Structural bias in the sentencing of felony defendants

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Abstract

As incarceration rates have risen in the US, so has the overrepresentation of African Americans and Latinos among prison inmates. Whether and to what degree these disparities are due to bias in the criminal courts remains a contentious issue. This article pursues two lines of argument toward a structural account of bias in the criminal law, focusing on (1) cumulative disadvantages that may accrue over successive stages of the criminal justice process, and (2) the contexts of racial disadvantage in which courts are embedded. These arguments are tested using case-level data on male defendants charged with felony crimes in urban US counties in 2000. Multilevel binary and ordinal logit models are used to estimate contextual effects on pretrial detention, guilty pleas, and sentence severity, and cumulative effects are estimated as conditional probabilities that are allowed to vary by race across all three outcomes. Results yield strong, but qualified, evidence of cumulative disadvantage accruing to black and Latino defendants, but do not support the contextual hypotheses. When the cumulative effects of bias are taken into account, the estimated probability of the average African American or Latino felon going to prison is 26% higher than that of the average Anglo.

1. Introduction

Rising incarceration rates in the US over the last four decades and the growing overrepresentation of blacks and Latinos among prison populations has fueled a robust, contentious, and equivocal literature on racial bias in the criminal courts. Studies through the 1970s suggested that bias was pervasive, but careful critiques showed that those findings were based on nonrepresentative data and underspecified models (e.g. Kleck, 1981). Research from the 1980s on was more rigorous, and its results more equivocal. The canonical strategy in this research was to build linear-additive models that tested the effects of “extralegal” ascriptive factors—particularly race, but also in some cases gender and age—controlling for legally legitimate factors such as offense seriousness and the defendant’s prior record. In these studies, strong bivariate associations between race and sentence severity tended to wither under the onslaught of the control variables, leading many researchers to conclude that racial disparities in punishment are due primarily, if not exclusively, to differential rates of offending.\(^1\)

Subsequent trends in crime and punishment have called that conclusion into question. Kleck’s (1981) influential critique hinged on the facts that evidence of racial differences in rates of offending are strongest for violent crimes, and until the 1980s the large majority of prison inmates in the US were violent offenders. But the recent explosion of incarceration rates has occurred mainly as a result of harsher sentences for nonviolent crimes, particularly drug offenses (Blumstein, 2002, pp. 453–454). Involvement with drugs varies hardly at all by race (National Institute on Drug Abuse, 2003), so evenhanded arrests and prosecutions for drug crimes should, if anything, have ameliorated racial imbalances in prisons. But the “war” on drugs disproportionately targeted minorities (Tonry, 1995, ch. 3), especially those in urban enclaves where schools, low-skill...
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2.1. Cumulative disadvantage in criminal justice

Cumulative disadvantage—or its reverse, cumulative advantage—refers to a dynamic process in which an unfavorable (or favorable) initial social position leads to further losses (or gains) in the future. From its initial coinage by Merton (1973) to account for reputational mobility among scientists, it has been generalized broadly in research on education, stratification, the life course, and crime (DiPrete and Eirich, 2006). Sampson and Laub (1997) have applied the cumulative disadvantage concept as an extension of their life-course model of delinquency and crime (1993a) to account for stability in delinquent careers. Their concern is mainly with interinstitutional mechanisms of disadvantage, especially the negative impact of an official delinquent label on future opportunities for education, employment, and marriage, and the reciprocal effect of failure in these areas on the likelihood of subsequent criminal behavior. My concern here, following a line of argument developed in several earlier studies (Auerhahn, 2007; Chen, 2008; Schlesinger, 2007; Zatz, 1987), is with cumulative disadvantage that is endogenous to the criminal courts, and that may operate across sequential stages of the court process to produce accelerating bias.
Criminal courts are fertile ground for the cumulative production of bias because, as Hagan (1989) argues, criminal justice agencies in the US form loosely coupled organizational systems: within agencies, vertical authority relations between supervisors and street-level decisionmakers are weak and often ignored, and actors who are lowest in the hierarchy make the most crucial decisions; and across agencies—between, say, prosecutors and public defenders (Sudnow, 1964)—relations are governed by informal negotiations and a ritualized “logic of confidence and good faith” (Meyer and Rowan, 1977, pp. 357–359) rather than formal legal or bureaucratic rules. Loose coupling, as Hagan emphasizes, is an adaptive trait because it allows criminal justice agencies to adapt to varied and changeable environmental pressures with minimal disturbance to routine work activities. But how are work activities routinized within agencies that are subject to conflicting demands, multiple and ambiguous formal goals, unclear technologies, and loose authority relations? The response, from the rich ethnographic literature on the topic, is that officials reduce uncertainty by orienting their decisions to practical logics that are shared by practitioners within and across agencies. These logics are informed by stereotypes about typical cases and typical offenders (Sudnow, 1964), the norms and priorities of particular agencies (Emerson, 1969, 1983), and local “images of danger and culpability” (Stein et al., 2005). This uncertainty-reduction perspective has been elaborated with regard to racial bias by Albonetti (1991, 1997), Bridges and Steen (1998), and Steen et al. (2005), among others, and is now widely accepted in the criminal justice literature. Disadvantage is particularly likely to accumulate in organizational domains of this sort because, given high caseload pressures and chronic uncertainty about particular cases, the most salient facts known to officials are upstream decisions by other officials (Garfinkel, 1967). In the criminal courts, as defendants move from one stage of the process to another, previous adverse decisions may be taken as evidence of “danger and culpability” calling for further punitive actions.

Pretrial decisions should be more vulnerable to bias because they are relatively informal. Research on pretrial detention yields mixed evidence of bias (Free, 2002), but this may be because many studies lump Latinos and Anglos together as “whites.” More discriminating analyses by Demuth (2003) and Schlesinger (2007) find that Latino and African American defendants are significantly more likely to be detained. A few studies have examined racial patterns in modes of conviction. Some find that black defendants are less likely than whites to plead guilty, but the evidence regarding Latinos is unclear (Albonetti, 1990; Frenzel and Ball, 2007; Kellough and Wortley, 2001; LaFree, 1985). Whether pretrial decisions are biased or not, a further important question is whether the effects of those decisions on sentencing vary by race or ethnicity. Sentencing research routinely finds that detained defendants are sentenced more harshly than those who are released pending trial, but analyses of race-ethnic differences in those effects is rare. One example is Auerhahn’s (2007) study of homicide defendants, which found that detention leads to longer sentences for older Latinos, and perhaps for older black defendants, than it does for Anglos. Most studies find evidence of significant sentence discounts for guilty pleas—or the converse, penalties for being convicted at trial—but a few find no such effects (see reviews in Kramer and Ulmer, 2009, pp. 140–141; Ulmer and Bradley, 2006, pp. 632–633). Some studies have directly examined racial disparities in sentencing based on mode of conviction. Albonetti (1997) found no racial-ethnic disparities in sentence discounts for guilty pleas among drug defendants in federal courts, and Ulmer et al.’s (2010) study of federal court sentencing found disparities in trial penalties that favored black male defendants. Studies of trial penalties using Pennsylvania data tend to show that black defendants are punished more severely than whites if convicted at trial, but there is no evidence of disparities affecting Latinos (Johnson, 2003; Kramer and Ulmer, 2009; Ulmer, 1997; Ulmer and Bradley, 2006). The evidence that mode of conviction interacts with race to affect sentencing is thus mixed. Moreover, none of these studies has tested for differences in the prior tendency to plead guilty. Recent studies that explicitly aim to test for cumulative disadvantage are helpful, but not definitive. Chen’s (2008) analysis of cumulative bias is based on aggregate data, so it is only suggestive about effects on individual defendants. Schlesinger (2007) studied the impact of biased pretrial detention patterns on individual sentences, but her evidence of racial bias on the latter is indirect. Thus while cumulative bias is often hypothesized, no study has systematically estimated its effects.

For this study, the cumulative disadvantage argument is taken to mean that both early bias and the rate at which bias may accumulate are contingent on the race and ethnicity of the defendant. Detection of such effects requires data that track defendants through the stages of the court process, and models that estimate the main effects of race and prior events at each stage, as well as their interactions. The general expectation is that minorities are more disadvantaged than Anglos by the negative stigma of pretrial detention, and are less likely to receive lenient sentences in return for pleading guilty. More specifically:

1. Blacks and Latinos who are detained before trial are less likely to plead guilty than detained Anglo defendants.
2. Convicted blacks and Latinos who are detained receive more severe sentences than detained Anglo defendants.
3. The sentence discounts given to black and Latino defendants who plead guilty are less than those given to similar Anglo defendants.

2.2. Jurisdictional context

Sociological researchers have long understood that decision-making patterns in US criminal courts are powerfully influenced by their social context (Dixon, 1995; Eisenstein and Jacob, 1991; Hagan, 1989; Kautt, 2002). Local environments have been the explicit focus of a great deal of research on aggregate rates of criminal sanctioning (Beckett and Western, 2001; Jacobs and Carmichael, 2001; Jacobs and Kleban, 2003; Sutton, 1987, 2004, 2012), but until recently context effects have mostly been ignored in quantitative research on case-level outcomes. In part this was, as Hagan (1989) and Sampson and
Laub (1993b) argue, because of the lack of an adequate macro-theory of criminal justice outcomes, but it is also due to the methodological difficulty of simultaneously analyzing micro- and macro-level variation. Over the last decade or so, however, criminologists have increasingly used multilevel models to analyze jurisdiction-level variation in both average case outcomes and the influence of individual-level predictors. Ulmer’s (2012, pp. 13–16) comprehensive review of the sentencing literature identifies four themes in the emergent research on contextual effects. The most conspicuous of these is research on the effects of “racial threat,” typically measured as the percent of minorities in the local population, on overall punitiveness and racial disparities in sentence outcomes (Feldmeyer and Ulmer, 2011; Helms, 2009; Kautt, 2002; Kramer and Ulmer, 2009; Ulmer and Johnson, 2004; Weidner and Frase, 2003; Weidner et al., 2005). Other foci include court organizational constraints, such as caseload pressures and the availability of alternative placements for offenders (Kramer and Ulmer, 2009; Ulmer and Bradley, 2006; Ulmer and Johnson, 2004); “socio-political” factors, such as crime rates, economic trends, and political or religious conservatism (Britt, 2000; D’Alessio and Stolzenberg, 2002; Fearn, 2005; Helms, 2009; Johnson, 2006; Ulmer et al., 2007; Wooldredge, 2007); and the racial-ethnic composition of the community of official court actors (Farrell et al., 2009; King et al., 2010).

Ulmer (2012) concludes that while multilevel analyses have shown substantial variation in sentencing practices across jurisdictions, they offer no clear support for any of the dominant hypotheses about how that variation is patterned. In particular, results concerning the racial threat hypothesis are “decidedly mixed” (Ulmer, 2012, p. 14): some studies show, as expected, that jurisdictions with larger proportions of minorities are more punitive, a few that they are less punitive, and many show no effects at all. My strategy in this analysis is to shift attention from minority presence (interpreted as an implicit threat to white dominance) to minority disadvantage. The theoretical foundation for this shift is laid by Sampson and Laub (1993b). They update the venerable “conflict” model, which treats official social control as an élite strategy to suppress threats from minorities and the poor, by emphasizing the symbolic nature of the challenge posed by underclass populations to the cultural sensibilities of the middle class. The “rabble class” poses no political or economic threat; their problem is that they are subjectively perceived to be rabble: poor minorities, and particularly the young males among them, signify aggressiveness, sexuality, and an insouciant disregard for middle-class norms. As specific predictors of racially disparate outcomes, Sampson and Laub point to racial inequality and the concentration of poverty: “counties characterized by racial inequality and a large concentration of the ‘underclass’... are more likely than other counties to be perceived as containing offensive and threatening populations and, as a result, are subject to increased social control” (1993b, p. 293). In this article they are writing specifically about juvenile justice, which due to its relative informality is especially likely to be influenced by extralegal community characteristics. But they make clear that these effects are likely to appear in criminal court outcomes as well, though perhaps in an attenuated form. Thus I hypothesize that in counties where black incomes are low relative to Anglos, and where black poverty is spatially concentrated, African American defendants will more often be detained and will receive more severe sentences; similarly, Latinos will more often be detained and will be sentenced more severely in counties where Latinos are relatively impoverished and poverty is highly concentrated. There is no straightforward prediction about effects on racial disparities in guilty pleas: a relatively high rate of pleading for blacks or Latinos may be evidence that prosecutors are offering more lenient plea deals to those groups, or it could be the result of a policy of aggressive overcharging targeted at minorities (Finkelstein, 1975).

3. Data and estimation

3.1. Data

The primary data for this study record the movement of individual felony defendants through criminal courts in urban US counties. These data are a subset of the State Court Processing Statistics database (U. S, 2007), which includes samples of felony defendants from the 75 most populous counties in the US, collected biannually since 1990. This analysis is based on the 11,505 cases involving male defendants distributed across 40 counties that were sampled in 2000. The year 2000 was chosen to coincide with the most recently available data from the U.S. Census. I restricted the sample to males (81% of all defendants) because prior research shows that both the severity of sanctions and the role of race in the decision-making process differ between males and females (Daly, 1989; Kruttschnitt and McCarthy, 1985; Spohn and Holleran, 2000; Spohn and Spears, 1997; Steffensmeier and Demuth, 2000; Steffensmeier et al., 1993). Since race effects are contingent on gender (and vice versa), including females and treating gender as a simple additive effect would be a misspecification. The alternative is to estimate separate models for males and females, but since race-ethnic differences in path dependencies are also likely to vary by gender this would more than doubly complicate the models and their interpretation. Table 1 shows descriptive statistics for all variables used in the analysis.

Separate models are estimated for three outcome variables: pretrial detention, guilty pleas, and sentence severity. The first two are treated as dichotomies. The measure of sentence outcomes, similar to that used by Wooldredge et al. (2005), comprises three categories: a noncustodial sentence (probation or fine), jail, or prison. These categories are ordered in terms of severity: as defendants, court officials, juries, and television audiences everywhere consistently recognize, incarceration is more severe than a noncustodial sentence, and a sentence to prison is harsher than a sentence to jail. Based on this modest assumption I use ordered logit regression to estimate models, which yields a single set of coefficient estimates that describes not particular outcomes, but the underlying dimension of punitiveness that those outcomes represent.
The pretrial detention dummy variable appears as a predictor in the models of guilty pleas and sentencing, and the guilty plea variable is a predictor in the sentencing model. African American and Latino defendants are identified by 1–0 dummy variables. The detention variable and the race and ethnicity indicators contain a nontrivial amount of missing values. Missingness appears to be random, at least with respect to other variables used in the analysis, and rather than discard observations with missing data I impute values as part of the estimation process, as I describe below. The menu of control variables used here is similar to those in other sentencing studies. I control for age, under the expectation that males in their 20s are likely to be perceived as especially dangerous (Steffensmeier et al., 1998), using a dummy variable taking the value 1 for defendants age 20–29 and zero otherwise. Type of attorney is measured by a dummy variable coded 1 for private counsel and 0 for a public defender or court-appointed attorney. The most important controls are for legally legitimate factors that are also likely to be correlated with race and ethnicity. Two dummy variables control for features of the present case that are likely to signify enhanced risk, and thus call for more severe treatment: whether the defendant is charged with a second (less serious) felony, and whether he was “active” in the criminal justice system at the time of arrest—i.e., on probation, parole, or diversion; a fugitive; or already in custody. The defendant’s criminal record is represented by dummy variables that indicate any prior felony conviction and any prior prison sentence.

The seriousness of the current offense is in principle the central legal determinant of sentence outcomes, and thus by implication of decisions leading up to sentencing. The measure used here is based on two simple assumptions: (1) measures of offense seriousness based on observable behavior—specifically, the associations of particular offenses to sentence severity—are preferable to those based on other sources, such as surveys and expert ratings (McDavid and Stipak, 1982); this is in large part because (2) prosecutors, defense attorneys, and experienced defendants are aware of the “going rates” for particular crimes (Sudnow, 1964), and orient their decisions to the expectations they generate. Following this or similar logic, studies of sentencing typically base their seriousness measures on the conviction offense, but here I focus on the initial arrest offense. There is an obvious argument for using this variable in the analyses of pretrial detention and guilty pleas, which are prior to conviction; but there is good reason to think that arrest offense seriousness is also preferable as a predictor of sentence outcomes. In the US, upwards of 90% of felony convictions are obtained through guilty pleas, and courts in most states operate under sentencing guidelines or determinate sentencing laws intended to limit judges’ discretion over sentencing, and that in many cases forbid prosecutors to bargain over sentences. Many scholars argue that these conditions open the door to widespread charge bargaining (Savelsberg, 1992)—or, put differently, the adjustment of charges by prosecutors in order to induce guilty pleas on satisfactory terms (Standen, 1993; Stuntz, 2001). Under these circumstances the conviction offense is a poor predictor because it is endogenous—in formal-legal terms it is the “cause” of the sentence, but in practice it is “the mechanism through which discretion operates” (Kessler and Piehl, 1998, p. 260, n. 4).

My strategy, following Kessler and Piehl (1998) and Piehl and Bushway (2007), is to measure offense seriousness as the defendant’s predicted sentence if he were convicted of the charge for which he is initially charged. The first step, using all of the cases in the sample that led to conviction, is to estimate a simple model in which the conviction offense predicts whether the defendant is sentenced to prison: more formally, define \( \Pr (y = 1) = x_C^\beta \) and \( x_C \) as a vector of dummy variables representing the 18 conviction charges reported in the SCPS data, and estimate \( \logit(x_C^\beta) = x_C^\beta \). Next, use the estimates in \( x_C^\beta \) to calculate, for each defendant, the predicted log odds of a prison sentence based on the arrest charges \( x_A \): \( \logit(\theta_A) = x_A^\beta \). The resulting estimates are predictions of each defendant’s expected sentence.

\(^2\) My measure differs from that used by Kessler and Piehl (1998) in that it uses all of the SCPS offense classifications to predict sentencing. Those offenses include murder, rape, robbery, assault, other violent felonies, burglary, larceny-theft, motor vehicle theft, forgery, fraud, other property felonies, drug sales, other drug felonies, weapons offenses, driving-related felonies, and public-order felonies.
Contextual data are assembled from tract- and county-level census data (GeoLytics, 2006). Racial inequality is measured as the ratio of Anglo to black (or Latino) mean per capita incomes in each county. The measure of poverty concentration is the class isolation index $P^r$, which yields the probability of interaction between members of the same racial-income group (Massey and Eggers, 1990, p. 1161). The index is calculated as $P^r = \sum (x_i/X) \times (x_i/t_i)$, where $x_i$ is the number of poor African Americans or Latinos in census tract $i$, $X$ is the total number of poor African Americans (Latinos) in the county, and $t_i$ is the total population of census tract $i$. As it turns out, $P^r$ is a synthetic indicator: black poverty concentration is highly correlated with the percent black population ($r = 0.80$) and black-Anglo residential segregation ($r = 0.79$), and Latino poverty concentration is correlated with percent Latino ($r = 0.77$) and Latino-Anglo residential segregation ($r = 0.68$). We may note, from Table 1, that in this sample of urban counties Latinos tend to be poorer than African Americans (the mean ratio of Anglo to Latino incomes is higher than the mean Anglo/black ratio), but black poverty is on average more concentrated.

3.2. Estimation

Models of pretrial detention and guilty pleas are estimated using multilevel binary logistic regression, and the sentencing model is estimated using multilevel ordered logistic regression. I describe the more complicated sentencing model here. The outcome variable is defined as:

$$ y_i = \begin{cases} 1 & \text{noncustodial sentence} \\ 2 & \text{jail} \\ 3 & \text{prison} \end{cases} $$

The model for $y_i$ can be written as a pair of binary logistic regressions, one that predicts incarceration rather than a non-incarcercative sanction:

$$ \Pr(y_i > 1) = \logit^{-1}(x_i^j \beta - C_1) $$

and a second that predicts a prison sentence rather than jail or nonincarceration:

$$ \Pr(y_i > 2) = \logit^{-1}(x_i^j \beta - C_2) $$

in which $C_1$ and $C_2$ are cutpoints between adjacent categories. Both regressions can be estimated in a single model because $x_i^j \beta$ is assumed to be the same for both comparisons.\(^3\) In this form, $\beta$ does not include an intercept. I use an alternate parameterization (Gelman and Hill, 2007, pp. 121–122) that includes an intercept and sets $C_1 = 0$. The individual-level model for defendant $i$ in county $j$ is

$$ \Pr(y_{ij} > k) = \logit^{-1}(\beta_0 + \beta_1 \times \text{Black defendant} + \beta_2 \times \text{Latino defendant} + \beta_3 \times \text{Pretrial detention} \\
+ \beta_4 \times (\text{Pretrial detention} \times \text{Black}) + \beta_5 \times (\text{Pretrial detention} \times \text{Latino}) + \beta_6 \times \text{Guilty plea} \\
+ \beta_7 \times (\text{Guilty plea} \times \text{Black}) + \beta_8 \times (\text{Guilty plea} \times \text{Latino}) + \beta_9 \times \text{Age} + \beta_{10} \times \text{Private attorney} \\
+ \beta_{11} \times \text{Second felony charge} + \beta_{12} \times \text{Criminal justice status} + \beta_{13} \times \text{Prior felony conviction} \\
+ \beta_{14} \times \text{Prior prison sentence} + \beta_{15} \times \text{Arrest charge seriousness} - C_2) $$

Note that the $j$ subscripts are omitted in coefficients $\beta_0$ through $\beta_{15}$. These coefficients are associated with control variables, and to ease the computational burden I treat these effects as fixed across counties. Parallel tests suggest that this changes estimates for the control variables very little, and for the variables of interest not at all.

At the macro level, the model treats the individual race-ethnicity effects as conditional on inequality and degrees of concentrated poverty:

$$ \beta_{1j} = \gamma_{10} + \gamma_{11} \times \text{Anglo/Black income ratio}_j + \gamma_{12} \times \text{Black poverty concentration}_j + e_{1j} $$

$$ \beta_{2j} = \gamma_{20} + \gamma_{21} \times \text{Anglo/Latino income ratio}_j + \gamma_{22} \times \text{Latino poverty concentration}_j + e_{2j} $$

Also of primary interest are the intercepts and the coefficients for pretrial detention, guilty pleas, and their interactions with race and ethnicity. These coefficients are allowed to vary, but are not otherwise modeled:

\(^3\) This is the “proportional odds” or “parallel regressions” assumption. Formal tests of this assumption—e.g. the Brant test—are not adapted to multilevel models. A straightforward alternative is to estimate two logit regressions, one for $\Pr(y_i > 1)$ (jail or prison sentence) and another for $\Pr(y_i > 2)$ (prison sentence), and compare the predictions from the fitted models. In this case the predictions are closely parallel, and correlated at $r = 0.92$, suggesting that the ordinal model is not a dangerous oversimplification. Estimates of individual coefficients revealed a couple of anomalies; these are addressed in the text below. Details, including a scatterplot of the predicted log-odds, are available from the author.
\[ \beta_{\text{cy}} = \gamma_{0,0} + \varepsilon_{\text{cy}} \]
\[ \beta_{\text{cy}} = \gamma_{1,0} + \varepsilon_{\text{cy}} \]
\[ \cdots \]
\[ \beta_{\text{cy}} = \gamma_{8,0} + \varepsilon_{\text{cy}} \]

Binary logit models are simplifications of the ordinal model. Given the sequential logic of the analysis, the detention analysis includes no prior events, and the analysis of guilty pleas includes only the effects of detention and its interactions with race-ethnicity. The macro models for the intercept and race-ethnicity effects are identical across all three outcomes.

Maximum likelihood estimation cannot be applied to multilevel models with qualitative outcomes. Instead, analysts have relied on approximate methods involving quasi-likelihoods. Research using both simulated and real data has shown that these methods result in substantially downward-biased estimates of both random and fixed effects (Rodriguez and Goldman, 1995, 2001). I use Bayesian estimation, which yields accurate results. Bayesian estimation requires prior specification of distributions for random effects and their variances. The micro-level \( \beta \) coefficients are assumed to be normally distributed across counties:

\[ \beta_{\text{cy}} \sim N(\beta_{\text{cy}}, \tau_{\text{cy}}^2) \]

The coefficient variances \( \tau^2 \) are given flat distributions with a generous range: \( \tau_{\text{cy}}^2 \sim U(10, 100) \). The \( \gamma_{\text{cy}} \) are given normal priors with zero means and large variances: \( \gamma_{\text{cy}} \sim N(0, 1000) \). These are “skeptical priors” (Weiss et al., 1999), so called because they tug against the data to yield conservative estimates. Data for binary covariates and indexes of case complexity and criminal history are centered at their grand means, and continuous measures are centered and divided by two standard deviations. Centering speeds convergence by reducing correlations among county-level effects coefficients and allows convenient interpretations of effects estimates. Each of the models reported below is based on 10,000 simulations, of which the first 5000 were treated as burn-in and discarded. Of the remaining simulations, 1000 were sampled and saved. Convergence was evaluated using traceplots and the \( R \) statistic (Gelman et al., 2004, pp. 296–297). All reported coefficient estimates are based on samples that converged at the optimal 1.0 level.

Bayesian estimation offers a convenient method for imputing missing values for pretrial detention and the race and ethnicity indicators (Gelman and Hill, 2007, ch. 25). Imputation proceeds by specifying a model that predicts values for each variable with missing values as a function of other variables from the model of interest. The predictive models used here included all of the control variables on the right-hand side (age, attorney type, second felony charge, criminal justice status, prior felony, prior prison sentence, and charge seriousness); preliminary analysis showed that these models yield strong predictions in each case. Models for detention and defendant’s race are then fit jointly and iteratively with the model for the outcome of interest. As the sampler converges on stable estimates of the missing values, those predictions are incorporated in the estimation of the main model.

### 4. Results

Models of pretrial detention, guilty pleas, and sentence severity appear in Tables 2–4 respectively. In interpreting these tables it is important to keep in mind some basic features of Bayesian estimation. In a Bayesian framework the data are assumed to be fixed, not random samples from some repeatable process, while the coefficient estimates are random draws from the posterior distributions. Results from a Bayesian model are thus distributions—not point estimates—that contain precise and explicit information about the uncertainty of a given estimate. The tables thus report the distributional characteristics of the posterior samples. The first column in each table shows the posterior means of the logistic coefficient

|   | Mean  | 2.5%   | 97.5%  | \( p|\beta| > 0 \) | Odds ratio |
|---|-------|--------|--------|----------------|------------|
| \( \gamma_0 \) | Intercept | –0.552 | –0.853 | –0.275 | 1.000 | 0.576 |
| \( \gamma_{10} \) | Black defendant | 0.299 | 0.140 | 0.454 | 1.000 | 1.349 |
| \( \gamma_{11} \) | Anglo-Black income ratio | 0.045 | –0.257 | 0.341 | 0.620 | 1.047 |
| \( \gamma_{12} \) | Black poverty concentration | –0.171 | –0.483 | 0.141 | 0.876 | 0.843 |
| \( \gamma_{20} \) | Latino defendant | 0.315 | 0.396 | 0.683 | 1.000 | 1.674 |
| \( \gamma_{21} \) | Anglo-Latino income ratio | 0.090 | –0.204 | 0.400 | 0.710 | 1.094 |
| \( \gamma_{22} \) | Latino poverty concentration | –0.174 | –0.493 | 0.145 | 0.876 | 0.840 |
| \( \beta_3 \) | Age 20–29 | 0.021 | –0.071 | 0.115 | 0.678 | 1.022 |
| \( \beta_4 \) | Private attorney | –1.037 | –1.173 | –0.901 | 1.000 | 0.355 |
| \( \beta_5 \) | Second felony charge | 0.288 | 0.198 | 0.384 | 1.000 | 1.334 |
| \( \beta_6 \) | Criminal justice status | 0.829 | 0.734 | 0.925 | 1.000 | 2.291 |
| \( \beta_7 \) | Prior felony conviction | 0.689 | 0.574 | 0.802 | 1.000 | 1.991 |
| \( \beta_8 \) | Prior prison sentence | 0.402 | 0.268 | 0.531 | 1.000 | 1.495 |
| \( \beta_9 \) | Arrest charge seriousness | 0.900 | 0.809 | 0.993 | 1.000 | 2.460 |
estimates, which are usually interpreted like the point estimates in classical regression. The next three columns describe the uncertainty of the estimates: the second and third columns report the upper and lower bounds of the central 95% of the posterior samples, and the fourth column reports the proportion of the sampled estimates that lie on the same side of zero as the mean. These proportions are precise measures of the degree of confidence that is warranted in a true—i.e. non-zero—effect. The last column in each table shows the posterior means in the form of odds ratios.

4.1. Pretrial detention

In the model predicting pretrial detention in Table 2, consider first the individual-level effects. The mean estimate of the intercept is -0.55, corresponding to a probability of detention of about 36% for the average male defendant. The main variables of interest here are race and ethnicity, and the estimates of \( \gamma_{10} \) and \( \gamma_{20} \) show clear evidence of bias. African American defendants are detained at a disproportionately high rate, and Latinos even more so: mean odds of detention for blacks are 4.135, or 35% higher than for the average defendant, and for Latinos 67% higher, net of other ascriptive, legal, and processual factors.\(^4\) For the black and Latino main effects the posteriors support 100% confidence in a true positive effect. Other individual-

\(^4\) Since all covariates are mean-centered, the appropriate reference for all dummy variables is the predicted mean, given by the intercept, not the omitted category.
level variables show predicted associations, with the exception of age: defendants age 20–29 are no more likely than average to be detained. Those represented by private attorneys are detained at less than half the average rate. Legally relevant factors do much of the heavy lifting in this model: a second felony charge, active status in the criminal justice system, a prior felony conviction, and a prior prison sentence all raise the likelihood of detention, and a two standard deviation increase in the seriousness of the arrest charge increases the odds of detention two and a half times. For control variables $\beta_4$ to $\beta_9$, posterior samples support 100% confidence.

Social context affects pretrial detention, if at all, in unexpected ways. Income inequality shows no effects on detention decisions for either black or Latino felony defendants ($c_{11}$ and $c_{21}$). The effects of poverty concentration appear to be negative ($c_{12}$ and $c_{22}$), suggesting that in this sense African Americans and Latinos may be treated more leniently in counties where they are most disadvantaged. This is, to say the least, counterintuitive. The posteriors offer nearly 90% support for the effects of poverty concentration for both groups.

4.2. Guilty pleas

The analysis of pretrial detention is to some degree a prelude to the analysis of guilty pleas, where we will apply the first tests of the cumulative disadvantage argument. Results from that analysis appear in Table 3. The intercept reflects the fact that on average felony defendants plead guilty in about two thirds of cases. Results suggest further that this figure is skewed by race and ethnicity. African American defendants may be slightly less likely to plead guilty than the average defendant, but the mean difference is small (the difference in odds is about 6%) and the posterior offers only about 78% confidence in a true effect. Black defendants appear to plead guilty at higher rates in counties where blacks are poor relative to whites, and at lower rates where poor blacks are spatially concentrated. Again, however, only modest confidence in the estimates is warranted (about 83%). Latinos in this sample are even more disinclined than black defendants to plead guilty, but they do so most often where they are most disadvantaged. Coefficient estimates for Latino income inequality and poverty concentration are both substantively strong, and come with over 99% confidence.

Cumulative effects are shown in the coefficients for pretrial detention and related interactions. The odds of pleading guilty for felony defendants who are detained before trial ($c_{3}$) are more than twice those for the average defendant. The impact of detention is weaker on African American defendants than others, but remains strongly positive, with net odds of $e^{0.843-0.214} \approx 1.9$. Detention effects do not differ for Latinos. The net impacts of the main and interaction effects can be illustrated with a plot of the predicted probabilities of pleading guilty, calculated from the posterior densities, conditional on race-ethnicity and detention status. Fig. 1 shows the resulting distributions in the form of boxplots. All groups of defendants plead guilty more often than not, with credible probabilities ranging between 50% and 90%. Within this range, pretrial detention is the key differentiating factor: regardless of race, probabilities of pleading guilty for defendants who are not detained are mostly under 65%; for those who were detained, the mass of the density is above 70%. But race-ethnic differences are apparent as well, with Latinos less likely to plead guilty than Anglos, whether detained or not; and detained black defendants less likely to plead guilty than detained Anglos.

Estimates for control variables contain a few surprises. Age has no apparent effect. Odds of pleading guilty for defendants with private attorneys are about 34% above average. Legal variables seem to point in different directions. Defendants who are charged with a second felony, who are active in the criminal justice system, and who have already been convicted of a felony all plead guilty at a higher than average rate. The logic here seems to be that any of these conditions puts the defendant at a disadvantage and makes it easier for prosecutors to extract a plea. But contrary to this reasoning, defendants who have served a term in prison and those arrested for relatively serious crimes are considerably less likely to plead guilty than the average defendant.
4.3. Sentencing

Table 4 shows results from the analysis of sentence severity. The intercept shows that the vast majority of convicted felons are incarcerated in jail or prison, with estimated odds of more than 4:1. Taking into account the second cut point $C_2$, the mean estimated odds of a prison sentence are $e^{1.48 - 2.4} \approx 0.4$. Put more intuitively, for the average convicted felon in this sample the probability of a noncustodial sentence is about 0.17, the probability of a jail sentence is about 0.55, and the probability of a sentence to prison is 0.28.

Estimated main effects of race and ethnicity show powerful disparities. For African American defendants, the odds of receiving the next-most severe sentence are about 26% higher than they are for the average defendant, and odds for Latinos are more than 30% higher. These tendencies are mostly unaffected by the racial environments of local court systems. Harsh sentencing of black defendants may be mitigated (unexpectedly) in counties with high black poverty concentration: the mean coefficient estimate is substantial, but confidence in a true effect is only about 70%. Anglo-Latino income inequality and Latino poverty concentration are not associated with racial disparities in sentencing.

Cumulative effects are strong, with some evidence that they are mediated by race, especially for Latinos. The posterior mean for $\gamma_3$ is positive, and shows that pretrial detention multiplies the average odds of a more severe sentence by three times. This effect does not differ for African Americans, but this may hide a more complicated reality. Results from the proportional odds test (see note 3) suggest that detention conspicuously raises the odds of incarceration for black defendants (for $y_1 > 1$, $\gamma_4$ is positive), but lowers their odds of going to prison (for $y_1 > 2$, $\gamma_4$ is negative). The detention effect is clearly attenuated for Latinos, to net odds of about 2.5—still strongly positive. Pleading guilty cuts the odds of a more severe sentence by two thirds across all defendants ($\gamma_6$). Sentence discounts may be slightly greater for black defendants, but support for the inference is only about 75%. Discounts are much larger than average for Latinos ($\gamma_8$). For them, the net effect of pleading guilty is 0.11—almost a 90% reduction in the odds of a more severe sentence.

These complex interactions are unpacked in Fig. 2, which shows predicted probabilities of being sentenced to prison for convicted Anglos, African Americans, and Latinos, broken out in terms of whether they were detained or released before adjudication, and whether they were adjudicated at trial or pled guilty. Note, first, that there is more uncertainty—the boxes are wider—for cases decided at trial. Perhaps some of this uncertainty arises from inherent randomness in sentences following trials. But more fundamental is the fact that relatively few defendants are convicted at trial, so estimates for subgroups are necessarily more vague than they are for cases that are pled out. Despite this relative uncertainty, differences associated with detention status, mode of conviction, and race-ethnicity are clear. The most obvious and expectable result is that guilty pleas reduce sentence severity across the board—but more so for Latinos than others, regardless of detention status. Pretrial detention clearly increases sentence severity. This difference is sharpest for cases decided by guilty pleas: in the lower half of the graph there is no meaningful overlap between distributions for detained and not-detained defendants.

Fig. 2. Posterior predictive densities: probability of prison sentence by detention status, mode of conviction, and race-ethnicity.

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5 Probabilities of imprisonment are calculated from the posterior samples by including $C_2$ in the prediction equations. This is strictly for clarity of presentation. Omitting $C_2$ yields estimated probabilities of any kind of carceral sentence (jail or prison). These probabilities are quite high; when they are plotted, the relationships among the densities are unchanged, but the boxplots are crowded to the right of the figure.
Race is the nub of the matter, and here large disparities remain after the effects of path dependencies are sifted out. Along each of the four paths analyzed here, sentences given to Anglos are markedly less severe than those given to African Americans or Latinos. Under three of the four scenarios Latino defendants fare the worst, most obviously those whose cases are adjudicated at trial. For Latinos who are tried and not detained, sentences are about the same as for Anglos who are tried and detained; Latinos who are detained and found guilty at trial are sentenced more harshly than any group analyzed here, with reasonable probabilities of a prison sentence between 70% and 90%. Black-Anglo disparities are apparent as well. Indeed among defendants who are detained and then plead guilty, black felons receive the harshest sentences. This is the result of the insufficiently understood bonus Latinos receive for pleading guilty. Otherwise, predicted probabilities of a prison sentence for black defendants lie between those for Anglos and Latinos.

Note, finally, that these racial-ethnic disparities are apparent notwithstanding the strong influences shown by most control variables. Only the age variable shows no association at all with sentence severity. Remarkably, having a private attorney appears to raise the odds of a more severe sentence by about 6%—albeit with only about 80% confidence. Estimates for the legally relevant variables conform entirely to expectations: defendants whose cases denote higher risk, who have more extensive criminal histories, and who are arraigned for more serious crimes are all likely to be sentenced more severely.

### 4.4. Estimating cumulative bias

The sentencing severity model in Table 4 and the predictions in Fig. 2 offer strong evidence of racial-ethnic bias affecting both black and Latino defendants, and demonstrate the crucial importance of taking path dependencies into account in estimating the degree of bias. But the picture remains incomplete because the model of sentencing outcomes represents observed path dependencies in only a truncated way, and therefore may underestimate the extent of cumulative racial disadvantage. For example, while it includes the proximate impact of pretrial detention, it does not include the fact that African Americans and Latinos are more likely than Anglos to be detained in the first place. Those influences can be factored in by calculating conditional probabilities of sentencing outcomes for all four combinations of detention/release and guilty plea/trial events, and comparing those probabilities across different racial-ethnic groups. To estimate these probabilities we can use the posterior densities shown in Figs. 1 and 2, plus analogous densities from the analysis of pretrial detention, to estimate these cumulative effects. One additional estimation step is required to bridge the gap between trial and sentencing: we must estimate the probabilities of a guilty verdict, given that the case went to trial, for detained and non-detained defendants.  

I estimated a model of guilty verdicts, using the 3943 cases that went to trial, containing the same predictors as the model of guilty pleas shown in Table 3, and incorporated those results into the calculation of the conditional probabilities. This model is not of intrinsic interest, and is not shown here because it lacks information—concerning the strength of the evidence, availability of witnesses, and so on—that would be required for a convincing explanatory model of trial outcomes.

The full set of conditional probabilities by path and race-ethnicity is shown in Table 5. Race-ethnic groups are arrayed on the columns and the pathways are arrayed on the rows, with the last row showing net probabilities of a prison sentence (column sums). The cell entries are the mean predicted probabilities that the average Anglo, black, or Latino felony defendant will follow a given path to a prison sentence, with 95% credible intervals in brackets. So, for example, the entry in the fourth row of the first column shows that for the average Anglo felony arrestee in the sample, the mean predicted chance of being detained and pleading guilty and receiving a prison sentence is 8.5%, with a 95% probability that the true value is between about 7% and 11%. Crucial comparisons are across the rows, and the important question is whether groups are over- or underrepresented on a particular path to prison. These comparisons appear in Fig. 3 in the form of density plots.

Looking first at the net probabilities, it appears that once prior events are fully taken into account, Latinos and blacks experience about the same rather large cumulative disadvantage: from the point where initial charges are filed, the average African American or Latino defendant has about a 19% chance of going to prison, while the rate for the average Anglo is about 15%—a 26% difference. These disparities arise by somewhat different routes for different groups, but they follow mostly from...
the differential influence of pretrial detention. Consider first the path that leads through detention and trial, shown in the second row of the table and plot (b) in Fig. 3: Black and Latino defendants are overrepresented by two and a half times relative to Anglos. Average disparities are smaller on the detention-plea path (third row of the table and plot (d)) but more sharply drawn: relative to Anglos, blacks are about 32% more likely to end up in prison by this route, and the predicted disparity for Latinos is 42%. Defendants who are not detained mostly escape racial-ethnic disparities. There are no group differences among those who are not detained and plead guilty; there may be differences among those who are not detained and go to trial—the average Latino is least likely to follow this path, and the average black defendant is most likely—but since the numbers here are so small, the differences may be regarded as trivial. When all is said and done, whether defendants plead guilty or go to trial has very little impact on racial disparities, but this non-effect happens in different ways for Latino and black defendants. For Latinos, process effects cancel each other out: they are less likely than any other group to plead guilty, which should raise average sentence severity; but those who do plead guilty receive a larger sentence discount than blacks or Anglos. The other way to put this, of course, is that Latinos who refuse to plead are penalized more harshly than Anglo or black trial defendants. The average black defendant is only slightly less likely than the average defendant to plead guilty, but blacks who are detained are much less likely to plead. For blacks, thus, pretrial detention has both direct and indirect effects (via the availability of plea deals) on sentence severity.

5. Discussion and conclusions

This article has sought to demonstrate that accurate assessment of racial disparities in criminal sentencing requires attention to structural forces that impinge on decisions about particular cases. I have outlined and tested a two-dimensional structural model of that emphasizes, first, cumulative disadvantages that emerge at preliminary stages of the court process and may accumulate across subsequent decision points; and second, the contexts in which criminal courts operate, particularly with regard to racial inequality and the concentration of minority poverty. The model was tested using data from a national sample of urban jurisdictions, analyzed with a series of multilevel models designed to identify both path- and context-dependent effects.

Three important findings stand out. First, results showed strong evidence of racial-ethnic bias at the sentencing stage of the criminal court process (Table 4 and Fig. 2). Going by main effects alone, the analysis in Table 4 showed that odds of the next-most severe sentence for convicted black defendants are 26% higher than for the average convicted defendant, and those for Latinos are more than 30% higher—estimates much larger than those shown in many studies. When we take into account the disparate effects of detention and guilty pleas as well, predictions in Fig. 2 show that, depending on the path defendants take through the system, mean black-Anglo and Latino-Anglo disparities in the probability of a prison sentence ranged from a low of 10% (between Anglos and Latinos who are detained and plead guilty) to a high of 100% (between Latinos and Anglos who are not detained and go to trial).

The second important finding is that cumulative effects are systematic and striking. Invidious main effects of race and ethnicity are strong in the earlier stages of the process, particularly the decision to detain, and these effects echo across
subsequent decisions. Blacks and Latinos are much more likely than Anglos to be detained before trial; detention directly increases the odds of a prison sentence more than three times, and it indirectly raises the odds for black defendants by lowering the rate of plea bargains. The impact of guilty pleas is more complex: on average, defendants receive sentence discounts of about 66% for pleading guilty, but the discount for Latinos is clearly much greater (nearly 90% lower odds) and the discount for black defendants may be slightly greater than average. Cumulative probabilities show a net sentencing disparity of 27% in favor of Anglos. This figure appears roughly the same as the disparities shown by the sentencing model alone (26–30%), but direct comparison is hazardous because they are based on different samples. The sentencing analysis is based on outcomes only for male defendants who are convicted of felonies; the cumulative results are based on the full sample of male defendants initially charged with felonies, most of whom are ultimately convicted of misdemeanors (11%) or never convicted at all (44%).

Third, results gave no support to hypotheses about contextual effects on sentencing. Indicators of racial inequality and poverty concentration are mostly unrelated to outcomes for minority defendants, and the associations that do appear cut against the grain. Income inequality has no impact on the use of detention or sentence severity. Inequality appears to encourage guilty pleas for both black and Latino defendants, but the reasons for this association are not at all clear; in any event, it is difficult to see it as evidence of racial oppression. There is no evidence at all that racial disparities are greater in counties with high minority poverty concentration.

The most important theoretical implications of these results have to do with the cumulative disadvantage hypothesis. The strict definition of cumulative disadvantage given by DiPrete and Eirich (2006) requires evidence of accelerating status differences across life events—in this case, widening disparities between Anglos and minorities. The clearest evidence in favor of the hypothesis is the net result that, while minorities are overrepresented in the initial sample of arraigned defendants, they are still more highly overrepresented among defendants receiving the harshest sentences. But when the analysis unpacked these net disparities by analyzing the sequence of events that is endogenous to the court process, results became considerably more complex. Anglo-minority disparities are widened most potently by the invidious use of pretrial detention, and Anglo-black disparity is further widened by a reduced tendency to plead guilty among black detainees. But while the sentencing phase of the process generates race-based disparities of its own, we see no further accumulation of disadvantage based on prior events; indeed, for Latinos, outcomes appear partially to offset prior disparities arising from detention and guilty pleas.

These results, along with the limitations of the analysis on which they are based, suggest fruitful lines of investigation for the future. First, it is not at all clear why cumulative disadvantage should operate at some stages of the criminal court process and not others. One explanation that fits with much of the literature is that judicial sentencing is the most formalized part of the process, hence the least likely to be influenced by labeling effects. But in a world where almost all sentences are based on guilty pleas, and where prosecutors have predominant power over the terms of acceptable pleas (Scott and Stuntz, 1992; Standen, 1993; Stuntz, 1997), formal sentencing may be redundant. Insofar as that is the case, research might more profitably plumb the murky depths of the prosecutor’s office. Second, while in these data black and Latino defendants experience about the same net disadvantage relative to Anglos, they are treated in different ways at different decision points. The fact that the data used here are from a national sample of urban jurisdictions suggests that these differences are not the adventitious results of idiosyncratic local cultures, but may in fact be structural. To unspool these differences requires closer attention to more fine-grained mechanisms of disadvantage than those studied here. For example this study treated pretrial detention as a binary event, but in fact it is the product of a series of decisions about whether the defendant is eligible for release under any circumstances, whether bail is required, and if so how high it should be (Albonetti, 1989; Demuth, 2003; Schlesinger, 2005). How these semi-independent decisions are linked to each other and to sentence outcomes requires further study. Finally, I would argue that this analysis by no means closes the books on the effects of jurisdictional differences on court outcomes. This study focused rather narrowly on two factors related to race—income inequality and concentrated poverty—and in doing so could have overlooked other more fruitful hypotheses. It may be, as Sampson and Laub (1993b) suggest, that effects of racial oppression operate only in the juvenile justice context, where procedures are typically more informal than in the criminal courts. Further work on this project will explore two factors that figure prominently in the macro-literature on punishment and the criminal courts: the role of conservative politics in producing more punitive and racially biased responses to crime (Beckett, 1997; Hagan, 2010; Jacobs and Carmichael, 2001; Jacobs and Helms, 1996), and the impact of caseload variation on strategic decision-making by prosecutors (Stuntz, 1997).

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