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Do You Receive a Lighter Prison Sentence Because You are a Woman? An Economic Analysis of Federal Criminal Sentencing Outcomes

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Abstract

The Federal criminal sentencing guidelines struck down by the U.S. Supreme Court in 2005 required that males and females who commit the same crime and have the same prior criminal record be sentenced equally. Using data obtained from the United States Sentencing Commission's records, we examine whether there exists any gender-based bias in criminal sentencing decisions. We treat months in prison as a censored variable in order to account for the frequent outcome of no prison time. Additionally, we control for the self-selection of the defendant into guilty pleas through use of a switching regression model with endogenous switching. A new decomposition methodology is employed. Our results indicate that women receive more lenient sentences even after controlling for circumstances such as the severity of the offense and past criminal history.

I. INTRODUCTION

Gender equity has been one of the major global social issues to emerge out of the 20th century. A major focus of economists in this regard is on disparate labor market outcomes for men and women. Emphasis is placed on human capital explanations for gender wage gaps though there is some scope for other explanations such as Becker taste-driven discrimination, statistical discrimination, and market power. There is the potential effect of labor market outcomes on subsequent criminal activities and the effect of criminal activities on subsequent labor market outcomes. The literature on the economics of crime is discussed below. This paper examines the gender equity issue in the criminal justice arena and notes that labor market outcomes and criminal justice outcomes can be jointly determined. A popular perception in the criminal justice system is that female criminal behavior is a less serious problem than male criminal behavior. Detailed statistics compiled by the Bureau of Justice Statistics do show that women commit fewer offenses than men and substantially different types of offenses than men. However, the statistics also reveal a rising trend in offenses committed by females and an increase in the incarceration of females in recent years. Beyond the labor market implications of gender equity in the criminal justice system is also a concern for allocative efficiency regarding resources devoted to deterrence and incarceration.

The Federal Sentencing Guidelines that arose out of the Sentencing Reform Act of 1984 and that were subsequently struck down by the U.S. Supreme Court in 2005 (consolidated cases of United States v. Booker, No. 04-104, and United States v. Fanfan, No. 04-105) required that males and females who commit the same crime and have the same prior criminal record receive equal sentences. Critics of the sentencing guidelines argue that women should be accorded separate treatment because females who are caught in the criminal justice system "enter it due to circumstances that are distinctly different from those of men"[1]. Others argue that gender is not a factor that should in anyway enter into the sentencing decision. The Supreme Court in its split 5 to 4 decision argued that the mandatory guidelines violated the rights of criminal defendants to have a jury rather than a judge decide if defendants had committed all elements of a given crime. Consequently, the guidelines are only advisory to judges who may increase the length of sentences if they determine that the circumstances based on jury determination or admission of the defendant merit a longer prison sentence (Chicago Daily Law Bulletin, 2005).

Whether the circumstances in which a crime is committed should be a consideration in criminal justice is not a question that we propose to answer here. Rather, we address the question of whether or not women do indeed receive more lenient sentences

[1] "Research on Women and Girls in the Justice System." National Institute of Justice Report (September 2000) at page iii. Available at http://www.ncjrs.gov/pdffiles1/nij/180973.pdf. .

despite the sentencing guidelines. The answer to this question is important to both sides of the debate. Those in the justice system who favor equal treatment but believe that women are let off too lightly may be especially harsh when judging a female accused of crime, while those who favor separate treatment of women, but believe that they are treated equally, may be less stringent. Thus perceptions of unequal treatment, when they are not based on systematic study and sound facts, may lead to actual inequality in the justice system. A systematic study of whether bias actually exists is therefore not only necessary but timely given the rising trend in offenses committed by women and the increase in female incarceration rates as evidenced by the data compiled by the Bureau of Justice Statistics. Further work can begin to better tie the relationship between gender equity in the criminal justice system with gender equity in the labor market.

An unpublished paper by Oaxaca and Sarnikar (2005) [hence forth OS] uses a rich data set on sentencing outcomes from the United State Sentencing Commission to estimate separate logistic regressions for men and women, where the dependent variable is a binary variable measuring whether or not convicted individuals received federal prison time. While summary statistics from their data set show that females are less likely to receive prison time than males, more sophisticated analysis can take account of covariates that can explain some or all of the gender sentencing differential.

In this paper, we consider outcomes from the sentencing process more broadly for a sample of whites who were convicted while the mandatory sentencing guidelines were still in effect. Specifically, we look beyond the binary Prison/No-Prison outcome to a continuous measure of prison sentence. Ideally, one would want to take into account the fact that defendants must choose whether or not to plea bargain or to take their chances in a trial . Given that we work with a sample of convicted individuals (we do not have data on acquittals), we model the probability of whether the conviction was the result of a trial versus a plea bargain. We treat sentences handed down due to guilty pleas as outcomes from one regime, while sentences given to defendants convicted in a trial are treated as outcomes from a separate regime. This approach allows characteristics to be weighted differently depending on the path to conviction. One would expect the average sentences of identical defendants facing identical charges should be lower in the *plea regime*.[2] In our data set, around 25% of all criminal sentences involve no prison time. Because of this considerable mass point at zero, it may be inappropriate to consider the distribution of sentencing outcomes to be continuous. Also, the plea vs. trial regime is a choice variable for the defendant so that we must account for self selection in our model. Accordingly, we treat the outcome variable as a mixed discrete continuous variable. Therefore, our econometric model is a censoring (Tobit) switching regression with endogenous switching, which we estimate by full information maximum likelihood (FIML).

To measure how much of the male/female sentencing differential can be attributed to differences in the characteristics of men and women, compared to how much of the differential can be explained by differences in the weights applied to these characteristics by judges, we develop a new decomposition. This decomposition builds upon Neuman and Oaxaca (2004), which addresses the issue of selectivity in the context of a Heckit model. We expand this analysis to decompose differentials in the switching regression model with censoring. Our approach takes account of the fact that predicted outcome means will not generally match sample outcome means because of the highly non-linear nature of the model.

Within our data set, the scarcity of observations of females and the preponderance of observation in the plea regime conspire to leave us with an insufficient number of observations of females to properly apply FIML to estimate the female sentence

[2] If the sentences were lighter in the *trial regime* it would be difficult to believe that defendants would ever do anything but plead not guilty, as this would generate a positive probability of facing no sentence at all.

determination model. In the decomposition we develop, we exploit an insight from Oaxaca and Ransom (1994) that allows us to decompose the male-female regime and sentencing differentials without actually estimating the model for females. Rather than comparing weights from a male only and female only model, we instead are able to compare to estimated parameters from the model for males and also to a pooled model for males and females.

One final issue we address in our analysis is a possible correlation between a defendant's choice of legal counsel and the plea decision. If it is the case that attorney quality affects outcomes differently in one of the regimes, we might expect defendants to base their choice of legal counsel on the regime they expect to end up in. As we use type of attorney (private or other) as a determinate of sentence length in our main model, this interdependence between the hiring decision and the likely regime selection would lead us to obtain inconsistent results for the effect of attorney on sentence outcome. To address this issue, we estimate a bivariate probit model of the attorney hiring decision and the conviction by plea vs. by trial outcome (henceforth referred to as the *trial regime*).

The rest of the paper proceeds as follows. Section II discusses the relevant literature. Section III describes the econometric model we use to obtain parameter estimates, while Section IV describes the decomposition we employ. Section V presents our results, and Section VI concludes.

II. LITERATURE

Since the seminal work of Becker (1968), there has been a significant amount of research aimed at understanding the economics of crime. In the basic economic model of crime, a rational individual decides whether or not to allocate his/her time to criminal activity by comparing the expected net returns from criminal activity to the expected returns from legitimate activity. The expected net return to criminal activity consists of the potential financial and psychic benefits (B) of committing the crime minus the cost (C) of committing the crime. The cost to the individual of committing the crime is determined as the product of the probability (p) of being caught by law enforcement and the severity of the punishment (S). If the returns to legitimate labor market activity is the wage (W), then a rational, risk-neutral individual will engage in criminal activity only if B-pS > W. This static model therefore predicts that criminal activity can be deterred by either increasing the probability of detection(p), the severity of punishment(S) and/or the wage rate (W) in the labor market.

Economists have since subjected these theoretical predictions to empirical testing using econometric models of varying degrees of sophistication. Ehrlich (1973) and Levitt (1997) estimate the impact of increased law enforcement presence on crime and find that increasing law enforcement efforts have the desired effect of lowering incidence of crime. Ehrlich (1975) estimated the deterrence effect of capital punishment on crime. Witte (1980) finds that the deterrence effect of higher legal wages was small compared to the deterrence effects of the severity and certainty of state imposed penalties. Block and Gerety (1995) reports on laboratory experiments that examine differences between the criminal population and the general population in the relative responsiveness to the deterrence effects of severity of punishment versus the deterrence effects of the certainty of punishment. The results showed that convicts were more deterred by increases in the certainty of punishment whereas the student subjects were more deterred by increases in the severity of punishment. Freeman (1996), Grogger (1998), and Gould et.al (2002) find that falling real wages were a significant determinant of increasing crime rates during the decades of the 1970s and 1980s.

The link between deterrence efforts and crime rates is an endogenous one. Decisions to increase law enforcement efforts are often made in response to increasing crime rates. Similarly, difficulty in finding legitimate labor market employment might push some individuals into criminal activity but the fact that an individual has engaged in criminal activity also would lower that individual's probability of finding legitimate employment. Myers (1983) investigates whether poor labor market prospects post-release affect the re-integration of ex-convicts into the mainstream. Using different datasets, Myers finds that better wages post-release significantly reduced recidivism. Witte and Reid (1980) also find that receiving a high wage on the first job after being released from prison decreases recidivism and that the wage rate received by prison 'releases' depends mostly on the demand side characteristics such as the industry and occupation rather than on the accumulated human capital of the 'releasee'. Imai and Krishna (2004) estimate a dynamic model of criminal behavior and show that expected future adverse consequences in the labor market prove to be an effective deterrent to crime. Waldfogel (1994) estimated the effects of conviction and imprisonment on post-conviction income and employment probabilities and found that the state imposed sanctions were much smaller in comparison to the "market sanction" estimated as the income lost due to conviction and imprisonment. Also the "market sanction" was significant only for those offenders who worked at jobs that required much trust. Grogger (1995) used longitudinal data and concluded that the strong negative correlation between arrests and subsequent labor market sanctions that was found in earlier cross-sectional studies was largely due to unobserved characteristics that influence both criminal and labor market behavior. Grogger (1995) however does find that there are significant negative consequences of arrests in the labor market but that they are short-lived.

Consistent with the predictions of the economic model of crime, the Sentencing Reform Act of 1984 (SRA 1984) increased the length of punishment for almost all crimes, eliminated probation and reduced the possibility of parole for good behavior. Kling (2004) estimates the effect of this increased severity of punishment on labor market prospects of criminals post-release. Kling finds that there is no significant adverse effect on employment or earnings of criminals due to longer incarceration lengths and concludes that this may be because prison rehabilitation programs may be offsetting the loss of potential work experience and human capital depreciation while in prison.

The sentencing guidelines formulated pursuant to the SRA 1984 aimed to provide uniform sanctions for the same crime by eliminating gender, age, or racial disparities in sentencing. While economists have studied the deterrence effect of severity of punishment quite extensively, relatively little literature exists on the optimality and desirability of uniform sentencing. Lott (1992) argues against uniform sentencing based on the finding that market sanctions in the form of lost incomes, opportunity costs of imprisonment and the adverse impact of incarceration on labor market prospects are disproportionately higher for individuals with higher incomes. Since the expected total monetary penalty includes the reduction in legitimate earnings capability post release, Lott argues that the state imposed punishments should be proportionately adjusted. Moreover, since mere conviction can restrict the post-conviction opportunities for higher income individuals more severely than for lower skilled people, Lott argues that rich people should be convicted much less frequently than low-income criminals. The sentencing guidelines however explicitly prohibited sentencing judges from considering factors such as the defendant's socioeconomic status, race, sex, age, and religion. The punishment was to be proportional to the severity of the crime and the defendant's criminal history alone. Judicial discretion to change the sentence based on characteristics of the defendant was thus severely restricted under the guidelines. Several studies in the criminology literature have examined gender and racial disparities in sentencing prior to the formulation of sentencing guidelines. See Tonry (1996) for a survey of these studies. Whether the guidelines have been successful in reducing the disparity has also been studied extensively both in the criminology and the law and economics literature. Anderson et al (1999), Kempf-Leonard and Sample

(2001) study sentencing disparities before and after the federal sentencing guidelines. Mustard (2001) looks at racial and gender disparities in sentencing under the federal guidelines and finds that observed disparities in sentencing are mainly due to the special circumstances when judges are allowed to depart from the guidelines and not due to discriminatory tastes of judges. Schanzenbach (2005) estimates the effect of judicial demographics on sentencing outcomes and finds that increasing the proportion of female judges increases the gender disparity in sentencing and interprets this as evidence that male judges are paternalistic and therefore lenient towards female offenders.

Almost all of the studies mentioned infer gender based discrimination in sentencing from the statistically significant coefficient on a dummy variable indicating the gender of the criminal offender. Sentencing discrepancies may be observed merely because a judge takes into account extralegal circumstances of the defendant. If the circumstances of male and female criminal defendants are substantially different, as claimed by several authors, then the consideration of circumstances by judges may appear as gender-based bias even when the judge exhibits no such discriminatory tastes. Verdier and Zenou(2004) show that when there is statistical discrimination in the labor market and everyone believes that blacks, for example, are more likely to engage in criminal activity then such beliefs lead to lower wages for blacks. When the opportunity cost of crime is thus lowered such beliefs become self-fulfilling and lead to higher crime rates among blacks. It is therefore important to thoroughly investigate whether any bias actually exists in the criminal justice system since perceived bias may itself lead to actual bias. Given the adverse labor market consequences of incarceration, unequal treatment of men and women in the criminal justice system may lead to unequal prospects for men and women in the labor market as well.

Our research design separates the effect of differences in circumstances from the effect of differences in weights attached to circumstances by judges. If a judge attaches different weights to the same circumstances of a male and a female offender, then we may attribute that to a gender-based bias. But if a judge attaches the same weights to circumstances but on average awards different sentences to male and female offenders then that difference in sentencing might be due to differences in circumstances of the two defendants. As discussed above, Oaxaca and Sarnikar (2005) use decomposition analysis to investigate whether there exists any leniency towards women in the binary decision of whether or not to imprison a convicted person. The results of this decomposition show that the differences in characteristics explain more than 100% of the gender sentencing gap. If, when determining whether or not to sentence a woman to prison, judges applied the same weights on characteristics as they use for men, women would actually be slightly less likely to face prison.

III. ECONOMETRIC MODEL

Below we describe the econometric methods used to estimate the necessary parameters to decompose the sentence differentials. First, we describe the model we use to decompose the sentence difference into an explained portion (differences in characteristics) and an unexplained portion (differences in weights). Because differences in these characteristics may also be due to different treatment received by males and females, we also consider a model determining the use of a private counsel by a defendant, one of our explanatory variables in the first model.

Sentencing

In our data set, we observe the sentencing outcomes for defendants whose cases reach the sentencing phase. Recall that there are two ways in which a defendant's case can reach the sentencing phase. While a significant number of defendants faced sentencing after being convicted by a jury, the most frequent way a defendant reached the sentencing phase was by pleading guilty. Plea bargains reached with a prosecutor are often the reason for this guilty plea; these defendants are sentenced under what we call the *plea regime*. When a defendant pleads not guilty, but is convicted in a trial, they are sentenced under the *trial regime*. We define y as the months in prison the defendant is sentenced to, X as the vector of the individual's characteristics, and β as the vector of weights on the defendant's characteristics in the respective regimes. Equation (1) represents sentencing outcomes when an individual pleads guilty or is convicted by trial:

$$y_i = \begin{cases} X_{Pi}\beta_P + \varepsilon_{P_i} \text{ if defendant is in plea regime} \\ X_{Ti}\beta_T + \varepsilon_{T_i} \text{ if defendant is in trial regime.} \end{cases} \tag{1}$$

Although the formal model permits differences in the covariates appearing in each sentencing regime, the empirical specification actually used in this paper restricts covariates to be identical in both sentencing regimes.

The very nature of a plea bargain suggests that the process determining the sentence of the defendant will not be the same in the two regimes. We would then expect the sentences received by two otherwise identical defendants to depend upon the way in which they reached the sentencing phase. Put another way, the weights applied to an individual's characteristics will be different depending on which sentencing regime the defendant is facing. Accordingly, it may be inappropriate to pool observations from individuals in these two regimes into a single sentencing equation. If individuals were exogenously selected into one of the two regimes, we could simply estimate the two models separately. Let π_P represent the probability of a guilty plea, $\pi_{T\&C}$ represent the probability of going to trial and being convicted, and $\pi_{T\&A}$ represent the probability of going to trial and being acquitted. The sum of these probabilities add to 1. Because we do not have observations on those who went to trial and were acquitted, we can only estimate the following conditional probabilities: $\pi_{PC} = \dfrac{\pi_P}{\pi_P + \pi_{T\&C}}$ and $\pi_{TC} = \dfrac{\pi_{T\&C}}{\pi_P + \pi_{T\&c}}$, which sum to 1 and where π_{PC} is the probability that one's conviction was from a guilty plea and π_{TC} is the probability that one's conviction was by trial. Let the variable s^* represent the conditional latent variable corresponding to a defendant's conviction by trial. The variable s takes on a value of 1 if the defendant's conviction is by trial, and a value of 0 if the defendant enters a guilty plea. The vector index variable Z_i is a set of variables affecting this probability.

$$s_i^* = Z_i\gamma + u_i \tag{2}$$

$$s_i = \begin{cases} 1 \text{ if } s_i^* > 0 \\ 0 \text{ if } s_i^* \leq 0 \end{cases} \tag{3}$$

Correlation between unobservables in the plea decision stage and unobservables in the sentencing stage will create non random selection that will prevent us from obtaining consistent estimates of the parameters if they are estimated by OLS or Tobit. To account for this self-selection, we model the sentence determination process using a switching regression model with endogenous switching. We assume that the error term from each regime's sentence determination equation follows a bivariate normal distribution with the error term from the selection equation. The structure of the error terms is given in the following variance-covariance matrix, where T denotes the trial regime, P denotes the plea regime, and s denotes the binary selection equation (the variance of which is normalized to 1)[3]:

$$V = \begin{pmatrix} 1 & \sigma_{Ps} & \sigma_{Ts} \\ \sigma_{Ps} & \sigma_P^2 & o \\ \sigma_{Ts} & o & \sigma_T^2 \end{pmatrix} \tag{4}$$

[3]The errors in the two sentencing regimes could be correlated. However, because the covariance between these errors are not identified we normalize the covariance to zero.

The likelihood function of the model is then:

$$\begin{aligned} L &= \prod_{i=1}^{N} \left\{ \frac{1}{\sigma_P} \phi \left(\frac{y_i - X_{Pi}\beta_P}{\sigma_P} \right) \Pr(u_i > -Z_i\gamma | \varepsilon_{Pi}) \right\}^{s_i} \\ & \left\{ \frac{1}{\sigma_T} \phi \left(\frac{y_i - X_{Ti}\beta_T}{\sigma_T} \right) \Pr(u_i \leq -Z_i\gamma | \varepsilon_{Ti}) \right\}^{1-s_i} \end{aligned} \tag{5}$$

This expression is simplified once we take account of the conditional distribution of u on ε :

$$\begin{aligned} L &= \prod_{i=1}^{N} \left\{ \frac{1}{\sigma_P} \phi \left(\frac{y_i - X_{Pi}\beta_P}{\sigma_P} \right) \Phi \left(\frac{Z_i\gamma - \frac{\rho_{Ps}}{\sigma_P}(y_i - X_{Pi}\beta_P)}{1 - \rho_{Ps}} \right) \right\}^{s_i} \\ & \left\{ \frac{1}{\sigma_T} \phi \left(\frac{y_i - X_{Ti}\beta_T}{\sigma_T} \right) \Phi \left(\frac{-Z_i\gamma - \frac{\rho_{Ts}}{\sigma_T}(y_i - X_{Ti}\beta_T)}{1 - \rho_{Ts}} \right) \right\}^{1-s_i} \end{aligned} \tag{6}$$

One additional econometric problem which we face is the non-continuous distribution of the dependent variable. Table 1 presents a summary of the share of sentences involving no prison time. Because sentence length cannot be negative, and nearly 25% of our sample receives no prison time, it may be necessary to account for this mass point at 0 in order to obtain consistent estimates.[4] In the context of our switching regression model, we treat the dependent variable as a mixed discrete continuous variable, with limit observations at 0. The sentence outcome is now represented as:

[4]We also estimate the model without accounting for censoring; the log-likelihood obtained is significantly lower than that obtained in the model where we account for the censoring.

$$
\begin{aligned}
y_i^* &= X_{Pi}\beta_P + \varepsilon_{P_i} \text{ if defendant is in plea regime} && (7)\\
y_i &= \begin{cases} y_{Pi}^* \text{ if } y_{Pi}^* > 0 \text{ and } s_i = 0 \\ 0 \quad \text{if } y_{Pi}^* \leq 0 \text{ and } s_i = 0 \end{cases} && (8)\\
y_i^* &= X_{Ti}\beta_T + \varepsilon_{T_i} \text{ if defendant is in trial regime} && (9)\\
y_i &= \begin{cases} y_{Ti}^* \text{ if } y_{Ti}^* > 0 \text{ and } s_i = 1 \\ 0 \quad \text{if } y_{Ti}^* \leq 0 \text{ and } s_i = 1 \end{cases} && (10)
\end{aligned}
$$

The likelihood for the switching regression with endogenous switching and censoring allows four different types of entries to the likelihood function: limit and non-limit observations in both of the regimes. The likelihood function is

$$
\begin{aligned}
L = {} & \prod_{i=1}^{N} \left\{ \Phi_2 \left(\frac{-X_{Pi}\beta_P}{\sigma_P}, Z_i\gamma, \rho_{Ps} \right) \right\}^{s_i l_i} \left\{ \Phi_2 \left(\frac{-X_{T_i}\beta_T}{\sigma_T}, -Z_i\gamma, \rho_{Ts} \right) \right\}^{(1-s_I)l_i} \\
& \left\{ \frac{1}{\sigma_P} \phi \left(\frac{y_i - X_{Pi}\beta_P}{\sigma_P} \right) \Phi \left(\frac{Z_i\gamma - \frac{\rho_{Ps}}{\sigma_P}(y_i - X_{Pi}\beta_P)}{1 - \rho_{Ps}} \right) \right\}^{s_i(1-l_i)} \\
& \left\{ \frac{1}{\sigma_T} \phi \left(\frac{y_i - X_{Ti}\beta_T}{\sigma_T} \right) \Phi \left(\frac{Z_i\gamma - \frac{\rho_{Ts}}{\sigma_T}(y_i - X_{Ti}\beta_T)}{1 - \rho_{Ts}} \right) \right\}^{(1-s_i)(1-l_i)} \qquad (11)
\end{aligned}
$$

where $l = 1$ for limit observations.

Counsel Choice and Plea Choice

One of the explanatory variables that appears in the determinants of conviction regimes and in the sentencing regimes is the choice of defense counsel. If the choice of defense counsel and the conviction regime are jointly determined, then the choice of defense counsel would be endogenous in the model. Therefore when estimating the model, we must consider the potential endogeneity of the counsel variable. Accordingly, we first estimate a model to determinate the decision to be represented by a private attorney:

$$
\begin{aligned}
a_i^* &= W_i\alpha + \xi_i && (12)\\
a_i &= \begin{cases} 1 \text{ if } a_i^* > 0 \\ 0 \text{ if } a_i^* \leq 0 \end{cases} && (13)
\end{aligned}
$$

where a_i^* is a latent variable representing the probability that individual i will choose to hire a private attorney, and a_i is an observed binary variable that indicates that the individual hired a private attorney. An index function, $W_i\alpha$, determines the probability of hiring a private attorney for individual i. Now recall the process determining the observed value of the binary variable representing sentence regime from (2) and (3).

If a defendant bases her choice of counsel on the regime in which she expects to select into, or if different types of attorneys are more likely to advise their clients to choose one regime than the other, we would expect there to be some correlation in the error process. Assume that ξ and u are jointly normally distributed, each with zero mean. The following variance covariance matrix allows for correlation between these two error terms:

$$
V = \begin{pmatrix} 1 & \sigma_{as} \\ \sigma_{as} & 1 \end{pmatrix} \tag{14}
$$

By estimating the model with a bivariate probit, we can account for this possible correlation in the two error terms in this model. The likelihood function of the bivariate probit is:

$$
\begin{aligned}
L = & \prod_{i=1}^{N} [\Phi_2(W_i\alpha, Z_i\gamma, \rho_{as})]^{s_i a_i} [\Phi_2(-W_i\alpha, Z_i\gamma, \rho_{as})]^{(1-a_i)s_i} \\
& \cdot [\Phi_2(W_i\alpha, Z_i\gamma, \rho_{as})]^{a_i(1-s_i)} [\Phi_2(-W_i\alpha, -Z_i\gamma, \rho_{as})]^{(1-s_i)(1-a_i)} && (15)
\end{aligned}
$$

If $\sigma_{as} = 0$, then equations (12) and (2) are recursive equations so that a_i is uncorrelated with u_i. For simplicity we account for gender differences in legal representation by including an indicator variable for females in this estimation.

IV. DECOMPOSING SENTENCING DIFFERENTIALS

To examine how much of the gender difference in sentences is due to leniency toward one sex or the other, we apply empirical methods developed in the labor economics literature to estimate gender bias in criminal sentencing outcomes. These methods have the advantage of decomposing gender differences in sentencing outcomes into two different components – one due to differences in observable circumstances of males and females convicted by the criminal justice system and another due to differences in unobserved circumstances or attitudes of judges towards the sexes. Such decomposition is achieved by a three-step analysis.

The first step typically involves estimation of our empirical model for males and females where the dependent variable is the length of the prison sentence. Here, instead of estimating the empirical model for both males and females, we estimate the model for males only. This approach is consistent with viewing the unexplained gap as a residual and is necessary for our purposes, as in our case, FIML does not exhibit satisfactory convergence properties for the female sample. Consequently, we cannot reliably estimate the model for females. This approach allows us to decompose the differential without ever estimating the female weights, thus circumventing the problem.

Our analysis departs from previous studies in the second step and adds greater insight into the decision-making process that might lead to gender-based differences in criminal sentencing. In the second step, we predict the average sentence length for females if they faced the male weights. In the third and final step, we use results from the first two steps and decompose the differences in length of sentences for males and females into two components: one attributable to male-female differences in circumstances and a second attributable to unobserved differences in attitudes of judges towards the sexes and unobserved differences in circumstances.

Decomposition methods such as the one described above were first developed in labor market studies of gender and racial wage differences [Oaxaca, 1973] but have not been used in studies of gender or racial bias in criminal sentencing decisions. Such a method of estimating bias is valuable since it not only estimates any gender-based differences in sentencing outcomes but it also identifies whether the observed bias is due to gender differences in circumstances or due to gender-based differences in weights attached to circumstances by judges.

In addition to the problems with identifying the female weights, we face two additional challenges which force us to expand beyond the Oaxaca (1973) decomposition. The issue of selection bias in decompositions is addressed by Neuman and Oaxaca (2004) in the context of a Heckit model. We are able build off of this work in the decomposition we develop, as the Heckit is essentially a special case of an endogenous switching regression model. Finally, we must account for the existence of the limit observations in our data set.

Decomposing Sentencing Outcomes by Regime

First, consider the sentence determination equation for the trial regime:

$$y_{Ti}^{*} = X_{Ti}\beta_T + \varepsilon_{Ti} \text{ if defendant is in the trial regime} \tag{16}$$

$$y_{Ti} = \begin{cases} y_{Ti}^{*} \text{ if } y_{Ti}^{*} > 0;\ s_i = 1 \\ 0 \ \text{ if } y_{Ti}^{*} \leq 0;\ \ s_i = 1 \end{cases} \tag{17}$$

The expected value of a sentence in the trial regime is derived in Appendix 1. Define the sample average sentence in the trial regime as $\bar{y}_{Tm}$ for males and $\bar{y}_{Tf}$ for females. The sample is composed of N_{Tm} men and N_{Tf} women. The average predicted value of sentences for males is defined as:

$$\widehat{y}_{Tm} = \frac{1}{N_{Tm}} \sum_{i=1}^{N_{Tm}} \widehat{y}_{Tmi}. \tag{18}$$

However, in a finite sample the predicted mean and the sample mean terms will not necessarily be equal, i.e.

$$\widehat{y}_{Tm} = \frac{1}{N_{Tm}} \sum_{i=1}^{N_{Tm}} \widehat{y}_{Tmi} \neq \overline{y}_{Tm} = \frac{1}{N_{Tm}} \sum_{i=1}^{N_{Tm}} y_{Tmi} \text{ in general.}$$

Assuming that the underlying model can be consistently estimated, we would have

$$\text{plim}(\widehat{y}_{Tm} - \overline{y}_{Tm}) = 0 \tag{19}$$

$$\text{plim}(\widehat{y}_{Tf} - \overline{y}_{Tf}) = 0. \tag{20}$$

When the predicted mean outcome does not match the sample mean outcome, we have sample mean prediction error. The proportionate sample mean prediction errors for males and females can be expressed as

$$\widehat{\delta}_{Tm} = \frac{\overline{y}_{Tm}}{\widehat{y}_{Tm}} \tag{21}$$

$$\widehat{\delta}_{Tf} = \frac{\overline{y}_{Tf}}{\widehat{y}_{Tf}}. \tag{22}$$

It follows from consistency that

$$\text{plim}(\widehat{\delta}) = \text{plim}\left(\frac{\overline{y}}{\widehat{y}}\right) = 1.$$

Appendix 2 contains a more detailed discussion of the use of sample mean error predictions in the nonlinear decompositions adopted in this paper.

The average value of sentences for females in the trial regime using male weights is defined as:

$$\hat{y}^0_{Tf} = \frac{\sum_{i=1}^{N_f} \hat{y}^0_{Tfi}}{N_{Tf}} \tag{23}$$

where $\hat{y}^0_{Tfi}$ is a fitted value of the ith female sentence had they faced the male weights. We decompose the difference in average sentences in the trial regime as follows:

$$\begin{aligned} \overline{y}_{Tm} - \overline{y}_{Tf} &= (\widehat{\delta}_{Tm}\widehat{y}_{Tm} - \widehat{\delta}_{Tm}\widehat{y}^0_{Tf}) + (\widehat{\delta}_{Tm}\widehat{y}^0_{Tf} - \widehat{\delta}_{Tf}\widehat{y}^0_{Tf}) + \left(\widehat{\delta}_{Tf}\widehat{y}^0_{Tf} - \widehat{\delta}_{Tf}\widehat{y}_{Tf}\right) \\ &= \widehat{\delta}_{Tm}(\widehat{y}_{Tm} - \widehat{y}^0_{Tf}) + (\widehat{\delta}_{Tm} - \widehat{\delta}_{Tf})\widehat{y}^0_{Tf} + \widehat{\delta}_{Tf}\left(\widehat{y}^0_{Tf} - \widehat{y}_{Tf}\right). \end{aligned} \tag{24}$$

The first term in eq (24) measures the explained sentencing gap while the unexplained gap is the sum of the last two terms. Note that the second term measures the contribution of gender differences in the sample mean prediction error while the last term measures the contribution of gender differences in the estimated parameters of the model.[5] It is therefore possible to separate out the effect of gender differences in $\hat{\delta}_T$ if the econometrician estimates both $\widehat{\delta}_{Tm}$ and $\widehat{\delta}_{Tf}$. While we are able to decompose the difference in outcomes into the portion caused by differences in weights and differences in characteristics, we will be unable to isolate the difference caused by weights into a portion caused by different $\hat{\delta}_T$ terms. However, if it is the case that $\widehat{\delta}_{Tm} - \widehat{\delta}_{Tf} \approx 0$, the unexplained gap is totally captured by $\widehat{\delta}_{Tf}\left(\widehat{y}^0_{Tf} - \widehat{y}_{Tf}\right) \approx \widehat{\delta}_{Tm}\left(\widehat{y}^0_{Tf} - \widehat{y}_{Tf}\right)$. Under these circumstances one could identify the predicted mean outcome for females as $\widehat{y}_{Tf} \approx \widehat{y}^0_{Tf} - \left(\frac{1}{\widehat{\delta}_{Tm}}\right)\left[\left(\overline{y}_{Tm} - \overline{y}_{Tf}\right) - \widehat{\delta}_{Tm}\left(\widehat{y}_{Tm} - \widehat{y}^0_{Tf}\right)\right]$

[5] Of course there are many instances in which there is no discrepancy between sample means and predicted sample means, e.g. the linear regression model with a constant term, the logit model with a constant term, and the second stage regression of a heckit sample selection model.

The decomposition of sentences in the plea regime follows closely that of the trial regime. Now using male weights from the plea regime, the fitted value of the length of sentence in the regime becomes $\hat{y}_P$, which differs slightly in form from $\hat{y}_T$.[6]

Decomposing Regime Choice

Now consider a decomposition of regime choice. Consider the regime determination model given in (2) and (3) where a positive outcome indicates conviction by trial. The observed proportion of females and males going to trial are, respectively

$$\bar{p}_{Tf} = \frac{\sum_{i=1}^{N_f} s_{fi}}{N_f} \tag{25}$$

$$\bar{p}_{Tm} = \frac{\sum_{i=1}^{N_m} s_{mi}}{N_m} \tag{26}$$

We define the difference in outcomes for males and females as the observed differences in proportions of males and females in the trial regime: $\bar{p}_{Tm} - \bar{p}_{Tf}$

Recall that we do not estimate the model separately for females. However, we are still able to decompose the difference in male and female outcomes into the portion caused by differences in characteristics and the portion caused by differences in weights. We go about these *single model decompositions* by decomposing differentials using only the estimated weights for males.

Here we decompose the difference in the propensity of males and females to be convicted by trial regime using only male weights. Consider the regime determination model estimated for males:

[6] The fitted value is now for individuals who are "selected in" in the plea equation, rather than the "selected out" observations in the conviction by trial equation. The form of the selectivity term will differ slightly. See Appendix 2 for the expressions governing the calculations of the mean outcomes.

$$
\begin{aligned}
s_{mi}^{*} &= Z_{mi}\gamma_m + u_i && (27) \\
s_{mi} &= \begin{cases} 1 \text{ if } s_{mi}^{*} > 0 \\ 0 \text{ if } s_{mi}^{*} \leq 0 \end{cases} && (28)
\end{aligned}
$$

The estimated weights in this model allow us to obtain a predicted probability of conviction by trial for each individual in the sample:

$$\hat{p}_{Tmi} = \Phi(Z_{mi}\hat{\gamma}_m) \tag{29}$$

We compute the average predicted probability by averaging the individual predicted probabilities:

$$\hat{p}_{Tm} = \sum_{i=1}^{N_m} \frac{\Phi(Z_{mi}\hat{\gamma}_m)}{N_m} \tag{30}$$

Note that in the probit model, unlike the logit model, the average predicted probability of entering the trial regime will not necessarily equal the proportion of the sample who do in fact enter the regime. In practice the difference is typically negligible. However, the selection probability parameters in our model are obtained from FIML applied to the joint estimation of the selection probability and sentencing equations. Hence, there is a need to scale the mean predicted probabilities when conducting a decomposition of gender differences in the propensity to be convicted via the trial regime. As above for the sentencing outcomes, the sample mean (probability) prediction errors for males can be expressed as follows:

$$\widehat{\delta}_{sm} = \frac{\bar{p}_{Tm}}{\hat{p}_{Tm}} \tag{31}$$

The same consistency argument applies here as in the case of sentencing outcomes.

We estimate the average predicted probability of females being in the trial regime had they faced the same weights as the males:

$$\hat{p}_{Tf}^{0} = \sum_{i=1}^{N_f} \frac{\Phi(Z_{fi}\hat{\gamma}_m)}{N_f} = \sum_{i=1}^{N_f} \frac{\hat{p}_{Tfi}^{0}}{N_f} \tag{32}$$

The difference in the average probability of conviction via the trial regime can then be decomposed as follows:

$$\bar{p}_{Tm} - \bar{p}_{Tf} = (\bar{p}_{Tm} - \widehat{\delta}_{sm}\hat{p}^0_{Tf}) + (\widehat{\delta}_{sm}\hat{p}^0_{Tf} - \bar{p}_{Tf}) \tag{33}$$

where the first term on the right hand side represents the difference in probabilities that can be attributed to differences in characteristics, and the second term represents the part of the difference that can be attributed to differences in weights.

Total Decomposition

Consider an algebraic decomposition of sentencing differences by regime. Define $\bar{y}_m$ as the average sentence for males in our sample, and $\bar{y}_f$ as the average sentence for females. Each gender's average sentence will be a weighted average of the average sentence in the two regimes:

$$\bar{y}_m = \bar{y}_{Tm}\bar{p}_{Tm} + \bar{y}_{Pm}\ (1 - \bar{p}_{Tm}) \tag{34}$$

$$\bar{y}_f = \bar{y}_{Tf}\ \bar{p}_{Tf} + \bar{y}_{Pf}\ (1 - \bar{p}_{Tf}) \tag{35}$$

The difference in average sentences can then be expressed as

$$\bar{y}_m - \bar{y}_f = \bar{y}_{Tm}\ \bar{p}_{Tm} + \bar{y}_{Pm}\ (1 - \bar{p}_{Tm}) - \bar{y}_{Tf}\ \bar{p}_{Tf} - \bar{y}_{Pf}\ (1 - \bar{p}_{Tf})$$

Adding and subtracting $\bar{y}_{Tf}\ \bar{p}_{Tm}$ we obtain

$$\begin{aligned} \bar{y}_m - \bar{y}_f &= \bar{y}_{Tm}\ \bar{p}_{Tm} + \bar{y}_{Pm}\ (1 - \bar{p}_{Tm}) - \bar{y}_{Tf}\ \bar{p}_{Tf} - \bar{y}_{Pf}\ (1 - \bar{p}_{Tf}) \\ &\quad + \bar{y}_{Tf}\ \bar{p}_{Tm} - \bar{y}_{Tf}\ \bar{p}_{Tm} \\ &= (\bar{y}_{Tm} - \bar{y}_{Tf})\ \bar{p}_{Tm} + \bar{y}_{Tf}\ (\bar{p}_{Tm} - \bar{p}_{Tf}) + \bar{y}_{Pm}(1 - \bar{p}_{Tm}) - \bar{y}_{Pf}\ (1 - \bar{p}_{Tf}). \end{aligned}$$

Now adding and subtracting $\bar{y}_{Pf}\ (1 - \bar{p}_{Tm})$ yields

$$
\begin{aligned}
\bar{y}_m - \bar{y}_f &= (\bar{y}_{Tm} - \bar{y}_{Tf})\ \bar{p}_{Tm} + \bar{y}_{Tf}\ (\bar{p}_{Tm} - \bar{p}_{Tf}) \\
&\quad + \bar{y}_{Pm}\ (1 - \bar{p}_{Tm}) - \bar{y}_{Pf}\ (1 - \bar{p}_{Tf}) + \bar{y}_{Pf}\ (1 - \bar{p}_{Tm}) - \bar{y}_{Pf}\ (1 - \bar{p}_{Tm}) \\
&= (\bar{y}_{Tm} - \bar{y}_{Tf})\ \bar{p}_{Tm} + (\bar{y}_{Pm} - \bar{y}_{Pf})\ (1 - \bar{p}_{Tm}) \\
&\quad + (\bar{y}_{Tf} - \bar{y}_{Pf})\ (\bar{p}_{Tm} - \bar{p}_{Tf}). \qquad (36)
\end{aligned}
$$

The first two terms in (36) can be interpreted as a weighted average of the differences in mean outcomes for men and women (weighted by the probability of being in each of the two regimes). The final term can be interpreted as the difference in mean outcomes that can be attributed to gender differences in the propensities of being in the trial regime (weighted by the differences in mean outcomes among females in the two regimes).

Recall how we decomposed each of the single decomposition terms. Denote the portion of the difference attributed to differences in characteristics (the *explained* portion) as E. The portion of the differences attributed to differences in the characteristics (the *unexplained* portion) is denoted as U. Each portion also contains a subscript denoting the part of the estimation from which it originates:

$$
\begin{aligned}
\bar{y}_{Tm} - \bar{y}_{Tf} &= \left[\widehat{\delta}_{Tm}(\widehat{y}_{Tm} - \ \widehat{y}^0_{Tf})\right] + \left[(\widehat{\delta}_{Tm} - \widehat{\delta}_{Tf})\widehat{y}^0_{Tf} + \widehat{\delta}_{Tf}\left(\widehat{y}^0_{Tf} - \ \widehat{y}_{Tf}\right)\right] \\
&= E_T + U_T \qquad (37) \\
\bar{y}_{Pm} - \bar{y}_{Pf} &= \left[\widehat{\delta}_{Pm}(\widehat{y}_{Pm} - \ \widehat{y}^0_{Pf})\right] + \left[(\widehat{\delta}_{Pm} - \widehat{\delta}_{Pf})\widehat{y}^0_{Pf} + \widehat{\delta}_{Pf}\left(\widehat{y}^0_{Pf} - \ \widehat{y}_{Pf}\right)\right] \\
&= E_P + U_P \qquad (38) \\
\bar{p}_{Tm} - \bar{p}_{Tf} &= (\bar{p}_{Tm} - \widehat{\delta}_{sm}\hat{p}^0_{Tf}) + (\widehat{\delta}_{sm}\hat{p}^0_{Tf} - \bar{p}_{Tf}) \\
&= E_s + U_s \qquad (39)
\end{aligned}
$$

The decomposition of the overall gender sentencing gap can then be expressed as

$$\begin{aligned}
\bar{y}_m - \bar{y}_f &= [(E_T + U_T)\ \bar{p}_{Tm} + (E_P + U_P)\ (1 - \bar{p}_{Tm})] \\
&\quad + (\bar{y}_{Tf} - \bar{y}_{Pf})\ (E_s + U_s) \\
&= \underbrace{E_T\ \bar{p}_{Tm} + E_P\ (1 - \bar{p}_{Tm}) + E_s\ (\bar{y}_{Tf} - \bar{y}_{Pf})}_{E} \\
&\quad + \underbrace{U_T\ \bar{p}_{Tm} + U_P\ (1 - \bar{p}_{Tm}) + U_s\ (\bar{y}_{Tf} - \bar{y}_{Pf})}_{U},
\end{aligned} \tag{40}$$

where E is the total amount of the overall gender sentencing gap that is explained by differences in characteristics, and U is the total unexplained gap associated with differences in weights.

We note that a more straight forward total decomposition of the mean sentencing differences between men and women can be calculated as

$$\bar{y}_m - \bar{y}_f = \left(\bar{y}_m - \hat{\delta}_m \hat{y}_f^0\right) + (\hat{\delta}_m \hat{y}_f^0 - \bar{y}_m) \tag{41}$$

where

$$\hat{y}_f^0 = \frac{\sum_i \left[\hat{p}_{Tfi}^0 \hat{y}_{Tfi}^0 + \left(1 - \hat{p}_{Tfi}^0\right) \hat{y}_{Pfi}^0\right]}{N_f}$$

and

$$\hat{\delta}_m = \left\{ \frac{\sum_i \left[\hat{p}_{Tmi} \hat{y}_{Tmi} + (1 - \hat{p}_{Tmi})\, \hat{y}_{Pmi}\right]}{N_m} \right\} \cdot \left\{ \frac{1}{\bar{y}_m} \right\}.$$

In this decomposition $\hat{y}_f^0$ is the mean fitted overall sentence for females using the male weights. Empirically, it turns out that both (40)and (41) yield virtually identical values of the total explained and unexplained portions of the overall gender sentencing gap. However, a shortcoming of the decomposition given by (41) is that it obscures the sources of the overall gender sentencing gap revealed by the more detailed decomposition given in (40).

V. RESULTS

The data used in this study are obtained from the United States Sentencing Commission's data collection efforts and pertain to cases that terminated in convictions over the period 1996-2002. The data set, available from the Federal Justice Resource Statistics Center, has information that allows for construction of the variables reported in Table 2 which we use in our sentence determination model. In order to abstract from sentencing issues associated with race and ethnicity, we have confined our attention to convicted white males and white females. There were a total of 45,060 sentencing cases in our sample (37,104 cases for males and 7,956 cases for women). While men on average are awarded longer prison sentences (42 months) than women (17 months), the severity of their offenses as measured by the final offense level scores are greater on average than those of women. Also, men on average have a higher past criminal history score than women. Convicted men are on average two years older than convicted women and are more likely to have private counsel. A higher percentage of men are college graduates (13% vs. 7%).

In Table 3 we present summary statistics pertaining to the average length of sentences imposed on both men and women in each of our sample years. Note that in each year the average male sentence is more than twice that of the average female sentence. Note that if one were to only consider these summary statistic and no covariates, it would appear that women receive considerably lighter sentences than do males, and that this difference is considerably greater in the trial regime. Overall and in the trial regime, average male sentences generally declined over the sample period while average female sentences actually rose. Average sentences in the plea regime tended to rise for both males and females.

Formal theory does not offer very much guidance on the actual specification of the regime selection and sentencing equations. The sentencing guidelines largely confined federal court judges to considering only current offense level and criminal history when passing sentence. Specifically, the guidelines exclude race, sex, national origin, creed, religion, and socioeconomic status. Furthermore, employment and family ties and responsibilities are also not to be considered in awarding criminal sentences. With only limited exception, age and education are not supposed to be relevant for sentencing decisions. Judges are permitted to award lighter prison sentences to elderly defendants. Since we have data on these various potential factors, we are able to empirically determine the extent to which they turn out to influence sentences because of, or despite, the guidelines. The variables that appear jointly in the regime selection and sentencing equations are indicators for females (in the pooled sample), education, marital status, the circuit court district, and year while the continuous variables appearing jointly pertain to prior criminal history, number of dependents, and age. An indicator for U.S. citizenship appears in the regime selection equation but not in the sentencing equations. An indicator for a defendant's fine being waived appears in the sentencing equation but not in the regime selection equation. This variable serves as a crude proxy for income. Also, a measure of the severity of the final offense level and the square of this measure appear in the sentencing equations but are excluded from the regime selection equation.

Although our data span individuals over time, it is not treated as a panel. The data are available as separate cross-sections by case for each year. Each case corresponds to all prosecutions ending in convictions of an individual in the given year and the total prison time awarded. While it is theoretically possible for an individual to appear in more than one year's cross-section, we suspect that this is not very common. Among males the average prison sentence is 3.5 years over a period of 7 years. This does not leave much time for multiple year convictions unless offenses are committed while the individual is in prison. In the case of females the average prison sentence is 1.4 years over the period of our study. This would allow for multiple year convictions except that the crime rate is still much lower for females. Female cases account for just under 18% of the total number of cases in our data set.

In Table 4 we present parameter estimates from a pooled model of males and females with an indicator variable for females. The estimated coefficient on the female indicator variable is negative and significant in the selection equation, indicating that women are less likely to obtain their convictions via the trial regime, where average sentences are higher. More educated and married individuals are more likely to obtain their convictions through trial rather than through guilty pleas. Having more dependents and being a U.S. citizen are associated with a lower probability of obtaining one's conviction via trial as opposed to a guilty plea. The chances that one would obtain their conviction via trial rather than via a guilty plea rise with age until around 67 years after which the trial regime probability declines. The circuit court district in which the conviction took place does affect the probability of conviction via trial vs. guilty plea. The year indicators suggest that the probability of obtaining conviction via trial relative to guilty plea steadily declined over time. A more extensive past criminal history was positively associated with conviction by trial vs. a guilty plea. Having a private defense counsel had no statistically significant impact on the conviction regime probability.

The estimated coefficients on the female gender indicator are negative and significant in both sentencing regimes, but of a greater magnitude (in absolute value) in the trial regime. Even before we allow all weights to differ by gender, this indicates that women may receive lighter sentences than men. This would seemingly violate the sentencing guidelines. Contrary to the guidelines, marital status and number of dependents do affect prison sentences. Married defendants receive longer sentences in the trial regime and shorter sentences in the plea regime. More dependents mean shorter sentences in both regimes. Age and education exhibit some effect on sentences though ordinarily these are not considered relevant by the guidelines. Sentence length rises with age and peaks at 63 years if one is convicted in the trial regime and peaks at 33 years in the plea regime. Although the guidelines permit lighter sentences for the elderly, a peak of 33 years in the plea regime and the strong significance of both the linear and quadratic age terms in the trial regime would not seem to be entirely consistent with the guidelines. Education does not appear to play any role in sentence determination in the plea regime though more education seems to be associated with longer sentences in the trial regime. Those who have been convicted and had fines waived receive longer sentences in both regimes. If this variable adequately proxies incomes of the defendants, then it would seem that poorer defendants receive longer sentences. As expected the extent of a defendant's criminal history and severity of current final criminal offense contribute to longer prison sentences in both regimes. Having a private defense counsel lowered prison sentences in both conviction regimes. Similar to the case with conviction regime selection, the circuit court district in which the conviction took place does affect sentence lengths. The estimated coefficients on the time indicator variables reveal that, cet. par., sentence length had been declining over time in both regimes, especially in the trial regime. Estimates of the correlations between the conviction regime error and the sentencing regime errors suggest that unobservables in the selection equation are negatively correlated with unobservables in the trial sentencing equation and positively correlated with unobservables in the plea regime. Roughly speaking, this means that those who are more likely to select into the conviction by trial regime can expect shorter sentences in the trial regime and longer sentences in the plea regime. While this is a sensible result, one potential problem is that the estimated correlation coefficient between the regime selection equation error term and the plea regime sentencing error term is close to the boundary value of 1. It is probably the case that this extreme estimate of the correlation coefficient is caused by the fact that only 5% of the sample represent convictions via trial.

In Table 5 we report the FIML estimates based on just the male sample. Since the results for males are qualitatively the same as those for the pooled sample, we do not separately discuss these estimates. The major purpose behind estimating the model separately for males is to provide us with the necessary parameter estimates to compute the decomposition of gender differences in prison sentences.

Before taking up the decompositions, we consider more formally the possible endogeneity of the private defense counsel indicator variable (DEFENSEP) in the conviction regime selection equation. We estimate a bivariate model to account for potential endogeneity in the decisions regarding counsel choice and regime selection. In the bivariate probit model we add to our equation for conviction regime determination an equation for selection of private counsel. The latter equation omits the district circuit court indicator variables as well as the number of dependents and final criminal history category. In Table 6 we present estimates from the bivariate probit model. Note that the error term correlation coefficient (ρ) in this estimation is insignificant, suggesting that the defense counsel model can be consistently estimated in a univariate probit. The parameter estimates in the regime selection equation are qualitatively similar to those obtained from FIML estimation of our full sentencing model. We observe that women are less likely to have private counsel, which, holding all else constant, would lead to women receiving less lenient sentences. Being older, married, and having more education increase the probability of retaining private counsel. Over the period of our study, the incidence of retaining private counsel has declined, with an especially sharp drop after 1998.

Decomposition results are reported in Tables 7 through 9. We begin with Table 7 which presents mean sentencing outcomes by regime and regime selection differences as well as predicted outcomes using estimated male weights. On average men are awarded nearly 25 more months of prison than women. This varies by sentencing regime. For those convicted by trial, men received an average of 69 more months of prison than women. Among those who plead guilty, men received an average of almost

22 more months of prison time than women. A higher percentage of men than women received their convictions via trial vs. a guilty plea, 5.5% vs. 3.5%. From the fitted (predicted mean) sentences for males, we are able to calculate the proportionate mean sample prediction errors. The most accurate prediction corresponds to the plea regime which is the one into which the vast majority of the cases fall. The last column of Table 7 reports the predicted outcomes for females using the FIML estimated weights for men and are comparable to the calculated fitted values for men reported in the next to the last column in Table 7. For the actual decompositions, the $\hat{\delta}$ proportionate mean prediction errors for men are applied to the predicted outcomes for women obtained using the estimated male weights. The figures in Table 7 clearly imply that if females had faced the same sentence determination process as men, they would have experienced longer prison sentences in each regime and would have had a higher propensity to have received their convictions from the trial regime as opposed to the plea regime.

Our decompositions of gender sentencing differences in each regime and gender differences in conviction regime probabilities are reported in Table 8. Differences in the female mean characteristics explain 44% of the gender sentencing differential in the trial regime and 67% of the sentencing differential in the plea regime. We observe that of the 69 month sentencing gap that favors women in the trial regime, nearly 39 months of the gap cannot be accounted for by gender differences in circumstances. Of the 22 month sentencing gap that favors women in the plea regime, 7 months of the gap cannot be accounted for by gender differences in circumstances. Only about 14% of the 2.1 percentage point gender gap in the propensity to obtain conviction in the trial regime can be explained by gender differences in characteristics. Females are also less likely to enter the trial regime, though their characteristics suggest they should actually be more likely to go to trial if they faced the male weights (though still less likely than males).

In Table 9 we parse out the components that add to the overall gender sentencing difference across both conviction regimes. These components weight the explained and unexplained portions of the sentencing gaps in each regime by the probabilities of being in each regime and gender differences in these probabilities. Of the nearly 25 month overall gender sentencing gap favoring women, 3.8 months (15.4%) arises from gender sentencing differences in the trial regime. Gender sentencing differences in the plea regime account for a little over 20 months (81.6%) of the overall gap. The remainder of less than one month (3.0%) is accounted for by gender differences in conviction regime probabilities. Overall, the explained portion of the gap accounts for about 15.5 months (62.0%) of the total gender sentencing difference. This leaves about 9.5 months (38.0%) that cannot be explained by gender differences in circumstances. Table 9 disaggregates the explained and unexplained portions of the overall sentencing gap by contributions from each sentencing regime and sentencing regime probabilities. The plea regime accounts for the largest contribution to the overall explained gap (13.6 months or 88.3%) and to the overall unexplained gap (6.7 months or 70.7%). In fact the largest single component of the constituent parts of the overall gender sentencing gap is the 13.6 month explained gap from the plea regime which accounts for 54.8% of the overall advantage of women in awarded sentences.

VI. CONCLUSION

Unlike any studies in the literature so far, our study separates observed gender differences in sentencing into two different components – one attributable to differences in circumstances of male and female criminal defendants and the second, attributable to differences in attitudes of sentencing judges towards male and female defendants and the differences due to unobservable characteristics of the male and female defendants. Our model takes account of the joint determination of sentences by regime and conviction regime selection as well as censoring occasioned by sentences that do not involve prison time. We are able to determine the role of gender differences in selection regime probabilities. Such decomposition provides a better insight into the decision-making process of sentencing judges. Knowing whether judges consider extralegal circumstances in their decision making is important but knowing how they consider extralegal circumstances is useful to policy makers in deciding how to reform sentencing guidelines to ensure equal treatment. This study not only examines whether judges consider extralegal circumstances but if they do, it asks whether they attach the same weight to circumstances of males and females. Even in light of the Supreme Court's decision in 2005 to strike down the Federal Sentencing Guidelines, our results may offer some guidance as to what to expect now that judges are less constrained in imposing sentences.

We find that women receive prison sentences that average a little over 2 years less than those awarded to men . Even after controlling for circumstances such as the severity of the offense and past criminal history, women receive more lenient sentences. Approximately 9.5 months of the female advantage cannot be explained by gender differences in individual circumstances. In other words if women faced the same sentencing structure as men, women would on average receive 15.5 months less prison time than men rather than 24.9 months less prison time. Most of the gender gap arises from convictions via guilty pleas which account for the vast majority of the convictions observed in our data. Besides gender, we find evidence that judges took into account factors such as family circumstances which are expressly prohibited from consideration when awarding sentences.

One should bear in mind that our data permit us to examine only the end stage of the criminal justice system. A more comprehensive treatment would take account of the fact that before arriving at the judge for sentencing, a defendant must also pass through a jury or possible plea bargain with a prosecutor. Before reaching this stage, other groups, such as the police and the prosecution, have the potential to create bias in the criminal justice system. Future work will focus on separating out differential outcomes layer by layer as well as making explicit the impact of gender bias in the criminal justice system on gender differences in labor market outcomes.

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Appendix 1: Expected Value of Dependent Variable with Censoring

The expected value of a censored dependent variable is simply the product of the probability of observing a non-limit observation and the expected value of the dependent variable given that it is a non-limit observation, plus the probability of observing a limit observation times the expected value of the dependent variable given that it is a limit observation. Because the censoring point is at zero, the expected value of limit observations is 0, causing the second term to drop from the expression, we first consider the trial regime:

$$
\begin{aligned}
E[y_{Ti}|s_i = 1] &= \Pr(y^*_{Ti} > 0|s_i = 1) \cdot E[y_{Ti}|y^*_{Ti} > 0 \cap s_i = 1] \\
&\quad + \Pr(y^*_{Ti} \leq 0|s_i = 1) \cdot E[y_{Ti}|y^*_{Ti} \leq 0 \cap s_i = 1] \\
&= \Pr(y^*_{Ti} > 0|s_i = 1) \cdot E[y_{Ti}|y^*_{Ti} > 0 \cap s_i = 1] \\
&\quad + \Pr(y^*_{Ti} \leq 0|s_i = 1) \cdot 0 \\
&= \Pr(y^*_{Ti} > 0|s_i = 1) \cdot E[y_{Ti}|y^*_{Ti} > 0 \cap s_i = 1] \qquad (42)
\end{aligned}
$$

Consider each of the two right hand size terms separately. First, consider the probability of observing a non-limit observation, conditional upon selection. From our specification of the data generating process for y^* and s, we can express this as the function of two random variables, ε and u.

$$\Pr(y^*_{Ti} > 0|s_i = 1) = \Pr(\varepsilon_{Ti} < X_{Ti}\beta_T|u_i < Z_i\gamma) \qquad (43)$$

By Bayes rule we can express this as the joint probability that a non-limit observation is selected into the trial regime, divided by the probability of that observation being in the trial regime. This term can then be expressed using values from the cumulative normal and cumulative bivariate normal distributions.

$$\begin{aligned}
\Pr(y^*_{Ti} &> 0|s_i = 1) = \frac{\Pr(\frac{\varepsilon_{Ti}}{\sigma_T} < \frac{X_{Ti}\beta_T}{\sigma_T} \cap u_i < Z_i\gamma)}{\Pr(u_i < Z_i\gamma)} \\
&= \frac{\Phi_2(\frac{X_{Ti}\beta_T}{\sigma_T}, Z_i\gamma, \rho_{sT})}{\Phi(Z_i\gamma)} \ . \qquad (44)
\end{aligned}$$

Finally, we must consider the expected value of the dependent variable, given that it is a non-limit observation in the trial regime. Recall that non-limit observations take on the value

$$\begin{aligned}
E[y_{Ti}|y^*_{Ti} &> 0 \cap s_i = 1] = E[y^*_{Ti}|y^*_{Ti} > 0 \cap s_i = 1] \\
&= E[y^*_{Ti}|y^*_{Ti} > 0 \cap s^*_i > 0] \\
&= E[y^*_{Ti}|\frac{\varepsilon_{Ti}}{\sigma_T} < \frac{X_{Ti}\beta_T}{\sigma_T} \cap u_i < Z_i\gamma] \ . \qquad (45)
\end{aligned}$$

This expected value appears similar to the expected value of the dependent variable in the main equation of the Heckit model: it is truncated by the draw for the error term in the selection equation. It also appears similar to the expected value of the dependent variable in the Tobit model: it is truncated by the draw for the error term in the main equation. This incidence of "double truncation" however, is substantially more complex than the single truncation in either the Tobit or the Heckit. We derive it for our model based on page 72 of Johnson and Kotz:

$$\begin{aligned}
E[y_{Ti}|y^*_{Ti} &> 0 \cap s_i = 1] = \frac{X_{Ti}\beta_T}{\Phi_2(\frac{X_{Ti}\beta_T}{\sigma_T}, Z_i\gamma, \rho_{sT})} \\
&\cdot \Bigg\{ \sigma_T\{\phi(\frac{-X_{Ti}\beta_T}{\sigma_T})\Phi(\frac{-1}{\sqrt{1-\rho^2_{sT}}}[-Z_i\gamma - \rho\frac{-X_{Ti}\beta_T}{\sigma_T}]) \\
&+ \rho_{sT}\phi(-Z_i\gamma)\Phi(\frac{-1}{\sqrt{1-\rho^2_{sT}}}[-X_{Ti}\beta_T - \rho(-Z_i\gamma)]) \Bigg\} \qquad (46)
\end{aligned}$$

The resulting expected value of the length of sentence in the trial regime is:

$$E[y_{Ti}|s_i = 1] = \frac{\Phi_2(\frac{X_{Ti}\beta_T}{\sigma_T}, Z_i\gamma, \rho_{sT})}{\Phi(Z_i\gamma)} * E[y^*_{Ti}] \tag{47}$$

We can then define the $\hat{y}_T(X, Z, \hat{\theta}_m) = E[y^*_{Ti}]$ as given above.

Appendix 2: A Note on Sample Mean Prediction Error in Decompositions

In decomposition analysis, the standard term to decompose is the difference between the sample mean of the dependent variable for two groups. Define the sample mean values for groups m and f as $\overline{y}_m$ and $\overline{y}_f$, where each group has N_m and N_f members, respectively. After estimating an econometric equation for both of the groups, we can then calculate fitted values $\widehat{y}_{mi}$ and $\widehat{y}_{fi}$ for each individual in groups m and f, respectively. The average fitted value for members of these groups is:

$$\widehat{y}_m = \frac{1}{N_m}\sum_{i=1}^{N_m}\widehat{y}_{mi} \tag{48}$$

$$\widehat{y}_f = \frac{1}{N_f}\sum_{i=1}^{N_f}\widehat{y}_{fi} \tag{49}$$

Define $\widehat{y}^{o}_{fi}$ as the fitted value of an observation in group f, had that individual faced the group m estimated parameters. The mean of this variable for group f is then:

$$\widehat{y}^0_f = \frac{1}{N_f}\sum_{i=1}^{N_f}\widehat{y}^0_{fi} \tag{50}$$

By adding and subtracting the $\widehat{y}^0_f$ term, the decomposition is then expressed as:

$$\overline{y}_m - \overline{y}_f = (\overline{y}_m - \widehat{y}^0_f) + (\widehat{y}^0_f - \overline{y}_f) \tag{51}$$

where the first term expresses the difference in the left hand side variable which can be attributed to differences in the characteristics of the two groups, and the second term expresses the difference caused by differences in the parameters the two groups face.

Assuming that the underlying model can be consistently estimated, we would have

$$\begin{aligned} \text{plim}(\widehat{y}_m - \overline{y}_m) &= 0 \qquad (52) \\ \text{plim}(\widehat{y}_f - \overline{y}_f) &= 0 \qquad (53) \end{aligned}$$

However, in a finite sample, the $\widehat{y}$ and $\overline{y}$ terms will not necessarily be equal. We can express the sample mean prediction error in the model as follows:

$$\begin{aligned} \overline{y}_m &= \widehat{\delta}_m \widehat{y}_m \qquad (54) \\ \overline{y}_f &= \widehat{\delta}_f \widehat{y}_f \qquad (55) \end{aligned}$$

It follows from consistency that

$$\text{plim}(\widehat{\delta}) = \text{plim}\left(\frac{\overline{y}}{\widehat{y}}\right) = 1$$

The decomposition can now be expressed as:

$$\overline{y}_m - \overline{y}_f = (\widehat{\delta}_m \widehat{y}_m - \widehat{y}_f^o) + (\widehat{y}_f^o - \widehat{\delta}_f \widehat{y}_f) \qquad (56)$$

The impact of the estimation error becomes more clear if, instead of adding and subtracting $\widehat{y}_f^o$, we instead add and subtract $\delta_m \widehat{y}_f^o$

$$\begin{aligned} \overline{y}_m - \overline{y}_f &= (\widehat{\delta}_m \widehat{y}_m - \widehat{\delta}_m \widehat{y}_f^0) + (\widehat{\delta}_m \widehat{y}_f^0 - \widehat{\delta}_f \widehat{y}_f) \\ &= (\widehat{\delta}_m \widehat{y}_m - \widehat{\delta}_m \widehat{y}_f^0) + \left(\widehat{\delta}_m - \widehat{\delta}_f\right) \widehat{y}_f^0 + \widehat{\delta}_f \left(\widehat{y}_f^0 - \widehat{y}_f\right) \qquad (57) \\ &= (\overline{y}_m - \widehat{\delta}_m \widehat{y}_f^0) + (\widehat{\delta}_m \widehat{y}_f^0 - \overline{y}_f) \qquad (58) \end{aligned}$$

Thus, the $\widehat{\delta}$ terms contribute to both the explained and unexplained portions of the mean decomposition.

In principle it is possible to separate out the effect of gender differences in the $\widehat{\delta}$ parameter from the effect of differences in other parameters eq (57). However, this is only feasible if the econometrician estimates both the $\widehat{\delta}_m$ and $\widehat{\delta}_f$ terms. In our case, we lack sufficient data to identify the weights in the model for females. Consequently, we only are able to decompose the difference in mean outcomes into the portion caused by differences in weights and differences in characteristics according to eq (58).

Table 1
Percentage of Sentences Involving No Prison Time

	Males			Females		
Year	Total (%)	Trial (%)	Plea (%)	Total (%)	Trial (%)	Plea (%)
1996	25.26	6.45	27.00	44.41	12.73	46.34
1997	25.25	4.83	26.99	41.85	21.74	42.80
1998	21.63	4.56	22.94	37.67	18.60	38.42
1999	21.98	9.76	22.74	39.97	34.88	40.15
2000	23.21	4.78	24.13	38.03	10.26	39.00
2001	21.67	9.90	22.10	35.84	14.81	36.32
2002	22.42	5.63	22.86	42.57	17.39	43.04

Table 2
Variable Definitions and Summary Statistics

Variable	Description	Overall		Males		Females	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
TOTALMONTHS	Length of prison sentence in months	37.27	73.12	41.67	78.03	16.76	37.07
REGIME	Indicator for trial regime	0.05	0.22	0.06	0.23	0.03	0.18
FINEWAIV	Indicator of fine being waived	0.84	0.37	0.83	0.38	0.87	0.34
HISCHOOL	Indicator of less than 13 years of education	0.24	0.43	0.23	0.42	0.28	0.45
GED	Indicator for general equivalency diploma	0.13	0.34	0.14	0.34	0.11	0.32
SOMECOLL	Indicator for some college attended	0.26	0.44	0.25	0.43	0.29	0.45
COLLGRAD	Indicator for a college degree or higher	0.12	0.32	0.13	0.33	0.07	0.26
NUMDEPEN	Number of dependents	1.13	1.41	1.13	1.44	1.09	1.29
MARRD	Indicator for married or cohabiting	0.26	0.44	0.26	0.44	0.25	0.43
CITIZN	Indicator for US citizen	0.95	0.21	0.95	0.22	0.97	0.16
DEFENSEP	Indicator for private counsel	0.36	0.48	0.37	0.48	0.30	0.46
XCRHISSR	Final criminal history category	2.11	1.60	2.23	1.66	1.57	1.16
XFOLSOR	Final offense level	16.80	8.30	17.37	8.35	14.11	7.51
XFOLSOR2	Final offense level squared	351.02	325.02	371.49	332.24	255.55	269.16
AGE	Age of defendant	37.74	11.14	38.08	11.22	36.16	10.59
AGE2	Age of defendant squared	1548.66	888.58	1576.29	900.04	1419.79	820.88
CIRC1	Circuit indicators	0.03	0.16	0.03	0.17	0.02	0.14
CIRC2	Circuit indicators	0.11	0.31	0.12	0.32	0.08	0.27
CIRC3	Circuit indicators	0.04	0.21	0.05	0.21	0.04	0.19
CIRC4	Circuit indicators	0.05	0.21	0.05	0.21	0.05	0.21
CIRC5	Circuit indicators	0.10	0.30	0.10	0.30	0.12	0.32
CIRC6	Circuit indicators	0.08	0.28	0.08	0.27	0.09	0.29
CIRC7	Circuit indicators	0.04	0.20	0.04	0.20	0.04	0.20
CIRC8	Circuit indicators	0.08	0.27	0.08	0.27	0.09	0.29
CIRC9	Circuit indicators	0.27	0.44	0.27	0.44	0.28	0.45
CIRC10	Circuit indicators	0.05	0.23	0.05	0.22	0.06	0.24
CIRC11	Circuit indicators	0.14	0.35	0.14	0.35	0.13	0.34
1996	Year indicators	0.13	0.33	0.13	0.33	0.12	0.33
1997	Year indicators	0.13	0.34	0.14	0.34	0.13	0.34
1998	Year indicators	0.13	0.34	0.13	0.34	0.14	0.35
1999	Year indicators	0.14	0.35	0.14	0.34	0.15	0.36
2000	Year indicators	0.14	0.35	0.14	0.35	0.15	0.35
2001	Year indicators	0.15	0.36	0.15	0.36	0.15	0.36
2002	Year indicators	0.17	0.37	0.17	0.38	0.16	0.36

Table 3
Mean Sentences in Months

Year	Males			Females		
	Total	Trial	Plea	Total	Trial	Plea
1996	43.26	133.44	34.92	15.00	44.37	13.21
1997	43.81	136.47	35.93	19.27	94.50	15.73
1998	42.00	124.29	35.66	16.07	36.17	15.28
1999	42.15	112.62	37.79	15.08	30.66	14.51
2000	40.12	108.01	36.75	15.93	44.85	14.92
2001	41.20	94.50	39.24	18.27	59.19	17.34
2002	39.87	111.85	38.00	17.58	55.26	16.88

Table 4
Censored Switching Regression with Endogenous Switching: Pooled Sample

	Regime Selection		Trial Regime		Plea Regime	
Variable	Parameter	Asmp Z	Parameter	Asmp Z	Parameter	Asmp Z
Constant	-2.719	-17.141	-804.315	-18.678	-68.556	-17.404
FEMALE	-0.165	-4.914	-45.299	-4.721	-9.310	-10.367
FINEWAIV			9.653	1.595	6.997	8.242
HISCHOOL	-0.040	-1.265	-13.260	-1.6	-0.801	-1.049
GED	-0.026	-0.717	-8.036	-0.85	1.129	1.413
SOMECOLL	-0.037	-1.189	-14.707	-1.794	-0.762	-1.072
COLLGRAD	0.199	5.165	38.897	3.722	-0.747	-0.696
CITIZN	-0.068	-2.277				
MARRD	0.084	2.628	19.815	2.377	-2.900	-4.142
NUMDEPEN	-0.015	-1.88	-3.586	-1.713	-0.790	-4.012
DEFENSEP	-0.015	-0.658	-2.700	-0.435	-4.678	-7.827
XCRHISSR	0.019	2.909	18.461	10.987	10.037	66.321
XFOLSOR			0.117	0.117	0.652	5.734
XFOLSOR2			0.161	8.26	0.128	59.474
AGE	0.039	5.509	10.514	5.596	0.287	1.626
AGE2x10^{-2}	-0.029	-3.434	-8.302	-3.673	-0.439	-1.99
CIRC2	-0.376	-5.59	-94.622	-5.459	-5.516	-2.734
CIRC3	-0.233	-3.003	-42.720	-2.104	1.080	0.464
CIRC4	-0.179	-2.325	-28.878	-1.452	12.279	5.534
CIRC5	-0.255	-3.697	-54.688	-3.053	11.460	5.643
CIRC6	-0.149	-2.215	-23.819	-1.336	8.306	3.898
CIRC7	-0.080	-1.059	-1.228	-0.061	18.106	8.15
CIRC8	-0.251	-3.722	-38.721	-2.213	-1.729	-0.869
CIRC9	-0.291	-4.689	-63.695	-3.947	3.031	1.594
CIRC10	-0.177	-2.414	-28.098	-1.492	3.336	1.511
CIRC11	-0.105	-1.674	-13.454	-0.834	10.193	5.301
1996	0.564	12.494	143.764	12.374	-1.359	-1.198
1997	0.573	12.815	149.387	13.163	-0.588	-0.538
1998	0.542	11.751	140.627	11.878	0.280	0.239
1999	0.360	8.207	82.315	7.455	1.821	1.724
2000	0.288	6.368	76.092	6.53	2.216	2.081
2001	0.154	3.359	38.399	3.172	1.854	1.803
σ_o	48.884	934.551				
ρ_{0u}	-0.754	-68.072				
σ_1	235.279	84.354				
ρ_{1u}	0.994	1192.465				
N	45060		2333		42727	
Log-Likelihood	-193821					

Table 5
Censored Switching Regression with Endogenous Switching: Males

	Regime Selection		Trial Regime		Plea Regime	
Variable	Parameter	Asmp Z	Parameter	Asmp Z	Parameter	Asmp Z
Constant	-2.585	-15.441	-692.438	-16.05	-67.283	-14.91
FINEWAIV			4.372	0.805	7.241	7.522
HISCHOOL	0.012	0.353	-1.534	-0.184	-1.531	-1.733
GED	0.036	0.964	7.436	0.801	0.919	1.014
SOMECOLL	0.019	0.591	0.793	0.096	-1.247	-1.525
COLLGRAD	0.164	4.026	26.609	2.606	-0.075	-0.062
CITIZN	-0.046	-1.734				
MARRD	0.042	1.232	8.375	0.991	-3.077	-3.822
NUMDEPEN	-0.008	-0.944	-1.957	-0.95	-0.864	-3.857
DEFENSEP	-0.054	-2.209	-13.561	-2.187	-5.579	-8.148
XCRHISSR	0.018	2.724	16.549	10.317	10.191	59.764
XFOLSOR			-1.493	-1.669	0.601	4.556
XFOLSOR2			0.192	11.034	0.133	53.767
AGE	0.033	4.336	8.447	4.43	0.189	0.935
AGE2x10^{-2}	-0.023	-2.549	-6.322	-2.767	-0.300	-1.192
CIRC2	-0.377	-5.549	-98.440	-5.865	-5.480	-2.407
CIRC3	-0.249	-3.154	-49.791	-2.521	0.593	0.225
CIRC4	-0.146	-1.864	-24.910	-1.28	12.234	4.847
CIRC5	-0.243	-3.428	-52.890	-3.018	9.890	4.269
CIRC6	-0.042	-0.605	-3.304	-0.187	6.233	2.575
CIRC7	-0.008	-0.101	10.923	0.551	15.752	6.261
CIRC8	-0.260	-3.781	-45.713	-2.673	-2.219	-0.98
CIRC9	-0.248	-3.951	-54.843	-3.468	1.558	0.724
CIRC10	-0.173	-2.324	-31.323	-1.712	2.312	0.914
CIRC11	0.004	0.055	8.206	0.519	8.797	4.047
1996	0.516	10.742	121.559	10.125	-1.563	-1.199
1997	0.495	10.382	116.782	10.036	-1.084	-0.857
1998	0.460	9.349	107.884	8.848	0.061	0.045
1999	0.348	7.432	74.586	6.528	1.646	1.341
2000	0.253	5.251	57.181	4.824	1.806	1.471
2001	0.123	2.527	23.424	1.905	1.866	1.578
σ_o	51.27286	837.949				
ρ_{0u}	-0.774964	-73.596				
σ_1	225.1057	89.875				
ρ_{1u}	0.994216	1451.176				
N	37104		2057		35047	
Log-Likelihood	-164383.2					

Table 6
Counsel Choice and Regime Choice: Bivariate Probit

	Regime Selection		Private Counsel	
Variable	Parameter	Asmp Z	Parameter	Asmp Z
Constant	-2.886	-12.087	-1.136	-14.544
FEMALE	-0.191	-3.672	-0.161	-9.569
HISCHOOL	0.017	0.154	0.331	18.278
GED	0.005	0.087	-0.130	-5.732
SOMECOLL	0.060	0.425	0.443	25.097
COLLGRAD	0.279	1.007	0.904	39.935
CITIZN	-0.028	-0.521	-0.059	-2.051
MARRD	0.093	0.844	0.358	21.533
NUMDEPEN	-0.001	-0.115		
DEFENSEP	-0.231	-0.282		
XCRHISSR	0.017	2.452		
AGE	0.039	5.801	0.005	1.370
AGE2	-0.025	-2.840	0.084	1.790
CIRC2	-0.353	-5.480		
CIRC3	-0.270	-3.756		
CIRC4	-0.210	-2.952		
CIRC5	-0.303	-4.675		
CIRC6	-0.077	-1.248		
CIRC7	-0.088	-1.259		
CIRC8	-0.196	-3.054		
CIRC9	-0.274	-4.707		
CIRC10	-0.234	-3.291		
CIRC11	0.006	0.098		
1996	0.602	6.875	0.331	13.622
1997	0.553	7.021	0.295	12.262
1998	0.497	7.142	0.250	10.326
1999	0.363	8.657	0.039	1.708
2000	0.274	6.150	0.086	3.797
2001	0.145	3.281	0.041	1.813
ρ_{01}	0.14	0.27		
N	45060			
Log-Likelihood	-35903			

Table 7
Mean Sentences and Conviction-by-Trial Probabilities

Variable	Males	Females	Difference	Male Fitted	Females Fitted (Male Weights)
$\bar{y}$	41.673	16.757	24.916	42.836	25.902
$\bar{y}_T$	120.845	51.736	69.109	142.651	90.326
$\bar{y}_P$	37.027	15.500	21.527	36.791	22.583
$\bar{p}_T$	0.055	0.035	0.021	0.065	0.051
$\hat{\delta}_T$	0.847				
$\hat{\delta}_P$	1.006				
$\hat{\delta}_s$	0.848				
$\hat{\delta}$	0.973				

Table 8
Decomposition by Part

Variable	Explained	Unexplained	Total Gap
$\bar{y}_{Tm} - \bar{y}_{Tf}$	30.519	38.590	*69.109*
$\bar{y}_{Pm} - \bar{y}_{Pf}$	14.444	7.083	*21.527*
$\bar{p}_{Tm} - \bar{p}_{Tf}$	0.003	0.018	*0.021*

Table 9
Contribution to Total

Explained		Unexplained		Total Gap	
$E_T \, \bar{p}_{Tm}$	1.692	$U_T \, \bar{p}_{Tm}$	2.139	$E_T \, \bar{p}_{Tm} + U_T \, \bar{p}_{Tm}$	3.831
$E_P \, (1 - \bar{p}_{Tm})$	13.643	$U_P \, (1 - \bar{p}_{Tm})$	6.690	$E_P \, (1 - \bar{p}_{Tm}) + U_P \, (1 - \bar{p}_{Tm})$	20.333
$E_s \, (\bar{y}_{Tf} - \bar{y}_{Pf})$	0.117	$U_s \, (\bar{y}_{Tf} - \bar{y}_{Pf})$	0.634	$E_s \, (\bar{y}_{Tf} - \bar{y}_{Pf}) + U_s \, (\bar{y}_{Tf} - \bar{y}_{Pf})$	0.752
E	15.452	U	9.464	$E + U$	24.916