

Racial Disparities in Criminal Sentencing Vary Considerably across Federal Judges

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Abstract

Studying 380,000 criminal cases in federal district courts from 2006 to 2019, we replicate previous findings that aggregate, conditional racial disparities in sentence lengths are large. We further show that estimated racial disparities in sentencing vary considerably across judges. Results suggest that judges assign white defendants sentences that are conditionally 13% shorter than Black defendants' and 19% shorter than Hispanic defendants', on average. A judge who is one standard deviation above average in terms of estimated Black-white disparity gives Black defendants sentences that are conditionally 39% longer than white defendants', compared to the average disparity of 13%. A judge who is one standard deviation above average in terms of estimated Hispanic-white disparity gives Hispanic defendants sentences that are conditionally 49% longer than white defendants', compared to the average disparity of 19%.

Note: A previous version of this work included estimates on individually identified judges. Thanks to helpful feedback, we no longer place enough credence in judge-specific estimates to make sufficiently confident statements on any individual judge. We encourage others not to rely upon results from earlier versions of this work.

Introduction

Existing research shows that the U.S. criminal justice system is rife with racial inequality and suggests that part of this inequality operates at the sentencing stage (Commission, 2018). With respect to criminal sentencing, average racial disparities are substantial, with federal judges giving Black and Hispanic defendants harsher sentences than similar white defendants. This is especially true among men: according to the U.S. Sentencing Commission, federal judges give white men sentences 19% and 5% shorter, respectively, than the sentences they give Black and Hispanic men who commit similar crimes.

Still, average racial disparities do not express the variability in judges' racially disparate sentencing patterns. Presumably, the conditional difference in sentences across racial groups is not the same for every judge.

With respect to federal criminal cases, we answer four primary questions: (1) What is the average disparity between the sentences of observationally equivalent Black and white defendants? (2) What is the average disparity between the sentences of observationally equivalent Hispanic and white defendants? (3) How much do conditional Black-white sentencing disparities vary across judges? (4) How much do conditional Hispanic-white sentencing disparities vary across judges?

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Literature on Aggregate Disparities

Racial disparities are a common, and well-researched, issue in the sentencing practices of U.S. federal courts. Most research on aggregate disparities in federal sentencing has focused on the disparity between Black and white defendants.* Black defendants consistently receive harsher sentences than white defendants (Feldmeyer and Ulmer, 2011; Mustard, 2001; Rachlinski and Wistrich, 2017). Young Black men, in particular, are sentenced most harshly (Doerner and Demuth, 2010). Yang (2015) finds that Black-white disparities in sentencing increased after *United States v. Booker*, in which the Supreme Court held the U.S. Sentencing Guidelines to be advisory rather than mandatory. However, others find that no such increase occurred (Starr, 2013). While scholars debate whether *Booker* increased Black-white disparities in sentencing, there is little debate on whether such disparities have existed both before and after the decision. These disparities also show up in state sentencing (Abrams et al., 2012) and state bail decisions (Arnold et al., 2018).

The literature on Hispanic-white sentencing disparities is more variable. Young Hispanic men do receive particularly harsh sentences (Doerner and Demuth, 2010). Still, some argue that the Hispanic-white sentencing disparity can be explained as a function of noncitizens being sentenced more harshly and Hispanic defendants being disproportionately noncitizens (Light, 2014; Light et al., 2014).

Literature on Interjudge Differences in Disparities

In addition to aggregate disparities, this paper addresses *differences across* federal judges in their sentencing disparities based on race. The literature on interjudge differences in racial disparities is much sparser than the literature on aggregate racial

*What research does exist on other groups finds that Asian American defendants are sentenced similarly to white defendants (Johnson and Betsinger, 2009). Due to unique federal jurisdiction in Indian Country, Native American defendants face much harsher sentences for crimes prosecuted federally than defendants of other races who commit them elsewhere and who would only face state prosecution (Droske, 2008). On the whole, though, Native American defendants do not receive harsher sentences than other defendants in the federal courts (Ulmer and Bradley, 2018). Young Native men, though, receive the harshest sentences of almost any group (Franklin, 2013).

disparities. Some relevant evidence exists among judges at a lower level, namely, judges in the Circuit Court of Cook County: in terms of interjudge differences in racial disparities, [Abrams et al. \(2012\)](#) find that Cook County judges differ substantially vis-à-vis incarceration rates but not vis-à-vis sentence lengths. The field also knows how much judges differ in terms of overall sentencing severity: both [Scott \(2010\)](#) and [Yang \(2014\)](#) find that interjudge differences in overall sentencing severity are wide and that the differences have generally grown Post-*Booker*.

Methods

Data

Source We analyze the JUSTFAIR (Judicial System Transparency through Federal Archive Inferred Records) database of criminal sentencing decisions in federal courts ([Ciocanel et al., 2020](#)). JUSTFAIR is compiled from five public sources, includes almost 600,000 records from fiscal years 2001-2018, and links information about defendants, their federal crimes, their sentences, and the sentencing judges. Here we briefly summarize the JUSTFAIR data pipeline presented by [Ciocanel et al. \(2020\)](#). Ciocanel and colleagues obtained information about criminal cases, defendants, and sentences from the U.S. Sentencing Commission (USSC) and merged this dataset with the Federal Judicial Center (FJC) Integrated Database to obtain court docket numbers for each case. The docket numbers allowed them to access the PACER system and retrieve the initials of the sentencing judges. Finally, they connected these initials with name, demographic, and education information of the judges from Wikipedia as well as by linking with the Federal Judicial Center Biographical Directory of Article III Federal Judges. As a result, the records in JUSTFAIR contain variables pertaining to the demographic characteristics of the sentenced individual; sentence characteristics, date, and federal district location; and sentencing judge name, appointment, and education information. Crucially to the current work, JUSTFAIR also includes the sections of the law relevant to the conviction and factors influencing the recommended sentence.

Because JUSTFAIR is a new database, we describe its limitations in detail in Appendix A.

We have extended the JUSTFAIR data pipeline to include the available 2018-2019 fiscal year federal sentencing data, which is updated yearly in the USSC datafile for individual offenders and quarterly in the FJC Integrated Database. Our merging of offender, sentence, and judge information proceeded largely as described above and by Ciocanel et al. (2020). Several USSC variables denoting the total prison sentence, the coding of the offense type, and the post-Booker reporting categories changed in the USSC database, therefore we adjusted the data processing approach of Ciocanel et al. (2020) to remain consistent with the variables in JUSTFAIR. This extended the dataset we analyze in this study by over 30,000 cases.

In our analysis, we include cases only from 2006 and later. We are principally concerned with racial disparities observed after the *Booker* decision, and so cases before 2006 lie outside of our target population. We further exclude immigration cases because of the unique use of fast-track sentencing in these cases and the extreme concentration of these cases in several southwestern district courts (Hartley and Tillyer, 2012). We also do not consider cases for which we cannot infer the sentence length; specifically, in the JUSTFAIR database, there are about 13,000 cases that resulted in a sentence length of zero according to the continuous sentence total variable but resulted in prison time according to the categorical variable of imprisonment type. These two features contradict each other, hence we consider the 13,000 cases to be missing the outcome. We therefore remove these cases from the analysis. After these pre-processing steps, the analytic sample represents about 380,000 cases corresponding to 1116 judges. The median number of cases per judge is 263 ($\mu = 358.7$, $\sigma = 389.6$).

Measures The outcome of interest is the length of the sentence assigned to the defendant. We cap the sentence length at 470 months because life sentences are generally coded as 470 months. We log-transform the outcome because its distribution

has a positive skew[†] (Bushway and Piehl, 2001). Accordingly, we interpret the results in terms of percentage changes rather than in terms of linear changes in months of prison time.

The case-level characteristic of principal interest is the defendant’s race and ethnicity, which we measure with the categories ‘Hispanic,’ ‘Non-Hispanic Black’ (henceforth ‘Black’), ‘Non-Hispanic White’ (henceforth ‘white’), and ‘Other Race/Ethnicity.’ We collapse the groups in this way because, unfortunately, the sample sizes of the various groups contained in the final category are not large enough for us to perform statistically informative cross-judge analyses. Using these definitions of race and ethnicity, the median judge imposed sentences in 41 cases with Hispanic defendants ($\mu = 97.3$, $\sigma = 210.6$) and in 69 cases with Black defendants ($\mu = 114.1$, $\sigma = 137.7$).

We include an extensive set of control variables:

- the guideline minimum sentence, with any statutory minimum sentences taken into account,
- the defendant’s criminal history points,
- crime type, namely ‘violent crime,’ ‘drug-related crime,’ ‘embezzlement, fraud, theft,’ or ‘other,’
- whether the case was settled by plea agreement or trial,
- sentencing year, and
- defendant demographics, namely sex, age, U.S. citizenship status, and educational attainment.

Arguably the most important of these control variables is the guideline minimum sentence, which is standardized based on factors like the severity of the crime. Thus, at

[†]Because the log of zero is undefined, we add one to every sentence before log-transforming so that nonincarceration outcomes (zero-month “sentences”) have a defined value in our estimation. It is challenging to address zero-month sentences in analyses where sentence length is the dependent variable, and there is no perfect solution to the issue. Adding one to all sentences is a common approach (Fischman and Schanzenbach, 2012; Light, 2021; Rehavi and Starr, 2014; Yang, 2015). This approach appreciates the fact that nonincarceration outcomes are real outcomes that can contribute to racial disparities, while also appreciating the fact that a nonincarceration outcome entails less incarceration time than any other sentence. Nevertheless, we acknowledge that this approach masks nuance in the difference between a nonincarceration outcome and a one-month sentence.

least in a theoretical world with no racial disparities, we would expect to see roughly equal sentences imposed on two defendants who are from different racial groups but who have the same guideline minimum sentence.

While the defendant's demographics are extralegal factors that judges ought not consider in their sentencing, we nevertheless control for these demographics because they may capture variation in relevant legal factors. For example, if a judge hears cases where many Hispanic defendants have a unique situation not captured by observed legal variables, and if this unique situation also is associated with educational attainment, then controlling for educational attainment accounts for some of the variation due to the unobserved prevalence of this situation.

Analytic Strategy

Empirical Model We estimate a hierarchical linear model of log transformed sentence lengths where cases (Level 1) are nested within federal judges (Level 2). In particular, we estimate the following model:

$$\text{(Level 1)} \quad \log(Y_{ijk}) = \beta_{0j} + \beta_{100}\mathbf{X}_{ij} + \beta_{1j}\mathbf{C}_{ij} + \epsilon_{ij} \quad (1)$$

$$\text{(Level 2, Intercepts)} \quad \beta_{0j} = \gamma_{000} + \zeta_{0j} \quad (2)$$

$$\text{(Level 2, Slopes)} \quad \beta_{1jk} = \delta_{100k} + \eta_{1jk} \quad (3)$$

where Y_{ijk} is the length of the sentence corresponding to case i by judge j for a defendant of race k , β_{0j} is the intercept for cases heard by judge j , \mathbf{X}_{ij} is a vector of defendant control characteristics corresponding to case i by judge j , β_{100} is a vector of slopes between control characteristics and log transformed sentence length, \mathbf{C}_{ij} is a vector of racial group binary indicators, β_{1j} is a vector of random slopes between

logged sentence length and each racial group indicator among cases heard by judge j , ϵ_{ij} is an idiosyncratic error term, γ_{000} is the overall intercept, ζ_{0j} is the deviation of the intercept for cases heard by judge j from the overall intercept, β_{1jk} is the random slope corresponding to racial group k represented in β_{1jk} , δ_{100k} is the overall slope between log transformed sentence length and racial group indicator k , and η_{1jk} is the deviation of the slope for cases heard by judge j from the overall slope corresponding to racial group k . Our model assumes that ϵ_{ij} , ζ_{0j} , and η_{1jk} each are normally distributed with mean zero.

We are primarily interested in the values of η_{1jk} for each judge. Taking the example where $k = Black$ and the reference category is white defendants, the value of $\eta_{1j,Black}$ will answer the following question: how much greater is the Black-white sentencing disparity when judge j hears cases compared to when the average judge hears cases, controlling for defendant and case characteristics? This value does not necessarily reflect directly unfair treatment based on race, one reason for this being that a judge may hear cases in which Black and white defendants are unbalanced with respect to unobserved legal characteristics, even above and beyond observed control variables. The general approach of conditioning on observed factors is nevertheless common in research on racial sentencing inequalities (Feldmeyer and Ulmer, 2011; Light, 2021), in part because cases do not seem to be randomly assigned to judges even within districts. Regarding variability in $\eta_{1j,Black}$ values, we note that, because our model estimation shrinks random slopes and intercepts for judges with a small number of cases, such judges do not cause random slopes and intercepts to appear unduly variable.

The model includes judge random effects instead of judge fixed effects because the former accommodate random slopes, which are the primary parameters of interest in this study. We forgo a hybrid model because it is less parsimonious and does not influence the estimated random slopes (Schunck, 2013), our primary interest. The model excludes district fixed effects because judges' racial disparities should be evaluated based on all other judges' disparities, rather than just those in the same district. Still, we estimated an alternative model with district fixed effects and the results did not

differ in any substantial way[‡]. Thus, even if the two specification options were equally compelling theoretically, our preferred specification is more parsimonious and does not affect the main results.

Results

Aggregate Disparities

Conditional on observed case and defendant characteristics, judges assign white defendants sentences that are about 13% shorter than Black defendants' and 19% shorter than Hispanic defendants', on average. In contrast, defendants in other racial groups receive sentences about 10% conditionally shorter than white defendants' sentences, on average (Table 1). Given the extremely small standard errors and p -values of all these estimates, sampling error is a very weak candidate for explaining these patterns.

Table 1. The average estimated racial disparities in logged sentence length. Each percent change in the first column represents what percent greater/lesser the conditional average sentence length is for defendants from the corresponding racial group, relative to white defendants. This quantity comes from the following formula, where δ_{100k} represents the estimated coefficient corresponding to racial group k , as shown in the "Estimate" column: Percent Change = $100 \times (e^{\delta_{100k}} - 1)$.

	% Change	Estimate	Std. Error	p -value
Intercept		2.32	0.02	$<2 \times 10^{-16}$
Black	12.77	0.12	0.01	$<2 \times 10^{-16}$
Hispanic	19.15	0.18	0.01	$<2 \times 10^{-16}$
Other Race	-10.28	-0.11	0.02	5.82×10^{-11}

Our aggregate results are in line with previous studies, though they perhaps point to even more aggregate disparities than found in earlier timespans with different sampling mechanisms. In an investigation of a 2000–2002 pre-*Booker* USSC dataset, **Feldmeyer**

[‡]All estimates of interest—average conditional racial disparities and interjudge standard deviations in conditional racial disparities—differed by less than 0.01. See the online supplementary materials for the corresponding code.

and Ulmer (2011) find that, after controlling for a considerable set of legal and extralegal factors, Black defendant sentences are 6% longer and Hispanic defendant sentences are 1% longer on average than white sentences. In an analysis of a 2006–2008 multi-agency-based dataset, Rehavi and Starr (2014) similarly find that, in the aggregate, Black defendants receive sentences that are 9% longer than those of similarly situated white defendants who commit the same crimes. Finally, using a federal sentencing dataset similar to ours but covering cases from 2000 to 2010, Yang (2015) finds that Black offenders receive 1.9 months longer sentences, and Hispanic offenders over 1.9 months longer sentences, than those of similar white offenders post-*Booker*.

Interjudge Variability in Disparities

How much do judges vary in their estimated racial disparities in sentencing? The estimates in the previous section show only the average extent of estimated racial disparities. We turn now to a discussion of how much judges are spread around this average. Table 2 shows that the spread is considerable for each racial group, with random slope standard deviations ranging from 0.21 to 0.31 log transformed years. The random intercepts, estimating judges’ sentencing severity against white defendants, also vary to a similar extent.

Table 2. Dispersion of random effects. Random intercepts— ζ_{0j} in Equation (2)—represent judges’ estimated sentencing severity toward white defendants. Random slopes— η_{1jk} in Equation (3)—represent judges’ estimated racial disparities compared to the average judge’s estimated racial disparities.

	Std. Dev.
Random Intercepts	0.35
Random Black Slopes	0.21
Random Hispanic Slopes	0.23
Random Other Race Slopes	0.31

Because interpreting the foregoing standard deviations is challenging given the log transformed dependent variable, we present a more intuitive account of the interjudge

variability in Table 3. As noted before, the average judge assigns Black defendants sentences that are conditionally 13% longer than white defendants'. However, a judge who is one standard deviation above average in terms of estimated Black-white disparity assigns Black defendants sentences that are conditionally 39% longer than white defendants', and a judge who is two standard deviations above average assigns Black defendants sentences that are conditionally 71% longer than white defendants'. Similarly, while the average judge assigns Hispanic defendants sentences that are conditionally 19% longer than white defendants', a judge who is one standard deviation above average in terms of estimated Hispanic-white disparity assigns Hispanic defendants sentences that are 49% longer than white defendants'. A judge who is two standard deviations above average assigns Hispanic defendants sentences that are conditionally 87% longer than white defendants'.

Table 3. The percent change in sentence length conditionally associated with the defendant being in different racial groups relative to being white by the average judge (column 1), by a judge one standard deviation above average (column 2), and by a judge two standard deviations above average (column 3), in terms of estimated racial disparities.

	% Change (Avg.)	% Change (1 SD)	% Change (2 SD)
Black	12.77	38.94	71.20
Hispanic	19.15	49.35	87.20
Other Race	-10.28	22.05	66.05

To test whether the variance in random slopes is significantly different from zero, we conduct a likelihood ratio test that compares our model to a model that excludes random slopes but is otherwise identical. The p -value resulting from this test is less than 2.2×10^{-16} , suggesting conditional racial disparities in sentencing really do vary across judges. The Bayesian Information Criterion for the model with random slopes is 1,209,679, compared to a much less favorable value of 1,211,157 for the model without random slopes. In short, if all judges' conditional racial disparities were actually the same, the foregoing values would be surprising.

Conclusion

Using the JUSTFAIR database of district court criminal sentences, we computed a hierarchical linear model of log transformed sentence length with cases nested within federal judges. We controlled for factors such as recommended sentence, crime type, presence of a plea agreement, sentencing year, defendant demographics, and more. From our model, we calculated the percentage by which judges' sentences given to Black and Hispanic defendants are conditionally greater than the sentences judges give to white defendants.

Our findings suggest that average racial disparities are sizeable and that judges vary nontrivially in terms of how racially disparate their sentencing patterns are. With respect to Black-white disparities, Black defendants on average receive 13% longer sentences than observationally equivalent white defendants receive, and a judge one standard deviation above average in Black-white disparities gives 39% longer sentences to Black defendants. With respect to Hispanic-white disparities, Hispanic defendants on average receive 19% longer sentences than observationally equivalent white defendants receive, and a judge one standard deviation above average in Hispanic-white disparities gives 49% longer sentences to Hispanic defendants. The online supplementary materials for this paper include a replication package with the data and code we used to yield these findings.

We emphasize some words of caution in interpreting our results. First, because cases are not randomly assigned to judges, we cannot know to what extent unobserved factors that systematically differ across judges drive the interjudge differences we find. A second limitation is our inability to observe every case, or even every district. Like most social science datasets, the JUSTFAIR database contains a sample rather than the population, and as with most social science datasets, one cannot know exactly what determines whether a case in the sampling frame is missing. If sample inclusion is unrelated to our measures of interest, then lacking the full population leaves our estimates more susceptible to random sampling error than they would be otherwise. If

sample inclusion is related to our measures of interest, then lacking the full population leaves our estimates more susceptible both to systematic error and random sampling error than they would be otherwise. In light of these limitations, our results should be seen as imperfect approximations for the degree of aggregate racial disparities and the interjudge variation therein.

Future research might extend analyses to state courts. While our work has examined criminal sentencing in federal district courts, we are cognizant that most sentencing in the United States is carried out in state courts. To understand interjudge variability in race-based sentencing disparities, it will be necessary to gather and analyze data from all 50 state court systems, as well as districts, territories, and other possessions. This will be challenging given that each of these systems has its own sentencing frameworks, data keeping practices, and levels of transparency, but will be worthwhile in order to help move the justice system towards greater equity.

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Appendix A: Data Limitations

Ciocanel et al. (2020) detail several measures they took to ensure the quality of the JUSTFAIR database. They validated merged records by checking for additional common variables (such as offense codes) in the original datasets, used two independent

sources to identify judge names from judge initials, and excluded records where sentencing dates fall outside the judges' activity periods. In addition, they carried out a manual data validation procedure for randomly sampled cases from the assembled dataset (Ciocanel et al., 2020). The validation set confirms the accuracy of the merging procedure: very few cases violate the assumption that the judge involved in a proceeding is the same as the sentencing judge. Nevertheless, while they corrected these cases in the validation set, there could be rare additional instances where a judge other than the sentencing judge became involved in proceedings post-sentencing, leading to an incorrect inference in the database.

While JUSTFAIR is, to our knowledge, the largest publicly-available database of federal sentences currently available, it nevertheless remains an incomplete database of the cases sentenced in 2001–2018 (extended in this work to 2019) due to issues pertaining to data quality and merging challenges. For example, when merging USSC and FJC sentence and defendant information, JUSTFAIR only retains cases where there is a unique matching. Similarly, when retrieving sentencing judge initials from PACER, criminal cases may include more than one defendant, and therefore JUSTFAIR only keeps records where all defendants with the same court docket number are associated with the same judge. JUSTFAIR also cannot include information on sealed federal cases. Other factors that prevent JUSTFAIR from being complete include the inability to distinguish between judges who have both the same initials and district, and the complete or partial lack of judge initials in certain districts or records. In particular, due to such data quality issues, JUSTFAIR contains no sentencing data from the Eastern District of North Carolina, the Southern District of West Virginia, the Southern District of Texas, the Middle District of Tennessee, the Northern District of Illinois, the District of Guam, and the District of the Northern Mariana Islands. The database also includes limited sentencing data (less than 33% of the starting USSC cases) from the Northern District of Texas, the Southern District of California, the District of Oregon, the District of New Mexico, the Western District of Oklahoma, and the Northern District of Florida.

Non-random assignment of cases to judges presents another limitation, not just in the case of the JUSTFAIR database but rather whenever federal judge effects are of interest. The Administrative Office of the US Courts claims that “The majority of courts use some variation of a random drawing” ([Administrative Office of the United States Courts, 2020](#)). This means that, “to assure equitable distribution of caseloads and avoid judge shopping” ([Administrative Office of the United States Courts, 2020](#)), the district courts have a rotation plan for cases assigned to judges; however, the US Courts Office also mentions that special expertise and geography are also considered in case assignment. Previous studies have exploited the random assignment of cases to judges in their analyses of sentencing equity ([Anderson et al., 1999](#); [Abrams et al., 2012](#); [Cohen and Yang, 2019](#)). Establishing random assignment has been considered key for these studies since it ensures that each judge receives a similar combination of cases and defendants (in terms of observable characteristics), so that unobservable characteristics can also be assumed to be similar across judges.

For instance, [Abrams et al. \(2012\)](#) analyze racial sentencing disparities in felony cases from Cook County, Illinois. To verify random assignment, they use a Monte Carlo simulation methodology for felony data from 1995 to 2001 to construct a randomly assigned dataset across characteristics such as defendant race, age, gender, and crime category, and use it to establish random assignment for their dataset ([Abrams et al., 2012](#)). Similarly, the study of the proprietary federal sentence dataset in [Cohen and Yang \(2019\)](#) relies on the assumption that cases are randomly assigned to judges in the same district court, focusing on observed case and defendant characteristics across Republican-appointed vs Democrat-appointed judges. Motivated by whether the political affiliation of a judge’s appointing president influences racial and gender gaps in sentencing decisions, the authors use a joint F-test to test whether there are significant differences in defendant characteristics by judge political affiliation (as well as by judge tenure and gender). Conditioning on sentencing year and district court fixed effects, they find that cases are randomly assigned to sentencing judges from each political affiliation ([Cohen and Yang, 2019](#)).

Our setting is different from these studies, given that we are 1) analyzing the large, publicly-available JUSTFAIR dataset of federal sentences from 2001-2018 (Ciocanel et al., 2020) and 2) interested in whether the cases in this dataset are assigned randomly to individual judges within each district (rather than to judges with different characteristics). We find that, when testing for random assignment using an F-test method similar to Cohen and Yang (2019) or using a Monte Carlo simulation method similar to Abrams et al. (2012), nearly every district shows evidence of nonrandom judge assignment. Specifically, nearly every district shows statistically significant between-judge differences in at least one case characteristic, such as defendant race, defendant sex, and offense type. Due to nonrandom assignment, some unknown component of between-judge variability in conditional racial disparities arises from differences in unobserved factors that should reasonably influence the sentence. Observed covariates probably make this component much smaller than it would be otherwise, but we cannot know how substantial the component remains after including these covariates.