Racial Disparities in Federal Sentencing: A Quantile Regression Approach

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Abstract

The Sentencing Reform Act of 1984 explicitly prohibits the use of demographic characteristics in determining prison sentence, yet researchers continue to find evidence of disparity in sentences on the basis of race, ethnicity and gender. We employ a quantile regression technique that estimates the black-white sentencing gap across the entire sentencing distribution, rather than only at the mean. Our results show that racial disparity exists for some types of offenses, however, the impact of race varies greatly dependent on the location along the sentencing distribution. For some types of offenses, disparity only exists for the lower half of the sentencing distribution. We also find that the OLS coefficient estimate for racial disparity may be misleading, suggesting disparity is much larger than what we find using quantile regression analysis. Finally, we find that much of the racial disparity in federal sentencing is due to departures from the Sentencing Guidelines from offenders providing substantial assistance to the government in the prosecution of others.

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1. Introduction

This research examines the disparity in prison sentences of federal criminal offenders across race. Over 79,000 people each year are tried and sentenced in federal court. It is well known that the majority of people in prison are racial and ethnic minorities, in large part due to the "war on drugs."[1] In addition, racial and ethnic minority offenders generally receive longer prison sentences than white non-Hispanic offenders. The popular press is also filled with stories of people impacted by what is known as the federal 'Crack/Cocaine Sentencing Disparity.'[2] Proponents for changing this 100 to 1 crack-powder sentencing disparity argue that the different mandatory minimum sentences for crack and powder cocaine result in vast racial disparities in sentencing. The efforts to reform the current disparity in sentencing are growing and in April 2009 the Obama administration urged Congress to end the racial disparity.[3]

The 100 to 1 crack-powder sentencing disparity is a disparity in legislative prison lengths; the laws are written so that crack offenders receive longer sentences than powder cocaine offenders and because crack offenders are more likely to be minorities, this leads to racial disparity.[4] Yet there appears to also be racial disparity in sentencing for the *same crime*. Some of that disparity is due to specific characteristics of the crime (e.g., the type of weapon involved) that warrant different sentence lengths; however, there remains a significant difference in sentence lengths across demographic characteristics.

Researchers historically report that black offenders are on average sentenced to more months in prison even after controlling for the type and severity of the crime and the offender's

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[1] In this paper, we examine only the racial disparity in sentencing, not the disproportionate number of minorities that comprise the prison population. The large disparity in prison population is an important current public policy issue. In 2008 Iowa and Connecticut passed legislation that requires lawmakers to examine the minority impact of any proposed bill, resolution, or amendment to sentencing laws. A number of other states are collecting data on how state sentencing guidelines impact minorities.

[2] Although crack and powder cocaine are different forms of the same drug and have a similar effect on users, a crack dealer who distributes 5 grams of crack cocaine receives a five year mandatory minimum sentence under federal law. It would take 500 grams of powder cocaine to result in the same sentence. Crack cocaine is also the only drug where mere possession triggers a federal mandatory minimum sentence.

[3] The sentencing disparity between crack and cocaine was reduced in 2007, but not eliminated. On December 10, 2007, the 7-2 Supreme Court decision *Kimbraugh v U.S.* allowed federal judges to consider the disparity in penalties when determining if offenders should be sentenced outside the Sentencing Guidelines. One month earlier, the U.S. Sentencing Commission (USSC) proposed an amendment to reduce the Guideline sentence for crack cocaine. It was not challenged by Congress and was subsequently made retroactive, leading to over 12,000 sentence reductions.

[4] We leave the legal disparity due to differences in powder/crack cocaine sentences to future work.

criminal history. The Sentencing Reform Act (SRA) of 1984 created the Sentencing Guidelines (a grid of maximum and minimum sentences for a given criminal offense and history) in order to reduce potential disparities generated by demographic characteristics. The SRA and Sentencing Guidelines are an expensive and time-intensive method of reducing disparity in prison sentences by explicitly prohibiting the use of race, ethnicity, gender, and other demographic characteristics in determining a prison sentence. Several studies have shown that although sentencing disparity declined after the SRA, there still exists large variation in prison sentences across individuals with different race, gender, education level, income, and citizenship status (Albonetti 1997; Bushway and Piehl 2001; Mustard 2001; Schanzenbach 2005; and Schanzenbach and Tiller 2006).

Discovering whether disparity in sentencing exists after controlling for all the aspects of the crime is important for two reasons. First, if disparity does exist, policymakers may wish to address the remaining disparity. If disparity does not exist, but there is *perceived* disparity, then some offenders (white offenders in this case) may receive unnecessarily harsh sentencing to make up for the perceived disparity.[5] By closely looking at where in the distribution of sentencing these racial disparities occur, this research may inform policymakers on where to focus policies designed to reduce sentencing disparity.

Although Mustard (2001) finds that racial disparity exists for all offenses, the largest black-white sentence disparities in his time frame occur for bank robbery and drug crimes. We follow Mustard and study the six most common types of offenses that appear in our data: Drug Trafficking, Firearms, Fraud, Larceny, Forgery, and Bank Robbery. We also examine the racial disparity in sentencing for Drug Possession. Conditional on the type of offense, we apply quantile regression techniques to evaluate whether the impact of race is different for less serious and more serious crimes. Although there is consistent evidence that racial disparity exists, all of the previous research has used OLS (and other mean based estimators) to study the issue. Linear models assume that any independent characteristic (such as race) has a constant effect along the entire distribution of prison sentences. As Britt (2009) discusses, the sentencing system itself

[5] Sarnikar, Sorensen and Oaxaca (2007) present the argument that females may receive especially harsh judgment by those in the justice system who favor equal treatment, but they find evidence that female offenders receive more lenient sentences even after controlling for severity of the crime and criminal history.

(both the Federal Sentencing Guidelines that we study and the state sentencing guidelines studied by other researchers) allows for characteristics of the crime to have non-linear effects on sentence lengths. The goal of Britt (2009) is to demonstrate the use of quantile regression techniques in studying criminal sentencing. Utilizing Pennsylvania sentencing data from 1998, he shows that OLS estimates often fail to capture how offender characteristics impact prison sentences. We build upon Britt (2009) in studying prison sentences for specific offense types within the Federal system. We specifically focus on racial disparity in sentencing of crimes that are most common among men in the Federal prison system.

Our quantile regression results show that racial disparity exists for some types of offenses, however, the impact of race varies greatly dependent on the location along the sentencing distribution. For some types of offenses, disparity only exists for the lower half of the sentencing distribution. We also find that the OLS coefficient estimate for racial disparity may be misleading, suggesting disparity is much larger than what we find using quantile regression analysis. Finally, we find that much of the racial disparity in federal sentencing is due to departures from the Sentencing Guidelines from offenders providing substantial assistance to the government in the prosecution of others. Generally, the amount of racial disparity in Federal sentences during 1999-2001 is very small (about one week) once we control for departures. In our robustness section, we also contribute to the literature by estimating censored quantile regression models; for the crimes of Drug Trafficking and Firearms we analyze the differences in prison sentence across the distribution while also accounting for the fact that many offenders receive zero months (probation).

The paper is organized as follows: Section 2 presents the data used for our analysis. Section 3 describes the methodology and results. Robustness checks are provided in the 4th section and the final section concludes.

2. Data

The data we use are from the “Monitoring of Federal Criminal Sentences” series collected by the United States Sentencing Commission (USSC). The USSC data include records for every offender sentenced under the Sentencing Guidelines and report key characteristics of the sentencing such as the primary offense, the offense level calculated by the court, and the length of the prison sentence. The offender's criminal history is also reported, as well as the offender's demographic characteristics.

We use sentencing years 1999-2001.[6] There are 99,424 valid cases that fall within this time period. We exclude cases with more than one count of conviction, more than one sentencing guideline computation, or missing sentencing information which yields 98,589 observations. We also exclude cases with sentences of "life in prison" or "death" rather than convert these sentences into a month-equivalent. The sample size is further reduced to 60,653 when dropping cases where the offender is a female or not an American citizen. We use these data exclusion rules to isolate the differences in sentencing across race from sentencing differences across gender or citizenship.[7] Finally, we exclude all cases where there is missing demographic and/or information on criminal offense characteristics that identify legal reasons for differences in sentencing. Our final sample of all offense types includes 55,485 cases.

2.1 Background on Sentencing Guidelines

The Federal Sentencing Guidelines take into account both the seriousness of the crime and the defendant's criminal record when determining sentencing length. To establish the seriousness of the crime, the Sentencing Guidelines assign each type of crime (murder, robbery, antitrust violations, etc.) a base offense level (BOL). The Guidelines also prescribe a complex set of rules on how the final offense level is calculated. For example, specific offense characteristics (e.g., carjacking or permanent bodily harm) either add or subtract from the base offense level and these characteristics vary across offenses. Then adjustments may be made based on victim characteristics, the offender's role in the offense, and whether or not obstruction of justice took place. Finally, after adjustments for multiple count adjustments and acceptance of responsibility are made, one derives the final offense level (FOL) used to determine sentencing length.[8]

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[6] One limitation of quantile regression techniques is that it requires a sufficiently large number of observations. For this reason we use multiple years of data. We choose to analyze three years of sentencing data because it is unlikely that an offender would appear twice in the federal justice system within such a short time period.
[7] See Abonetti (1997) and Sarnikar et al. (2007) for evidence of gender disparity. Abonetti (1997) also finds evidence of sentencing disparity by citizenship.
[8] Note that the offense level is defined differently than the offense type; offense level, which ranges from 1-43, is adjusted by secondary characteristics of the offense type which ranges from 1-35.

The Guidelines account for an offender's criminal record by assigning criminal history points which place the offender in one of six possible criminal history categories. The total points assigned by the judge depend on the number of prior adult convictions and how long the offender was imprisoned for each prior adult offense. Table 1 reproduces the Federal Sentencing Table that depicts how both the final offense level and criminal history category determine sentencing. The Sentencing Guidelines explicitly state that the offender's race, sex, national origin, creed, religion, and socioeconomic status are never relevant to the determination of any sentence. Theoretically, two offenders of different races with the exact same crime characteristics should be sentenced to the same prison term. Yet this is not always the case.

In addition to discretion on where the sentence falls within the sentencing range, judges may "depart" from the Guidelines. Departures may be granted when the defendant has provided substantial assistance to the government in the prosecution of others, with the agreement of the prosecutor. These "substantial assistance departures" are the most common reason for a sentence outside the range of the Sentencing Guidelines. Second, the judge may depart if it can be shown that the circumstances of the case or offender are unusual and lay outside the "heartland" (ordinary crimes) of the Guidelines; however the Guidelines prohibit judicial departures due to race, sex, citizenship or religion. In 2003, the Feeney Amendment to the PROTECT act was passed by Congress to reduce the number of downward departures from the Federal Sentencing Guidelines.[9] Many judges were unhappy with the restrictions of judicial discretion this instituted. In 2005, the Feeney Amendment was found unconstitutional by the Supreme Court in the ruling *U.S. v. Booker*.[10] The Sentencing Guidelines now are considered *advisory* rather than *mandatory*. Scholars are still waiting to see what the overall impact of this change will be. In a subsequent version of this paper we will examine whether making the Guidelines advisory, and thus potentially reducing some of the uniformity, has expanded the racial gap in sentencing. This will be done using data from 2006-2008.

[9] Freeborn and Hartmann (2009) show that the Feeney Amendment led to a decreased likelihood of downward departures and longer average sentences.
[10] The Supreme Court ruled that the Sentencing Guidelines violated the sixth amendment (the right to a jury trial). Under the Guidelines, lower court judges could sentence defendants based on additional findings that had not been proven to a jury beyond a reasonable doubt.

2.2 Background on Racial Disparity and Descriptive Analysis

The Sentencing Reform Act (SRA) of 1984 created the Sentencing Guidelines in order to reduce potential disparities in sentences generated by demographic characteristics (Anderson, Kling and Stith 1999; Weinstein 2003).[11] Whites convicted of a crime in the fiscal year 1982 were sentenced on average to 38.8 months in prison versus 65.8 months for blacks (U.S. DOJ, 1984). The Sentencing Guidelines have brought some uniformity in sentencing for similar crimes, but have not eliminated racial disparity even after 20 years of usage. For example, the Department of Justice reported that whites were sentenced to an average of 59.3 months for drug-related crimes in 2001, while blacks were sentenced to 102.2 months. The differential at the median is smaller, albeit still quite large at 40 months for whites and 77 months for blacks (U.S. DOJ, 2003).[12]

Drawing conclusions about racial differences in sentencing using aggregate data is problematic. Some of the observed disparity is due to the type of crime for which the offender is convicted and specific characteristics of the crime. In order to focus solely on the disparity of sentencing across race, we examine sentences imposed for the six most frequent offense types plus Drug Possession. The pattern of black offenders receiving longer sentences than white offenders holds for our sample.[13] Figure 1 displays the density of sentences for white and black offenders for the seven offense types we study. As seen in the figure, a large proportion of white sentences are lower than black sentences for Drug Trafficking, Drug Possession, Firearms, and Bank Robbery. The density of sentences for Fraud, Larceny, and Forgery do not exhibit the same obvious racial disparity, however Mustard (2001) finds that black offenders receive significantly longer sentences than white offenders for Fraud crimes (about 1 month) using data for fiscal years 1992-1994.

[11] See Stith and Cabranes (1998) for an in-depth discussion of the Sentencing Guidelines as well as the history of federal sentencing and sentencing reform.
[12] There is also some evidence that race of the judge may matter. Schanzenbach (2005) finds that for less serious crimes, black offenders were sentenced more lightly in districts with more black judges. The proportion of black judges does not impact the sentence length for those convicted of more serious crimes.
[13] For this paper, we limit our analysis to white and black offenders and analyze the black-white sentence gap. The USSC data includes categories for two other races (American Indian/Alaskan Native and Asian/Pacific Islander) as well as an "Other" category. Offenders who are neither white nor black represent less than 5% of the sample.

We pay special attention to Drug Trafficking because Mustard (2001) finds strong evidence for racial sentencing disparity for these types of cases and because it is the most common offense type in the Federal sentencing data. Racial disparity in sentencing for Drug Trafficking crimes is quite notable. The majority of whites convicted of Drug Trafficking are sentenced to prison terms less than 8 years (96 months). In contrast, there is a greater mass at longer sentences for blacks. At the 25th percentile, whites are sentenced on average to 23 months of prison verses 48 months for blacks. The gap in months increases with the percentile. Whites are sentenced on average to 70 months at the 75th percentile while blacks have an average sentence of 135 months, almost twice as long as white offenders. Clearly, the average convicted black offender receives a longer sentence than a white offender for Drug Trafficking irrespective of the location on the sentencing distribution. Note that both black and white drug offenders receive sentences of zero months; however, the proportion of zero month sentences is larger for whites than blacks.

Next we examine the sentencing gap itself; that is, we subtract the prison sentence length for white offenders at the n^{th} percentile from the prison sentence length for black offenders at the n^{th} percentile and define this as the sentence gap (similar to the gender wage gap constructed in the labor literature). Figure 2 shows the distribution of the sentencing gap for all seven offense types. Although it is not monotonic, the overall trend of the sentencing gap (in months) between whites and blacks for Drug Trafficking is increasing with the percentile. The sentence gap is 37 months at the median, but increases to 61 months at the 75th percentile.[14] We also observe a relatively large and non-monotonic sentencing gap with Drug Possession. The sentencing gap is also always positive and generally increasing for Firearms crimes, though the uppermost part of the distribution exhibits large variance. For the other five offense types, we observe a non-zero black-white sentence gap for some region of the distribution. This gap, however, is quite small

[14] We could also calculate the relative gap (i.e., do blacks consistently receive a 50% longer sentence than whites) by taking the log of each offender's prison sentence and computing the black-white log-sentence gap. While this is valuable information, we choose to report months in prison in this paper for several reasons. First, it is straightforward to convert months into percentages to discuss the relative gap. Also, because we are studying months in prison where offenders are removed from society, the period of confinement may be more relevant than the relative difference. A 5% longer sentence for a black offender receiving 100 months is 5 months, which is twice the number of months an offender would serve if given a 25% longer sentence on a 10 month prison term. Last, we report sentence length in months rather than logs because we observe many offenders who receive zero months in prison and log months are undefined at zero.

(less than 4 months in most cases) relative to the sentencing gaps that occur with Drug Trafficking and Firearms.

3. Methodology and Results

3.1 Quantile Regression

The descriptive analyses above do not control for the type and severity of the crime nor the offender's criminal history. To find evidence of racial disparity, we must control for the differences in criminal history and offense level that warrant different sentences for the same crime. Albonetti (1997), Mustard (2001), Schanzenbach (2005), and Schanzenbach and Tiller (2006) all find that on average, blacks are sentenced to more months in prison even after controlling for the type and severity of the crime and the offender's criminal history.

We study the disparity in sentencing using a quantile regression approach rather than using the traditional ordinary least squares (OLS) method. An OLS regression of prison sentence on race and crime characteristics reveals the impact of race on the mean of the conditional distribution of prison sentence and does not allow for the possibility that the impact of covariates may vary across the distribution. As shown in the panels of Figure 2, the black-white sentencing gap varies across the distribution. OLS does not allow for the effect of independent variables to change at different points of the distribution. Thus using OLS (and other mean based estimators) is inappropriate for studying discrimination in sentencing and does not provide a complete picture of the disparity that exists.

Instead we employ the quantile regression technique, commonly used by labor economists to study earnings distributions (e.g., Buchinsky 1994; Hamilton 2000), to identify differences in the conditional mean of sentences at different points in the distribution for whites and blacks.[15] As Britt (2009) argues, distributional analysis is particularly relevant for studying sentencing guidelines, because quantile regression methods make no assumptions on the error terms and "effectively deal with the non-normal distribution of errors that is inherently built into a sentencing guidelines grid" (p. X). Quantile regression allows for a full characterization of the

[15] A number of other sub-fields also employ quantile regression methods. For example, Carillo and Yezer (2009) apply the quantile regression approach to the homeownership gap between white and minority households.

conditional distribution of prison sentence. Moreover, we are able to distinguish how the racial disparity varies at specific quantiles, where the lower quantiles represent less serious crimes (that warrant lower sentences) and the upper quantiles represent more serious crimes.

The quantile regression model assumes that the conditional quantile of a random variable *y* is linear in the regressors *X*. That is, $Q_\theta = X\beta(\theta)$ where Q_θ is the θ^{th} conditional quantile of y and $\beta(\theta)$ measures the impact of the covariates *X* at the various quantiles. Estimation of $\beta(\theta)$ is the solution to

$$\min\left\{\sum_{i:y_i\geq X_i\beta(\theta)}\theta|y_i - X_i\beta(\theta)| + \sum_{i:y_i<X_i\beta(\theta)}(1-\theta)|y_i - X_i\beta(\theta)|\right\}.$$ [16]

3.2 Quantile Regression Specification

The form of the quantile regressions we estimate is:

$$Q_\theta[SL] = \alpha_\theta + \beta_\theta W + \delta_\theta D + \gamma_\theta O.$$

Sentence Length (*SL*) is the total prison sentence in months, *W* is an indicator for whether the offender is white, *D* is a vector of offender demographic characteristics, and *O* is a vector of offense characteristics that help determine the sentence length.[17]

The demographic variables include the offender's age, age squared, education level (less than high school, high school, some college including trade school and associates' degree, or college graduate), whether the offender was represented by private counsel, the defendant's number of dependents, and a dummy for whether the offender is Hispanic. Table 2 provides the summary statistics for the variables of interest.

We also control for the final offense level and criminal history. Britt (2009) reviews how other researchers account for offense level and criminal history. The most common method includes dummy variables for each unique cell position in the grid (e.g., Mustard 2001).

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[16] For more on quantile regression, see Koenker and Bassett (1978) and Buchinsky (1998).

[17] As discussed above, a log specification for prison term was not used because it is more difficult to interpret the estimated coefficients when the dependent variable is in logs. Also, from a public policy point of view we are interested in the size of the sentencing gap in absolute terms, because a prison sentence is time removed from society which dramatically affects people's lives.

Because there are 43 offense levels and 6 criminal history categories, this method results in 258 dummy variables. As part of our robustness checks, we re-estimate some of our quantile regression models controlling for the censored nature of the data (i.e., the large mass at a prison sentence of 0 months). Unfortunately, regressions that correct for censoring have difficulty converging when there are many non-continuous variables such as dummy variables.[18] So that our censored models are comparable to the un-censored quantile regression models, we capture the interaction between final offense level (*fol*) and criminal history (*crh*) in determining the sentencing range with the following bivariate cubic polynomial:

$$= fol^3 + (fol^2 * crh) + (fol * crh^3) + crh^3.$$

This specification allows for a nonlinear relationship between final offense level and criminal history, which is not accounted for when using cell-level dummy variables.

For the models on drug crimes, we include a control for the type of drug to separate out racial disparity from the institutional disparity in sentencing that is legally allowed under legislative mandates: powder cocaine (representing 20% of the cases), crack cocaine (28% of the cases), marijuana (28%), or some other type of drug including methamphetamine and heroin (the remaining 24% of cases). Finally, for all offense types we also include circuit dummy variables to capture geographic variation in sentencing across the federal court system. Figure 6 displays a graph of the U.S. circuits.

4 Results

4.1 Quantile Regression Estimates – Drug Trafficking

In this section, we present the results from our quantile regression models for the crime of Drug Trafficking. We focus on Drug Trafficking because it is the most common offense in our data and Mustard (2001) finds significant racial disparity in prison sentences for Drug Trafficking. Table A.1 in the appendix provides the coefficient estimates of the White dummy variable for the other crime categories (Bank Robbery, Fraud, Firearms, Forgery, Larceny, and Drug Possession).

[18] Schanzebach and Tiller (2006) report convergence problems in tobit regressions that control for censoring. To address the convergence issue, they use a fifth-order polynomial in the numeric final or base offense level, dummies for criminal history, and an interaction between criminal history level and the numeric offense level. Sarnikar, Sorensen and Oaxaca (2007) also use polynomials to control for offense level.

4.1.1 Specification 1: No controls for departures

Table 3 reports the results for the coefficient on the White dummy using OLS, Tobit, and quantile regression specifications. We do not report coefficients for the control variables; however, these results are available upon request. On average for Drug Trafficking, blacks are sentenced to 4.7 more months of jail than whites, even after controlling for the characteristics of the crime, the circuit where the offender was sentenced, and offender demographics. To account for the offenders who receive a zero month prison sentence, we estimate the White dummy coefficient using Tobit regression.[19] When we account for censoring with Tobit, white offenders are sentenced to 5.2 fewer months. Both OLS and Tobit assume that the errors are normally distributed with constant variance and the coefficient has a constant value across the distribution of sentences.

In the first row of Table 3 (columns 3-7) we report how the disparity varies across the sentencing distribution using quantile regression. We report the coefficients from the tenth, twenty-fifth, fiftieth, seventy-fifth, and ninetieth percentiles. All of the coefficient estimates reported in Table 3 are significantly different from zero. The coefficient on white is largest at the 10th percentile (implying whites are sentenced to 3.8 fewer months than blacks), but becomes smaller at the upper percentiles. Recall from Figure 2 that the raw black-white sentence gap for Drug Trafficking appeared to be increasing, though not monotonically. When we control for offender and crime characteristics, we observe that the sentence gap becomes smaller at the top end of the distribution. The overall declining trend of the black-white sentence gap in Drug Trafficking is consistent with the sociological 'liberation hypothesis' (Spohn and Cederblom 1991) that judges have more discretion in the least severe punishment cases.

4.1.2 Specification 2: Control for Substantial Assistance

Mustard (2001), Freeborn and Hartmann (2009), Bushway and Piehl (2001), and Wu and Spohn (2008) show that black offenders are less likely than whites to receive a downward departure in sentence. Recall that a sentence departure may be due to either the offender

[19] Roughly 6% of the offenders in our sample are assigned no prison time. When one does not correct for the censoring, OLS underestimates the effect of the X's on the "true" dependent variable. Because there is a bias toward zero, the "true" sentencing gap between blacks and whites is higher than predicted if one does not control for the censored nature of the data.

providing assistance to the prosecution (Substantial Assistance), or the district judge sentencing the offender outside the Guidelines due to unusual circumstances (Judicial Departure).

In the second row of Table 3, we present OLS, Tobit, and quantile regression estimates of the White coefficient when a control for substantial assistance is included. The magnitudes of all the coefficient estimates decrease relative to Specification 1, suggesting that some portion of the black-white sentencing gap is due to the offender providing substantial assistance to the prosecutor. For example, the OLS estimates imply that white offenders receive only 1.3 fewer months than black offenders convicted of drug trafficking when we control for substantial assistance, as opposed to 4.7 months without the control. Also the quantile regression coefficient estimates of White are not significantly different from zero for the 50th, 75th, or 90th quantile. Once we control for substantial assistance, white offenders do not receive shorter sentences than black offenders for the more serious drug trafficking crimes.

4.1.2 Specification 3: Control for Judicial Departures and Substantial Assistance

Under certain circumstances, federal judges are permitted to sentence an offender outside of the ranges imposed by the U.S. Sentencing Guidelines. For example, USSC (2001a) states that a judge may depart from the Guidelines if "the court finds that there exists an aggravating or mitigating circumstance of a kind, or to a degree, not adequately taken into consideration by the Sentencing Commission in formulating the guidelines that should result in a sentence different from that described." Freeborn and Hartmann (2009) find that blacks are less likely than whites to receive this type of departure from the Sentencing Guidelines.

The third row of Table 3 includes controls for both substantial assistance and judicial departures from the Guidelines. Once again, the magnitudes of the coefficients decrease meaning that the size of the black-white sentencing gap is smaller when we control for departures. White offenders receive significantly shorter sentences than black offenders, but only for the least serious Drug Trafficking crimes (10th and 25th quantiles), and the difference is less than one month.

4.2 Quantile Regression Graphs – All Offense Types

A more efficient and straightforward way to present information on the OLS coefficient and quantile regression coefficients is with a series of graphs as seen in Figure 3. In each panel the OLS coefficient is displayed with a dashed horizontal line and the 95% confidence interval around the OLS coefficient is shown with two dotted lines. The bold dashed line represents the quantile regression coefficient. The 90% confidence band around the quantile regression coefficient estimate is shown with a gray shaded band.

4.2.1 Specification 1 Graphs

The panels of Figure 3 show that the OLS coefficients do a poor job of representing the impact of White on sentence length. Specifically, the OLS coefficients for Drug Trafficking, Drug Possession and Firearms crimes are generally below the quantile regression coefficient estimates of White; thus, OLS overstates the racial disparity for these crimes. The impact of race is increasing (moving toward zero) for both drug trafficking and firearms crimes, implying that disparity is decreasing as we move up into longer sentences. The non-monotonicity of the quantile coefficient estimate is expected given the non-monotonicity observed in the distribution of sentencing. Drug possession tells a different story; disparity increases (the coefficients become more negative) as we move along the sentence distribution and the quantile regression coefficient estimate of white approaches the OLS coefficient after the 0.75 quantile. The OLS coefficient on White for the crime of Bank Robbery is significant at the 10% level, however, the quantile regression coefficient estimates suggest that there not significant differences in sentences across race. On the other hand, the OLS coefficient is not significant for the crime of Forgery, however, the quantile regression coefficients suggest that whites receive significantly shorter sentences for the more serious Forgery offenses (above the 65th percentile). For the crimes of Fraud and Larceny the OLS coefficient is not significantly different from zero. The coefficient estimates from quantile regression for these crimes confirm the OLS result.

Our quantile regression results shown in Figure 3 confirm the liberation hypothesis that discrimination in Drug Trafficking and Firearms is larger at the lower ends of the sentencing spectrum where sentence lengths are fairly short and disparity is smaller at the upper end where prison sentences are for long periods of time. That is, when the crime is the most serious (and thus carries with it longer sentences), the race of the offender is less likely to lead to a different sentence than when the crime is less serious and the sentence is relatively short.

4.2.1 Specification 2 Graphs

In Figure 4 we present the graphs of the quantile regression coefficient estimates of White using models that include a control for whether the offender provided assistance to the government (Specification 2). Note from Figure 4 that the magnitude of the OLS coefficients and the quantile regression coefficients have become closer to zero relative to those displayed in Figure 3. For the crimes of Drug Trafficking, Drug Possession, and Firearms, we still find significant differences in the sentences of white and black offenders for some parts of the sentencing distribution; however, the size of the difference is much smaller.

Recall that our set of controls includes a dummy for whether the offender had private legal representation (as opposed to a court-appointed or public defender). Conditional on the same representation and providing substantial assistance to the prosecution, whites are sentenced to shorter prison terms than blacks for Drug Possession, Firearms offenses, and the less serious Drug Trafficking crimes. Although we observe that whites are more likely to have received a sentence departure from providing substantial assistance, the data do not offer explanations as to why minorities do not take advantage of this sentencing option. [20]

Once again, although the OLS coefficient of White is positive and significant for Bank Robbery, the quantile regression coefficients are not significantly different from zero. The use of OLS to assess racial disparity in Bank Robbery for these years would imply white offenders receive longer sentences than black offenders, which we find is not the case. We also observe the same pattern with Forgery as in Specification 1; above the 75th percentile white offenders are sentenced to shorter prison terms than black offenders. For the crimes of Fraud and Larceny,

[20] One might wonder if white offenders are more likely to offer assistance to prosecutors than black offenders, or if prosecutors are offering the sentence reduction opportunity to white offenders more often than to black offenders. Mustard (2001) also suggests that an explanation for minorities receiving fewer departures is that law enforcement officials may be more likely to approach whites for assistance (another explanation he offers is that minorities are less trusting of law enforcement). We leave the possible institutional disparity arising from differences in prosecutors granting substantial assistance departures to future work.

both the OLS and quantile regression estimates of White are not significantly different from zero.

4.2.1 Specification 3 Graphs

In Figure 5 we control for both judicial downward departures and substantial assistance to the government. The general shapes of the graphs are similar to those in Figure 4. For the crimes of Forgery, Fraud, and Larceny, the OLS coefficient is not significantly different from zero. The quantile regression coefficients are significant for a few quantiles of the Fraud crimes, but overall the quantile regression confirms the OLS finding of no racial disparity in the sentencing of these crimes. With the crime of Forgery, there appears to be some racial disparity in the 75th to 95th percentiles of the sentencing distribution. Although the OLS coefficient on White for Bank Robbery is significant, the quantile regression coefficients suggest that race does not impact sentencing for Bank Robbery.

Consistent with Figures 3 and 4, the OLS coefficients on race are significant for Drug Trafficking, Drug Possession and Firearms. The quantile regression coefficient estimates, however, conflict with the OLS estimates. For Drug Trafficking, we find that controlling for both types of departures essentially eliminates the disparity except at the lowest quantiles. With Drug Possession, the OLS estimate suggests that white offenders receive 3.7 fewer months of prison sentence. The quantile regression results show that white offenders receive significantly shorter sentences, but only for the quantiles between the 0.10 and the 0.85 quantile. Lastly, the racial disparity is most pronounced for Firearms offenders in the lower half of the sentencing distribution. The impact of race is almost two times as great as the OLS coefficient suggests for quantiles below 0.15, and after about the 0.50 quantile the effect of White is generally not significantly different from zero.

5. Robustness Check: Censored Quantile Regression

Although we learn something about how the sentence disparity varies across the distribution of sentence with our quantile regression estimates, we have not accounted for the censored nature of the data. As we observed from the Tobit analysis of Drug Trafficking sentences in Table 3, the coefficient estimates are biased toward zero when the censoring problem is ignored. Therefore, these quantile regression coefficients underestimate the size of the true gap across the distribution. To get a true measure of the black-white sentence gap, we must estimate a censored quantile regression model. In this section we report coefficient estimates of White from Drug Trafficking and Firearms crimes using censored quantile regression models. We focus on Drug Trafficking again because it represents the most frequent crime in the data and because there is previous evidence in the literature that racial disparity exists for drug crimes. Firearms crimes are also reported because we found evidence of significant racial disparity in sentencing using quantile regression models that did not account for censoring.[21]

Powell (1984) proposed the censored least absolute deviations (CLAD) estimation method to deal with this censoring problem. The regression estimates are derived from alternating between deleting observations with estimates of $X\beta(\theta)$ that are less than zero and estimating $\beta(\theta)$ by applying least absolute deviations to the remaining data.[22] The CLAD estimator has been shown to be a consistent estimator under the assumption that the error terms have a conditional median of zero, allowing for errors to be non-normal and/or heteroskedastic.

Ideally, we would estimate the coefficients on White using censored quantile regression with the same set of control variables used in Table 3. However, the original set of controls includes dummy variables for 11 judicial circuits to capture geographic differences in sentencing.[23] In theory, all offenders are sentenced under the same federal law and so the circuit where an offender is sentenced by a district judge should not impact the prison sentence. As a general rule, however, district judges must abide by how their circuit has interpreted the law. If there are significant differences across circuits, the Supreme Court may clarify which circuit has the correct interpretation. The Supreme Court is not required to hear these cases and as such there exist differences in how circuits apply the law. In Table 4 we report the coefficients on circuit dummies from the quantile regression model that does not account for censoring

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[21] Although we found significant racial disparity in the sentencing for Drug Possession, the number of observations (1254) is relatively small and so we cannot perform a censored quantile regression. The other crime types (Fraud, Forgery, Larceny and Bank Robbery) did not exhibit any significant racial disparity in sentencing.
[22] See Chay and Powell (2001) for a description of the CLAD estimator developed for use in STATA. The "ado" files are available at http://elsa.berkeley.edu/~kenchay/.
[23] Figure 6 displays the judicial circuits.

(Specification 1). We also perform joint significance tests of the circuit dummy variables in the OLS and Tobit regressions and find they are jointly significant. Although offenders in different circuits are tried and sentenced under the same federal law, there is some empirical evidence that variation in sentencing exists across circuits.[24]

Unfortunately, we are unable to include the set of circuit dummy variables in the censored quantile regression model. The CLAD command for Censored Least Absolute Deviations estimator in STATA has difficulty converging with large sets of dummy variables. Because the model would not converge with the set of circuit dummy variables, we re-estimate all models without controlling for the circuit.

We report the White coefficient estimates for Drug Trafficking and Firearms crimes using OLS, Tobit and quantile regression in Table 5 and Table 6. Although we are unable to present graphs of the censored quantile regression coefficients, we report coefficient estimates from the tenth, twenty-fifth, fiftieth, seventy-fifth, and ninetieth percentiles. In all models, circuit dummy variables are excluded and we estimate Specifications 1-3 for both offense types. Recall that our quantile regression graphs in Figures 3-5 show that the majority of the racial disparity is eliminated for Drug Trafficking and reduced for Firearms when we include controls for departures from the Sentencing Guidelines.

5.1 Drug Trafficking

The first row of Table 5 reports the quantile regression coefficients without accounting for the censored nature of the data (Uncensored Quantile Regression) for comparison to Specification 1 of Table 3 which includes circuit dummy variables.[25] The White coefficient estimates in Table 5 are larger in magnitude than the corresponding model coefficients in Table 3. When the circuit dummies are excluded, the White coefficient captures some of the differences in how circuits treat offenders of different races. Although the results presented in Table 5 may suffer from omitted variable bias because we are unable to include circuit dummy

[24] Wu and Spohn (2008) also find evidence of variation in sentencing across districts in Minnesota, Nebraska and Southern Iowa between 1998 and 2000.

[25] We also provide the OLS and Tobit coefficient estimates excluding circuit dummies in Table 5. The magnitudes of the coefficients when circuit variables are excluded are always larger than the corresponding value when circuit dummies are included.

variables, we may reasonably suspect that this bias is negative (away from zero) and these results may be viewed as upper bounds of the magnitude of the coefficients.

The second row of Table 5 presents the results from the censored quantile regression model for Drug Trafficking with no controls for departures. The magnitudes of the coefficients on White are generally larger than those in row 1, the uncensored quantile regression model. Overall the results when we control for censoring are similar; we find that blacks receive significantly longer sentences than whites at the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 90^{th} quantile, even after controlling for the final offense level, the criminal history of the drug offender, and the type of drug.

In the third row of Table 5, we report the coefficients on White for censored quantile regression models that include a control for whether the offender provided assistance to the government (Specification 2). At every percentile, the White coefficient becomes smaller in magnitude relative to Specification 1 without controls for providing assistance. In fact, the White coefficient at the 90^{th} percentile is no longer significant. Providing government assistance explains a large degree of the black-white sentence gap. The gap remains large at the lowest quantiles, however, with black offenders receiving sentences of 4.2 more months than whites at the 10^{th} percentile. At all other percentiles reported racial disparity is less than one month when we control for substantial assistance, suggesting that providing prosecutor assistance is responsible for between 50% and 75% of the racial sentencing gap in Specification 1. Mustard (2001) finds that, at the mean, about two-thirds of the racial disparity in drug sentencing is due to departures from the Guidelines.

The fourth row of Table 5 reports the White coefficients when we control for both prosecution-based substantial assistance departures and judicial downward departures from the Sentencing Guidelines. Note that the coefficient on White is only significant for the 10^{th}, 25^{th}, and 50^{th} percentiles and is no longer significant at the upper part of the sentence distribution. Although we still find a significant difference in sentence length for whites and blacks for the lower half of the distribution, the magnitude of the difference has dropped dramatically. Now, at the 10^{th} percentile of sentences blacks are sentenced to 0.5 more months than white offenders, instead of the 4-5 months when we do not control for departures. These results suggest that most of the difference in drug crime sentencing for blacks and whites is due to substantial assistance and judicial departures from the Sentencing Guidelines. Even controlling for departures, we find that the racial disparity in sentencing remains for some quantiles in the sentencing distribution; our results are consistent with the finding of Mustard (2001) that when black offenders receive any type of downward departure, the downward departures are smaller than those for white offenders.

5.2 Firearms

Table 6 presents the results when we only analyze Firearms crimes and exclude circuit dummy variables. In the first row, the size of the sentencing gap for Firearms is similar to that of Drug Trafficking for the lower quantiles (around 3 months), but diminishes in the upper quantiles. The second row reports the censored quantile regression estimates of White; once again the size of the gap is largest at the 10^{th} and 25^{th} percentile and is generally close to one month for the 50^{th}, 75^{th}, and 90^{th} percentiles. As expected, the magnitude of the sentencing gap increased as we control for sentencing. When we control for both types of departures from the Sentencing Guidelines, the magnitude of the gap decreases but remains statistically significant for the lower part of the sentencing distribution.

The magnitude of the sentencing gap for Firearms crimes when we control for departures is generally less than one month. At the 10^{th} percentile, however, the coefficient estimate is -3.4, suggesting whites are sentenced to at least 3 fewer months in prison for the least serious Firearms crimes. Given that the 10^{th} percentile of the sentencing distribution is 5 months, our estimate of the sentencing gap at the lower end of the distribution represents considerable racial disparity.

6. Conclusion

This paper studies the disparity in sentencing for black male offenders relative to white male offenders. Previous literature has consistently shown black males receive longer sentences than white males, even after controlling for characteristics of the crime such as criminal history and final offense level. Rather than evaluate the difference in sentencing only at the mean, we employ quantile regression techniques to study the disparity across the entire distribution of prison sentences.

After controlling for the demographic characteristics of the offender, criminal history and the final offense level, we find that significant racial disparity exists along the entire distribution of sentences for Drug Trafficking, Drug Possession and Firearms crimes. The other common offenses (Bank Robbery, Fraud, Forgery, and Larceny) do not appear to exhibit racial disparity in sentencing. With Drug Trafficking and Firearms crimes, the disparity is larger for the lower half of the sentence range and approaches zero as the quantile increases. This suggests that black offenders receive longer sentences than white offenders for the less serious Drug Trafficking and Firearms crimes that carry shorter sentences. Drug Possession exhibits the opposite property; disparity in sentencing increases with the quantile so that white offenders receive shorter sentences than black offenders for the more serious Drug Possession crimes.

Given that Mustard (2001) and Freeborn and Hartmann (2009) show black offenders are less likely than whites to receive sentencing departures from the Guidelines, we also control for whether the offender provided assistance to the prosecution and whether the offender received a judicial downward departure. When we control for substantial assistance departures, the degree of disparity is reduced but not eliminated. Controlling for both assistance to the prosecutor and judicially-based departures eliminates most of the racial disparity in sentencing for Drug Trafficking, however, significant differences in sentences across race still exist for Drug Possession and the lower half of the distribution for Firearms sentences.

Our main set quantile regression results do not control for the large number of offenses that result in probation or a sentence of zero months. That is, we do not account for the censored nature of the data. We focus on Drug Trafficking and Firearms crimes and employ a censored quantile regression estimation method developed by Powell (1984). The magnitudes of the coefficients on White increase across the reported quantiles for Drug Trafficking crimes relative to the uncensored quantile regression estimates. Unfortunately, these models do not control for the circuit where the offender was sentenced, and so still may suffer from omitted variable bias. The coefficients remain largest in magnitude for the lower half of the sentence range, suggesting that while whites receive shorter sentences than blacks for all sentences, the effect is stronger for less serious Drug Trafficking crimes. We find the same pattern with Firearms crimes; the sentence gap is significant for the lower part of the sentencing distribution, and not significantly different from zero for the most serious Firearms crimes.

Overall we find relatively little evidence of racial disparity in federal prison sentences using quantile regression techniques when we account for prosecutor-based and judicial departures. Both types of departures explain a large portion of the racial gap for Drug Trafficking and Firearms; the size of the gap is reduced across the sentence distribution and is no longer significant for the upper range. We interpret our results to be that most of the racial gap in sentencing is due to departures from the Sentencing Guidelines, either through the offender providing assistance to the government or the judge choosing a downward departure based on extenuating circumstances.

Table 1: U.S.S.C. Federal Sentencing Table

	Offense Level	Criminal History Category (Criminal History Points) I (0 or 1)	II (2 or 3)	III (4, 5, 6)	IV (7, 8, 9)	V (10, 11, 12)	VI (13 or more)
	1	0-6	0-6	0-6	0-6	0-6	0-6
	2	0-6	0-6	0-6	0-6	0-6	1-7
	3	0-6	0-6	0-6	0-6	2-8	3-9
	4	0-6	0-6	0-6	2-8	4-10	6-12
Zone A	5	0-6	0-6	1-7	4-10	6-12	9-15
	6	0-6	1-7	2-8	6-12	9-15	12-18
	7	0-6	2-8	4-10	8-14	12-18	15-21
	8	0-6	4-10	6-12	10-16	15-21	18-24
	9	4-10	6-12	8-14	12-18	18-24	21-27
Zone B	10	6-12	8-14	10-16	15-21	21-27	24-30
Zone C	11	8-14	10-16	12-18	18-24	24-30	27-33
	12	10-16	12-18	15-21	21-27	27-33	30-37
	13	12-18	15-21	18-24	24-30	30-37	33-41
	14	15-21	18-24	21-27	27-33	33-41	37-46
	15	18-24	21-27	24-30	30-37	37-46	41-51
	16	21-27	24-30	27-33	33-41	41-51	46-57
	17	24-30	27-33	30-37	37-46	46-57	51-63
	18	27-33	30-37	33-41	41-51	51-63	57-71
	19	30-37	33-41	37-46	46-57	57-71	63-78
	20	33-41	37-46	41-51	51-63	63-78	70-87
	21	37-46	41-51	46-57	57-71	70-87	77-96
	22	41-51	46-57	51-63	63-78	77-96	84-105
	23	46-57	51-63	57-71	70-87	84-105	92-115
	24	51-63	57-71	63-78	77-96	92-115	100-125
	25	57 71	63 78	70 87	84 105	100 125	110 137
	26	63-78	70-87	78-97	92-115	110-137	120-150
	27	70 87	78 97	87 108	100 125	120 150	130 162
Zone D	28	78-97	87-108	97-121	110-137	130-162	140-175
	29	87-108	97-121	108-135	121-151	140-175	151-188
	30	97-121	108-135	121-151	135-168	151-188	168-210
	31	108-135	121-151	135-168	151-188	168-210	188-235
	32	121-151	135-168	151-188	168-210	188-235	210-262
	33	135-168	151-188	168-210	188-235	210-262	235-293
	34	151-188	168-210	188-235	210-262	235-293	262-327
	35	168-210	188-235	210-262	235-293	262-327	292-365
	36	188-235	210-262	235-293	262-327	292-365	324-405
	37	210-262	235-293	262-327	292-365	324-405	360-life
	38	235-293	262-327	292-365	324-405	360-life	360-life
	39	262-327	292-365	324-405	360-life	360-life	360-life
	40	292-365	324-405	360-life	360-life	360-life	360-life
	41	324-405	360-life	360-life	360-life	360-life	360-life
	42	360-life	360-life	360-life	360-life	360-life	360-life
	43	life	life	life	life	life	life

Table 2: Descriptive Statistics

	All Drugs	Drug Trafficking	Drug Possession	Fraud	Firearms	Larceny	Forgery	Bank Robbery
Offender Demographic Characteristics								
White	0.58	0.58	0.61	0.70	0.46	0.62	0.52	0.55
Hispanic	0.25	0.26	0.13	0.07	0.08	0.07	0.06	0.06
Age	32.32	32.27	33.46	40.44	32.28	36.36	31.35	32.59
Number of Dependents	1.55	1.56	1.30	1.40	1.34	1.31	1.15	0.92
High School Grad	0.37	0.37	0.42	0.30	0.39	0.40	0.38	0.44
Trade School	0.01	0.01	0.02	0.02	0.01	0.01	0.01	0.01
Some College	0.15	0.15	0.16	0.28	0.11	0.25	0.24	0.16
College Grad	0.02	0.02	0.05	0.22	0.01	0.08	0.05	0.02
Associate Degree	0.01	0.01	0.01	0.02	0.01	0.02	0.02	0.02
Private Counsel	0.23	0.23	0.23	0.33	0.14	0.19	0.16	0.07
Offense Sentencing Characteristics								
Sentence in months	69.43	71.70	19.82	10.13	52.38	6.41	9.83	69.14
Offense level	23.93	24.42	13.25	11.73	18.52	8.76	9.81	22.50
Criminal History	2.52	2.52	2.45	1.82	3.64	2.07	2.59	3.46
Jud. Departure	0.12	0.12	0.06	0.11	0.12	0.08	0.07	0.15
Sub. Assistance	0.33	0.34	0.12	0.21	0.10	0.09	0.13	0.11
N†								
Black	11,941	11,446	759	1954	3532	819	819	823
White	16,758	15,999	495	4625	3006	903	903	1001
Total	28,699	27,445	1,254	6,579	6,538	2,444	1,722	1,824

†Because missing observations are dropped, the number of observations is always lower for the models with controls for substantial assistance and judicial departures.

Table 3: Coefficients on White-Dummy Variable for Drug Trafficking: OLS, Tobit, Quantile Regression

			Quantile Regression Percentile				
	OLS	Tobit	10th	25th	50th	75th	90th
Specification 1	-4.676***	-5.154***	-3.750***	-3.707***	-2.186***	-0.981***	-1.036***
No Departure Controls	(0.633)	(0.657)	(0.643)	(0.465)	(0.208)	(0.176)	(0.248)
Specification 2	-1.297**	-1.605***	-1.627***	-0.855***	-0.225	-0.256	-0.282
(Sub. Assistance Control)	(0.541)	(0.558)	(0.532)	(0.276)	(0.142)	(0.289)	(0.322)
Specification 3	-0.948*	-1.243**	-0.923*	-0.239*	-0.219	-0.196	-0.233
(All Departures Controls)	(0.519)	(0.535)	(0.478)	(0.123)	(0.174)	(0.293)	(0.294)

Note: [1] Dependent variable in sentence in months. Standard errors are given in parentheses. [2] In all model specifications, we include demographic characteristics of the offender and characteristics of the offense. *, **, and *** indicate significance at the 10, 5, and 1% levels, respectively.

Table 4: Circuit Dummy Variables from Uncensored Quantile Regression For Drug Trafficking (Specification 1)

	Percentile				
	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}
Circuit 2	34.81***	33.97***	3.20***	3.13***	3.14***
	2.67	2.00	0.92	0.79	1.13
Circuit 3	19.65***	19.43***	-4.53***	0.22	0.20
	2.51	1.87	0.87	0.75	1.06
Circuit 4	22.76***	19.54***	-6.20***	0.096	0.22
	2.59	1.94	0.90	0.77	1.10
Circuit 5	33.17***	30.21***	3.10***	3.85***	3.10***
	2.44	1.82	0.84	0.73	1.03
Circuit 6	35.25***	31.87***	2.52***	2.85***	2.77**
	2.42	1.81	0.84	0.72	1.03
Circuit 7	31.26***	26.46***	-1.90**	1.69**	1.25
	2.45	1.84	0.85	0.73	1.04
Circuit 8	40.60***	37.01***	3.57***	2.45***	2.01*
	2.51	1.88	0.87	0.75	1.07
Circuit 9	28.24***	24.92***	2.41***	1.31*	0.49
	2.46	1.84	0.85	0.73	1.05
Circuit 10	27.92***	23.99***	-6.01***	-2.14***	-0.39
	2.48	1.85	0.85	0.74	1.05
Circuit 11	30.07***	28.98***	1.53*	2.76***	1.71
	2.55	1.91	0.88	0.76	1.09
Circuit 12	36.09***	31.61***	2.39***	2.31***	1.21
	2.43	1.82	0.84	0.73	1.04

Note: In each cell, the upper number indicates the coefficient, while the lower number represents the standard error for the corresponding coefficient. The omitted circuit includes Maine, New Hampshire, Massachusetts and Rhode Island. *, **, and *** indicate significance at the 10, 5, and 1% levels, respectively.

Table 5: Coefficient on White: OLS, Tobit, and Quantile Regression for Drug Trafficking (Uncensored and Censored) Excluding the Circuit Dummy Variables

			Percentile				
	OLS	Tobit	10th	25th	50th	75th	90th
Uncensored Quantile Regression (Specification 1)			-3.883***	-4.116***	-3.968***	-1.243***	-1.049***
			(0.564)	(0.462)	(0.241)	(0.170)	(0.235)
Censored Specification 1 No Departure Controls	-5.352***	-5.836***	-5.020***	-4.321***	-4.008***	-1.243***	-1.049***
	(0.635)	(0.659)	(0.711)	(0.477)	(0.389)	(0.230)	(0.318)
Censored Specification 2: Substantial Assist. Control	-2.323***	-2.661***	-4.206***	-0.961***	-0.836***	-0.602***	-0.361
	(0.544)	(0.562)	(0.775)	(0.181)	(0.176)	(0.218)	(0.403)
Censored Specification 3: All Departures Controls	-1.123**	-1.404***	-0.496**	-0.289***	-0.390***	-0.168	-0.325
	(0.518)	(0.535)	(0.194)	(0.107)	(0.134)	(0.239)	(0.391)
Sentence Length Statistics	71.70		11	24	57	100	151

Note: Dependent variable in sentence in months. Standard errors are given in parentheses. In all model specifications, we include demographic characteristics of the offender and characteristics of the offense. *, **, and *** indicate significance at the 10, 5, and 1% levels, respectively.

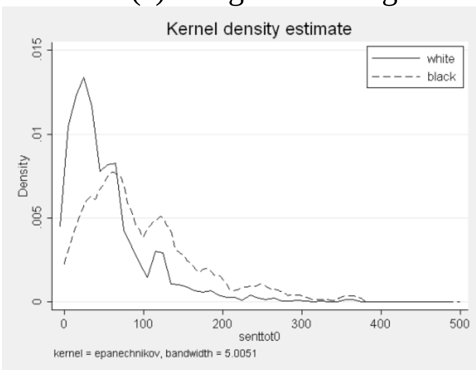
Table 6: Coefficient on White: OLS, Tobit, and Quantile Regression for Firearms (Uncensored and Censored) Excluding the Circuit Dummy Variables

			Percentile				
	OLS	Tobit	10th	25th	50th	75th	90th
Uncensored Quantile Regression (Specification 1)			-3.406***	-2.918***	-0.656***	-0.668***	-0.666**
			(0.638)	(0.381)	(0.202)	(0.265)	(0.280)
Censored Specification 1 No Departure Control	-2.717***	-3.325***	-4.635***	-4.713***	-0.955***	-1.109***	-0.879
	(0.57)	(0.593)	(-1.081)	(0. 462)	(-0.228)	(-0.231	(-0.369)
Censored Specification 2: Substantial Assist. Control	-2.137***	-2.591***	-5.999***	-1.969***	-0.667***	-0.962***	-0.763*
	(0.519)	(0.551)	(1.089)	(0.522)	(0. 212)	(0.274)	(0.436)
Censored Specification 3: All Departures Controls	-1.592***	-1.947***	-3.392**	-0.825***	-0.481**	-0.689**	-0.323
	(0.479)	(0.506)	(0.466)	(0.253)	(0.187)	(0.284)	(0.328)
Sentence Length Statistics	52.38		5	21	37	65	120

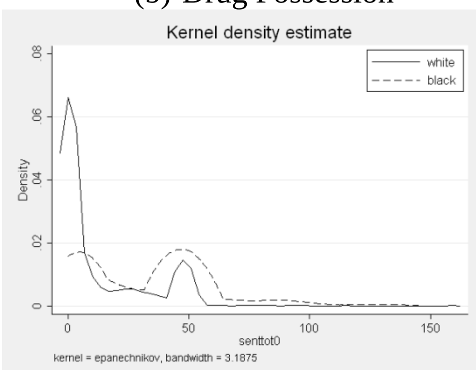
Note: [1] Dependent variable in sentence in months. Standard errors are given in parentheses. [2] In all model specifications, we include demographic characteristics of the offender and characteristics of the offense (excluding drug type). [3] *, **, and *** indicate significance at the 10, 5, and 1% levels, respectively.

Figure 1: Density of Sentences for White and Black Offenders

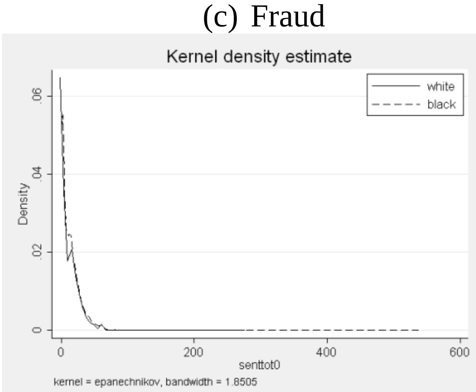
(a) Drug Trafficking



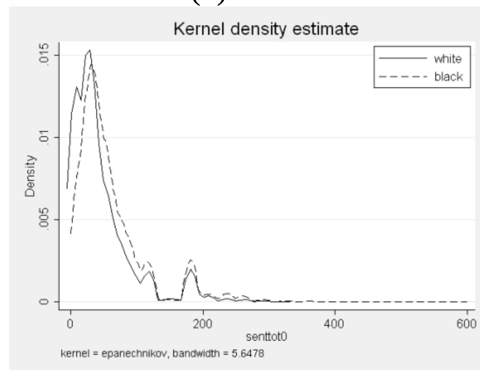
(b) Drug Possession



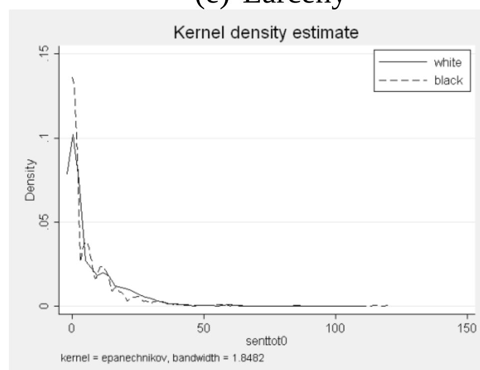
(c) Fraud



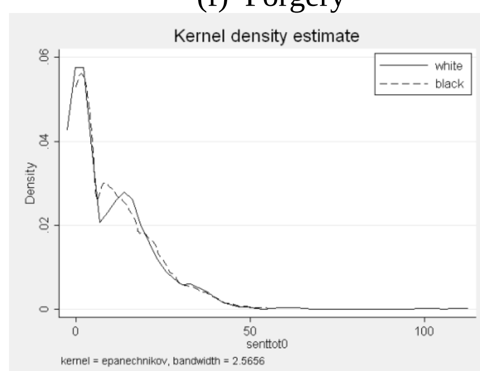
(d) Firearms



(e) Larceny



(f) Forgery



(g) Bank Robbery

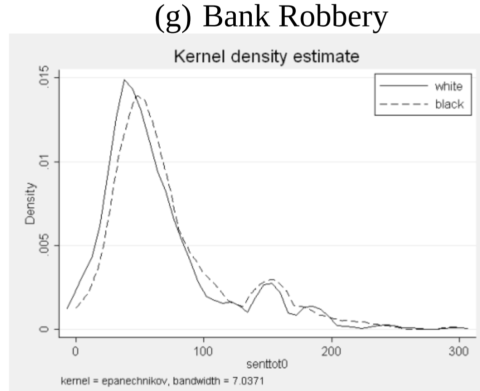


Figure 2: Distribution of Sentencing Gap

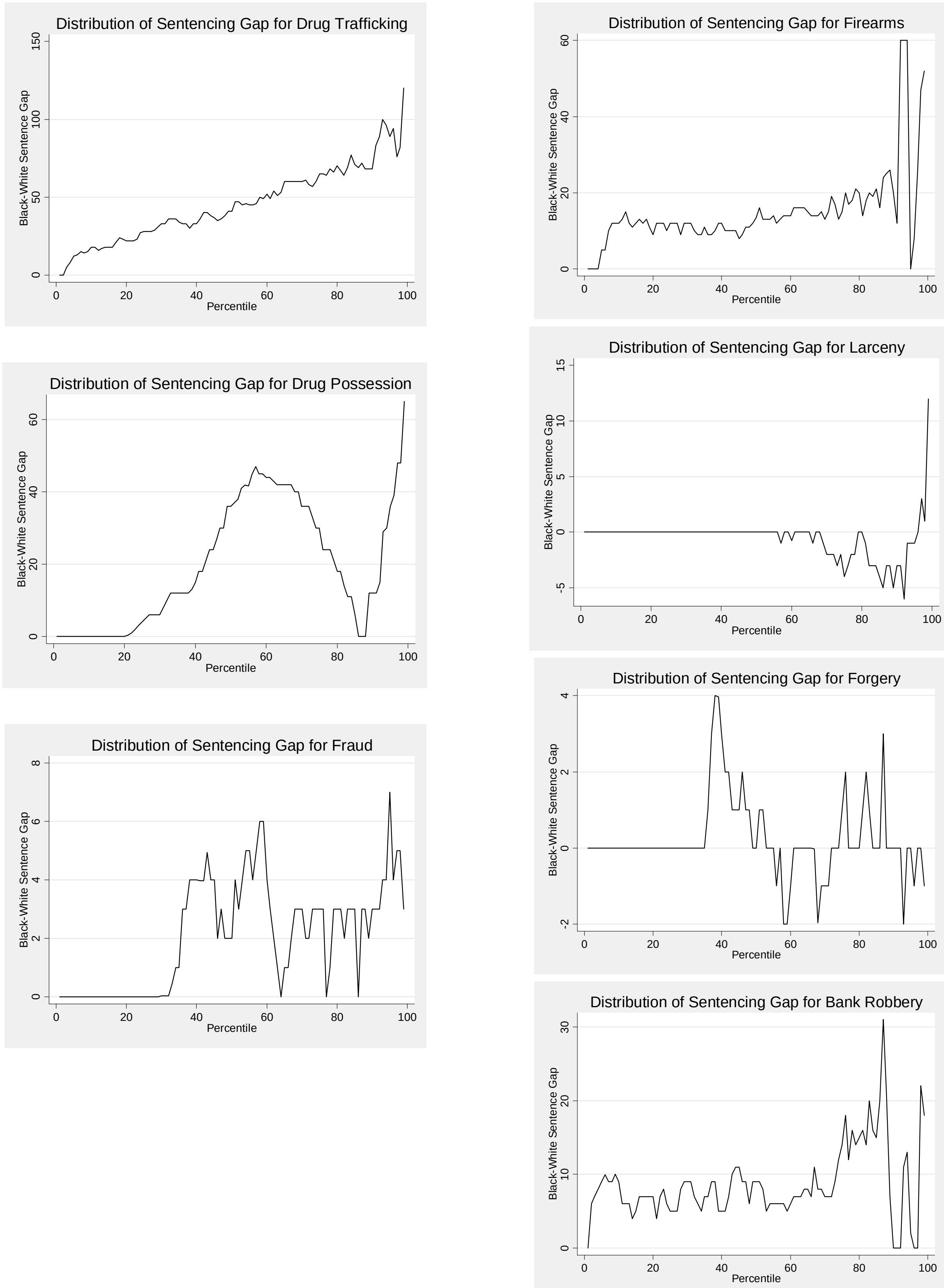
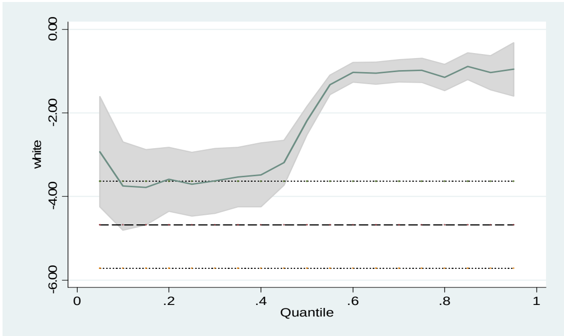
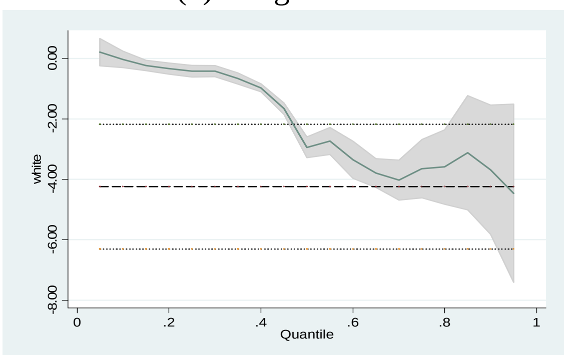


Figure 3: Quantile Regression Coefficient Estimate of White by Offense Type (Spec 1)

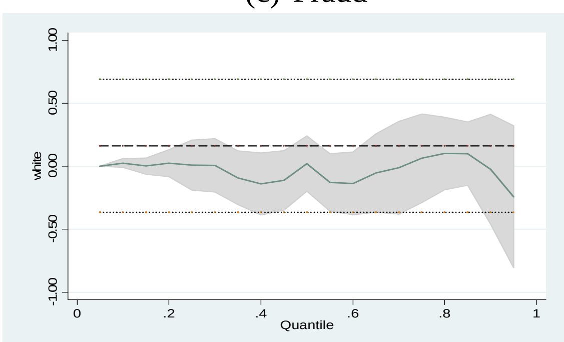
(a) Drug Trafficking



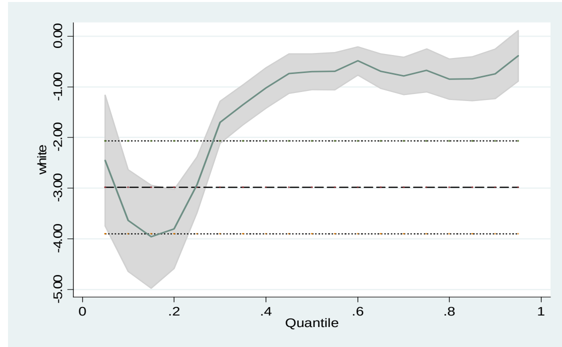
(b) Drug Possession



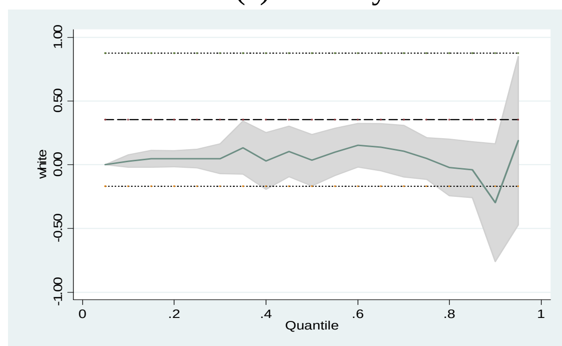
(c) Fraud



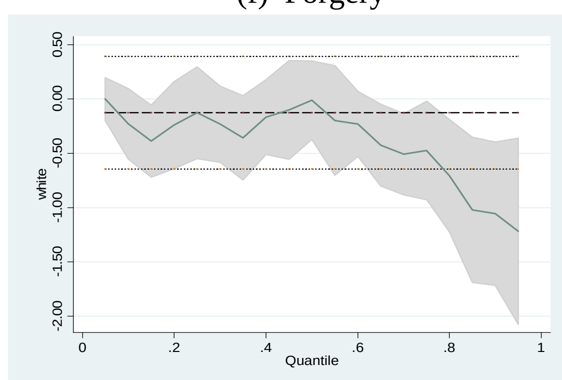
(d) Firearms



(e) Larceny



(f) Forgery



(g) Bank Robbery

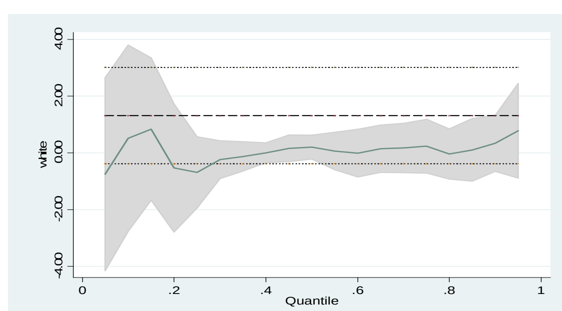
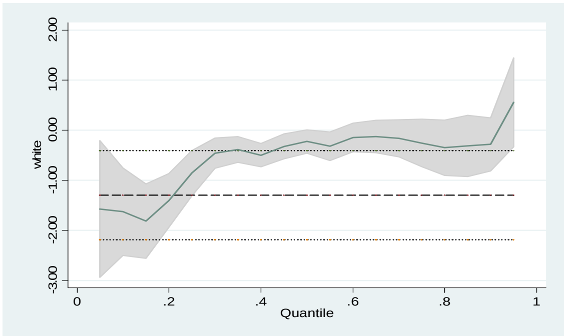
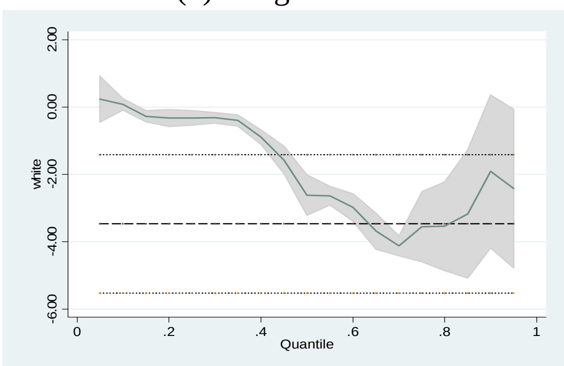


Figure 4: Quantile Regression Coefficient Estimate of White by Offense Type (Spec 2)

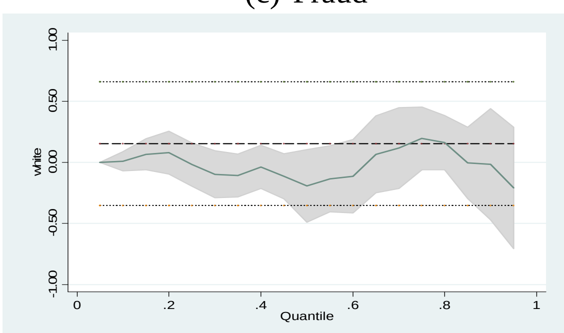
(a) Drug Trafficking



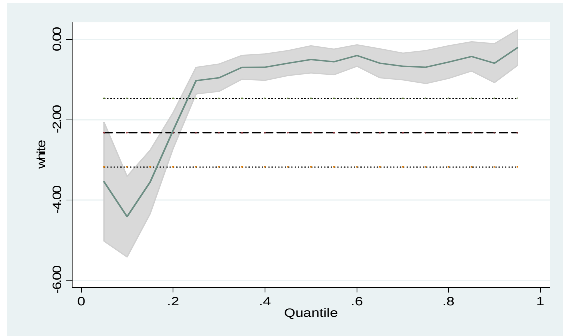
(b) Drug Possession



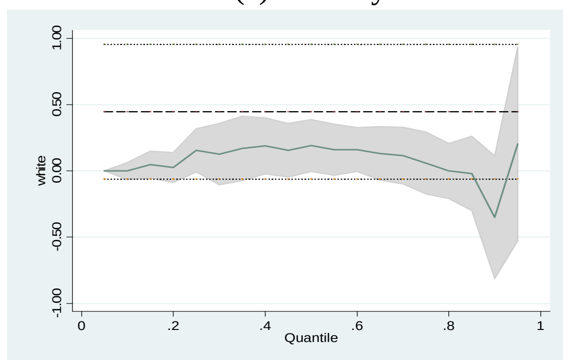
(c) Fraud



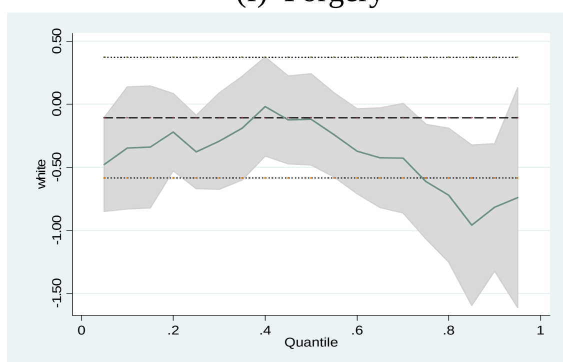
(d) Firearms



(e) Larceny



(f) Forgery



(g) Bank Robbery

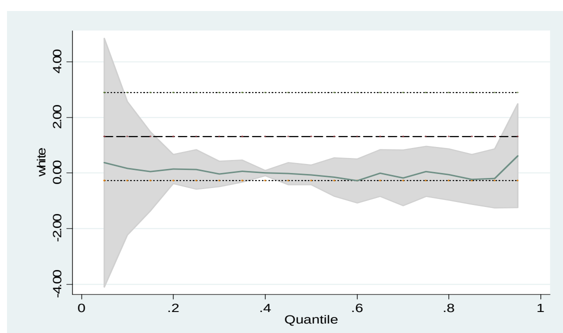
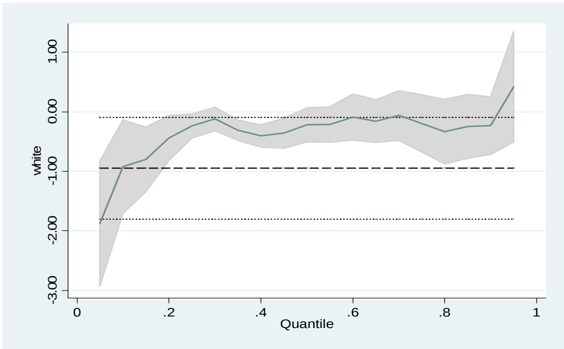
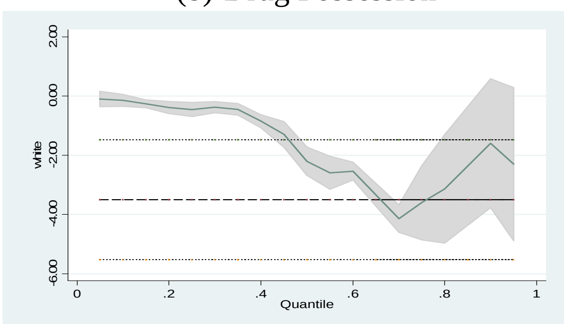


Figure 5: Quantile Regression Coefficient Estimate of White by Offense Type (Spec 3)

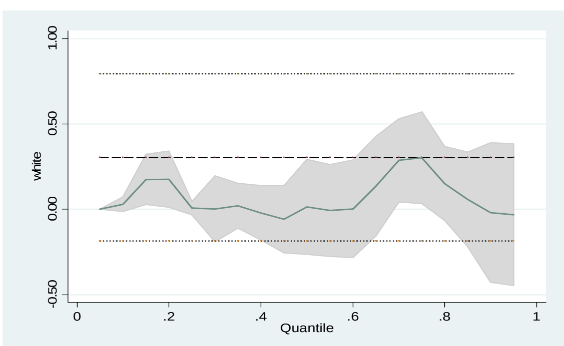
(a) Drug Trafficking



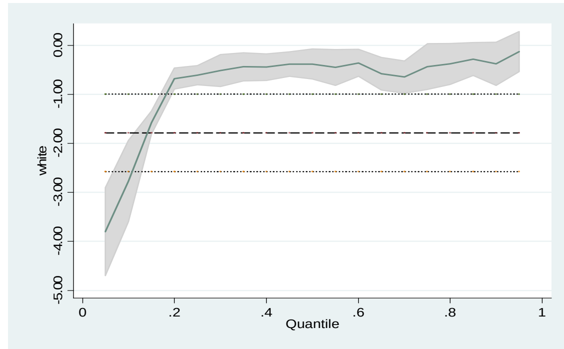
(b) Drug Possession



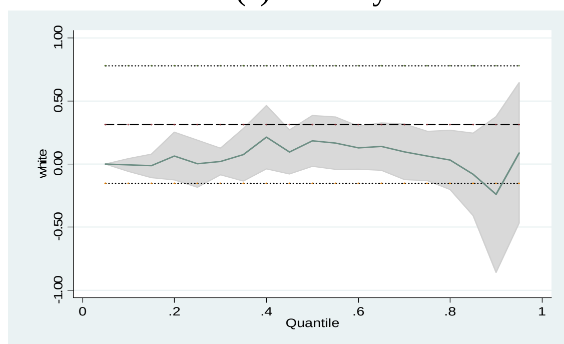
(c) Fraud



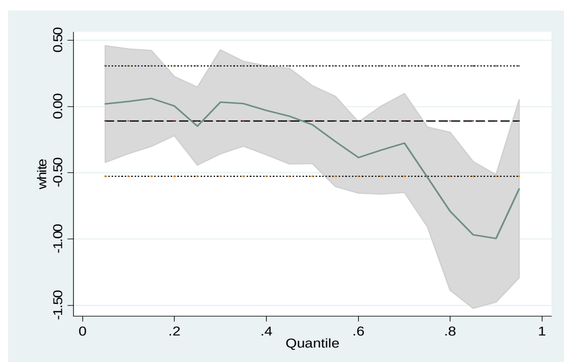
(d) Firearms



(e) Larceny



(f) Forgery



(g) Bank Robbery

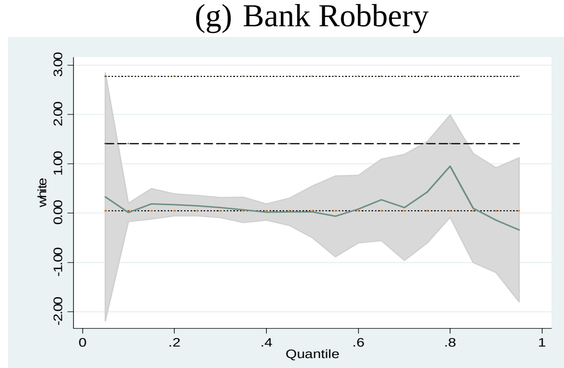
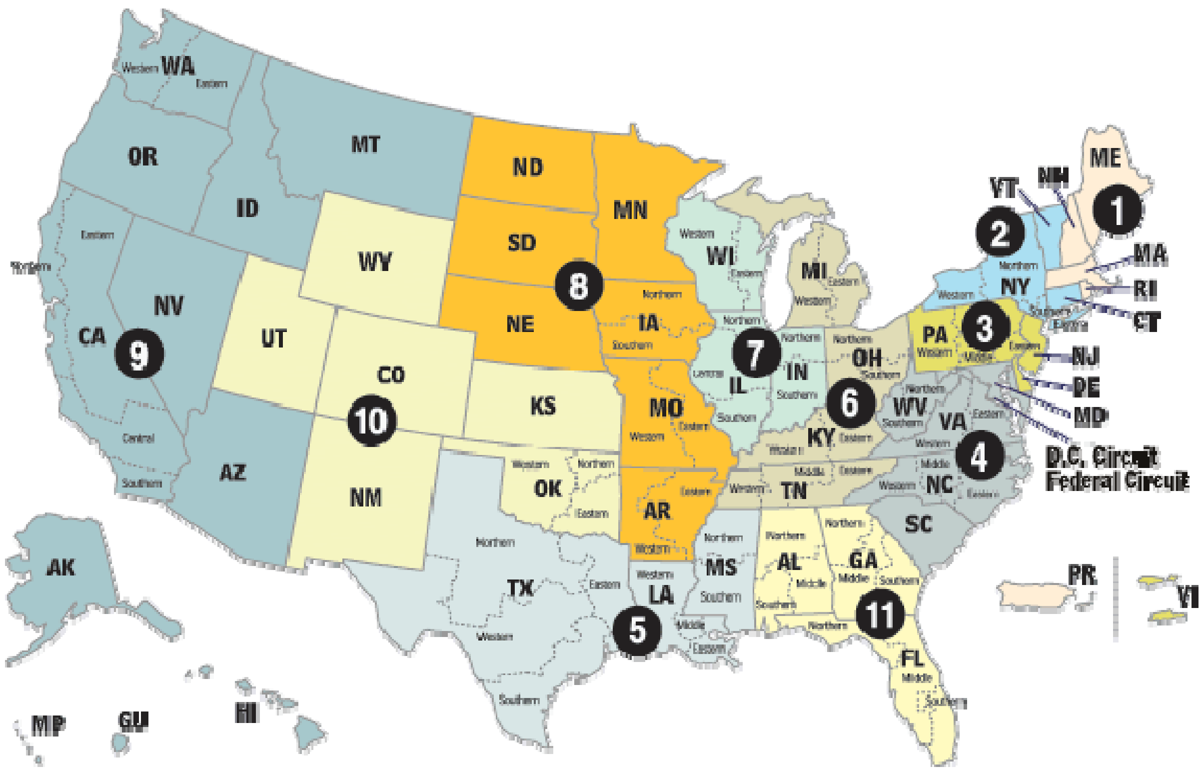


Figure 6: Geographic Boundaries of U.S. Court of Appeals



Source: http://www.uscourts.gov/courtlinks/

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