

Are American juries racially discriminatory? Evidence from over a quarter million felony grand jury cases

Mark Hoekstra¹, Suhyeon Oh², Meradee Tangvatcharapong³

¹Department of Economics, Texas A&M University; NBER; IZA

²Department of Economics, Texas A&M University

³Institute of Economic Research, Hitotsubashi University

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Abstract

To what extent are the large racial disparities in the criminal justice system caused by taste-based or statistical discrimination based on race? We examine this question using over a quarter of a million felony cases from Texas in which grand juries decided whether or not the case should be prosecuted. We estimate disparate impact—defined as whether juries treat Black defendants differently from White defendants with the same underlying level of felony guilt—by exploiting the quasi-random assignment of cases to grand juries to purge omitted variable bias. Results from cases involving defendants with racially identifiable names indicate a small, but statistically significant, disparate impact of 0.8 percent against Black defendants. In order to distinguish racial bias and statistical discrimination from alternative—and potentially justifiable—sources of disparate impact, we also compare Black and White defendants with similarly-White-sounding names, and who were thus racially indistinguishable to grand jurors. Results indicate a disparate impact of the same magnitude. This suggests that while jury decision-making does impose a small but statistically significant disparate impact on Black defendants, there is no evidence jurors engage in statistical or taste-based discrimination.

1 Introduction

Racial disparities are pervasive throughout the U.S. criminal justice system. Perhaps the most stark disparity is with respect to felony charging and conviction. Thirty-three percent of Black adult males have a felony conviction, compared to only 12.8 percent of the total adult male population (Shannon et al., 2017). Unsurprisingly, this large disparity in felony conviction manifests itself in similarly large differences in incarceration, where 32.3 percent of Black males are likely to go to state or federal prison, compared to only 5.9 percent of White males (Bonczar, 2003).

To what extent are these racial disparities due to discriminatory practices in the criminal justice system? While there are large literatures examining this question in a variety of contexts, juries are of particular interest, for two reasons. The first is that conviction decisions are either made directly by juries, or are negotiated by prosecutors and defendants under threat of what a jury would decide if the case went to trial—that is, "under the shadow of the law". To the extent juries are racially discriminatory, it would directly or indirectly impact every case in the criminal justice system. Second, since juries are composed from a panel of randomly selected citizens, understanding the extent to which juries are discriminatory provides a measure of whether the broader population is discriminatory. This is important not only for understanding racial bias in the criminal justice system, but also more generally.

This study addresses racial bias by examining the decisions of grand juries. It does so using data on more than a quarter of a million felony cases heard by grand juries in Harris County, Texas, between February of 1990 and July of 2022. These data include the race of the defendant, and whether the grand jury “true billed” the case, or pushed it forward for prosecution. While race is not usually directly observed by grand jurors, they are often able to infer race based on the defendant’s name. As a result, we use whether the first or last name of the defendant is racially identifiable as Black as a measure of whether grand jurors believed the defendant was Black. We also show results are robust to an alternative approach of inferring perceived race. We focus on White and Black defendants and distinguish between Black defendants whose race is identifiable as Black based on name, as well as those whose race would most likely, and incorrectly, be perceived by grand jurors as

White. These data are then linked to court records indicating whether cases that were “true-billed” by the grand jury (i.e., pushed forward rather than dismissed) ended in a guilty felony outcome.

In order to assess whether Black defendants are true-billed more often than Whites with similar levels of underlying felony guilt, we exploit the fact that cases are quasi-randomly assigned across grand juries, some of which are less lenient than others. Consistent with our understanding of case assignment, we show empirically that grand jury leniency is uncorrelated with case and defendant characteristics. This enables us to employ the clever method proposed by Arnold, Dobbie, and Hull (2022) to purge omitted variable bias from our estimate of racial bias. Intuitively, we first estimate the underlying felony guilt of *all* Black and White defendants by asking how often they would subsequently be found guilty of a felony when facing a particularly tough grand jury that “true bills” every case that it sees. We then use this measure of true underlying felony guilt to rescale the disparity between Black and White defendants. The resulting estimate captures what Arnold, Dobbie, and Hull (2022) term disparate impact, which is the sum of racial bias, statistical discrimination, and other sources of disparate impact capturing the extent to which White and Black defendants with similar potential outcomes (i.e., felony guilt, evidence of guilt, etc.), are treated differently. Importantly, this method does this without imposing monotonicity assumptions that are required for alternative approaches, such as Arnold, Dobbie, and Yang (2018).

Results indicate that grand jury decisions impose a disparate impact of 0.8 percent against Black defendants who are likely, and correctly, identified by grand jurors as such. Put differently, felony cases against Black defendants proceed 0.8 percent more often than do felony cases against White defendants with similar levels of felony guilt.

This finding raises the important question of what part of this disparate impact, if any, is due to taste-based racial bias or statistical discrimination, both of which are illegal under U.S. law. Understanding the source of the disparate impact is important both for its own sake, and for properly assessing the legality of the disparate impact. An important advantage of our study is that we can exploit the “blinded” cases featuring White and Black defendants with similarly-White names in order to get inside the black box of what is driving the disparate impact estimate. In doing so, our

study borrows from the approach used in the seminal papers by Grogger and Ridgeway (2006) and Goldin and Rouse (2000) that use the veil of darkness (i.e., difference in ambient light) and blinded and unblinded auditions to study racial and gender bias, respectively.¹

Strikingly, results indicate a similar, if not slightly larger, disparate impact when comparing Black and White defendants who had similarly-White names, and were thus racially indistinguishable to grand jurors. That is, compared to racially-identifiable White defendants, Black defendants *who were likely believed to be White by grand jurors* were 0.9 percent more likely to have their felony cases pushed forward. The similarity of findings across the “unblinded” and “blinded” samples indicates that the disparate impact estimated between White and Black defendants is not caused by either taste-based or statistical discrimination, but rather is due to similar treatment on the basis of some other factor that differs across race. This is important because while taste-based and statistical discrimination are illegal, the legality of equal treatment on the basis of some other factor that differs across race—such as having a lower threshold of guilt for some types of cases, which may be more common among Black defendants—is more ambiguous.

In assessing the extent to which Black and White defendants with the same potential outcome are treated differently by grand juries, this paper is most similar to Arnold, Dobbie, and Hull (2022), who study racial bias in the context of bail decisions. Our study is similar in that, like judges who are tasked with making bail decisions based on the likelihood of pretrial misconduct, grand jurors are also asked to make decisions based on a one-dimensional consideration—the likelihood of guilt—when deciding whether to true bill a case. This is much simpler than other contexts. For example, prosecutors can and likely do consider a wide range of factors, other than guilt, when making decisions on whether to prosecute a case. We believe the primary difference between our study and that of Arnold, Dobbie, and Hull (2022)—other than studying racial bias in a very different context—is that the grand jury setting enables us to get inside the black box of the

¹There is a large literature using the veil of darkness to study racial profiling by police. See, for example, Horrace and Rohlin (2016), Pierson et al. (2020), Kalinowski et al. (2021), Worden, McLean, and Wheeler (2012), and Brewer (2023).

disparate impact estimate without imposing a structural model of the sort used by Arnold, Dobbie, and Hull (2022). In short, an advantage of the grand jury setting is that it allows for comparisons across both unblinded and blinded racial groups of defendants. This enables us to provide a simple and intuitive test of whether disparate impact is due to race, or to equal treatment on the basis of some other factor correlated with race.

In addition, the paper also contributes to the literature on jury bias. This includes the seminal paper by Anwar, Bayer, and Hjalmarsson (2012) that used random variation in jury panel composition, as well as subsequent studies that use similar approaches by Flanagan (2018) and Hoekstra and Street (2021). The advantage of this study is threefold. First, we are able to assess bias by adjusting the difference in outcomes for the difference in underlying guilt. This enables us to directly estimate whether Black defendants are treated more harshly than White defendants with similar underlying levels of guilt, rather than assessing the interaction of juror and defendant characteristics. This is not possible in the context of trial juries, since there is no way to assess underlying guilt. Second, we are able to get inside the black box of disparate impact by exploiting the fact that some grand jury cases are essentially “blinded”, while others are “unblinded”. This is also not possible in the context of trial juries. Third, our approach and sample provide us with vastly more statistical power to detect effects. In particular, we show that the minimum detectable effects in other studies from the impact of changing the race of only one in six jurors range from 23 percent to 78 percent. This amplifies the concerns expressed by Ioannidis and Doucouliagos (2017), which is that underpowered studies are more likely to be published if they happen to find a statistically significant result, as opposed to an imprecise null result. By comparison, the approach used in our study can detect an effect of only 0.17 percent.

These results have important implications. The first is that at least in the context of grand juries, U.S. citizens do not seem to engage in taste-based or statistical discrimination based on race. The second is that our finding of relatively modest disparate impact of less than one percent casts some doubt that the large racial disparities observed in felony charging and convictions are due to unwarranted disparate impact.

2 Background and Data

A unique feature of the criminal justice system in Texas is that every felony case must first go before a grand jury before it is prosecuted. Grand juries consist of 12 grand jurors and four alternates.² Each grand jury hears all types of felony cases; there is no specialization. After hearing a case, each juror must choose whether to "true bill" a case, in which the case proceeds forward through the system, or "no bill" a case, at which point the case is dropped. If at least 9 out of the 12 seated grand jurors vote to "true bill" a case, then it moves forward in the criminal justice system. If not, the case is "no billed", which is the end of the case. As a result, at the conclusion of a grand jury the case can i) move forward with at least one felony charge (if that charge is "true billed"); ii) move forward with at least one misdemeanor charge (if the felony charge is "no billed" but at least one misdemeanor charge is "true billed");, or iii) be closed at that point, with no further action taken. Grand jurors are asked to use a standard of "probable cause" when deciding whether to true bill a charge, which is a lower standard than the "beyond a reasonable doubt" standard used in jury trials.³ The term for each grand jury is three months. Over that time period jurors meet twice per week, and make judgments on 50+ cases per day.

The Texas Code of Criminal Procedure mandates that only the presenting prosecutor is allowed to be in the room with the grand jurors, along with court reporters. In some cases there may also be an expert witness, if one is needed to help explain the evidence to the grand jurors, or translators, if needed. Video and photographs are not usually shown; the exceptions are the more complex cases.

There are significant constraints in scheduling cases before a grand jury. The main one is that Texas law requires the State to present the case within 90 days if the defendant is in custody, and all cases must be heard within 180 days. Thus, the main priority of each prosecutor is to make sure they meet these requirements. The typical process for assignment is that prosecutors who want to present one or more cases to the grand jury typically ask an administrative assistant in the Grand

²Prior to 2015, the number of alternates was limited to two. However, with the passing of HB 2150, the number increased to four.

³The full ranking of strength of evidence in the legal system, from lowest to highest, is reasonable suspicion, probable cause, preponderance of evidence, clear and convincing, and beyond a reasonable doubt.

Jury Division for a certain day of the week that fits their schedule. The administrative assistant then randomly assigns the prosecutors to one of the two grand juries that meets on that day of the week. As a result, conditional on the timing of that case, cases could have been heard by one grand jury or another, which can differ with respect to their leniency. As a result, we control for year-by-month-by-week fixed effects throughout our analyses.

Another unique feature of the grand jury system is that because the defendant is not present at the hearing, the race or ethnicity of the defendant is not directly observed by the grand jurors. Similarly, while we do not have data on whether prosecutors somehow cue the race of the defendant, anecdotally prosecutors have been warned *not to* signal race or ethnicity in any way during the hearing, for fear of the case being thrown out on the basis of that later. However, grand jurors do observe the full name of the defendant. In addition, they sometimes observe the neighborhood in which the crime occurred, which may be indicative of the defendant's likely race or ethnicity.

Our data include every grand jury case filed from February of 1990 through July of 2022. After excluding cases for defendants identified in the administrative records as neither Black nor White, there are a total of 695,500 cases.⁴ We then link these cases to data on case disposition received from the Office of Harris County District Clerk. As a result, for each charge in each case—including felony charges—we observe whether that charge resulted in a guilty outcome.

These data provide three important advantages, relative to prior work. The first is that we have a measure of the outcome of interest, which is the only factor that grand jurors are told to consider in deciding how to vote on the case. That is, just as Arnold, Dobbie, and Hull (2022) observe whether an individual released on bail was arrested prior to the hearing, we observe whether defendants who were true billed were found guilty of a felony later in the process. This is not possible in the setting of trial juries, because there is no measure of underlying guilt one can use to assess the extent to which Black and White defendants were actually guilty.⁵

⁴We do not observe in the administrative data whether or not defendants are Hispanic.

⁵As a result, the literature on jury bias instead asks whether the interaction of juror and defendant race matters. The limitation of this is that there is even in the presence of a nonzero effect, it is difficult to know whether White decision-makers are biased for White defendants, against Black defendants, or if Black decision-makers are biased for Black defendants, or against White defendants, or some combination of the above.

The second advantage of this setting is that we can get inside the black box of disparate impact, without imposing a structural model of the sort used by Arnold, Dobbie, and Hull (2022). We can do so because unlike in other contexts, where race is always observed, in the grand jury setting race can only be inferred using name and, perhaps in some cases, the location of the crime. As a result, we use the first name and last name of the defendants in our sample to identify defendants who fall into one of three groups: White defendants with identifiably-White names, Black defendants with identifiably-Black names, and Black defendants with identifiably-White names. Formally, we identify the “Whiteness” and “Blackness” of names by using the “`predictrace`” package in R. We classify a Black defendant as having an identifiably-Black name if the probability of being Black is greater than 0.5 for either his first name or his last name. We classify defendants as having an identifiably-White name if the probability of being White is greater than 0.5 for both the first name and the last name.⁶

By comparing identifiably-White defendants to identifiably-Black defendants, we capture the sum of taste-based bias, statistical discrimination, and non-race-based disparate impact. Similarly, by comparing identifiably-White defendants to Black defendants who are likely perceived as White by jurors, we capture only the effect of non-race-based disparate impact. As a result, we can decompose the aggregate estimate into a component that is due to racial bias (taste-based + statistical), and a component based on non-race disparate impact.

Finally, the third advantage of studying racial bias in this context is practical. One challenge in assessing racial bias in other contexts—especially when using the more compelling research designs that use a fraction of the total variation in race—is statistical power. This is a particular challenge when studying trial juries, since the vast majority of cases do not go to trial. This is

⁶In the robustness section, we show that our findings are robust to using alternative, higher thresholds. In addition, we also report results in which the Whiteness and Blackness of names is based on last name and location, which accounts for the possibility that jurors may be able to infer race to the extent the location of the crime is demographically similar to one’s residential neighborhood. Results from this approach are summarized in Panel B of Table 5, while the full set of results is shown in Appendix A. This approach uses the `wru` package in the statistical software R, which uses data in which name, race, and residential information are known to predict the probability that an individual is White, Black, Hispanic, Asian, or Other race/ethnicity. We classify someone as White if the predicted probability of White is greater than 0.5, and classify someone as having a Black-sounding name (and location) if the predicted probability of Black is greater than 0.5.

evident in Figure 1, which shows the number of cases studied by the seminal paper on racial bias by juries by Anwar, Bayer, and Hjalmarsson (2012), as well as subsequent papers on jury bias by Flanagan (2018) and Hoekstra and Street (2021). These papers utilized a total of 712, 737, and 1,481 cases, respectively. By comparison, even when we limit our analysis to those cases involving Black or White defendants with names that are identifiable as White or Black, we have a total of 315,995 “cases” representing a total of 350,560 felony charges.⁷

That stark difference in sample size, combined with the approach enabled by the use of outcome data, results in much more statistical power. This is shown in Panel B of Figure 1, which shows the minimum detectable effect (MDE) at 80 percent power for all four studies. For the first three studies, the treatment effect is defined as the effect of having one more juror of a different race or gender, out of six.⁸ The minimum detectable effect in the Anwar, Bayer, and Hjalmarsson (2012), Flanagan (2018), and Hoekstra and Street (2021) papers are 78 percent, 23 percent, and 26 percent, respectively. By comparison, the minimum detectable effect in this study is 0.17 percent. This has important implications, as Ioannidis and Doucouliagos (2017) question whether underpowered papers would publish if they were to find an imprecise, null effect, rather than a very large, statistically significant one. In addition, we note that even with a sample of our size, statistical power can be an issue using other approaches. For example, if we use the methodology proposed by Arnold, Dobbie, and Yang (2018), we estimate a statistical zero with a standard error of 8 percentage points. We view this as an uninformative, imprecise zero, and one that we suspect would go unpublished.

Summary statistics are shown in Table 1. Column (1) shows results for the full sample of

⁷Each defendant-charge in our data is given a unique case number. However, some defendants are associated with multiple cases heard by the same grand jury on the same day, which arose from the same event. To make an apples-to-apples comparison to the three other studies, which have multiple charges per defendant-case, For the purpose of Figure 1 we count situations in which a defendant has multiple charges heard by the same grand jury on the same day as a single “case”. Throughout our analyses we keep our data at the defendant-charge level (for which we observe a unique “case” number in the administrative data), and weight each observation by the inverse of the number of charges heard on that defendant on that particular day.

⁸One could argue that to make those studies comparable to this one, which simply compares Black and White defendants, one should rescale the MDE for these other studies to be the effect of going from 0 to 6 out of 6 jurors of a different race or gender. Doing so would require multiplying each of those estimates by 6, which would obviously make the difference in MDE even more stark.

695,500 grand jury cases filed between February of 1990 and July of 2022. It shows that 53 percent of defendants are White, while 47 percent are Black. Eighty-two percent of defendants are male, with an average age of 32. With respect to charge characteristics, 12.1 percent of charges are 1st degree felonies, 22.5 percent are 2nd degree felonies, and 29.6 percent are 3rd degree felonies. The average number of charges per case is 1.15.

With respect to outcomes, 97.1 percent of the cases are true billed. Sixty-two percent of cases result in felony guilt. Conditional on a true bill from the grand jury, 64 percent of cases result in felony guilt.

Column (2) of Table 1 shows summary statistics for White defendants with racially identifiable White names, Black defendants with racially identifiable Black names, and Black defendants with racially identifiable White names. This is the sample used throughout the analysis. Defendants in this sample are slightly older (33.9 versus 32.4 years old for the full sample), and are slightly more likely to have had a prior offense (70.1 versus 66.8 percent). The seriousness of the felony charges faced is similar to that of the full sample, as is the number of charges. In addition, the true bill rate for this sample of 35,560 defendants is identical to the full sample (97.1 percent).

Column (3) of Table 1 shows summary statistics for White defendants with racially identifiable White names. It shows that the predicted likelihood of being Black for these individuals is only 15 percent. Column (4) shows summary statistics for Black defendants with racially identifiable Black names. The predicted likelihood of being Black for these individuals is 70 percent. Thus, it is clear that for the set of White and Black defendants shown in Columns (3) and (4), race is highly identifiable even without directly observing the individual or their race. This is important, because a comparison of these two samples enables us to assess the extent to which identifiably-Black defendants are treated differently than identifiably-White defendants for whom felony guilt is similar.

Column (5) shows summary statistics for Black defendants with racially identifiable White names. For these individuals, the predicted likelihood of being Black is only 26 percent, which is substantively lower than for the Black defendants with identifiably-Black names (70 percent), and

only somewhat higher than for White defendants with identifiably-White names (15 percent).

Columns (3) and (4) of Table 1 also show that there are substantive differences between defendants that jurors would likely identify as Black and White. Black defendants shown in Column (3) are somewhat younger (32.4 versus 34.6 years old), and are more likely to have a prior offense (74 versus 62 percent). In addition, the identifiably-Black defendants in Column (4) face more serious charges; they are more likely to face a 1st degree felony charge (12.6 versus 8.1 percent), slightly more likely to face a second degree felony charge (22.6 versus 20.5 percent), and less likely to face a 3rd degree felony charge (26.9 versus 31.9 percent). Identifiably-Black defendants are true billed at somewhat higher rates than White defendants (97.4 versus 96.6 percent), and are more likely to be found guilty of a felony conditional on a true bill outcome (64.9 versus 64.5 percent).

In contrast to the substantive differences between the cases of identifiably-White and identifiably-Black defendants, there are at most few such differences between the identifiably-Black defendants in Column (4), and the Black defendants in Column (5) who are likely to be (incorrectly) perceived as White. Of cases with identifiably-Black (identifiably-White) defendants, 12.6 (12.7), 22.6 (22.8), and 26.9 (27.1) percent are 1st, 2nd, and 3rd degree felonies, respectively. This is helpful for our approach to distinguishing between statistical or taste-based bias from other non-race-based behaviors that have disparate impact, as our approach assumes that the latter would be similar across the two groups of Black defendants shown in Columns (4) and (5). Table 1 suggests this is a reasonable assumption, as the cases of both groups of Black defendants are similar to each other, and different from those of identifiably-White defendants.

3 Methodology

3.1 Disparate Impact

In order to estimate disparate impact, we follow the methodology proposed by Arnold, Dobbie, and Hull (2022), who test for disparate impact in the context of bail judges. The estimate from this method captures the sum of racial bias and statistical discrimination as well as disparate impact caused by equal treatment on the basis of a factor that is more prevalent for defendants of one race than the other. Intuitively, following Arnold, Dobbie, and Hull (2022), we can estimate the disparate impact by rescaling the true bill rate of each race with the observed felony guilt outcome and mean underlying felony guilt of each race. The hurdle is that we do not normally observe mean underlying felony guilt. Rather, we only observe the felony guilt outcome of defendants who were true billed.

To overcome this issue, we exploit the fact that there is random assignment of cases to grand juries, and that some grand juries are less lenient than others. This enables us to estimate the mean underlying felony guilt of each race by looking at the outcome of cases handled by a hypothetical grand jury that true bills every case. In practice, we do this by extrapolating the trend observed among the different grand juries we observe to estimate what the average felony guilt rate would be for Black and White defendants if their cases were handled by a grand jury that true billed every case. In this way, we estimate the underlying felony guilt of each racial group. One advantage of doing this in our setting is that it requires much less extrapolation than it does in other settings. In particular, the mean true bill rate in our data is 97.1 percent. By comparison, in Arnold, Dobbie, and Hull (2022) extrapolated in a setting where the mean rate of interest was 73 percent.

Below, we formalize and explain the methodology in more detail.

Defining disparate impact

In this section, we formally define disparate impact in a similar fashion as in Arnold, Dobbie, and Hull (2022). Let $D_{ij} \in \{0, 1\}$ denote the grand jury j 's true bill decision on defendant i . $R_i \in \{w, b\}$ is the race of defendant i . $Y_i^* \in \{0, 1\}$ signifies underlying felony guilt of defendant i . In other

words, Y_i^* indicates whether defendant i would be found guilty of a felony if they were true billed by the grand jury. $Y_i \in \{0, 1\}$ is the observed felony guilt of defendant i , which is always 0 when the case was not true billed ($D_{ij} = 0$) and equals to Y_i^* when the case is true billed ($D_{ij} = 1$).

We define the disparate impact in grand jury j 's decisions Δ_j as the difference in their true bill rates of black and white defendants with the same underlying level of felony guilt. Δ_{j0} is the true bill rates disparity between black and white defendants without underlying felony guilt ($Y_i^* = 0$). And Δ_{j1} is the true bill rates disparity between black and white defendants with underlying felony guilt ($Y_i^* = 1$).

$$\Delta_{j0} = E[D_{ij}|R_i = b, Y_i^* = 0] - E[D_{ij}|R_i = w, Y_i^* = 0] \quad (1)$$

$$\Delta_{j1} = E[D_{ij}|R_i = b, Y_i^* = 1] - E[D_{ij}|R_i = w, Y_i^* = 1] \quad (2)$$

Grand jury j 's average disparate impact Δ_j is then the weight average of Δ_{j0} and Δ_{j1} .

$$\Delta_j = \{1 - Pr(Y_i^* = 1)\}\Delta_{j0} + Pr(Y_i^* = 1)\Delta_{j1} \quad (3)$$

Since $\bar{\mu} = E[Y_i^*] = Pr(Y_i^* = 1)$,

$$\Delta_j = (1 - \bar{\mu})\Delta_{j0} + \bar{\mu}\Delta_{j1} \quad (4)$$

To estimate disparate impact Δ_j , we would need $\delta_{jry} \equiv E[D_{ij}|R_i = r, Y_i^* = y]$ and $\bar{\mu}$. This presents a challenge because underlying felony guilt (Y_i^*) is not observed for those who were not true billed.

Estimating disparate impact

As shown earlier, we need $\delta_{jr0} = E[D_{ij}|R_i = r, Y_i^* = 0]$ and $\delta_{jr1} = E[D_{ij}|R_i = r, Y_i^* = 1]$ to estimate disparate impact Δ_j . Following Arnold, Dobbie, and Hull (2022), we show below that we can estimate these two terms with the observed felony guilt outcome Y_i , true bill decision D_i , and the race-specific underlying felony guilt μ_r .

First, using the law of iterated expectation, we show that

$$\begin{aligned}
E[D_{ij}(1 - Y_i)|R_i = r] &= Pr(R_i = r, D_{ij} = 1)E[D_{ij}(1 - Y_i)|R_i = r, D_{ij} = 1] \\
&= Pr(R_i = r, D_{ij} = 1)E[D_{ij}(1 - Y_1^*)|R_i = r, D_{ij} = 1] \\
&= E[D_{ij}(1 - Y_i^*)|R_i = r] \\
&= Pr(R_i = r, Y_i^* = 0|R_i = r)E[D_{ij}(1 - 0)|R_i = r, Y_i^* = 0] \\
&= (1 - \mu_r)E[D_{ij}|R_i = r, Y_i^* = 0]
\end{aligned} \tag{5}$$

Therefore, with quasi-random assignment of cases to grand juries,

$$\begin{aligned}
\delta_{jr0} &= E[D_{ij}|R_i = r, Y_i^* = 0] \\
&= \frac{E[D_{ij}(1 - Y_i)|R_i = r]}{1 - \mu_r} = \frac{E[D_i(1 - Y_i)|R_i = r, Z_{ij} = 1]}{1 - \mu_r}
\end{aligned} \tag{6}$$

Likewise,

$$\begin{aligned}
E[D_{ij}(Y_i)|R_i = r] &= Pr(R_i = r, D_{ij} = 1)E[D_{ij}(Y_i)|R_i = r, D_{ij} = 1] \\
&= Pr(R_i = r, D_{ij} = 1)E[D_{ij}(Y_1^*)|R_i = r, D_{ij} = 1] \\
&= E[D_{ij}(Y_i^*)|R_i = r] \\
&= Pr(R_i = r, Y_i^* = 1|R_i = r)E[D_{ij}|R_i = r, Y_i^* = 1] \\
&= \mu_r E[D_{ij}|R_i = r, Y_i^* = 1]
\end{aligned} \tag{7}$$

Therefore,

$$\begin{aligned}
\delta_{jr1} &= E[D_{ij}|R_i = r, Y_i^* = 1] \\
&= \frac{E[D_{ij}Y_i|R_i = r]}{\mu_r} = \frac{E[D_iY_i|R_i = r, Z_{ij} = 1]}{\mu_r}
\end{aligned} \tag{8}$$

where Z_{ij} is a binary variable indicating that defendant i was assigned to grand jury j .

Substitute δ_{jr0} from Equation 6 and δ_{jr1} from Equation 8 into Equation 4, we get

$$\begin{aligned}
\Delta_j &= \bar{\mu}\Delta_{j1} + (1 - \bar{\mu})\Delta_{j0} \\
&= \bar{\mu}\{\delta_{jb1} - \delta_{jw1}\} + (1 - \bar{\mu})\{\delta_{jb0} - \delta_{jw0}\} \\
&= E\left[\left(\frac{\bar{\mu}Y_i}{\mu_b} + \frac{(1 - \bar{\mu})(1 - Y_i)}{1 - \mu_b}\right)D_i \mid R_i = b, Z_{ij} = 1\right] \\
&\quad - E\left[\left(\frac{\bar{\mu}Y_i}{\mu_w} + \frac{(1 - \bar{\mu})(1 - Y_i)}{1 - \mu_w}\right)D_i \mid R_i = w, Z_{ij} = 1\right] \\
&= E[\Omega_i D_i \mid R_i = b, Z_{ij} = 1] - E[\Omega_i D_i \mid R_i = w, Z_{ij} = 1]
\end{aligned} \tag{9}$$

where

$$\Omega_i = \left(\frac{\bar{\mu}Y_i}{\mu_r} + \frac{(1 - \bar{\mu})(1 - Y_i)}{1 - \mu_r}\right) \tag{10}$$

Since $\bar{\mu} = Pr(R_i = w)\mu_w + Pr(R_i = b)\mu_b$ and we observe felony guilty outcome Y_i and true bill decision D_i , we only need to know μ_r to estimate disparate impact Δ_j .

Extrapolations of underlying felony guilt

In most settings, μ_r , which is the average underlying felony guilt of race r cannot be estimated because we do not observe the underlying felony guilt (Y_i^*) of defendants who were not true billed. However, with the random assignment of cases to grand juries, the defendants assigned to each grand jury have the same underlying felony guilt on average. Specifically, the average underlying felony guilt of defendants of each race assigned to a grand jury (j) would be the same as the average underlying felony guilt of defendants of that race μ_r .

$$\mu_r = E[Y_i^* \mid R_i = r] = E[Y_i^* \mid R_i = r, Z_{ij} = 1] = E[Y_i^* \mid R_i = r, Z_{ij^*} = 1] \tag{11}$$

In the case of the maximally tough grand jury j^* that true billed every case, we would be able to observe the underlying felony guilt Y_i^* of all defendants assigned to that jury. This gives us an estimate of the average underlying felony guilt of *all* defendants within a given racial group. This is because true bill decision D_{ij} would be equal to 1 and $Y_i = Y_i^*$ for all defendants of this maximally

tough grand jury j^* .

$$E[Y_i^* | Z_{ij^*} = 1, R_i = r] = E[Y_i | D_{ij} = 1, Z_{ij^*} = 1, R_i = r] \quad (12)$$

Combining Equations 11 and 12, we show that in a setting featuring the random assignment of cases to grand juries, we can estimate the race-specific underlying felony guilt μ_r from the guilty outcome of the defendants who were true billed by the maximally tough grand jury that true billed all cases $E[Y_i | D_{ij} = 1, Z_{ij^*} = 1, R_i = r]$.

$$\mu_r = E[Y_i | D_{ij} = 1, Z_{ij^*} = 1, R_i = r] \quad (13)$$

Similar to Arnold, Dobbie, and Hull (2022), there are two issues that we need to address in order to estimate the race-specific underlying felony guilt μ_r . First, we do not have a maximally tough grand jury in each time period of our data that true billed every case. Moreover, we want to minimize any sampling error that would arise given the finite sample of cases heard by a maximally tough grand jury. We, therefore, obtain the race-specific average underlying felony guilt μ_r by statistical extrapolation. In practice, this requires little extrapolation because the average true bill rate in our sample is 97.1 percent. Second, in our setting, grand juries were only quasi-randomly assigned conditional on year-month-week of the hearing. We have to take out these time effects from our variables. We explain the procedure used to take out the time effects as well as the extrapolation process below.

Step 1: regress true bill decision D_i and felony guilty outcome Y_i on year-month-week fixed effects, grand jury fixed effects, and the interactions of black defendant dummy and grand jury fixed effects.

$$D_i = \sum_j \alpha_j Z_{ij} + \sum_j \beta_j Blk_i Z_{ij} + \gamma_t + u_i \quad (14)$$

$$Y_i = \sum_j \rho_j Z_{ij} + \sum_j \omega_j Blk_i Z_{ij} + \gamma_t + u_i \quad (15)$$

Step 2: construct the time-effects adjusted $E[D_i | Z_{ij} = 1, R_i = r]$ and $E[Y_i | D_i = 1, Z_{ij} = 1, R_i = r]$

from the estimated coefficients as follow:

$$\begin{aligned}
E[D_i|Z_{ij} = 1, R_i = w] &= \alpha_j \\
E[D_i|Z_{ij} = 1, R_i = b] &= \alpha_j + \beta_j \\
E[Y_i|D_i = 1, Z_{ij} = 1, R_i = w] &= \rho_j \\
E[Y_i|D_i = 1, Z_{ij} = 1, R_i = b] &= \rho_j + \omega_j
\end{aligned} \tag{16}$$

Step 3: Regress and plot $E[Y_i|D_i = 1, Z_{ij} = 1, R_i = r]$ on $E[D_i|Z_{ij} = 1, R_i = r]$ and extrapolate the average underlying felony guilt μ_r by predicting the value of $E[Y_i|D_i = 1, Z_{ij} = 1, R_i = r]$ at $E[D_i|Z_{ij} = 1, R_i = r] = 1$.

Once we extrapolate μ_r , we can estimate the average underlying felony guilt of the whole defendant population $\bar{\mu}$, and then use Equation 9 and Equation 10 to obtain an unbiased estimate the disparate impact Δ_j . Standard errors are two-way clustered at the defendant and grand jury levels.

3.2 Mechanism behind disparate impact

In addition, as alluded to above, one advantage of the context we study is that in contrast to both trial juries and judges in other contexts, grand juries do not directly observe race. This provides an opportunity to us to employ a strategy similar to the “veil of darkness” literature following the seminal paper by Grogger and Ridgeway (2006), or even other studies that have compared across blinded and unblinded settings. In this way, our study deviates from the approach used by Arnold et al. (2022), who use a structural model to tease out the extent to which disparate impact is due to racial bias, versus other factors.

In particular, we use the method explained in the earlier subsection to estimate the disparate impact against Black defendants who have Black names (i.e., those who are likely perceived to be Black). The comparison group is White defendants with identifiably-White names. This is our

main specification, as it captures the sum of taste-based bias, statistical discrimination, and non-race-based disparate impact against defendants perceived by jurors to be Black.

Next, we estimate the disparate impact against Black defendants with identifiably White names—that is, Black defendants likely to be perceived by the jurors as White. Again, the comparison group is White defendants with identifiably-White names. This estimate of disparate impact captures only the effect of non-race-based disparate impact against defendants perceived by jurors to be Black. In contrast, it does not capture either taste-based or statistical discrimination based on race, since grand jurors would not be able to identify that the defendants are Black.

Under the assumption that the non-race-based disparate impact against identifiably-Black defendants is the same as that against Black defendants perceived to be White, the difference in the two measures of disparate impact captures the combined effect of taste-based and statistical discrimination based on race. We view this assumption as reasonable because as shown in Table 1, the case characteristics of Black defendants with identifiably-White names are similar to those with identifiably-White names (i.e., Column (3) versus Column (4)), even while both are substantively different from White defendants. It is these substantive differences across race that provide scope for non-race-based disparate impact. For example, grand jurors could use a lower threshold for guilt for certain crimes that are disproportionately committed by Black defendants.

4 Results

4.1 Grand jury leniency is uncorrelated with case and defendant characteristics

Prior to showing estimates of disparate impact between Black and White defendants, we first provide empirical evidence that the leave-one-out measure of grand jury leniency is uncorrelated with defendant and case characteristics. This is important because random assignment is required in order to obtain an unbiased estimate of the likelihood of felony guilt for the full populations of Black and White defendants. We do this by using the variation in grand jury leniency to perform a

(slight) extrapolation to estimate the guilty rate for defendants if they were put before a hypothetical grand jury that true bills every case.

Results are shown in Table 2, in which the leave-out-out measure of grand jury leniency was regressed on all defendant and case characteristics. Column (1) shows results for the full set of White and Black defendants. Results for the sample of White defendants with racially-identifiable White names, Black defendants with racially-identifiable Black names, and Black defendants with racially-identifiable White names are shown in Columns (2), (3), and (4), respectively. At the bottom of each column, we report the results from an F-test of joint significance for all of the coefficients on defendant and case characteristics. Each regression also includes year-by-month-by-week fixed effects. Intuitively, this test answers the following thought experiment: Conditional on being heard during the same week, are cases that are heard by the less lenient grand jury observably similar to those that are heard by the more lenient grand jury?

Results are consistent with random assignment. Of the 33 estimates shown, three are significant at the five percent level. While this is somewhat more than one would expect due to chance, it is telling that the magnitude of even the statistically significant estimates is very small. In particular, the absolute magnitude of all three statistically significant estimates is less than 0.001, which indicates a tiny correlation between factors such as male and felony type and grand jury leniency. Moreover, despite the large number of observations, one cannot reject the null hypothesis that the coefficients are all equal to zero for any of the four samples shown.

4.2 Disparate impact on Black defendants with Black names

Next, we turn to our main estimate of disparate impact between Black and White defendants. As noted earlier, however, because actual race is not directly observed by the grand jury, we focus first on comparing White defendants who are likely identified as White, to Black defendants who are likely identified as Black.

Results are shown in Table 3. Panel A shows the estimated mean risk by race for both White and Black defendants. Intuitively, these estimates measure the fraction of White and Black

defendants who would be found guilty of a felony if every defendant were to be true-billed. Results indicate that across the entire population of identifiably-White and identifiably-Black defendants, Black defendants are somewhat more guilty than White defendants (65 percent versus 63.5 percent).

Panel B shows the estimate of disparate impact between White and Black defendants. We show results using three different methods: linear extrapolation, local linear extrapolation with an Epanechnikov kernel with a rule-of-thumb bandwidth, and local linear with a Gaussian kernel with rule-of-thumb bandwidth.⁹ Estimates are 0.0076, 0.0084, and 0.0085, respectively, all of which are statistically significant at the one percent level using bootstrapped standard errors. This indicates that grand juries are approximately 0.8 percentage points, or 0.8 percent relative to the mean of 0.971, more likely to true bill a case with a Black defendant than with a White defendant whose underlying felony guilt is similar.

4.3 Disparate impact on Black defendants with White names

While the results in the previous section provide strong evidence that Black defendants are subjected to a small, but statistically significant, disparate impact, it is less clear *why* this is the case. Potential explanations include behavior that is specifically targeted on the basis of race, such as taste-based or statistical discrimination. However, while both of these underlying sources of the disparate impact are illegal, other sources of disparate impact against Black defendants may not be. As a result, while understanding the extent to which there is disparate impact is useful, some important questions are left unanswered.

In order to examine the extent to which the disparate impact is caused by taste-based or statistical discrimination, rather than differential treatment on the basis of something correlated with race, we borrow a methodology employed by both the “veil of darkness” literature as well as tests of blinded and unblinded behavior. The logic of the test is straightforward: If the disparate impact documented

⁹We do not show results from a quadratic extrapolation given how little we are extrapolating (i.e., mean true bill rate = 0.971).

in Table 3 is due entirely to taste-based or statistical discrimination based on race, then we should see no effect *when race cannot be inferred by the grand jurors*.

To implement this test, we show results when we compare White defendants with White names to Black defendants who also have White names. As a result, jurors are unlikely to infer, consciously or otherwise, that these two groups of jurors differ with respect to race. As a result, any nonzero disparate impact estimate will be due to non-race-based disparate impact. Results are shown in Table 4, which takes the same form as Table 3. Strikingly, results indicate that estimates of disparate impact are similar to those shown in Table 3 and, if anything, are slightly larger. Estimates across the three extrapolation methods are 0.98, 0.96, and 0.94 percentage points. In no case is the estimate in Table 4 smaller than the corresponding estimate in Table 3. In contrast, if anything disparate impact estimates against Black defendants who are likely inferred as White are slightly larger (e.g., 0.0098 versus 0.0076 in Column (1)), which is the opposite of what we would expect if some or all of the disparate impact in Table 3 were due to taste-based or statistical discrimination based on race.

In short, results in Table 3 indicate there is similar disparate impact against Black defendants *even when race is unobserved by the grand jurors*. This indicates that whatever the cause of the disparate impact against identifiably-Black defendants documented in Table 3, it is unlikely to be taste-based racial bias or statistical discrimination.

4.4 Rescaling estimates and robustness to an alternative method of measuring juror perception of race

One potential concern with the estimates from Tables 3 and 4 is that jurors are unlikely to perceive that every Black defendant with a Black name is Black, or that every Black defendant with a White name is White. Indeed, Table 1 shows that the predicted likelihood of being Black is 70.2 percent for the Black defendants with Black names, and 26.1 percent for Black defendants with White names. In short, while our proxy for the perceived “Blackness” of a name clearly captures differences, it is not perfect. In this way, estimates in Tables 3 and 4 capture reduced-form effects.

Panel A of Table 5 shows the estimates when they are rescaled to account for the imperfect nature of our proxy for the Blackness (or Whiteness of names). The first row shows the difference between the reduced-form estimates shown in Tables 3 and 4. Under the assumption that the non-race-based “disparate impact” component of the estimates in Table 3 is the same as in Table 4, the difference captures the sum of statistical and taste-based discrimination against perceived-Black defendants. Positive estimates indicate the presence of race-based bias against Black defendants, while negative estimates indicate race-based bias against Whites, relative to Black defendants.

The second row shows this same difference, except rescaled to account for the imperfect proxies of Blackness we use.¹⁰ None of the estimates is positive, and thus none suggests the presents of taste-based racial bias or statistical discrimination against identifiably-Black defendants. Rather, estimates in Columns (2) and (3) are close to zero and statistically insignificant. The estimate in Column (1), from linear extrapolation, is negative and significant, and is thus the opposite of what one would expect in the presence of taste-based or statistical discrimination based on race against Black defendants.

Next, we show differences in disparate impacts using an alternative approach for predicting the “Whiteness” and “Blackness” of names. In particular, we predict perceived race using last name and Census Block Group using the “wru” package in R. The intuition for doing so is that while jurors do not directly observe an individual’s neighborhood, to the extent the crime location is demographically similar to one’s neighborhood, or to the extent that witness names or characteristics are correlated with the demographics of one’s own neighborhood, jurors may be able to infer race based on that. Moreover, this method enables us to test whether using a substantively different approach provides similar answers. As with our main approach, we use a 50 percent threshold for determining what jurors would infer with respect to the defendant’s race.

The full set of results that mirror the main results reported above are shown in Appendix A. Results are largely similar to those presented in the main analysis. Estimates of disparate impact

¹⁰We rescale by dividing the difference in the first row by $(0.702 - 0.261)$, or 0.441. Equivalently, the difference in predicted race between White defendants with White predictions and Black defendants with Black predictions is $(0.702 - 0.151)$, while the difference between White defendants and Black defendants with White predictions is $(0.261 - 0.151)$. The difference between these two is 0.441.

are slightly larger at one percent, but are again the same both for Black defendants with identifiable-Black names, and for Black defendants with White names.

Panel B of Table 5 shows the estimated difference in disparate impacts using that approach, as well as the rescaled difference in disparate impacts. As in Panel A, the differences in disparate impact estimates are small. The rescaled differences are 0.0013, -0.0011, and -0.0011, none of which are statistically significant. Moreover, the magnitude is very small. Taken literally, and under the assumption that non-race-based disparate impact against Black defendants with identifiable-names is the same as against Black defendants with White names, the estimates would imply that the sum of statistical and taste-based bias is 0.13 percentage points against Black defendants, or 0.11 percentage points against White defendants.

In summary, results in Table 5 indicate that grand jurors do not engage in statistical or taste-based discrimination against Black defendants. Rather, the small but statistically significant 0.8 percent disparate impact shown in Table 3 appears to be due to jurors applying a slightly lower threshold for guilt to cases that tend to be slightly more common among Black defendants, compared to White ones.

4.5 Robustness to alternative thresholds for predicting “Whiteness” and “Blackness”

As described above, our main analysis uses the 50 percent threshold for classifying a defendant as likely to be perceived by jurors as White, or likely to be perceived by jurors as Black. While Columns (3) and (4) of Table 1 demonstrate that this threshold has, on average, a clear association with actual defendant race, in this section we also show results for cutoffs ranging from 50 to 80 percent.¹¹

Results are shown in Figure 2. As shown in Tables 3 and 4, estimated disparate impact is approximately 0.8 percentage points for both White defendants with White names compared to

¹¹Using a threshold of 80 percent implies we retain less than 12 percent of our main sample of Black defendants with White names, and less than one-third of our sample of Black defendants with Black names.

Black defendants with Black names, and for White defendants with White names compared to Black defendants with White names. Figure 2 also shows, consistent with Tables 3 and 4, that the disparate impact estimates for Black defendants with White names is slightly higher than those for Black defendants with Black names, which is the opposite of what we would expect in the presence of taste-based or statistical discrimination based on race. Figure 2 shows that this remains true from thresholds of 50 percent through 75 percent. From thresholds of 75 to 80 percent there is a slight divergence, where the disparate impact estimates against Black defendants with very Black names is somewhat larger than that against Black defendants with White names. The magnitude of this divergence depends substantively on the extrapolation method being used. Moreover, estimates in that range are being identified off of a small share of the overall population of Black defendants.

Overall, results in Figure 2 are qualitatively consistent with the results reported above: There is disparate impact against identifiably-Black defendants, compared to White defendants. But we estimate a disparate impact that is just as large, and typically slightly larger, when comparing White defendants to Black defendants who are likely perceived as White by the grand jury. This suggests that whatever is driving the disparate impact, it does not seem to be either racial bias or statistical discrimination.

5 Conclusion

There has been much interest in the extent to which implicit or explicit racial discrimination is responsible for racial disparities in the criminal justice system. In this paper, we test for racial bias in the context of grand juries. This setting provides three important advantages. The first is that because grand juries make decisions about whether a felony case should move forward, we observe the outcome for cases that are true billed. This, combined with the quasi-random assignment of cases across grand juries that differ in leniency, allows us to use a recent method to purge omitted variable bias from the estimated Black-White disparity.

The second advantage is that because grand juries do not directly observe the race of the

defendant, we can provide estimates for cases that are unblinded (i.e., race can be easily inferred based on first and last name, which are observed), as well as for cases that are blinded (i.e., comparing White defendants to Black defendants with White names). This enables us to perform a simple, intuitive test of whether any disparate impact is due to taste-based racial bias or statistical discrimination—both of which are illegal—or if it is due to similar treatment on the basis of something correlated with race, the legality of which is less clear.

Finally, the setting of grand juries enables us to test whether a representative set of U.S. citizens engages in racial bias using a data set of cases that is vastly larger than any previous jury data set. As a result, the minimum detectable effect in the next-most-powered study of jury bias is over 130 times larger than the minimum detectable effect in this study, which is 0.17 percent. Put differently, the context of grand juries gives us the statistical power to provide a precise and informative—and thus likely publishable—answer, even if that answer is statistically indistinguishable from zero.

Results indicate that grand juries treat defendants who can easily be identified as Black approximately 0.8 percent more harshly compared to White defendants with a similar level of underlying felony guilt. This estimate is statistically significant at the one percent level. However, it is also a small fraction of the estimates reported in other studies, both in the context of juries and elsewhere.

In addition, we show that this disparate impact seems to be caused entirely by factors other than taste-based or statistical discrimination. We show this by documenting a disparate impact of nearly identical magnitude when comparing White defendants to Black defendants who, by virtue of their first and last names, are racially indistinguishable to the grand jurors, who do not directly observe race. This suggests that whatever the source of the small but statistically significant disparate impact against Black defendants, it is not taste-based or statistical discrimination based on race.

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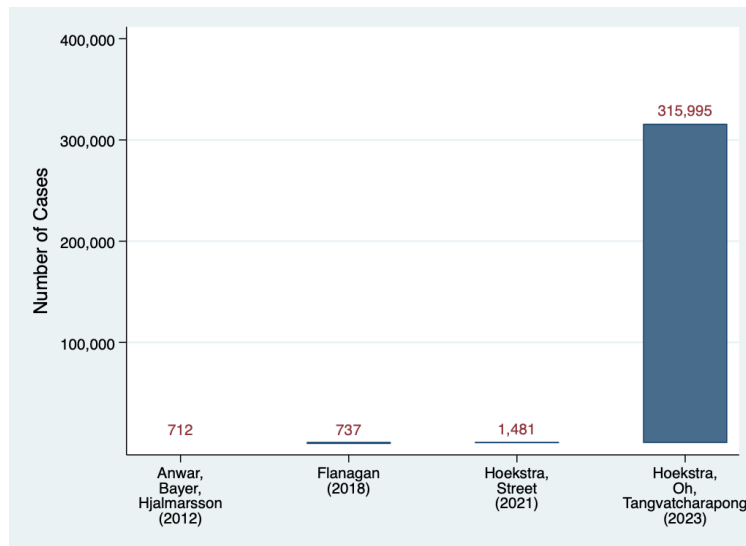
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Figures

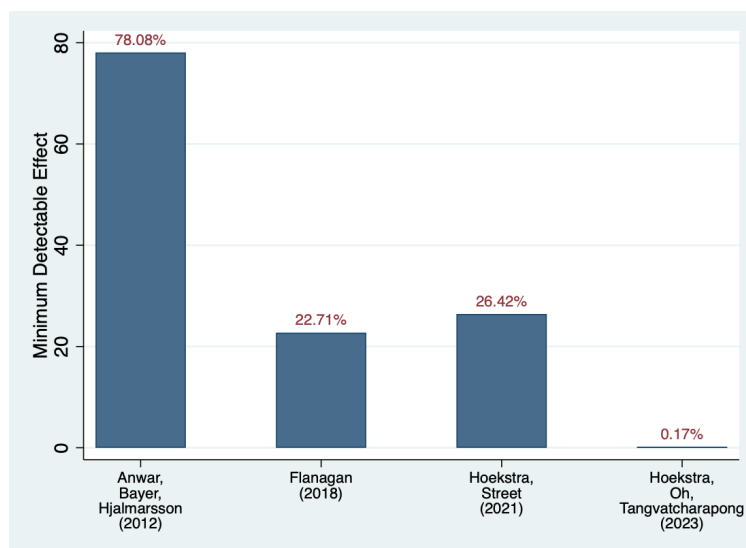
Figure 1: Sample size (# Cases) and Minimum Detectable Effects in Jury Bias Literature

Panel A: Sample Size



Notes: Panel A shows the total number of criminal cases examined by each study, the fourth of which is this one.

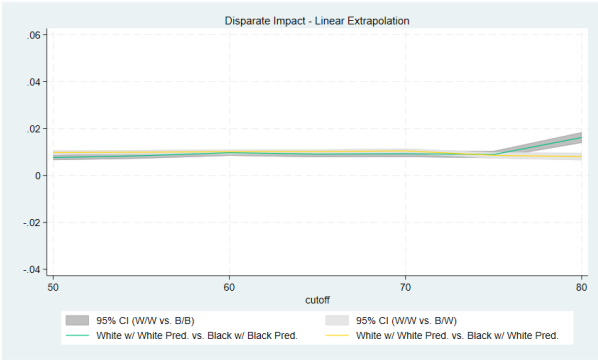
Panel B: Minimum Detectable Effect



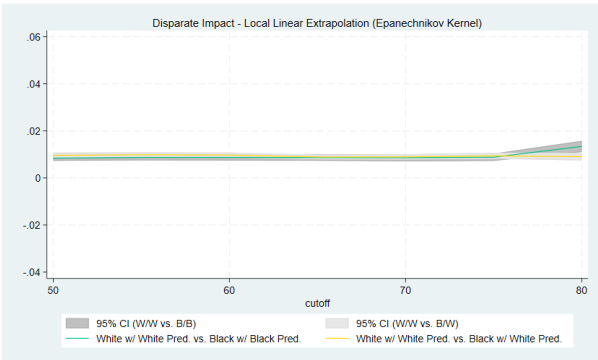
Notes: Panel B shows the minimum detectable effect (MDE) at 80 percent power in each study, defined as 2.8 times the standard error from the main estimate of the average effect. For the first three papers, the treatment effect is defined as the effect of having an additional juror (out of six) of a different race or gender. In the current study shown in the fourth bar, treatment is defined as the disparate impact between Black and White defendants.

Figure 2: Robustness to Alternative Thresholds

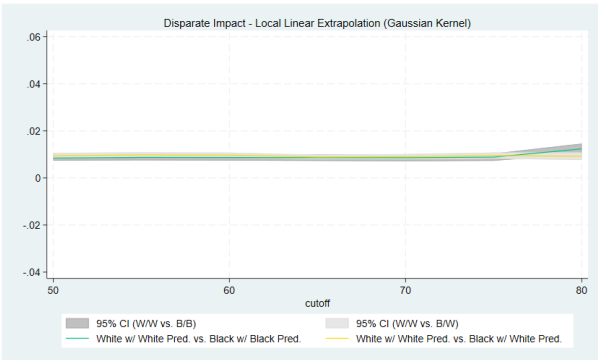
Panel A: Linear Extrapolation



Panel B: Local Linear Extrapolation Epanechnikov



Panel C: Local Linear Extrapolation Gaussian



Notes: This figure provides disparate impacts and 95% confidence intervals using linear extrapolation for thresholds ranging from 50% (shown in main results) to 80%. Estimates in green are disparate impact estimates against Black defendants with identifiably-Black names, while estimates in yellow are disparate impact estimates against Black defendants with White names who are therefore likely perceived as White by grand jurors.

Tables

Table 1: Summary Statistics

	All defendants	Sample w/ racially identifiable names	White w/ White Prediction	Black w/ Black Prediction	Black w/ White Prediction
	(1)	(2)	(3)	(4)	(5)
<i>Panel A: Race Characteristics</i>					
White	0.533	0.387	1.000	0.000	0.000
Black	0.467	0.613	0.000	1.000	1.000
Predicted White	0.433	0.860	1.000	0.000	1.000
Predicted Black	0.074	0.140	0.000	1.000	0.000
Black Prediction Value	0.197	0.280	0.151	0.702	0.261
<i>Panel B: Defendant Characteristics</i>					
Male	0.822	0.823	0.785	0.814	0.858
Age at grand jury hearing	32.398	33.860	34.733	32.547	33.532
Age at filing	32.269	33.736	34.611	32.418	33.409
Prior Offense	0.668	0.701	0.622	0.738	0.754
<i>Panel C: Charge Characteristics</i>					
Felony 1st degree	0.121	0.109	0.081	0.126	0.127
Felony 2nd degree	0.225	0.219	0.205	0.226	0.228
Felony 3rd degree	0.296	0.289	0.319	0.269	0.271
Felony Capital degree	0.003	0.003	0.002	0.004	0.004
Felony State degree	0.354	0.379	0.392	0.375	0.370
Offense degree in linear	3.243	3.324	3.419	3.276	3.262
Number of Charges	1.149	1.151	1.144	1.152	1.156
<i>Panel D: Case outcomes</i>					
Truebill	0.971	0.971	0.966	0.974	0.975
Felony Guilty Conviction	0.621	0.634	0.621	0.631	0.644
Any Guilty Conviction	0.745	0.748	0.747	0.740	0.750
Felony Guilty Conviction when True-billed	0.641	0.653	0.645	0.649	0.661
Any Guilty Conviction when True-billed	0.768	0.770	0.775	0.760	0.770
Observations	695,500	350,560	134,903	49,033	166,624

Notes. This table summarizes the main analysis sample using the inverse of the number of charges as weights. The sample consists of grand jury hearings that were quasi-randomly assigned to grand jury panels between February 1990 and July 2022. Race prediction is based on the likelihood of an individual being White or Black, computed by the R package ‘predictrace,’ with a threshold of 50%.

Table 2: Balance Tests

	(1) All defendants	(2) White defendants w/ White Prediction	(3) Black defendants w/ Black Prediction	(4) Black defendants w/ White Prediction
Black	0.000 (0.000)			
Male	0.000 (0.000)	-0.000 (0.000)	0.001** (0.000)	0.000 (0.000)
Age at grand jury hearing	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000* (0.000)
Felony 1st degree	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
Felony 2nd degree	-0.000** (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
Felony 3rd degree	-0.000** (0.000)	-0.000* (0.000)	0.000 (0.000)	-0.000 (0.000)
Felony Capital degree	0.000 (0.000)	-0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
Prior Offense	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Number of Charges	-0.000* (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000* (0.000)
Joint F-test	0.895	0.848	1.032	1.276
p-value	0.529	0.560	0.410	0.253
Observations	642,652	122,653	45,293	153,711

Notes. This table reports OLS estimates of regressions of grand jury leniency on defendant and case characteristics using an inverse of the number of charges as weights. Each specification controls for year-by-month-by-week-of-year fixed effects. Grand jury leniency is estimated using data from other cases assigned to a given grand jury with weights. The p-values reported at the bottom of each column are from F-tests of the joint significance of the variables. Robust standard error, two-way clustered at the defendant and the grand jury panel level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Mean Risk and Total Disparate Impact Estimates: Black Defendants with Black Predictions vs. White Defendants with White Predictions

	Linear Extrapolation	Local Linear Extrapolation Epanechnikov (ROT)	Local Linear Extrapolation Gaussian (ROT)
<i>Panel A: Mean Risk by Race</i>	(1)	(2)	(3)
White Defendants	0.6240 (0.0007)	0.6356 (0.0013)	0.6361 (0.0013)
Black Defendants	0.6455 (0.0009)	0.6533 (0.0016)	0.6541 (0.0016)
<i>Panel B: Total Disparate Impact</i>			
Mean Across Cases	0.0076*** (0.0006)	0.0084*** (0.0006)	0.0085*** (0.0006)
Juries	646	646	646

Notes. Panel A shows the estimated mean likelihood of being found guilty of a felony for the full population of White and Black defendants. This is computed using variation in leniency across grand juries to extrapolate (slightly) to what the felony guilt rate would be if a grand jury were to true bill every defendant. Panel B shows the estimated total disparate impact, which is the sum of taste-based discrimination, statistical discrimination, and non-race-based disparate impact. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Mean Risk and Total Disparate Impact Estimates: Black Defendants with White Predictions vs. White Defendants with White Predictions

	Linear Extrapolation	Local Linear Extrapolation Epanechnikov (ROT)	Local Linear Extrapolation Gaussian (ROT)
<i>Panel A: Mean Risk by Race</i>	(1)	(2)	(3)
White Defendants	0.6391 (0.0003)	0.6357 (0.0045)	0.6335 (0.0046)
Black Defendants	0.6584 (0.0005)	0.6588 (0.0027)	0.6571 (0.0027)
<i>Panel B: Total Disparate Impact</i>			
Mean Across Cases	0.0098*** (0.0004)	0.0096*** (0.0006)	0.0094*** (0.0006)
Juries	646	646	646

Notes. Panel A shows the estimated mean likelihood of being found guilty of a felony for the full population of White and Black defendants. This is computed using variation in leniency across grand juries to extrapolate (slightly) to what the felony guilt rate would be if a grand jury were to true bill every defendant. Panel B shows the estimated total disparate impact. In this case, because the Black defendants are not identifiable as Black by the grand jury, disparate impact captures only non-race based disparate impact, such as using a lower threshold of guilt for some types of cases that are more common among Black defendants. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Taste-based racial bias and statistical discrimination against identifiably-Black defendants

	Linear Extrapolation	Local Linear Extrapolation Epanechnikov (ROT)	Local Linear Extrapolation Gaussian (ROT)
<i>Panel A: Predicting race using either first name or last name</i>			
Difference in disparate impacts	-0.0022*** (0.0007)	-0.0012 (0.0008)	-0.0009 (0.0008)
Rescaled Difference in disparate impacts	-0.0050*** (0.0016)	-0.0027 (0.0019)	-0.0020 (0.0019)
<i>Panel B: Predicting race using either first name or last name - Median</i>			
Difference in disparate impacts	-0.0002 (0.0006)	0.0012* (0.0007)	0.0009 (0.0006)
Rescaled difference in disparate impacts	-0.0007 (0.0022)	0.0041* (0.0024)	0.0031 (0.0022)
<i>Panel C: Predicting race based on last name and address together</i>			
Difference in disparate impacts	0.0008 (0.0010)	-0.0007 (0.0010)	-0.0007 (0.0010)
Rescaled difference in disparate impacts	0.0013 (0.0016)	-0.0011 (0.0016)	-0.0011 (0.0016)

Notes. The first row in each panel is the disparate impact estimate against Black defendants with Black names minus the disparate impact against Black defendants with White names. Under the assumption that the non-race-based disparate impact is similar across both groups of Black defendants, this difference captures the sum of taste-based and statistical discrimination against identifiably-Black defendants. The second row shows the same difference in disparate impacts, except rescaled by the difference in the likelihood of being perceived as Black for Black defendants with Black versus White names. Panel B and C show results when using the same prediction method but a median as a threshold instead of 50%, and results when using last name and address to predict the perceived race of the defendant, respectively. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix A: Results from using race predictions based on surname and address

Table A.1: Summary Statistics

	All defendants	Sample w/ racially identifiable names	White Defendants w/ White Prediction	Black Defendants w/ Black Prediction	Black Defendants w/ White Prediction
	(1)	(2)	(3)	(4)	(5)
<i>Panel A: Race Characteristics</i>					
White	0.533	0.255	1.000	0.000	0.000
Black	0.467	0.745	0.000	1.000	1.000
Predicted White (50%)	0.172	0.315	1.000	0.000	1.000
Predicted Black (50%)	0.404	0.685	0.000	1.000	0.000
Likelihood of being White	0.196	0.281	0.765	0.068	0.659
Likelihood of being Black	0.391	0.610	0.087	0.830	0.195
<i>Panel B: Defendant Characteristics</i>					
Male	0.822	0.798	0.771	0.806	0.820
Age at grand jury hearing	32.398	32.771	34.327	32.244	32.151
Age at filing	32.269	32.640	34.198	32.113	32.012
Prior Offense	0.668	0.711	0.605	0.752	0.691
<i>Panel C: Charge Characteristics</i>					
Felony 1st degree	0.121	0.113	0.075	0.127	0.118
Felony 2nd degree	0.225	0.222	0.202	0.228	0.223
Felony 3rd degree	0.296	0.287	0.327	0.272	0.283
Felony Capital degree	0.003	0.003	0.002	0.004	0.002
Felony State degree	0.354	0.375	0.394	0.369	0.374
Offense degree in linear	3.243	3.305	3.438	3.258	3.291
Number of Charges	1.149	1.154	1.141	1.158	1.157
<i>Panel D: Case outcomes</i>					
Truebill	0.971	0.972	0.964	0.975	0.974
Felony Guilty Conviction	0.621	0.624	0.604	0.632	0.613
Any Guilty Conviction	0.745	0.739	0.737	0.741	0.727
Felony Guilty Conviction when True-billed	0.621	0.624	0.604	0.632	0.613
Any Guilty Conviction when True-billed	0.745	0.739	0.737	0.741	0.727
Observations	695,500	278,688	70,371	191,709	16,608

Notes. This table summarizes the main analysis sample using the inverse of the number of charges as weights. The sample consists of grand jury hearings that were quasi-randomly assigned to grand jury panels between February 1990 and July 2022. Race prediction is based on the likelihood of an individual being White or Black, computed by the R package ‘wru,’ with a threshold of 50%.

Table A.2: Balance Tests

	(1) All defendants	(2) White defendants w/ White Prediction	(3) Black defendants w/ Black Prediction	(4) Black defendants w/ White Prediction
Black	0.000 (0.000)			
Male	0.000 (0.000)	-0.000** (0.000)	0.000** (0.000)	0.000 (0.001)
Age at grand jury hearing	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000* (0.000)
Felony 1st degree	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	0.001 (0.001)
Felony 2nd degree	-0.000** (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.001)
Felony 3rd degree	-0.000** (0.000)	-0.000 (0.000)	-0.000** (0.000)	0.000 (0.001)
Felony Capital degree	0.000 (0.000)	-0.001 (0.003)	-0.001 (0.001)	-0.004 (0.005)
Prior Offense	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.001 (0.001)
Number of Charges	-0.000* (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)
Joint F-test	0.895	1.582	1.405	0.869
p-value	0.529	0.127	0.191	0.542
Observations	642,652	63,852	177,437	15,157

Notes. This table reports OLS estimates of regressions of grand jury leniency on defendant and case characteristics using an inverse of the number of charges as weights. Each specification controls for year-by-month-by-week-of-year fixed effects. Grand jury leniency is estimated using data from other cases assigned to a given grand jury with weights. The p-values reported at the bottom of each column are from F-tests of the joint significance of the variables. Robust standard error, two-way clustered at the defendant and the grand jury panel level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Mean Risk and Total Disparate Impact Estimates: Black Defendants with Black Predictions vs. White Defendants with White Predictions

	Linear Extrapolation	Local Linear Extrapolation Epanechnikov (ROT)	Local Linear Extrapolation Gaussian (ROT)
<i>Panel A: Mean Risk by Race</i>	(1)	(2)	(3)
White Defendants	0.6140 (0.0013)	0.6093 (0.0016)	0.6099 (0.0016)
Black Defendants	0.6442 (0.0009)	0.6422 (0.0010)	0.6413 (0.0010)
<i>Panel B: Total Disparate Impact</i>			
Mean Across Cases	0.0104*** (0.0005)	0.0098*** (0.0005)	0.0099*** (0.0005)
Juries	646	646	646

Notes. Panel A shows the estimated mean likelihood of being found guilty of a felony for the full population of White and Black defendants. This is computed using variation in leniency across grand juries to extrapolate (slightly) to what the felony guilt rate would be if a grand jury were to true bill every defendant. Panel B shows the estimated total disparate impact, which is the sum of taste-based discrimination, statistical discrimination, and non-race-based disparate impact. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

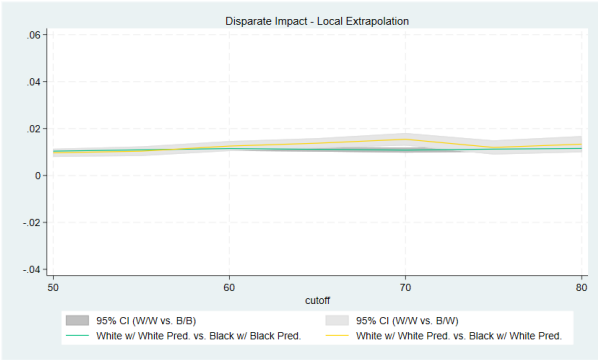
Table A.4: Mean Risk and Total Disparate Impact Estimates: Black Defendants with White Predictions vs. White Defendants with White Predictions

	Linear Extrapolation	Local Linear Extrapolation Epanechnikov (ROT)	Local Linear Extrapolation Gaussian (ROT)
<i>Panel A: Mean Risk by Race</i>	(1)	(2)	(3)
White Defendants	0.6040 (0.0013)	0.6116 (0.0019)	0.6119 (0.0019)
Black Defendants	0.6292 (0.0018)	0.6374 (0.0024)	0.6380 (0.0024)
<i>Panel B: Total Disparate Impact</i>			
Mean Across Cases	0.0097*** (0.0009)	0.0105*** (0.0009)	0.0105*** (0.0009)
Juries	646	646	646

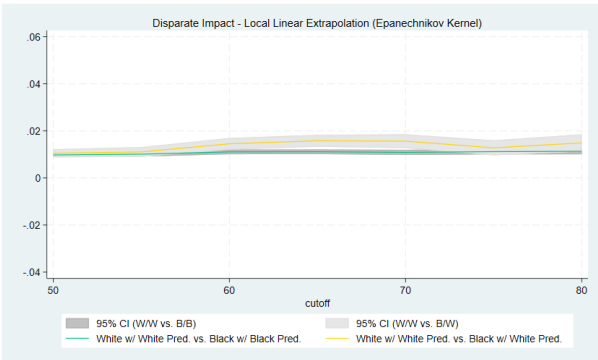
Notes. Panel A shows the estimated mean likelihood of being found guilty of a felony for the full population of White and Black defendants. This is computed using variation in leniency across grand juries to extrapolate (slightly) to what the felony guilt rate would be if a grand jury were to true bill every defendant. Panel B shows the estimated total disparate impact. In this case, because the Black defendants are not identifiable as Black by the grand jury, disparate impact captures only non-race based disparate impact, such as using a lower threshold of guilt for some types of cases that are more common among Black defendants. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A.1: Robustness to Alternative Thresholds

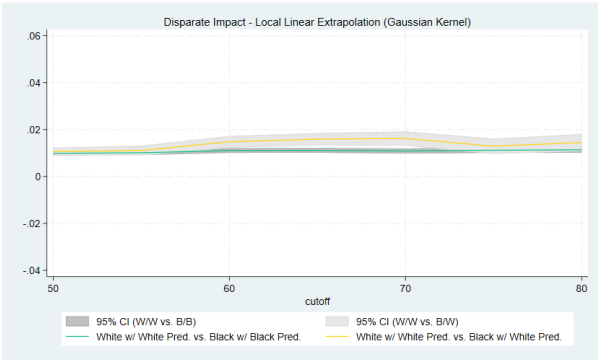
Panel A: Linear Extrapolation



Panel B: Local Linear Extrapolation Epanechnikov



Panel C: Local Linear Extrapolation Gaussian



Notes: This figure provides disparate impacts and 95% confidence intervals using linear extrapolation for thresholds ranging from 50% (shown in main results) to 80%. Estimates in green are disparate impact estimates against Black defendants with identifiably-Black names/locations, while estimates in yellow are disparate impact estimates against Black defendants with White names/locations who are therefore likely perceived as White by grand jurors.

Appendix B: Results from using race predictions based on first name and surname with a median threshold

Table B.1: Summary Statistics

	All defendants (1)	Sample w/ racially identifiable names (2)	White w/ White Prediction (3)	Black w/ Black Prediction (4)	Black w/ White Prediction (5)
<i>Panel A: Race Characteristics</i>					
White	0.533	0.208	1.000	0.000	0.000
Black	0.467	0.792	0.000	1.000	1.000
Black Prediction Value	0.197	0.277	0.086	0.475	0.182
<i>Panel B: Defendant Characteristics</i>					
Male	0.822	0.810	0.796	0.818	0.809
Age at grand jury hearing	32.398	32.768	34.399	32.399	32.280
Age at filing	32.269	32.640	34.276	32.270	32.151
Prior Offense	0.668	0.714	0.618	0.746	0.733
<i>Panel C: Charge Characteristics</i>					
Felony 1st degree	0.121	0.119	0.082	0.128	0.130
Felony 2nd degree	0.225	0.224	0.205	0.228	0.229
Felony 3rd degree	0.296	0.280	0.319	0.269	0.272
Felony Capital degree	0.003	0.004	0.002	0.004	0.004
Felony State degree	0.354	0.373	0.392	0.371	0.366
Offense degree in linear	3.243	3.288	3.417	3.260	3.248
Number of Charges	1.149	1.155	1.145	1.158	1.158
<i>Panel D: Case outcomes</i>					
Truebill	0.971	0.973	0.965	0.975	0.974
Felony Guilty Conviction	0.621	0.629	0.617	0.636	0.628
Any Guilty Conviction	0.745	0.741	0.745	0.742	0.738
Felony Guilty Conviction when True-billed	0.641	0.647	0.641	0.653	0.645
Any Guilty Conviction when True-billed	0.768	0.762	0.773	0.762	0.758
Observations	695,500	412,089	85,056	162,526	164,507

Notes. This table summarizes the main analysis sample using the inverse of the number of charges as weights. The sample consists of grand jury hearings that were quasi-randomly assigned to grand jury panels between February 1990 and July 2022. Race prediction is based on the likelihood of an individual being White or Black, computed by the R package ‘predictrace,’ with a median as a threshold.

Table B.2: Balance Tests

	(1) White defendants w/ White Prediction	(2) Black defendants w/ Black Prediction	(3) Black defendants w/ White Prediction
Male	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
Age at grand jury hearing	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
Felony 1st degree	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)
Felony 2nd degree	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Felony 3rd degree	-0.000 (0.000)	-0.000 (0.000)	-0.000* (0.000)
Felony Capital degree	0.002 (0.001)	0.000 (0.001)	-0.001 (0.001)
Prior Offense	0.000*** (0.000)	-0.000 (0.000)	0.000 (0.000)
Number of Charges	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Joint F-test	1.809	0.568	1.221
p-value	0.072	0.805	0.284
Observations	77,427	150,375	152,127

Notes. This table reports OLS estimates of regressions of grand jury leniency on defendant and case characteristics using an inverse of the number of charges as weights. Each specification controls for year-by-month-by-week-of-year fixed effects. Grand jury leniency is estimated using data from other cases assigned to a given grand jury with weights. The p-values reported at the bottom of each column are from F-tests of the joint significance of the variables. Robust standard error, two-way clustered at the defendant and the grand jury panel level, are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.3: Mean Risk and Total Disparate Impact Estimates: Black Defendants with Black Predictions vs. White Defendants with White Predictions

	Linear Extrapolation	Local Linear Extrapolation Epanechnikov (ROT)	Local Linear Extrapolation Gaussian (ROT)
<i>Panel A: Mean Risk by Race</i>	(1)	(2)	(3)
White Defendants	0.6259 (0.0013)	0.6233 (0.0018)	0.6232 (0.0017)
Black Defendants	0.6475 (0.0009)	0.6471 (0.0010)	0.6467 (0.0010)
<i>Panel B: System-Wide Discrimination</i>			
Mean Across Cases	0.0096 (0.0005)	0.0093 (0.0005)	0.0093 (0.0005)
Juries	646	646	646

Notes. Panel A shows the estimated mean likelihood of being found guilty of a felony for the full population of White and Black defendants. This is computed using variation in leniency across grand juries to extrapolate (slightly) to what the felony guilt rate would be if a grand jury were to true bill every defendant. Panel B shows the estimated total disparate impact, which is the sum of taste-based discrimination, statistical discrimination, and non-race-based disparate impact. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.4: Mean Risk and Total Disparate Impact Estimates: Black Defendants with White Predictions vs. White Defendants with White Predictions

	Linear Extrapolation	Local Linear Extrapolation Epanechnikov (ROT)	Local Linear Extrapolation Gaussian (ROT)
<i>Panel A: Mean Risk by Race</i>	(1)	(2)	(3)
White Defendants	0.6361 (0.0003)	0.6122 (0.0027)	0.6152 (0.0027)
Black Defendants	0.6472 (0.0005)	0.6362 (0.0015)	0.6366 (0.0013)
<i>Panel B: System-Wide Discrimination</i>			
Mean Across Cases	0.0098 (0.0004)	0.0081 (0.0005)	0.0084 (0.0004)
Juries	646	646	646

Notes. Panel A shows the estimated mean likelihood of being found guilty of a felony for the full population of White and Black defendants. This is computed using variation in leniency across grand juries to extrapolate (slightly) to what the felony guilt rate would be if a grand jury were to true bill every defendant. Panel B shows the estimated total disparate impact, which is the sum of taste-based discrimination, statistical discrimination, and non-race-based disparate impact. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$