Do Judges Have Tastes for Racial Discrimination?
Evidence from Trial Judges

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Abstract

There are numerous studies that find trial judges issue racially disparate sentences; however, whether these patterns reflect tastes for discrimination remains unclear. An alternative explanation is that black-white differences are legally warranted to the extent that racial groups differ along unobserved legal dimensions. Another possibility is that judges engage in statistical not taste-based discrimination. Building on Anwar and Fang (2006), this paper uses an empirical approach that distinguishes taste-based discrimination from these alternative explanations. The intuition is that if ordering of judicial incarceration rates depends on race, then this is symptomatic of taste-based discrimination. I find that in 3 of the 4 largest judicial districts in Kansas, there is evidence that trial judges exhibit tastes for racial discrimination.

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1 Introduction

On June 11, 2013, Supreme Court Chief Justice John Roberts places Judge Edith Jones of the 5th Circuit under formal review. At issue are a number of racially insensitive remarks that she made during a speech a few months prior at the University of Pennsylvania School of Law.¹ Her statements are problematic to the extent that they reflect latent racial prejudice and having prejudicial views is a precursor to discriminatory behavior. On the other hand, there is no ironclad rule that states a judge with prejudicial views must engage in racial discrimination. Judges with strong attachments to their official Code of Conduct could suppress any personal prejudices in order to maintain high levels of professional integrity (Gibson (1978)). The goal of this paper is to empirically assess whether judges engage in racial discrimination.

This paper focuses on the criminal sentencing decisions that trial court judges make. There are two important complications in trying to empirically identify discrimination in criminal sentencing. First, it is nearly impossible for the researcher to observe all of the relevant legal factors that influence judicial sentencing decisions.² This omitted variables problem undermines the modal approach in the empirical sentencing literature, which tries to identify discrimination by estimating racial sentencing disparities conditional on all observables available in data. Without the judge’s full information set, estimates of racial sentencing disparities will not reflect pure prejudice because they are based on comparisons across inframarginal rather than the marginal black and white felon (Becker (2010)).³

The second challenge is the potential for statistical rather than taste-based discrimination

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¹For example, she states that some groups including blacks and Hispanics are predisposed to committing more violent and heinous crimes. Judge Jones formerly served as Chief Judge of the 5th circuit and was on a short list of potential Supreme Court nominees under both Bush Presidents.

²A felon’s family role (Bickle and Peterson (1991)), employment status (Unnever et al. (1980)), educational attainment (Mustard (2001)), skin tone (Blair et al. (2004)), victim’s race (Baldus et al. (1983)), level of remorse (Ward (2006)) and other factors are known to influence sentencing decisions, but it is rare for all relevant characteristics to be included in data. Many of these variables also highly correlate with race.

³A number of studies exploit federal or state sentencing guidelines to estimate black-white sentencing gaps. Conditioning on the guideline sentence does not achieve identification to the extent that there are unobserved racial differences within sentencing cells.
(Phelps (1972), Arrow (1973), Coate and Loury (1993)). Statistical discrimination builds on the premise that while a felon’s latent criminality plays an important role in the judge’s decision calculus, the judge does not observe the felon’s true type with perfect certainty. The judge will try to circumvent this informational problem by trying to predict the felon’s true type based on observable characteristics. To the extent that race provides the judge with an informative signal regarding a felon’s type, her sentencing decisions will systematically vary with race. The more accurately race predicts latent criminality, the more differentiated sentencing will be. In this case, discrimination arises as race-neutral judges optimize under informational constraints.

This paper conducts an empirical exercise that confronts both of these fundamental challenges to identification. The exercise is motivated by a simple model that is similar to Anwar and Fang (2006), which is a study of police but not judicial discrimination. The model is useful because it allows for both taste-based and statistical discrimination and in doing so, generates an empirical prediction that distinguishes between the two. The prediction is that if judges engage in taste-based discrimination, then the rank-order of judge-specific incarceration rates will depend on the felon’s race. For example, if a judge has the highest white incarceration rate and the lowest black incarceration rate, then this is a tip off of taste-based discrimination. The intuition is that judges will not be inconsistent in their behavior towards different racial groups in relation to other judges unless they have tastes for discrimination. If judges only engage in statistical discrimination, the rank-order of judge-specific incarceration rates will not depend on race.

This paper builds on Anwar and Fang (2006) by allowing for richer heterogeneity in judicial preferences. Anwar and Fang (2006) assumes that police officers only differ from one another along the racial dimension. Theirs is a test of whether or not the average black or white officer engages in discrimination. The implicit assumption is that police officers have homogeneous preferences within racial groups. While this may reflect reality among police officers, the empirical literature on judicial behavior shows little evidence that a judge’s
race affects sentencing decisions (Spohn (1990), Uhlman (1978), Welch et al. (1988)). There is more evidence that shows substantial variation in sentencing behavior across individual judges (Mason and Bjerk (2013), Abrams et al. (2008)). In the context of judicial behavior, allowing for individual level heterogeneity is a more appropriate test of discrimination.

The empirical analysis uses administrative data from the four largest judicial districts in the state of Kansas. This dataset has the attractive feature in which all criminal cases are randomly assigned to judges. Random case assignment is important for identification. It rules out the possibility that cases are strategically assigned such that judges exhibit inconsistency even in the absence of prejudice. For example, if judge A is assigned the most violent black criminals, whereas judge B is assigned the least violent black criminals, then these judges will differ in minority sentencing for legal rather than taste-related reasons. Random case assignment precludes this possibility. It ensures that racial differences in both observed and unobserved covariates are balanced across all judges. Differences in case composition across judges will not drive the empirical results.

Both descriptive and statistical evidence show that the ordering of judicial incarceration rates depends on felon’s racial group in 3 out of the 4 largest judicial districts in Kansas. In Topeka, Wichita, and Kansas City, several judges show substantial deviations between their ranks of black and white incarceration rates. For example, in Topeka, there is a judge with the 2nd highest black incarceration rate but the 9th highest white incarceration rate among 9 total judges in the district. The formal test suggest that these deviations are unlikely to be due to statistical chance. These results imply that in each of these 3 districts, at least one judge violates equal protection by engaging in taste-based discrimination against some racial group. These results are neither explained by election year effects nor the possibility that judges have heterogeneous sentencing preferences towards certain types of crime.

The rest of the paper is organized as follows. In section 2, I discuss identification issues associated with conventional empirical approaches in the existing literature on judicial discrimination. Section 3 provides the theoretical framework that motivates the empirical
test. Section 4 describes the data and demonstrates that racial differences in covariates are balanced across judges. In section 5, I show both descriptive and formal statistical evidence on whether or not the ordering of judicial incarceration rates depend on race. In section 6, I conclude.

2 Previous Research

In the empirical literature on judicial discrimination, the modal approach is to estimate racial sentencing disparities conditional on all of the available observable characteristics in data. Estimates of the black-white gap are computed using some version of the following regression model:

$$y_i = \alpha + \beta b_i + X\gamma + \varepsilon_i$$

Where $y_i$ represents the sentencing outcome (incarceration, sentence length, or capital punishment), $b_i$ is an indicator for race, $X$ is a vector of fact patterns (the felon’s criminal history, severity of the crime, and etc.), and $\varepsilon_i$ captures the unobserved variation in sentencing outcomes. The key parameter of interest is $\beta$. The presumption is that race-neutral judges will sentence defendants who share identical case facts the same way regardless of their race. Testing the null hypothesis $H_0$: $\beta = 0$ against the alternative hypothesis $H_A$: $\beta \neq 0$ constitutes the modal test of judicial discrimination.4

In general, the discourse on racial sentencing disparities focuses on what variables belong in the conditioning set $X$. A number of studies find - not surprisingly - that racial differences in the severity of the crime and criminal histories explain a large portion of the black-white gap (Hagan (1973), Wolfgang and Riedel (1973), Albonetti (1997), Spohn and Holleran (2000), Steffensmeier et al. (1998)). So does the race of the victim. Black defendants who

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4The test is two-sided to allow for the possibility of reverse discrimination. This assumes that there is no discrimination in earlier stages of criminal proceedings or if there is, it is unobserved by the judge. Otherwise, it is possible that judges are more lenient towards black felons in order to compensate for prosecutorial or police discrimination (Miethe and Moore (1986)). In this case, judges can be race-neutral and we can have $\beta < 0$. 

5
murder or sexually assault white victims are substantially more likely to receive aggravated sentencing in comparison with defendants whose victims are black (Baldus et al. (1983), LaFree (1985)). Attorney quality is also important. Defendants who are represented by a private versus public attorney receive more lenient sentences on average (Holmes et al. (1996)). These and other relevant legal covariates are usually observed and can be included in the conditioning set.\footnote{Some of the variation in legal covariates may actually be due to judicial discrimination. In this case, estimates of $\beta$ will understate discrimination.}

More problematic for estimating $\beta$ are extra-legal determinates of sentencing, such as a felon’s level of educational attainment (Albonetti (1997)), income (Mustard (2001)), employment status (Nobiling et al. (1998)), facial features (Blair et al. (2004)), expressions of remorse (Ward (2006)), and family structure (Daly (1989)). Extra-legal factors are problematic because they influence sentencing decisions, highly correlate with race, and are rarely observed by the researcher. When researchers do access extra-legal factors, they are usually limited to some subset rather than the full information set of the judge. This poses issues for empirical methods that presume “selection on observables” (Heckman and Robb (1986)). For matching, it will not be the case that sentences for white felons reflect the counterfactual sentences for black felons once we condition on the observed $X$ (i.e. $E[Y_{wi}|X,W] \neq E[Y_{wi}|X,B]$).\footnote{Where $Y_{wi}$ represents the sentencing outcome for white felons, $W$ stands for white, and $B$ stands for black.} For OLS, there will be a correlation between the residual variation in race and the unobservables (i.e. $E[\varepsilon_i(b_i - E[b_i|X])] \neq 0$). This complicates interpreting $\hat{\beta}$. Estimates of $\hat{\beta} > 0$ could be driven by taste-based discrimination, but they could just as well reflect the inability to compare across the marginal black and white felon.

Sentencing guidelines are not a panacea for this problem. After the Sentencing Reform Act of 1984, scholars have increasingly leaned on either federal or state sentencing guidelines to help identify judicial discrimination (Mustard (2001), Bushway and Piehl (2001), Albonetti (1997)).\footnote{Under sentencing guidelines, each crime is generally associated with a guideline sentence that is a function of the severity of the crime and the felon’s prior criminal history, but not race. Judges are allowed} This empirical strategy augments equation (1.1) by conditioning explicitly
on guideline sentences \((s_g)\):\(^8\)

\[
y_i = \alpha + \beta b_i + X\gamma + s_g + \varepsilon_i
\]  

(2)

The implicit assumption of this model is that after conditioning on the guideline sentence \((s_g)\), the only difference between black and white felons is their race. This assumption is questionable. Guideline sentences are usually a function of the severity of the crime and felon’s criminal history. While conditioning on \(s_g\) allows for a more flexible dependence on severity and criminal history, it does not account for racial differences that are likely to exist beyond these margins. Systematic racial differences in income, education, or other unobserved extra-legal factors are likely to exist even after conditioning on \(s_g\). In this case, judges can differentially sentence blacks and whites for reasons unrelated to prejudicial tastes.\(^9\)

An alternative approach measures the degree to which judges differ in their treatment towards black defendants (Abrams et al. (2008)).\(^{10}\) Abrams et al. (2008) find evidence of substantial heterogeneity in the black-white incarceration gap across judges in Cook County, IL.\(^{11}\) This variation is assured to be driven by heterogeneity in judicial behavior and not differences in case composition because cases are randomly assigned to judges in Cook County.

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\(^8\)Studies differ in how they control for \(s_g\). Some scholars control for the minimum sentence length within the discretionary limits and others condition on the midpoint. Others include indicator variables for each severity-by-criminal history combination.

\(^9\)An interesting empirical exercise that is beyond the scope of this paper would be to decompose total variation in extra-legal factors to across and within sentencing guideline components.

\(^{10}\)This can be done by first adding judge-fixed effects \((\tau_j)\) and interactions between race and the judge-fixed effects \((b_i\tau_j)\) to equation (1.1):

\[
y_{ij} = \alpha + \beta b_i + X\gamma + \tau_j + b_i\tau_j + \varepsilon_{ij}
\]  

(3)

The interactions are the key parameters of interest and reflect judge-specific black-white sentencing disparities. Once the interactions are estimated, it is straightforward to compute various measures of inter-judge dispersion, including the variance, differences between the 90th and 10th percentile judge, and the inter-quartile difference.

\(^{11}\)They find an 18 percentage point difference in the black-white incarceration gap between the 10th and 90th percentile judge. They conduct statistical inference by approximating the limiting distribution of the relevant statistic using a bootstrap method.
Less clear is what motivates the differences in judicial behavior. One explanation is that judges vary in their treatment towards blacks because some judges have more intense tastes for discrimination than others. A competing explanation is that all judges are race-neutral; however, judges differ in the degree to which they engage in statistical, not taste-based, discrimination. This approach does not distinguish between these two observationally equivalent models of discrimination.

Abrams et al. (2008) is not unique in this aspect. In the empirical literature on judicial discrimination, there are no papers that I am aware of that try to distinguish between taste-based and statistical discrimination. This is in stark contrast with labor market and police discrimination literatures, where differentiating the two models is an active area of research (Mobius and Rosenblat (2006), Charles and Guryan (2008), Knowles et al. (2001), Anwar and Fang (2006)). This paper bridges these two literatures by employing an empirical test that addresses this fundamental challenge. The test is closest to Abrams et al. (2008) in the sense that it focuses on relative judicial behavior. The difference is that Abrams et al. (2008) is interested in quantifying the variation in judge-specific black-white gaps, while in this paper, the degree of difference across judges is irrelevant. Instead, this test asks whether the ordering of judge-specific incarceration rates is consistent across different racial groups.

3 Empirical Test of Discrimination

This section introduces the theoretical framework that motivates the empirical test of taste-based discrimination. I relegate the details of the model to the Appendix. Instead, I briefly describe model preliminaries; the judge’s information set, her optimization problem, and her decision rule. I then highlight that the rank-order test can distinguish between two observationally equivalent models of discriminatory sentencing, taste-based versus statistical discrimination. I also discuss necessary and sufficient conditions needed to identify taste-based discrimination. I present all of this analysis through a series of simple graphs, which
will help convey the key intuitions.

3.1 Model Setup

Consider a judge who has to decide whether or not to send a convicted felon to prison. An important determinate is her assessment of the felon’s latent criminality; whether or not the felon is a high (H) or low (L) risk type. High risk felons are more likely to recidivate and commit severe crimes, whereas low risk types are less likely to recidivate and commit less severe crimes. The judge does not observe the felon’s type as it is private information. Instead, the judge has prior beliefs, denoted by \( \pi^r \), that a felon of racial group \( r \) is a high risk type. The judge also observes numerous case facts, including the severity of the crime, the felon’s criminal history, the felon’s physical appearance, and more. I collapse this vector of case facts into a unidimensional index, \( \theta \). I assume that the distribution of \( \theta \) depends both on the felon’s type, \( \tau \), and racial group, \( r \), \( f_\tau^r(\theta) \). I also assume the monotone likelihood ratio property (MLRP); \( \frac{f_H(\theta)}{f_L(\theta)} \) is strictly increasing in \( \theta \). This implies that the felons with high values of \( \theta \) are associated with a higher relative likelihood of being high risk than those with low \( \theta \) values.

Given \( \theta \), the judge will update her priors to form posterior beliefs using Bayes Rule. Her posterior beliefs are important because the payoffs to incarceration depend on the felon’s type. I assume there is a common benefit to incarcerating high risk felons, but incarcerating low risk felons is costly. The costs of incarcerating low risk felons is motivated by the idea that appeal and subsequent reversal is costly to the judge, but their likelihood increases when judges incarcerate low risk types. The costs are judge-specific and can depend on the felon’s race, \( c_j(r) \). Given the judge’s posteriors and payoffs, she computes and then compares the expected net benefits of incarceration versus probation. The rule that governs the incarceration decision is as follows:

\[
\frac{\pi^r \ f_H^r(\theta)}{1 - \pi^r \ f_L^r(\theta)} \gtrless c_j(r) \tag{4}
\]
There are two ways to interpret this decision rule. One is in the usual cost-benefit framework. The left-hand side reflects the incremental benefits to incarceration and the right-hand side shows the incremental costs. The judge incarcerates when the benefits exceed the costs, but otherwise imposes probation. The benefits are high when the relative likelihood that the felon is type H versus L is high. Alternatively, the decision rule can be expressed explicitly in terms of $\theta$. Figure 1 shows that because $f_H(\theta)$ is strictly increasing in $\theta$ and $c_j(r)$ is independent of $\theta$, there exists a unique value of $\theta$, denoted as $\theta_j^*(r)$, for which the judge is indifferent between incarceration and probation. This is the legal standard that determines judicial sentencing. If a felon has a value of $\theta > \theta_j^*(r)$, then the judge will incarcerate, but if $\theta < \theta_j^*(r)$, then the judge will not. The first interpretation emphasizes judicial preferences, $c_j(r)$, whereas the second underscores the importance of the legal facts associated with the case, $\theta$.\footnote{The difficulty with the regression approach to identifying discrimination is that $\theta_j^*(r)$ is unobserved.}
3.2 Taste-based versus Statistical Discrimination

This framework allows for two observationally equivalent models of judicial discrimination. First, a judge may have Becker-style tastes for discrimination, which is modeled by allowing her incarceration costs to differ for black and white felons, \( c_j(B) \neq c_j(W) \). Panel A of Figure 2 depicts a scenario in which judge \( j \) has tastes for discriminating against black felons, \( c_j(B) < c_j(W) \), but the incremental benefits of incarceration are the same across both racial groups,

\[
\frac{\pi^B}{1-\pi^B} \frac{f^B_H(\theta)}{f^B_L(\theta)} = \frac{\pi^W}{1-\pi^W} \frac{f^W_H(\theta)}{f^W_L(\theta)}.
\]

In this case, the judge imposes race-specific legal standards, and in particular, uses a lower legal standard for blacks relative to whites, \( \theta^*_j(B) < \theta^*_j(W) \).

The consequence of race-specific legal standards is discriminatory sentencing. Consider a black and white felon who share the same value of \( \theta = k \), where \( \theta^*_j(B) < k < \theta^*_j(W) \). The black felon will be incarcerated because \( \frac{\pi^B}{1-\pi^B} \frac{f^B_H(k)}{f^B_L(k)} > c_j(B) \), but the white felon will not be incarcerated because \( \frac{\pi^W}{1-\pi^W} \frac{f^W_H(k)}{f^W_L(k)} < c_j(W) \). When a judge has tastes for discrimination, black and white felons receive disparate sentences even though they share identical case facts, \( \theta \).

An alternative model is statistical discrimination, which I depict in Panel B of Figure 2. In this case, the judge does not have tastes for discrimination, \( c_j(B) = c_j(W) \); however, the incremental benefits of incarceration are no longer the same across both racial groups. In particular, I assume that black felons have a greater relative likelihood of being a High versus Low Risk type than white felons for any given value of \( \theta \). In this case, the judge will impose race-specific legal standards, which again, leads to discriminatory sentencing. A black felon with \( \theta = k \), where \( \theta^*_j(B) < k < \theta^*_j(W) \), will be incarcerated, whereas a white felon who shares the same value of \( \theta \) faces probation. In this model, racially disparate sentences arise as race-neutral judges make optimal sentencing decisions in the face of informational constraints. Because race predicts unobserved latent criminality, judges sentence based on race.
Figure 2: Taste-based vs. Statistical Discrimination

(a) Taste-based Discrimination

\[
\frac{\pi^B}{1 - \pi^B} \frac{f^B_\theta(\theta)}{f^L_\theta(\theta)} = \frac{\pi^W}{1 - \pi^W} \frac{f^W_\theta(\theta)}{f^L_\theta(\theta)}
\]

\[c_j(W)\]
\[c_j(B)\]
\[\theta_j(B)\]
\[\theta_j(W)\]

(b) Statistical Discrimination

\[
\frac{\pi^B}{1 - \pi^B} \frac{f^B_\theta(\theta)}{f^L_\theta(\theta)} = \frac{\pi^W}{1 - \pi^W} \frac{f^W_\theta(\theta)}{f^L_\theta(\theta)}
\]

\[c_j(B) = c_j(W)\]
\[\theta_j(B)\]
\[\theta_j(W)\]
3.3 Rank-Order Test of Discrimination

In this section, I demonstrate how the rank-order test distinguishes between these two observationally equivalent models of discrimination. The key insight is that if judges have tastes for discrimination, then the ordering of judicial legal standards can depend on race. However, if all judges are race-neutral, then judicial legal standards will be independent of race.

Figure 3 illustrates this point. In Panel A, I consider three judges \( j_0, j_1, \) and \( j_2 \), none of whom harbors any tastes for discrimination. There are, however, incentives to engage in statistical discrimination because

\[
\frac{\pi^B f_{L}^B(\theta)}{1 - \pi^B f_{L}^B(\theta)} > \frac{\pi^W f_{L}^W(\theta)}{1 - \pi^W f_{L}^W(\theta)}
\]

for all values of \( \theta \). In this case, judge \( j_2, j_1, \) and \( j_0 \) has the highest, 2nd highest, and lowest legal standard, respectively, and this ordering is true for both black and white felons, \( \theta^*_j(W) > \theta^*_j(B) > \theta^*_j(W) \) and \( \theta^*_j(B) > \theta^*_j(B) > \theta^*_j(B) \). In contrast, Panel B shows how taste-based discrimination can result in a rank-order that depends on race. In this case, judge \( j_0 \) is race-neutral, but judge \( j_1 \) has tastes for discrimination towards black felons, \( c_{j_1}(B) < c_{j_1}(W) \). Notice that the rank-order of judge-specific legal standards now varies with race. Judge \( j_0 \) applies a higher legal standard for blacks than judge \( j_1, \theta^*_{j_0}(B) > \theta^*_{j_1}(B) \), but applies a relatively lower legal standard for whites, \( \theta^*_{j_0}(W) < \theta^*_{j_1}(W) \). This is the key intuition of the model. The only way that the rank-order of judicial legal standards can depend on race is if at least one judge has tastes for discrimination against some racial group. I restate this in the following proposition.

**Proposition 1** If no judge engages in taste-based discrimination, the rank-order of judicial legal standards will be independent of the felon’s racial group, \( r \), and the following two equations will hold:

\[
\theta^*_{j_0}(B) > \theta^*_{j_1}(B) > \ldots > \theta^*_{j_{n-1}}(B) > \theta^*_{j_n}(B)
\]

\[
\theta^*_{j_0}(W) > \theta^*_{j_1}(W) > \ldots > \theta^*_{j_{n-1}}(W) > \theta^*_{j_n}(W)
\]
Figure 3: Rank-Order of Judge-Specific Legal Standards

(a) Rank-Order Preserved

(b) Rank-Order Reversed
Comparing the ordering of judicial legal standards across racial groups motivates a test of taste-based discrimination. If the ordering depends on race, then at least one judge engages in taste-based discrimination against some racial group.

### 3.4 Identification Conditions

In this section, I describe necessary and sufficient conditions in order for the rank-order test to identify taste-based discrimination. Panel A of Figure 4 shows that the rank-order test does not hinge on the assumption that the cost function is independent of $\theta$. The figure depicts a scenario in which judges are race-neutral, there are incentives to statistically discriminate, 

$$
\frac{π^B}{1-π^B} \frac{f^B_1(θ)}{f^B_2(θ)} > \frac{π^W}{1-π^W} \frac{f^W_1(θ)}{f^W_2(θ)},
$$

but now the incarceration costs are linearly decreasing in $\theta$. The linearity assumption is not necessary and is made only to ease exposition. The important observation is that the ordering of judicial legal standards does not depend on race, even though costs decrease in $\theta$. It is still true that the only way the rank-order will depend on race is if incarceration costs differ across racial groups for some values of $\theta$.

Panel B illustrates a similar scenario except now the cost functions exhibit the single crossing property, in which the derivative of the judge $j_0$’s cost function with respect to $\theta$ is everywhere steeper than judge $j_1$’s. In this case, the ordering of judicial legal standards will depend on race, even though neither judge $j_0$ nor $j_1$ harbors any tastes for discrimination. Now the rank-order test has little empirical content because the ordering of judicial legal standards conveys no information regarding a judge’s racial preferences. The main problem is that the cost functions intersect in the interior of $\theta$’s support.

Identification of taste-based discrimination requires additional structure on judicial cost functions. A sufficient condition is that incarceration costs are affine functions that satisfy either of the following two properties:

$$
c_j(θ) = α_j + β_j θ \quad (7)
$$

$$
c_j(θ) = α + β_j θ \quad (8)
$$
Figure 4: Rank Dependence on Race with Race-Neutral Judges

(a) Rank Independence

(b) Rank Dependence
These equations suppress the dependence on race for convenience. If cost functions are affine with judge-specific intercepts and a common slope or with a common intercept and judge-specific slopes, then the rank-order test will be able to identify taste-based discrimination. In general, we can allow for non-linear cost functions. In this case, the necessary condition is as follows. Consider $c_j(\theta) : [0, \overline{\theta}] \rightarrow \mathbb{R}$. Choose any $\theta_0 \in \text{int}[0, \overline{\theta}]$. If there exists an $r > 0$ such that $\forall \theta \in (\theta_0 - r, \theta_0 + r)$, there does not exist a $c_{j'}(\theta)$ between $c_j(\theta_0 - r)$ and $c_j(\theta_0 + r)$ for all $j' \neq j$, then the rank-order test is still valid.

There are two additional points worth making. First, the rank-order test is a conservative test of judicial discrimination in that it has low power (Anwar and Fang (2006)). Under the null hypothesis that no judge engages in discrimination, the ordering of judicial legal standards should not depend on race. However, the converse is not necessarily true; it is possible for judges to have tastes for discrimination and for the ordering to be independent of race. Figure 5 depicts a scenario in which the rank-order of judge-specific legal standards do not depend on race, even though judge $j_1$ discriminates against blacks. In this example, judge $j_1$ has such high costs of incarceration that she employs higher legal standards than judge $j_0$ towards both black and white felons. This shows that a failure to reject rank independence does not necessarily imply race-neutrality.
Second, the rank-order test provides no information on which judge discriminates or which racial group is being discriminated against. To see this, consider the following ordering: \( \theta_{j_0}^*(B) > \theta_{j_1}^*(B) \) and \( \theta_{j_0}^*(W) < \theta_{j_1}^*(W) \). Because the ordering depends on race, we know that at least one judge engages in discrimination. However, the ordering is consistent with multiple cost structures; for example, both \( c_{j_1}(B) < c_{j_0}(B) = c_{j_0}(W) < c_{j_1}(W) \) and \( c_{j_0}(W) < c_{j_1}(W) = c_{j_1}(B) < c_{j_0}(B) \) can generate this ordering of legal standards. This is problematic for identifying either who discriminates or which group is being discriminated against because in the first case, \( j_1 \) discriminates against blacks, whereas in the second case, \( j_0 \) discriminates against whites. Distinguishing between the two requires additional assumptions on the directionality of discrimination. If we assume that there is no reverse discrimination (i.e. no discrimination against whites), then we can conclude that judge \( j_1 \) discriminates against blacks.\(^{13}\) The rank-order test involves a trade off; it is difficult to identify individual-level discrimination, but its comparative advantage is the ability to distinguish between taste-based and statistical discrimination.

### 3.5 Implementation

The rank-order test is based on a theoretical prediction regarding the ordering of judicial legal standards. However, judicial legal standards are unobserved in data. Empirical implementation of the test requires predictions on observed judicial behavior. Fortunately, the key insights of the rank-order test apply to judicial incarceration rates, which are observed. To see this, note that in equilibrium, a judge incarcerates race \( r \) felons at the rate of \( P(\theta > \theta_j^*(r)) \), which can be expressed as

\[
i_j(r) = \pi^r(1 - F_H(\theta_j^*(r))) + (1 - \pi^r)(1 - F_L(\theta_j^*(r)))
\]

It is straightforward to show that incarceration rates are strictly decreasing in legal standards. Judges with lower legal standards will incarcerate felons at higher rates, since lower legal standards reflect a higher willingness to incarcerate felons with low values of \( \theta \). This

\(^{13}\)However, notice that even with the assumption of no reverse discrimination, individual discrimination is not fully identified, because it is possible that \( j_0 \) also has tastes for discrimination, \( c_{j_1}(B) < c_{j_0}(B) < c_{j_0}(W) < c_{j_1}(W) \).
implies that the ordering of judicial incarceration rates will mirror the ordering of judicial legal standards. If legal standards are independent of race, then incarceration rates will be as well. If legal standards depend on race, then so will incarceration rates. This motivates the following proposition:

**Proposition 2** If no judge engages in taste-based discrimination, the rank-order of judicial incarceration rates will be independent of the felon’s racial group, \( r \), and the following two equations will hold:

\[
\begin{align*}
    i_{j_0}(B) & > i_{j_1}(B) > \ldots > i_{j_{n-1}}(B) > i_{j_n}(B) \\
i_{j_0}(W) & > i_{j_1}(W) > \ldots > i_{j_{n-1}}(W) > i_{j_n}(W)
\end{align*}
\]

(9) \hspace{1cm} (10)

Comparing the ordering of judicial incarceration rates across racial groups constitutes the test of taste-based discrimination. If the ordering depends on race, then at least one judge engages in taste-based discrimination against some racial group.

4 Data

For the empirical analysis, I use administrative criminal sentencing data from the state of Kansas. This dataset contains the universe of convicted felons from Kansas from mid-1997 to 2003. I restrict attention to four judicial districts, which include Wichita, Overland Park, Topeka, and Kansas City. Approximately 80% of Kansas’ black residential population and 70% of all black felons are from these four districts. In these districts, the average judge has 420 cases, of which 234, 151, 35 involve white, black, and Hispanic felons, respectively. I exclude Hispanics due to the small number of cases per judge. I also exclude judges whose caseload is less than a 1 standard deviation below the average judge. This drops 194 cases, which is less than 1% of the sample. On the whole, these restrictions focus the analysis on districts, judges, and racial groups in ways that should increase the statistical power of the
There are two important features of the data worth noting. First, even though Kansas is a guideline state, judges have discretion in criminal sentencing. Judges can formally depart from the sentencing guidelines along either extensive or intensive margins. In cases that involve a special rule violation, judges have even more discretion. Examples of special rule violations include assaulting a police officer, possessing a firearm, discharging a firearm, aggravated endangerment of a child, and committing a crime while on probation, parole, conditional release, or post-release supervision. Approximately, 78% of all special rule violations fall under the latter category and 20% of all criminal cases involve a special rule violation. In these cases, judges can incarcerate a felon even when the guideline sentence is probation. These deviations from the guidelines are not subject to formal review.

Second, in these districts, criminal cases are randomly assigned to judges, which is important for identification. Without randomization, it is possible for the judicial ranks to depend on race because of legal rather than prejudicial reasons. For example, if judge $j_0$ is assigned the most hardened black criminals and the softest white criminals, while judge $j_1$ has the opposite case characteristics, then the ordering of judicial incarceration rates will vary with race, but this dependence will be warranted on legal grounds. The rank-order test can only identify taste-based discrimination if racial differences in legal characteristics are evenly distributed across judges. Randomization is valuable because it ensures that this condition is satisfied.

Table 1 presents descriptive statistics that confirm racial differences in covariates are balanced across judges. For each judge, I compute the average black-white difference in case facts, such as the severity of the crime. Within each district, I then order judges according to their respective black-white gaps and then compute differences between the 25th and 75th percentile judge. If randomization is successful, the racial differences in covariates across the 25th and 75th percentile judge should be relatively small in magnitude and not statistically significant. I conduct statistical inference by constructing 10,000 bootstrapped inter-quartile
statistics, where the samples are constructed by randomly assigning cases across judges within district. P-values are shown in brackets and are the fraction of bootstrapped statistics that are greater than or equal to the observed statistic.

The table shows that a few of the covariates are not balanced across judges. For example, in the 3rd district, the black-white age gap is 2.4 years higher for 75th percentile judge in comparison with the 25th percentile judge. The inter-quartile racial difference in criminal severity is 0.676. Both of these inter-quartile differences are statistically significant at the 5% level. However, for most of the case facts, the inter-quartile differences are not statistically improbable under random assignment. In the 18th and 29th districts, none of the inter-quartile differences are statistically significant at the 5% level. In addition, there is little correlation across case facts within judge. In other words, judges with higher racial differences in criminal severity are not also associated with higher racial differences in criminal history. On the whole, this suggests that cases are not strategically assigned to judges along racial lines.

5 Empirical Results

5.1 Descriptive Evidence

In this section, I present graphs that convey qualitative evidence of whether or not the ordering of judicial incarceration rates depend on race. Figure 6 plots judicial rankings of race-specific incarceration rates in the 3rd district (Topeka). On the x-axis and y-axis are judicial rankings of white and black incarceration rates, respectively. Smaller values indicate higher rankings; for example, a judge with a ranking of 1 has the highest incarceration rate among all judges in the district. The dashed blue line is the 45 degree line. If a data point lies on the 45 degree line, then this judge has the same relative ranking for both black and white felons. If no judge engages in taste-based discrimination, then all the data points will lie on the 45 degree line. However, if all the data points lie on the 45 degree line, then
Table 1: Inter-Quartile Racial Difference in Case Characteristics

<table>
<thead>
<tr>
<th></th>
<th>3rd District</th>
<th>10th District</th>
<th>18th District</th>
<th>29th District</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>2.440**</td>
<td>0.737</td>
<td>1.114</td>
<td>1.712</td>
</tr>
<tr>
<td></td>
<td>[0.040]</td>
<td>[0.823]</td>
<td>[0.717]</td>
<td>[0.395]</td>
</tr>
<tr>
<td>Female</td>
<td>0.039</td>
<td>0.050</td>
<td>0.051</td>
<td>0.062</td>
</tr>
<tr>
<td></td>
<td>[0.735]</td>
<td>[0.517]</td>
<td>[0.509]</td>
<td>[0.414]</td>
</tr>
<tr>
<td>Counts</td>
<td>0.226</td>
<td>0.046</td>
<td>0.179</td>
<td>0.051</td>
</tr>
<tr>
<td></td>
<td>[0.253]</td>
<td>[0.841]</td>
<td>[0.146]</td>
<td>[0.919]</td>
</tr>
<tr>
<td>Severity (Non-Drug Crimes)</td>
<td>0.676**</td>
<td>0.221</td>
<td>0.162</td>
<td>0.231</td>
</tr>
<tr>
<td></td>
<td>[0.011]</td>
<td>[0.579]</td>
<td>[0.988]</td>
<td>[0.937]</td>
</tr>
<tr>
<td>Severity (Drug Crimes)</td>
<td>0.270</td>
<td>0.183</td>
<td>0.333</td>
<td>0.257</td>
</tr>
<tr>
<td></td>
<td>[0.111]</td>
<td>[0.438]</td>
<td>[0.072]</td>
<td>[0.321]</td>
</tr>
<tr>
<td>Criminal History</td>
<td>0.494</td>
<td>0.205</td>
<td>0.454</td>
<td>0.440</td>
</tr>
<tr>
<td></td>
<td>[0.193]</td>
<td>[0.803]</td>
<td>[0.146]</td>
<td>[0.430]</td>
</tr>
<tr>
<td>Person Crime</td>
<td>0.091</td>
<td>0.052</td>
<td>0.081</td>
<td>0.092</td>
</tr>
<tr>
<td></td>
<td>[0.149]</td>
<td>[0.444]</td>
<td>[0.160]</td>
<td>[0.266]</td>
</tr>
<tr>
<td>Drug Crime</td>
<td>0.108</td>
<td>0.077**</td>
<td>0.039</td>
<td>0.067</td>
</tr>
<tr>
<td></td>
<td>[0.066]</td>
<td>[0.038]</td>
<td>[0.923]</td>
<td>[0.507]</td>
</tr>
<tr>
<td>Special Rule Violation</td>
<td>0.035</td>
<td>0.041</td>
<td>0.062</td>
<td>0.095</td>
</tr>
<tr>
<td></td>
<td>[0.796]</td>
<td>[0.755]</td>
<td>[0.337]</td>
<td>[0.058]</td>
</tr>
<tr>
<td>Private Counsel</td>
<td>0.054</td>
<td>0.044</td>
<td>0.062</td>
<td>0.105</td>
</tr>
<tr>
<td></td>
<td>[0.502]</td>
<td>[0.660]</td>
<td>[0.408]</td>
<td>[0.127]</td>
</tr>
<tr>
<td>Plea</td>
<td>0.022</td>
<td>0.050**</td>
<td>0.027</td>
<td>0.017</td>
</tr>
<tr>
<td></td>
<td>[0.602]</td>
<td>[0.011]</td>
<td>[0.901]</td>
<td>[0.973]</td>
</tr>
</tbody>
</table>

Note: The numbers in the top row are differences in the Black-White gap between the 25th and 75th percentile judge in each district. P-values are in brackets. To obtain p-values, I construct 10,000 bootstrapped samples in which cases are randomly assigned to judges with replacement. The inter-quartile racial differences are computed for each sample and the p-value is the fraction of bootstrapped statistics that are greater than the observed inter-quartile difference.
this does not guarantee that all judges are race-neutral. The further away data points are from the 45 degree line, the more likely it is that at least one judge engages in taste-based discrimination.

Figure 6 shows that most of the judges are near the 45 degree line. For example, there are 3 judges who are directly on the 45 degree line; specifically, the judges with the highest, 4th, and 6th highest white incarceration rate also have the highest, 4th, and 6th highest black incarceration rate, respectively. There are, however, two judges who are noticeably removed from the 45 degree line. First, there is the judge with the 2nd highest black incarceration rate but the lowest white incarceration rate. Relative to other judges in her district, this judge is the 2nd most punitive judge towards blacks, but is the most lenient judge towards whites. Second, there is the judge with the 5th highest white incarceration rate, but the lowest black incarceration rate in the district. These two judges exemplify the type of inconsistent sentencing that is symptomatic of taste-based discrimination.

Figure 7 shows similar plots for all four of the judicial districts. The plots show mixed patterns across the judicial districts. In the 10th district, all of the data points are relatively close to the 45 degree line; no judge has a ranking differential that is greater than 2. In contrast, in the 18th and 29th districts, several data points lie far off the 45 degree line. For example, in the 18th district, there is a judge who has the highest black incarceration rate
and 10th highest white incarceration rate. There is another judge who has the 6th highest black incarceration rate and the 16th highest white incarceration rate. In the 29th district, there is a judge who has the 4th highest white incarceration rate and the 15th highest black incarceration rate, while a different judge has the 7th highest black incarceration rate and the 15th highest white incarceration rate. In summary, in the 3rd, 18th, and 29th districts, the graphical evidence is more consistent with taste-based discrimination than in the 10th district, where the rankings are located closer to the 45 degree line. In the next section, I formally test whether the observed rank dependence on race is due to sampling variation or actually reflects discrimination.

5.2 Statistical Test

The statistical test builds on the intuition that under the null hypothesis of no taste-based discrimination, all of the data points would lie directly atop the 45 degree line, in which case, the correlation of race-specific judicial ranks should be exactly 1. Thus, testing the null hypothesis $H_0 : \rho = 1$ against the alternative $H_A : \rho < 1$ constitutes the statistical test of judicial discrimination, where $\rho$ denotes the correlation of race-specific judicial ranks. I compute two non-parametric measures of the rank correlation, the Spearman and Kendall
rank correlation coefficients, which are denoted as $\rho_s$ and $\rho_k$, respectively. The substantive difference is that the Kendall coefficient is a function of the sum of the number of concordances and discordances, whereas the Spearman coefficient is a function of the sum of actual concordances and discordances. While statistical inference does not generally diverge across the two measures, I compute both as a robustness check.

To conduct statistical inference, I employ the non-parametric bootstrap (Efron (1987)). I choose $B=10,000$ since the bootstrap procedure increases in accuracy as $B \to \infty$, where $B$ denotes the number of bootstrapped samples. Each sample is drawn with replacement from judge-by-race cells. I compute Spearman and Kendall correlation coefficients for each bootstrapped sample. This generates an empirical distribution that should converge to the true distribution assuming regularity conditions hold (Bickel and Freedman (1981)). Using the empirical distribution, I construct one-sided 95% confidence intervals defined as $[\rho_{500}, \rho_{\text{max}}]$, where $\rho_{500}$ is the 500th lowest value and $\rho_{\text{max}}$ is the maximum value of all 10,000 bootstrapped correlations. If it is true that no judge engages in taste-based discrimination, then a positive share of the simulated correlation coefficients should have the value of 1. If $\rho_{\text{max}} < 1$, then we can reject the null hypothesis and conclude that at least one judge engages in taste-based discrimination.

Table 2 shows the main results of the simulation. The first column presents the actual Spearman and Kendall rank correlation coefficients in each of the 4 judicial districts. The Kendall coefficients are a little lower than the Spearman coefficients, but both suggest a positive correlation in judicial rankings, which is consistent with the plots from the previous section. The lowest value is the Kendall coefficient in the 3rd district ($\rho_k=0.317$) and the highest value is the Spearman coefficient in the 10th district ($\rho_s=0.881$).

The second and third columns show the lower and upper limits of the 95% confidence intervals. Under the null hypothesis that no judge engages in taste-based discrimination, judicial ranks should be perfectly correlated in at least some of the simulations, which implies

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14 Convergence of bootstrapped statistics depend on $N \to \infty$, but large $B$ improves accuracy of the approach.
that $\rho_{\text{max}} = 1$. However, in 3 out of the 4 judicial districts, the 95% confidence intervals do not include the value of 1. In the districts of Topeka, Wichita, and Kansas City, none of the 10,000 simulated correlation coefficients are consistent with the null hypothesis of no taste-based discrimination. Thus, in these 3 districts, I can reject the null hypothesis and conclude that at least one judge engages in taste-based discrimination against some racial group. In the district of Overland Park, I cannot reject the null hypothesis of no discrimination. These results hold using either the Spearman or Kendall rank correlation coefficients.

### 5.3 Robustness

I conduct two robustness checks of the main results. The first check is motivated by the possibility that judicial cost functions may cross. This is especially relevant when there is sufficient judicial heterogeneity in the gradient between the cost function and case facts, $\theta$; or in other words, if some judges are much more punitive towards certain types of crimes than other judges. For example, if some judges find drug crimes to be particularly egregious and
drug crimes are disproportionately committed by blacks, then sentencing ranks can depend on race, even though all judges may be race-neutral.

I address this issue by isolating the variation in judicial incarceration rates that is orthogonal to the variation in case facts, while allowing the effects of case facts to be judge-specific. I do this by running the following regression separately for each judge and racial group:

\[ y_i = \alpha + \beta \theta_i + \varepsilon_i \]  

Where \( y_i \) is an indicator for incarceration, \( \theta_i \) is a vector of case facts including severity of the crime, criminal history, an indicator for drug related crimes, and an interaction between severity and drug crimes. The parameters are judge and race-specific, \( \alpha_j(r) \) and \( \beta_j(r) \), because equation 11 is run separately for each judge and racial group. The parameter of interest is \( \alpha_j(r) \) and represents the rate at which judge \( j \) incarcerates race \( r \) felons for committing non-drug related crimes after partialling out the effects of legal covariates. I then compute actual and simulated correlation coefficients between \( \alpha_j(B) \) and \( \alpha_j(W) \). The value-added of this exercise is that it examines the ordering of incarceration rates after adjusting for heterogeneous responses to \( \theta \).

Table 3 shows the results. As before, in the 10th district (Overland Park), we cannot reject the null hypothesis that judicial incarceration rates are independent of race using either the Spearman or Kendall rank correlation coefficients. However, in the other 3 districts, none of the 10,000 simulated correlation coefficients have the value of 1. In these districts, the rank-order of adjusted incarceration rates depends on race, and this dependence is not likely to be an artifact of statistical chance. These results are qualitatively identical to the main results, which suggests that the rank dependence found in Topeka, Wichita, and Kansas City is not driven by judicial heterogeneity in responses to case facts.

The second check is motivated by a literature that finds trial judges increase sentencing severity in election years in response to electoral pressure (Gordon and Huber (2007), Huber
Table 3: Adjusted Correlation of Judicial Ranks

<table>
<thead>
<tr>
<th></th>
<th>Spearman Correlation ($\rho_s$)</th>
<th>5% Confidence Interval</th>
<th>Kendall Correlation ($\rho_k$)</th>
<th>5% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>3rd District (Topeka)</td>
<td>0.233</td>
<td>-0.483 to 0.983</td>
<td>0.545</td>
<td>-0.389 to 0.944</td>
</tr>
<tr>
<td>10th District (Overland Park)</td>
<td>0.222</td>
<td>-0.167 to 1.000</td>
<td>0.381</td>
<td>-0.143 to 1.000</td>
</tr>
<tr>
<td>18th District (Wichita)</td>
<td>0.690</td>
<td>-0.040 to 0.843</td>
<td>-0.112</td>
<td>-0.029 to 0.657</td>
</tr>
<tr>
<td>29th District (Kansas City)</td>
<td>0.500</td>
<td>-0.468 to 0.753</td>
<td>-0.117</td>
<td>-0.333 to 0.600</td>
</tr>
</tbody>
</table>

Note: The Spearman correlation coefficient is defined as $\rho_s = 1 - \frac{6 \sum_{i=1}^{n}(R_i^w - R_i^b)^2}{n(n^2 - 1)}$, where $R_i^w - R_i^b$ is the difference in white and black ranks for a given judge $j$. The Kendall correlation coefficient is defined as $\rho_k = \frac{N_c - N_o}{\frac{1}{2}n(n-1)-\frac{1}{2}n(n-1)_c}$, where $n_c$ refers to the number of positive rank differentials and $n_o$ counts the number of negative rank differentials. In both, $n$ denotes the number of judges in the district.

and Gordon (2004), Berdejo and Yuchtman (2009)). In another paper that also uses Kansas sentencing data, I find that incarceration rates increase in the election year for black but not white felons. This is potentially problematic for the rank-order test because some judges are on different election cycles from others. This implies that the ordering of judicial incarceration rates could depend on race because of judicial politics rather than racial preferences. To assess this possibility, I exclude all criminal cases that are sentenced in election years. Table 4 shows that the results are qualitatively similar even after imposing this sample restriction, which suggests that election effects are not driving the main results.

6 Conclusion

This paper provides evidence that criminal defendants in 3 of the 4 largest judicial districts in Kansas are not being judged fairly under the law. This claim is backed by empirical results from a test that circumvents both the omitted variables problem and the possibility of statistical discrimination, which complicates the identification of taste-based discrimin-
Table 4: Correlation of Judicial Ranks (Non-Election Years)

<table>
<thead>
<tr>
<th>District</th>
<th>Spearman Correlation ($\rho_s$)</th>
<th>95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>3rd District (Topeka)</td>
<td>0.483</td>
<td>-0.083 - 0.983</td>
</tr>
<tr>
<td>10th District (Overland Park)</td>
<td>0.714</td>
<td>-0.119 - 1.000</td>
</tr>
<tr>
<td>18th District (Wichita)</td>
<td>0.729</td>
<td>0.397 - 0.921</td>
</tr>
<tr>
<td>29th District (Kansas City)</td>
<td>0.671</td>
<td>0.050 - 0.909</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Kendall Correlation ($\rho_k$)</th>
<th>95% Confidence Interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>3rd District (Topeka)</td>
<td>0.389</td>
</tr>
<tr>
<td>10th District (Overland Park)</td>
<td>0.500</td>
</tr>
<tr>
<td>18th District (Wichita)</td>
<td>0.524</td>
</tr>
<tr>
<td>29th District (Kansas City)</td>
<td>0.517</td>
</tr>
</tbody>
</table>

Note: The Spearman correlation coefficient is defined as $\rho_s = 1 - \frac{6\sum_{i=1}^{n}(r_i^w - r_i^b)^2}{n(n^2-1)}$, where $R_i^w - R_i^b$ is the difference in white and black ranks for a given judge. The Kendall correlation coefficient is defined as $\rho_k = \frac{n_c - n_d}{\frac{1}{2}n(n-1)}$, where $n_c$ refers to the number of positive rank differentials and $n_d$ counts the number of negative rank differentials. In both, $n$ denotes the number of judges in the district.

The basic idea is that if judges have tastes for discrimination, then they will exhibit inconsistent sentencing relative to other judges towards different racial groups. For example, in the 3rd district, we observe a judge with the 2nd highest black incarceration rate but the lowest white incarceration rate among all judges in the district. This type of inconsistency along the ordinal scale is symptomatic of taste-based discrimination. In contrast, if judges only engage in statistical discrimination, then they will not exhibit inconsistency in the sense that the rank-order of incarceration rates will not depend on race. Formal statistical tests corroborate the existence of taste-based discrimination in Kansas.
Appendix

A judge has to decide whether or not to incarcerate a convicted felon, $I$, or place the felon on probation, $P$. A key determinate is whether or not the felon is a high ($H$) or low ($L$) risk type, which is private information. High risk types are more likely to recidivate and conditional on recidivating, commit more severe crimes than low risk types. Thus, the net benefit of incarceration is higher for high risk types. In particular, I assume that the net benefit of incarcerating a high risk type is positive, $b > 0$, but that incarcerating a low risk type is costly, $c_j(r) < 0$. One way to motivate this is that incarcerating low risk types is more likely to trigger appeal and possible reversal which is costly for the judge. Note that the costs of incarcerating low risk types, $c_j(r)$, are race and judge-specific. This allows for two sources of judicial heterogeneity; 1) judges may have tastes for racial discrimination and 2) judges may have heterogeneous sentencing preferences independent of race.

Next, I describe how the judge forms beliefs regarding the felon’s risk type. I assume that the judge has prior beliefs, $\pi^r$, which is the actual fraction of race $r$ felons that are high risk types. She updates her priors given the information she learns about the case and the felon. In particular, the judge observes $n$ case facts, which include the severity of the crime, the felon’s criminal history, attorney quality, the felon’s physical appearance, and much more. I assume that there is a function $g : \mathbb{R}^n \to \mathbb{R}$ that maps the $n$ dimensional vector of case facts into a unidimensional index, $\theta$. Thus, $\theta$ summarizes all of the legal and extra-legal facts associated with a given case. I assume that the distribution of $\theta$, denoted as $f^r_\tau(\theta)$, depends both on the felon’s type, $\tau$, and racial group, $r$. This comports with the intuition that case facts are likely to systematically vary with risk type and race. Finally, I assume that $f^r_\tau(\theta)$ satisfies the monotone likelihood ratio property (MLRP) such that $\frac{f^r_H(\theta)}{f^r_L(\theta)}$ is strictly increasing in $\theta$. High values of $\theta$ are associated with a higher relative likelihood of being type H versus L felons in comparison with low values of $\theta$.

We can now write down the judge’s optimization problem. A judge $j$ compares her expected utility from incarceration $E[U_j(I)|\theta]$ versus the expected utility from placing a
felon on probation $E[U_j(P)|\theta]$ conditional on $\theta$. The judge will decide to incarcerate the felon if $E[U_j(I)|\theta] > E[U_j(P)|\theta]$. Note that I can set both the level and the scale of utility without altering the judge’s optimization problem. I set the level of utility by normalizing $E[U_j(P)|\theta] = 0$ and set the scale by dividing through by the net benefit of incarceration, $b$. We can then re-write the decision rule as:

$$\max_{I,P} [P(H|\theta) - (1 - P(H|\theta))c_j(r), 0]$$

Where $c_j(r)$ should now be interpreted as the incarceration cost as a share of the benefits and $P(H|\theta)$ is the judge $j$’s posterior belief that the felon is a high risk type. Using Bayes Rule we can write her posterior beliefs as:

$$P(H|\theta) = \frac{f^r_H(\theta)\pi^r}{f^r_H(\theta)\pi^r + f^r_L(\theta)(1 - \pi^r)}$$

After plugging in equation 13 into 12 and solving, we get the decision rule that the judge will incarcerate when:

$$\frac{\pi^r f^r_H(\theta)}{1 - \pi^r f^r_L(\theta)} > c_j(r)$$

If the inequality is reversed, then the judge places the felon on probation. The MLRP yields the threshold property that characterizes the judge’s decision.
References


