on the estimated odds ratio for the individual covariate as a function of a county-level covariate (black

line), posterior uncertainty in this quantity (gray lines), and estimates specific to each county (numbered points).

Consider first the top left plot of Figure 3. The estimated ICVIOL1 odds ratio decreases as crime rate increases (posterior mean for the ICVIOL1 by CCRIME interaction from Table 2 is negative). In particular, in non-Southern counties without guidelines, the ICVIOL1 odds ratio when CCRIME is at its sample minimum, 214 (1.7 standard deviations below the mean), is $\exp(2.6 - (1.7 \times -0.1))$ or 16.6; when CCRIME is at its sample maximum, 906 (1.5 standard deviations above the mean), it is $\exp(2.6 + (1.5 \times -0.1))$ or 10.4. The black line in the plot shows the ICVIOL1 odds ratio decreasing from 16.6 at the left of the graph to 10.4 at the right. The dashed line is a "no effect" reference line for an odds ratio of one.

Moving to the top center plot, the ICVIOL1 odds ratio is marginally lower in Southern counties without guidelines, by a multiplicative factor of $\exp(-0.03)$ or 0.97 (the -0.03 has been rounded to -0.0 in Table 2). For example, when CCRIME is 1,039 (2.1 standard deviations above the mean), the odds ratio is $\exp(2.6 - 0.03 + (2.1 \times -0.1))$ or 9.3. Similarly, moving to the top right plot, the ICVIOL1 odds ratio is marginally higher in non-Southern counties with guidelines, by a multiplicative factor of $\exp(0.03)$ or 1.03. Similar calculations apply for the other plots in Figure 3, for ICVIOL1 interactions with CUNEMP, CPCTAA, and CCONS. The plots show that while convictions for the more severe violent charge category are strongly associated with increased odds of a prison sentence, the effect varies with county-level covariates, in particular increasing as the percentage African American increases. On the other hand, there is little difference between counties by region and whether the county is subject to state sentencing guidelines.

Estimates of precision for these odds ratios cannot be obtained from Table 2, since the posterior samples for the individual main effects and individual-county

interactions are correlated. Instead, we enable visualization of our level of uncertainty in the odds ratio estimates by using posterior samples directly in the predictor effect plots. For example, the gray lines in the top left plot of Figure 3 represent 100 posterior samples for the ICVIOL1 and ICVIOL1 by CCRIME interaction parameters. Similarly, it is possible to visualize estimation precision for the odds ratios in the other plots in Figure 3 using the gray lines as a guide.

Finally, the numbered points represent estimated odds ratios for each county. These are calculated by exponentiating the posterior mean of the sum of the ICVIOL1 main effect, the ICVIOL1 interactions evaluated at the county's covariate values, and the appropriate $\boldsymbol{\alpha}_j$. Thus, although the average ICVIOL1 effect is about 13, it is as high as 50 in one particular county (this county has a low unemployment rate and high percentage African American which combine to produce a particularly high odds ratio).

We constructed predictor effect plots for all individual-level covariates and interactions with county-level covariates; for space considerations we present only a selection here. Figure 4 contains predictor effect plots for the largest ICVIOL2 and ICPROP main effects and interactions. The plots show that the effect of the less severe violent charge category on the odds of a prison sentence varies mainly with index crime rate (decreasing), percentage African American (increasing), and region (increased in the South). On the other hand, with respect to the effect of the property offense charge category on odds of a prison sentence, counties with low crime rates, high African American populations, or which are not subject to state sentencing guidelines appear to demonstrate increased odds of a prison sentence.

[FIGURE 4 ABOUT HERE]

Figure 5 contains predictor effect plots for the largest ICTRAF and ICDRUG main effects and interactions. There is an indication of increased odds of a prison sentence for drug trafficking in counties with low unemployment rates or which are subject to state sentencing guidelines. By contrast, the effect of the drug

possession charge category on the odds of a prison sentence varies mainly with index crime rate (decreasing), percentage African American (increasing), and percentage conservative (increasing).

[FIGURE 5 ABOUT HERE]

Figure 6 contains predictor effect plots for the largest IPPRIS, ITRIAL, and IMALE main effects and interactions. The effect of a prior stay in state prison on the odds of a prison sentence varies mainly with unemployment rate (increasing), percentage African American (decreasing) and region (decreased in the South). The effect of conviction by trial rather than plea bargain appears to decrease with crime rate. However, there is little county-level variation in the effects of gender, other than a slight increasing trend with percentage conservative.

[FIGURE 6 ABOUT HERE]

Figure 7 contains predictor effect plots for the largest IBLACK, IACTCJS, IDETAIN, and IREVOKE main effects and interactions. The effect of individual (African American) race, while very small as a main effect, does become apparent as county-level crime rate increases. There is little county-level variation in the effect of an active criminal justice status at the time of the offense, other than a slight increasing trend with percentage conservative. However, there are indications of decreased odds of a prison sentence for offenders detained after being charged in Southern counties, and also increased odds for defendants whose pretrial release is revoked in strongly conservative counties.

[FIGURE 7 ABOUT HERE]

Finally, effects on sentence severity can be considered from the perspective of the county-level covariates. From Table 2, the unemployment rate main effect of -0.6 indicates that in general the odds of being sentenced to prison appears to decrease as unemployment goes up. However, the individual-county interactions modify this effect for different categories of individual. For example, the unemployment

rate effect for convictions in the more severe violent charge category is $\exp(-0.6 - 0.1)$ or 0.5. So, a one standard deviation increase in a county's unemployment rate decreases the odds of a more severe violent offender being sentenced to prison by an estimated 0.5 times. Similar calculations can be done for the effects of one standard deviation increases in index crime rate, percentage African American, and percentage conservative, as well as for Southern region and state guideline effects.

These quantities are summarized in Figures 8 and 9, with the 50% and 95% intervals allowing visualization of the uncertainty in the estimates. Overall, unemployment rate and Southern region effects tend to be negative, while crime rate and percentage conservative effects tend to be positive. Percentage African American and state sentencing guideline effects are more varied: positive or neutral with most individual characteristics, but negative with others.

[FIGURES 8 AND 9 ABOUT HERE]

7 Discussion

This article shows how individual-level covariates combine with county-level contextual covariates to affect sentence severity. It demonstrates the utility of Bayesian multilevel modeling applied to BJS-collected sentencing data from 39 of the 75 most populous counties in 17 states. These populous counties have a disproportionate impact on criminal justice system resources and on number of offenders affected. In 1998, the 75 most populous counties represented by this analysis accounted for 37% of the U.S. population, 50% of reported serious violent crime, and 40% of felony convictions (Reaves, 2001, p.1). Moreover, use of this national sample afforded the rare opportunity to quantify the effect of Southern region on sentence severity.

This sampling frame presents some limitations as well. In particular, we were unable to control for the effect of urbanization on sentencing decisions (Ulmer, 1997; Ulmer and Kramer, 1996), as others have done (Myers and Talarico, 1987; Steffensmeier et al., 1993). Also, it was not possible to control for size of jurisdiction (Eisenstein and Jacob, 1977; Eisenstein, Flemming, and Nardulli, 1999) due to limited variability; two of the sampled counties have populations of 5.2 and 9.2 million, while the rest cluster between 0.6 and 3.2 million. More generally, the sampled counties are a small subset of the population of more than 3,100 U.S. counties.

That said, there are several noteworthy findings to emphasize, particularly in regard to the county-level covariates. Our analysis suggests that county unemployment level has a negative effect on sentence severity, after controlling for the individual-level covariates. This finding contradicts the notion that punishment will be more severe in jurisdictions with greater proportions of individuals perceived as posing a threat because of their economic circumstances (Mears and Field, 2000). Yet this economic threat hypothesis is not consistently supported by empirical research (Arvanites, 1992; Barkan, 2001). For example, whereas Greenberg and West (2001) found level of unemployment to have an impact on imprisonment rates, Michalowski and Pearson (1990) did not. Similarly, in the realm of research on sentencing decisions, while Myers and Talarico (1987) found that higher levels of unemployment increase the likelihood of incarceration, Britt (2000) found that unemployment levels did not have an effect either on the decision to incarcerate or on sentence length.

A county's African American population proportion generally had a positive effect on prison use. While it could be the case that this relationship relates to the (perceived) threat that a larger minority population poses to the economically and politically powerful, it is also possible that it results from states with higher African American representation being more likely to imprison all races alike (Carroll and Cornell, 1985). As for index crime rate, its positive effect overall is

consistent with some sentencing studies (for example, Myers and Talarico, 1987), but inconsistent with others (for example, Britt, 2000). That political conservatism has a generally positive impact on prison use is consistent with prior studies based on analysis of individual court cases (Huang et al., 1996; Nardulli et al., 1988) and states and counties (Sorensen and Stemen, 2002; Weidner and Frase, 2003).

Research using states or counties as the units of analysis (for example, Michalowski and Pearson, 1990) commonly finds Southern region to have a positive effect on punitiveness. However, we found it to have a negative effect for most individual covariates (for example, offenders detained after being charged or who have had a prior stay in state prison), but more neutral for others (for example, less severe violent charges). The present study's use of large urban counties may explain these results. Analysis of data from the National Judicial Reporting Program (NJRP), which reports sentences for convicted felons in 344 counties selected to be nationally representative (Durose, Levin, and Langan, 2001), finds large Southern counties to be quite different from medium and small ones in terms of sentencing. NJRP data from 1998 show that 48% of convicted felons in Southern counties received prison sentences, compared to 35% elsewhere. However, for NJRP counties that were among the 75 most populous, Southern counties were slightly less likely to sentence to prison than non-Southern counties (40% compared to 41%), whereas among medium and small counties, those in the South were more likely to sentence to prison (49% compared to 33%).

Finally, the finding that sentencing policy, defined here as presence of mandatory or voluntary sentencing guidelines, has a generally positive impact on prison use is inconsistent with research using state imprisonment rates as the outcome measure (Sorensen and Stemen, 2002). However, this finding is not too surprising, considering that sentencing guidelines vary greatly across states in terms of purpose and scope (Frase, 1999). Guidelines have been associated with both increased and decreased prison use, depending upon their political and practical underpinnings, for example, whether "their formulation is explicitly linked to

prison capacity" (Sorensen and Stemen, 2002, p. 469).

This article demonstrates the importance of modeling interactions between individual-level and key contextual factors. However, since it considers data from only one point in time (i.e. 1998), it is unable to account for temporal variations in the relationship between punishment and contextual factors that have been demonstrated in prior research. For example, in a study based in part on the work of Rusche and Kirchheimer (1939), Michalowski and Carlson (1999) found that the strength and direction of the relationship between unemployment and imprisonment in the U.S. varied greatly across four distinct periods in the twentieth century. Furthermore, future research on sentencing decisions would benefit by accounting for the effect of several other contextual factors, such as level of bureaucratization (Dixon, 1995) and additional indicators for sentencing policy. Such research could also be enhanced by considering alternative outcome measures such as sentence length (or actual time served) and by comparing the use of prison relative to jail sentences.

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Table 1

County-level covariates and summary statistics. Means and standard deviations are raw statistics (i.e. not population weighted) for 39 counties representing 24% of the U.S. population.

Covariate	Description	Mean	S.D.	Min.	Max.
CCRIME	Index* (known to police) crime rate per 10,000 residents	587	220	214	1,095
CUNEMP	Unemployment rate (%)	4.4	1.8	2.3	10.0
CPCTAA	Census estimate of African American population (%)	18.9	12.4	1.8	45.9
CCONS	Share of vote for Bush in 2000 (%)	38.2	13.3	11.8	55.7
CSOUTH	1: located in a Southern state, 0: otherwise	0.28	-	0	1
CGUIDE	1: voluntary or mandatory state sentencing guidelines, 0: otherwise	0.23	-	0	1

* Index crimes include murder, rape, robbery, aggravated assault, burglary, larceny/theft, motor vehicle theft, and arson.

Table 2

Posterior summaries for $\boldsymbol{\eta}$: means (standard deviations). The first row contains the county-level main effects, the first column contains the individual-level main effects, while the remainder of the table contains interactions. Bold indicates that the absolute value of the posterior mean is larger than the posterior standard deviation.

		County					
Individual		CCRIME	CUNEMP	CPCTAA	CCONS	CSOUTH	CGUIDE
	−5.2	**0.4**	**−0.6**	0.0	**0.6**	**−0.7**	0.1
	(0.4)	(0.3)	(0.4)	(0.3)	(0.3)	(0.6)	(0.6)
ICVIOL1	**2.6**	−0.1	−0.1	**0.5**	0.2	−0.0	0.0
	(0.3)	(0.2)	(0.3)	(0.2)	(0.3)	(0.3)	(0.4)
ICVIOL2	**1.6**	**−0.3**	0.2	**0.4**	0.1	**0.5**	−0.1
	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.3)	(0.3)
ICTRAF	**1.5**	−0.0	−0.2	0.0	−0.0	−0.1	**0.5**
	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.3)	(0.4)
ICDRUG	**0.4**	**−0.3**	0.2	**0.4**	**0.3**	0.1	0.2
	(0.2)	(0.2)	(0.3)	(0.2)	(0.2)	(0.3)	(0.4)
ICPROP	**1.4**	**−0.2**	−0.0	**0.3**	−0.1	−0.3	**−0.7**
	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.3)	(0.3)
IPPRIS	**1.7**	−0.1	**0.3**	**−0.3**	−0.1	−0.2	−0.1
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.2)	(0.2)
ITRIAL	**0.7**	**−0.2**	−0.0	−0.2	0.1	0.2	0.1
	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.3)	(0.3)
IMALE	**0.5**	0.0	−0.0	0.0	0.0	0.1	
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	
IBLACK	0.0	**0.2**	−0.0	0.1	0.0	−0.0	
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	
IACTCJS	**0.8**	0.0	0.0	−0.1	0.1	0.1	
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.2)	
IDETAIN	**1.9**	0.1	−0.2	−0.1	0.1	**−0.5**	
	(0.1)	(0.2)	(0.2)	(0.1)	(0.2)	(0.2)	
IREVOKE	**1.3**	0.1	**0.2**	−0.1	**0.2**	−0.2	
	(0.2)	(0.2)	(0.2)	(0.2)	(0.2)	(0.3)	

Definitions of the covariates are provided in Table 1 and Figure 1.

Fig. 1. Binary individual-level covariates: sample means, descriptions, and percent missing data (in parentheses). Covariates for "most serious conviction charge" (ICVIOL1, ICVIOL2, ICTRAF, ICDRUG, and ICPROP) are relative to a reference category of weapons, driving-related, and other public order offenses.

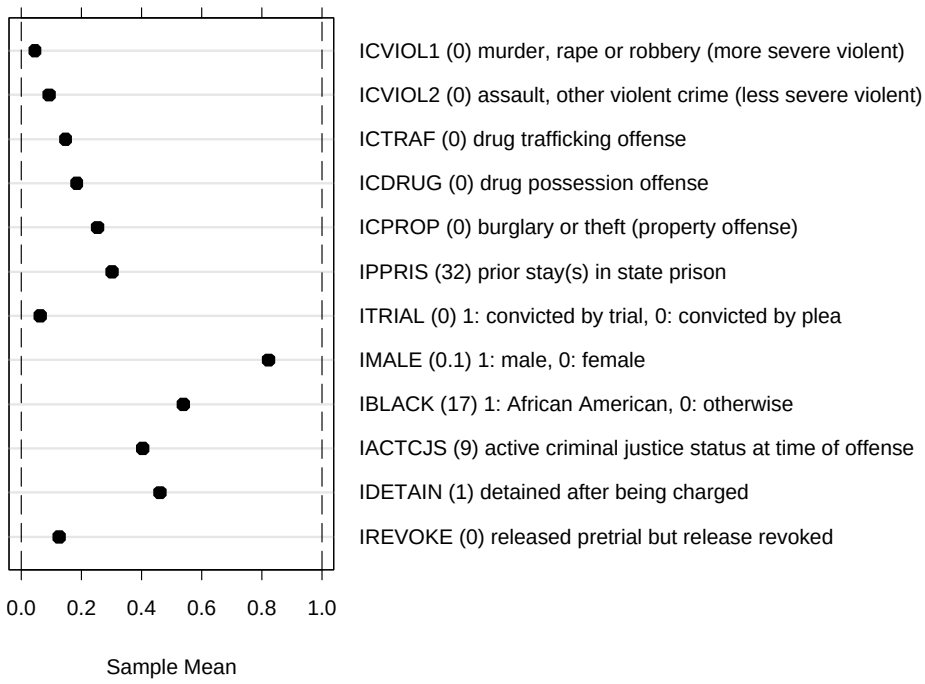

Fig. 2. Bayes marginal model plot with $h = \boldsymbol{X}_i^T \boldsymbol{G}_j \hat{\boldsymbol{\eta}} + \boldsymbol{X}_i^T \hat{\boldsymbol{\alpha}}_j$, where $\hat{\boldsymbol{\eta}}$, $\hat{\boldsymbol{\alpha}}_j$ are posterior means. Data are jittered vertically to aid visualization of relative density and the spline smooths have six effective degrees of freedom.

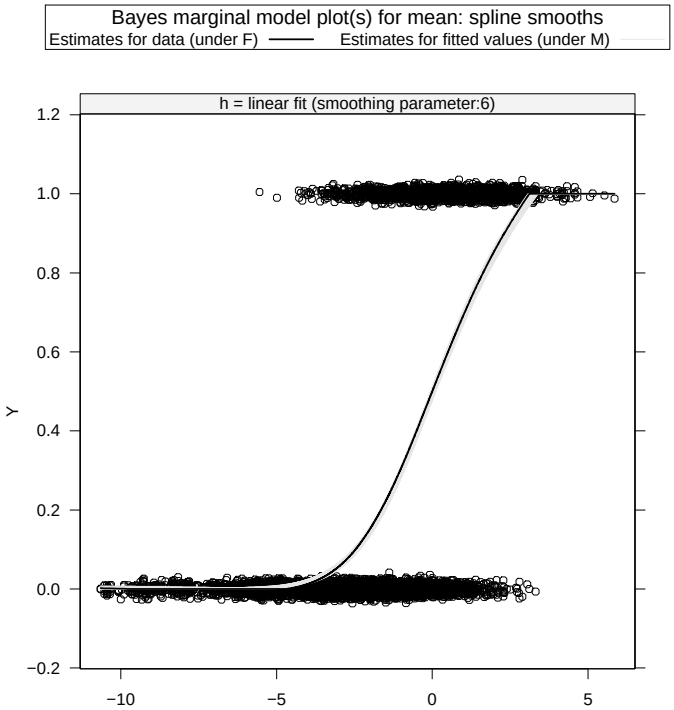

Fig. 3. ICVIOL1 odds ratios (black lines), posterior samples (gray lines), and county estimates (numbered points) by county-level covariates. Dashed lines represent no effect.

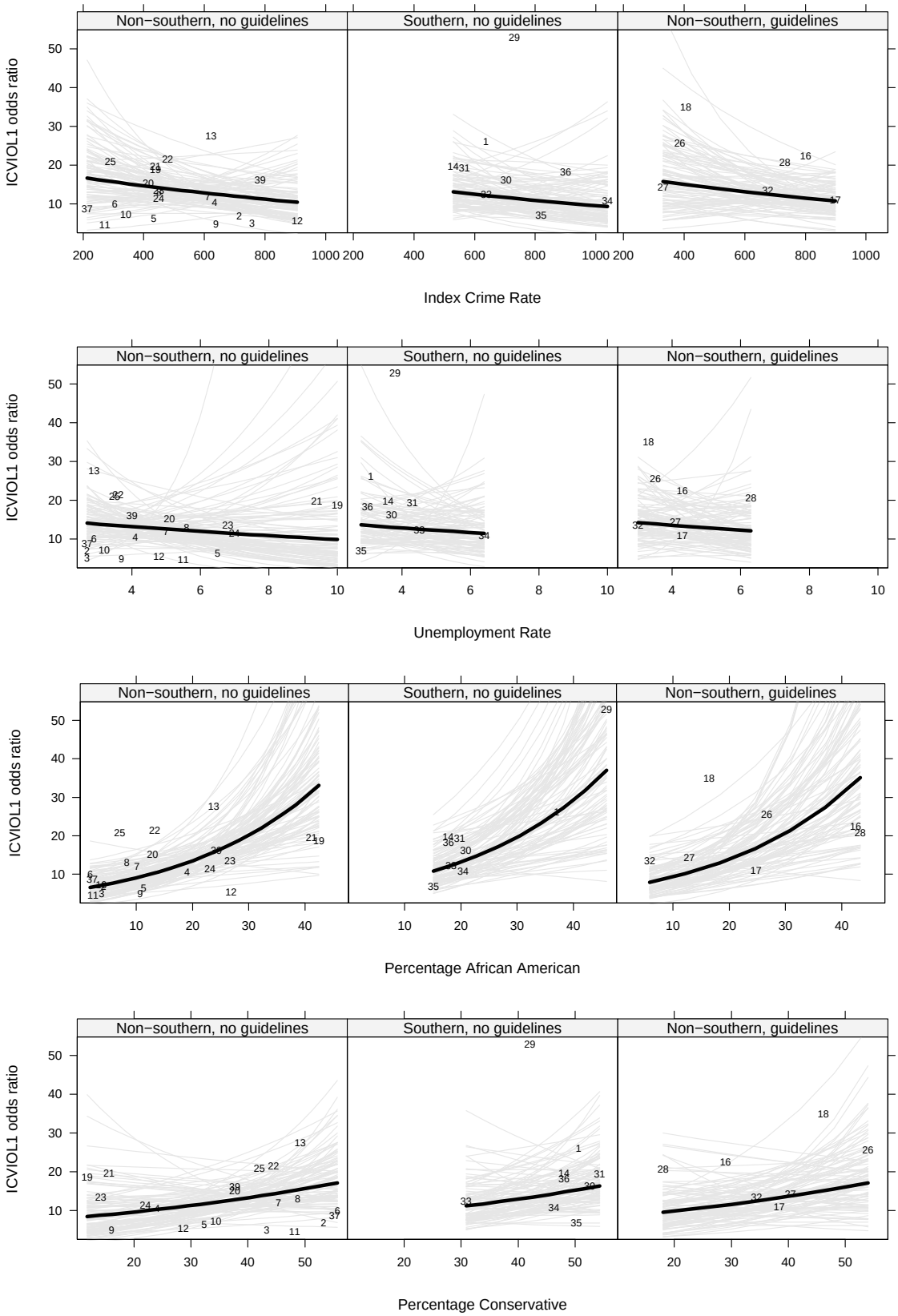

Fig. 4. ICVIOL2 and ICPROP odds ratios (black lines), posterior samples (gray lines), and county estimates (numbered points) by county-level covariates.

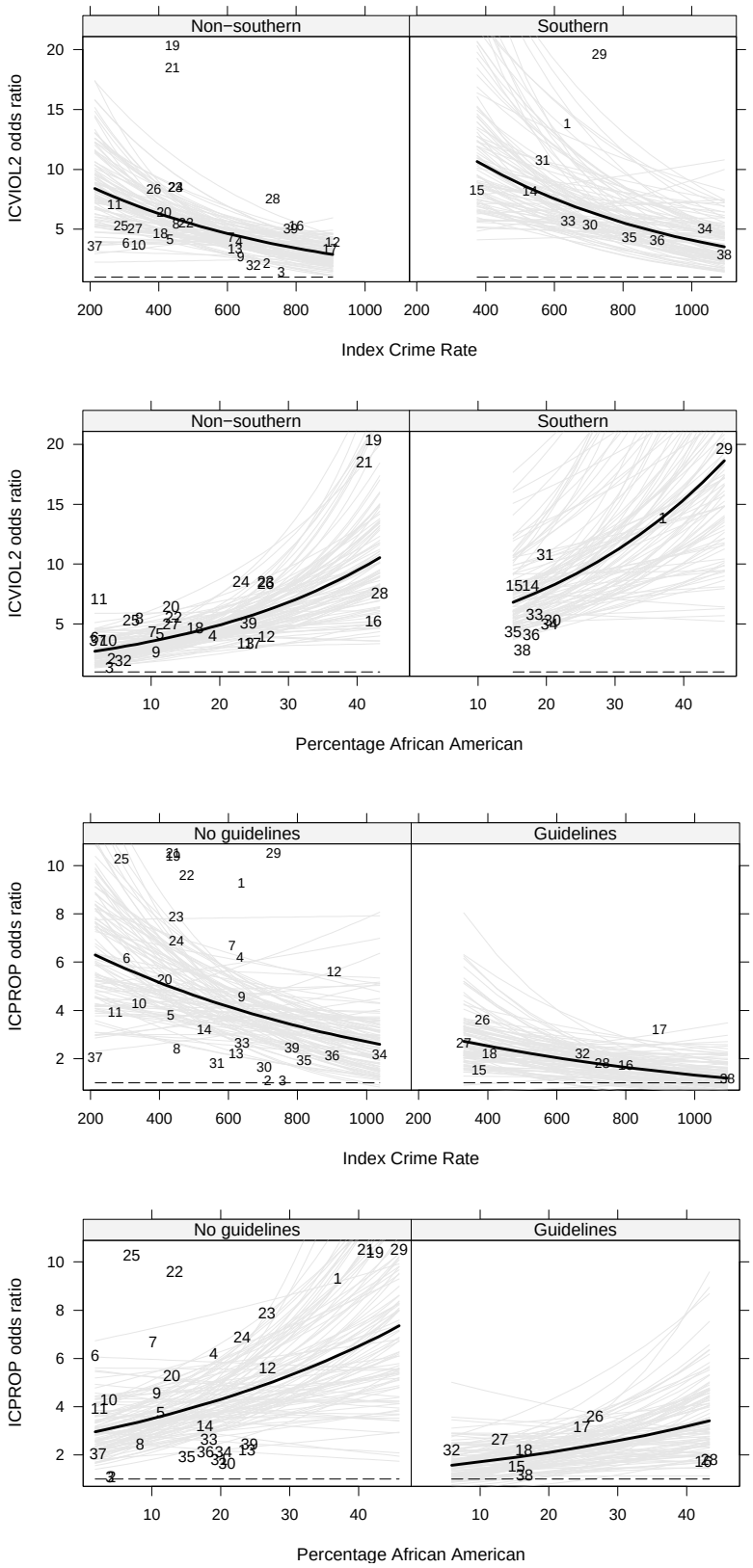

Fig. 5. ICTRAF and ICDRUG odds ratios (black lines), posterior samples (gray lines), and county estimates (numbered points) by county-level covariates.

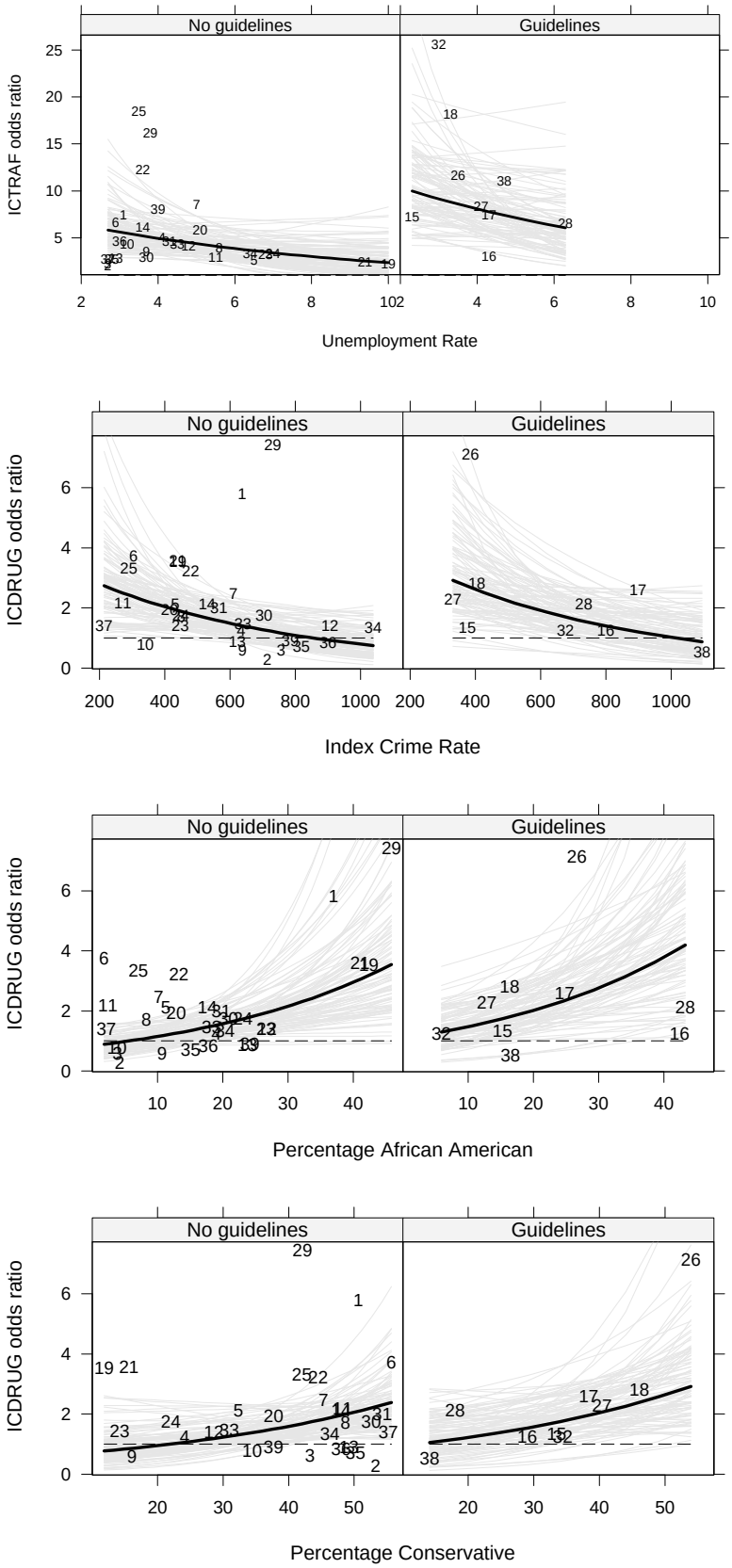

Fig. 6. IPPRIS, ITRIAL, and IMALE odds ratios (black lines), posterior samples (gray lines), and county estimates (numbered points) by county-level covariate.

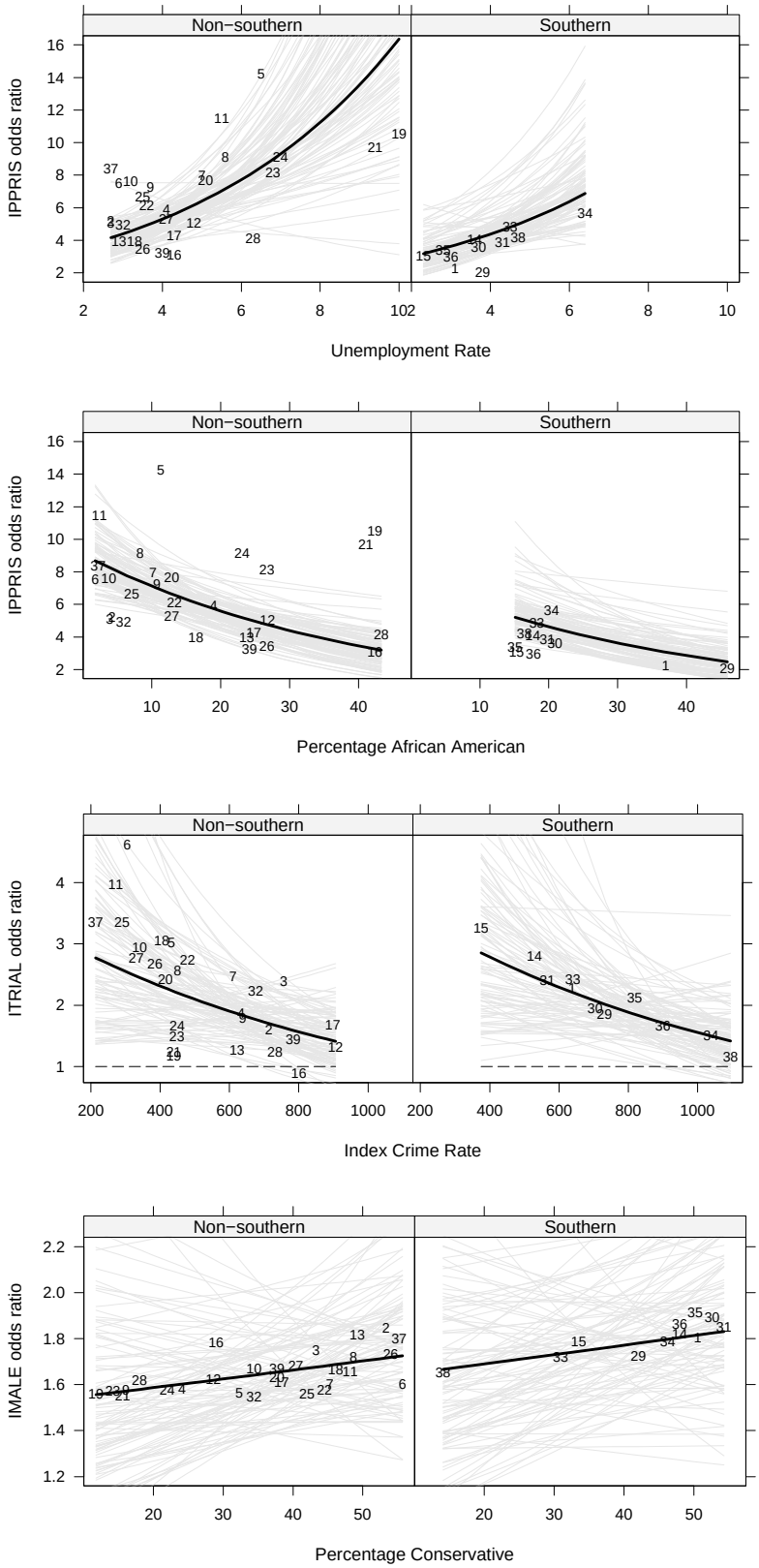

Fig. 7. IBLACK, IACTCJS, IDETAIN, and IREVOKE odds ratios (black lines), posterior samples (gray lines), and county estimates (numbered points) by county-level covariate.

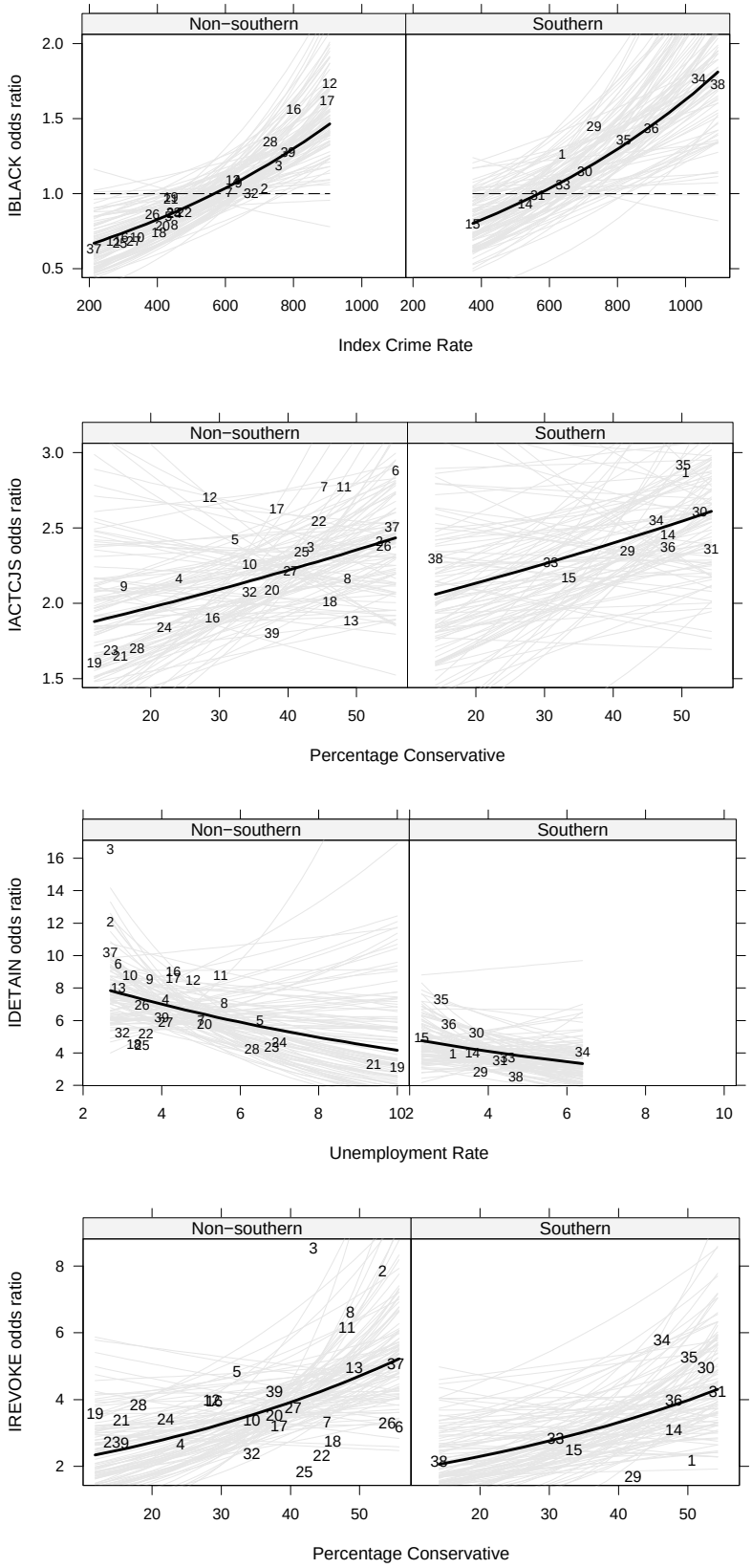

Fig. 8. Odds ratios (thick black lines) for one standard deviation increases in CCRIME, CUNEMP, and CPCTAA for different categories of individual. Bars represent 50% and 95% intervals.

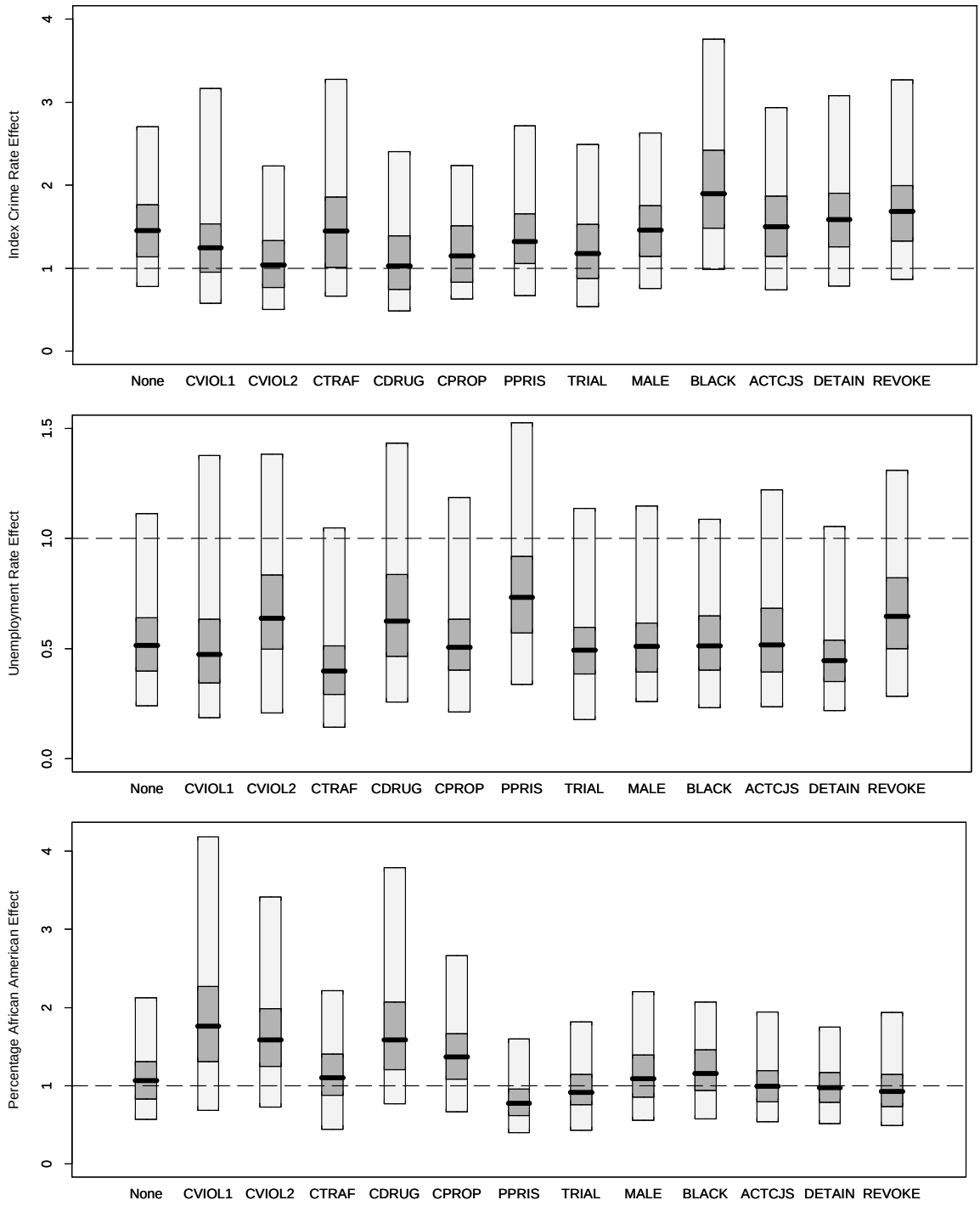

Fig. 9. Odds ratios (thick black lines) for a one standard deviation increase in CCONS, and Southern region and state guideline effects for different categories of individual. Bars represent 50% and 95% intervals.