THE UNIVERSITY OF CHICAGO

# WHAT CAN PLEA BARGAINING TEACH US ABOUT RACIAL BIAS IN CRIMINAL JUSTICE?

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*DEDICATION*

*For everyone who was not heard alone, may you all be heard together.*

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# ABSTRACT

I develop a model of plea bargaining focused on sources of racial bias in the criminal justice system. Defendants demand more trials and receive shorter sentences when the cases brought against them are weak. Defendants demand more trials but receive longer sentences when prosecutors are biased against them. Data from Chicago, IL show that black defendants demand more trials and receive shorter sentences than white defendants facing the same charges. Viewed through the lens of my model, these results suggest that criminal courts bring weaker cases against black defendants. I estimate the structural parameters of my model, and these estimated parameters also indicate that criminal courts bring weaker cases against black defendants. Further, when Chicago police file charges against a black defendant, those charges are more likely to be thrown out by the State's Attorney during preliminary felony review. All of my results are consistent with the hypothesis that cases against black defendants are weaker because police in Chicago are more likely to charge black defendants without strong evidence.

# CHAPTER 1

# INTRODUCTION

The incarceration rate for African American adults in the United States as of 2017 was 1,549 per 100,000. This is 5.7 times higher than the comparable rate for white Americans (Bronson 2019). There are many possible explanations for this disparity. Incarceration rates reflect underlying rates of criminal behavior, but they also reflect the actions and decisions of police, prosecutors, judges, and juries. This paper studies data from Chicago, where both prosecutors and police have faced scandals related to racial animus.[1] There is reason to suspect such animus may contribute to incarceration rate disparities, but the criminal justice system is too complex to easily separate the effects of bias from other factors.

This paper examines bias by focusing on a key step in the criminal justice system: plea bargaining. A plea bargain is an arrangement where the defendant in a criminal case agrees to submit a guilty plea in return for an agreed-upon sentence. Prosecutors benefit from plea bargains because they avoid the time and effort of a formal trial. Defendants benefit from plea bargains because they avoid the uncertainty of a formal trial. As a result, the vast majority of criminal cases in the United States conclude with plea bargains. Nearly every party in the criminal justice system is involved, directly or indirectly, with the plea bargaining process. The prosecutor must decide what sentence to offer. The defendant must decide whether to accept the offer. Each must also consider the strength of the case brought

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1. In the 1980s, the Cook County State's Attorney's Office was scandalized by the "Two Ton Contest":

> There was an ongoing competition among prosecutors to be the first to convict defendants whose weight totaled 4,000 pounds. Men and women, upon conviction, were marched into the room and weighed. Because most of the defendants were African-American, Goggins recalls now, with no small degree of discomfort, the competition was described in less sensitive terms behind closed doors–"N****rs by the Pound." (Possley 1999)

Likewise, a 2017 US DOJ report found "Recurrences of unaddressed racially discriminatory conduct by [Chicago Police Department] officers further erodes community trust and police effectiveness," citing several instances where CPD officers referred to black citizens with slurs and dehumanizing rhetoric. (United States Department of Justice 2017) by the police and the attitude of the judge who would hear that case. Lastly, the outcome of plea bargaining and the circumstances surrounding the bargaining process are more likely than police activity to be clearly recorded in detailed data available to researchers.

In Chapter 3, I develop an economic model of plea bargaining based on the screening model of Bebchuk (1984). Risk-neutral prosecutors make sentence offers to heterogeneously risk-averse defendants. Trials are costly, and prosecutors wish to avoid them. Prosecutors know how likely they are to win at trial, but they do not know the risk-aversion of any given defendant. They make optimal sentence offers that trade off higher plea bargain sentences against the probability that the defendant will accept. Defendants follow a cutoff rule for accepting offers. This rule depends on the strength of the case against them, their potential sentence if convicted in a trial, and their risk aversion. Prosecutors and defendants together determine the average sentence length and the percentage of cases that go to trial.

My model shows how two key factors shape these outcomes. The first key input to plea bargaining in my model is the strength of the case. The defendant and prosecutor share a common prior about the probability, $\theta$, that the defendant would be convicted if the case were to advance to trial. Most cases are resolved by guilty pleas, but bargaining outcomes still depend on what would happen in the counterfactual scenario where the case does go to trial. A defendant who is more likely to be convicted at a trial will accept longer plea bargain sentences in lieu of that trial. Exactly how plea bargain sentences change as case strength changes is up to the prosecutor. The prosecutor chooses what deal to offer in order to obtain an optimal mix of long plea bargain sentences and few costly trials. When the probability of conviction changes, that optimal mix also changes. A prosecutor working with a stronger case can leverage that advantage into both a longer plea bargain sentence and a lower probability of trial. Case strength depends on evidence gathered by the police, but other factors may also matter. The skill of the prosecutor and the defense attorney can influence the probability of conviction, as can the attitude of the judge or jury.[2] However, I do not model an effort choice on the part of the prosecutor or defendant. Each must take $\theta$ as given. I also assume that the robust discovery rules in criminal court give the prosecutor and defendant common knowledge about $\theta$.

The second key determinant of plea bargaining outcomes in my model is the prosecutor's perceived cost of going to trial. Prosecutors make plea bargain offers in order to avoid costly trials. A prosecutor who perceives a trial as less costly will pursue an aggressive bargaining strategy that makes trials more common. My model includes a real cost of going to trial, $c$, and a multiplier, $k$, on the prosecutor's reward to securing a sentence of any given length. The prosecutor's *perceived* trial cost ultimately depends on their ratio: $c/k$. I will say that a prosecutor who perceives a lower trial cost for black defendants is biased against black defendants.[3] Holding case strength constant, this bias will lead the prosecutor to offer black defendants plea bargains with longer sentences that are accepted less often and therefore result in more trials.

As in the rest of the discrimination literature, it is important not to confuse the prosecutor bias discussed above with other meanings of the word. One could say there is bias against black defendants if they are systematically less likely to afford skilled lawyers, if police arrest them with less evidence, or if judges are more inclined to rule against them. However, these forms of bias, along with any others outside the narrow scope of $c/k$, will instead enter my model as differences in $\theta$, the probability that the defendant is convicted at trial.

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2. Juries are rarely relevant in practice. Only 6% of trials in my estimation sample are jury trials.

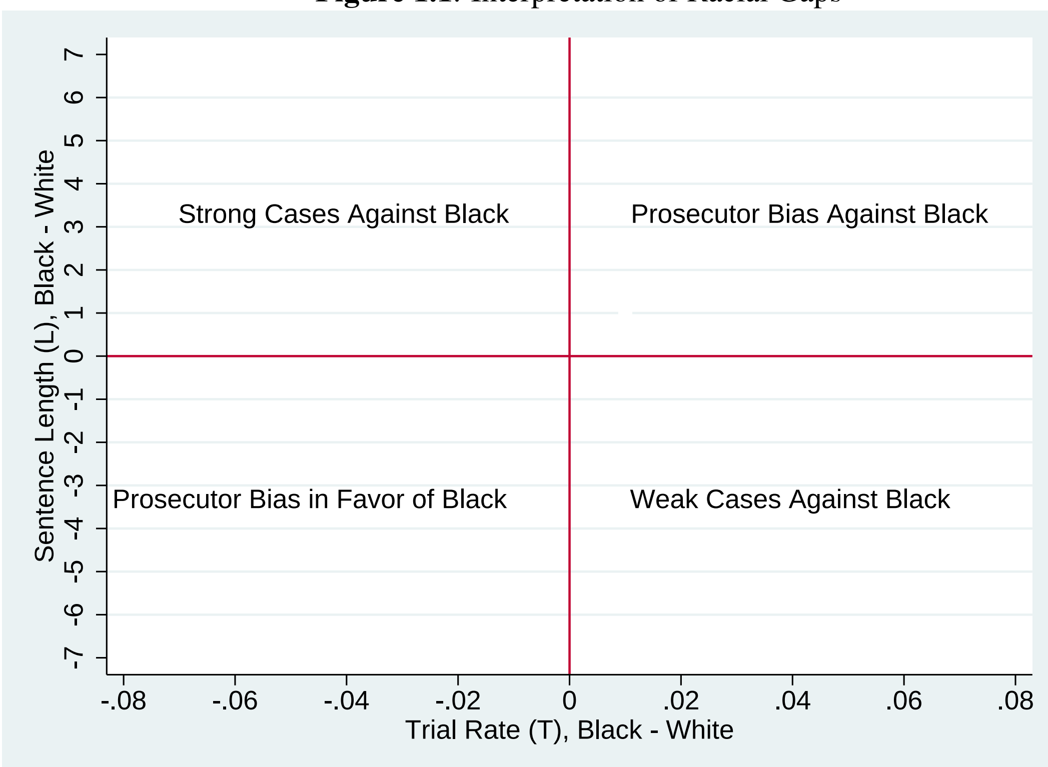
3. In the model, $c$ does not vary by race and $k$ does. I could have instead allowed $c$ to vary and held $k$ fixed. This means that race-based differences in the real cost of trial would be interpreted as prosecutor bias in my framework

Both probability of conviction and perceived cost of trial can affect plea bargaining outcomes. When two observationally identical defendants receive different plea sentence offers, it is not immediately clear why. The defendant offered the longer sentence may have faced a stronger case, or the prosecutor may have had greater bias against that defendant. Neither $\theta$ nor $k$ is directly observable in the data, but my model shows that it may be possible to distinguish between them by examining in tandem the two observable plea bargaining outcomes: sentences and trial rates. If $\theta$ is higher for black defendants, prosecutors will have more leverage when bargaining with them. Prosecutors use this leverage to secure both longer plea bargain sentences and fewer trials. If instead $k$ is higher for black defendants, prosecutors will perceive a lower cost of going to trial against them. This changes the relative value prosecutors place on plea sentences as compared to trials, but it does not change the menu of plea sentence-trial probability bundles they must choose from. In this case, more biased prosecutors must ultimately trade longer sentences for more trials.

Figure 1.1 captures these ideas. The horizontal axis measures $\Delta T$, the trial rate for black defendants minus the trial rate for white defendants. The vertical axis measures $\Delta L$, the average sentence length for black defendants minus the average sentence length for white defendants. Each quadrant is labeled with a conclusion about either case strength or prosecutor bias. Data that fall into one of these quadrants, if they were generated by my model of plea bargaining, imply the conclusion written in that quadrant. For example, if data show that black defendants have both longer sentences and more trials, there must be greater prosecutor bias against black defendants, but cases brought against black defendants could be weaker or stronger than cases brought against white defendants. In Chapter 4, I lay out the precise conditions and assumptions under which the reasoning of Figure 1.1 holds.

In Chapter 6, I analyze 35 years of Chicago felony court data from the Circuit Court of Cook County. I find that in these data, black defendants are more likely to go to trial

**Figure 1.1**. Interpretation of Racial Gaps



($\Delta T > 0$) and receive shorter sentences ($\Delta L < 0$) than their white counterparts. Following Figure 1.1, these results imply that black defendants, conditional on observable case characteristics, face weaker cases in court. In Chapter 8, I confirm this reduced form result by structurally estimating my model using the Simulated Method of Moments. My estimated parameters indicate that black defendants face both substantially weaker cases and bias from prosecutors.

This evidence suggests that black inhabitants of Chicago are incarcerated at a higher rate not because they have a greater probability of conviction nor because they receive longer sentences, but simply because the overwhelming majority of felony defendants are black. This disparity, together with the fact that $\theta$ tends to be lower for black defendants, suggests that the populations of white and black defendants are not selected according to the same rules. In Chapter 9, I develop a simple model of police behavior to flesh out this insight. In it, police apply a threshold rule in $\theta$ when choosing whether to arrest a suspect. If they have a greater incentive (or a lower cost) to arrest black suspects, they will set a lower $\theta$ threshold for them. In turn, this will both increase the number of black suspects arrested and decrease the quality of the arrests made. I find that these differences will manifest even if police decisions are subjected to an unbiased felony review process. This is because biased police are more likely to decline to arrest a white suspect who actually has a high $\theta$, and this disparity that cannot be reversed later.

I then test the proposition that police set a lower arrest threshold for black suspects in a setting where police decisions are quickly and directly evaluated. Before an arrest proceeds to court, it must be accepted by the Cook County State's Attorney in a process known as felony review. I follow the outcome test logic of Knowles, Persico, and Todd (2001), treating felony review as the outcome. If the police are biased against black suspects, the set of black suspects they choose to arrest will be less likely to pass felony review.

Using felony review data from the Cook County State's Attorney's Office, I find that black arrestees are indeed less likely to pass felony review than white arrestees.

The remainder of the paper is organized as follows: Chapter 2 reviews prior work. Chapter 3 presents my model of plea bargaining, its solution, and its comparative statics. Chapter 4 establishes a link between the conclusions of the model and what can be observed in data. Chapter 5 describes the Cook County Circuit Court and Cook County State's Attorney data. Chapter 6 presents my regression estimations of $\Delta T$ and $\Delta L$. Chapter 7 considers alternative explanations for these results. Chapter 8 structurally estimates my model using SMM. Chapter 9 investigates the mechanism of police bias. Chapter 10 concludes.

# CHAPTER 2

# PRIOR WORK

The literature on legal settlement models begins with Landes (1971). It attempts to explain why most, but not all, court cases conclude with a pretrial settlement. Trials are costly and uncertain, so a settlement that avoids trial is typically the most efficient outcome. However, attempts to reach a mutually agreeable settlement can break down in the presence of asymmetric information. In Grossman and Katz (1983) or Bebchuk (1984), defendants are better-informed than prosecutors, so plea bargain offers serve a screening function. In Reinganum (1988), prosecutors are better-informed than defendants, so plea bargain offers serve a signaling function. In Priest and Klein (1984), both prosecutors and defendants have imperfect information and go to trial when their signals disagree. Daughety & Reinganum (2017) provide a review of recent work in settlement models. Most recent developments have focused on aspects of the legal system specific to civil cases. Recent theoretical extensions of criminal plea bargaining (Kim 2010, Lee 2014) have focused primarily on the question of the defendant's innocence. Silveira (2017) structurally estimates the Bebchuk (1984) model using data from North Carolina.

The model in this paper blends settlement models with economic models of racial bias. My model builds off of the settlement screening model of Bebchuk (1984). Defendants have private information, and prosecutors know only the distribution of this information. Prosecutors make plea bargain offers that balance obtaining a long sentence against engaging in a costly trial. Trials happen because it is suboptimal for prosecutors to make plea bargain offers that are acceptable to the full distribution of defendants. In the model of Bebchuk (1984), the defendants are risk neutral and their private information is the probability of conviction at trial. In my model, I assume that the probability of conviction at trial is common knowledge, and each defendant's private information is their degree of risk aversion. This assumption is motivated by the strong discovery provisions in criminal law, which compel both prosecution and defense to share all evidence they intend to present.[1] This choice also clarifies the discussion of how probability of conviction influences sentencing and trial outcomes.

My model also advances the racial bias literature by adding a bias term to the prosecutor's preferences that distorts their tolerance for trials. This idea follows Becker (1957), who modeled bias as a coefficient in a decisionmaker's preferences that varies with the race of the subject and distorts their tolerance for unsuccessful outcomes. For example, if loan officers have a bias towards white applicants, they set a looser standard for white applicants. This leads to more defaults among accepted white applicants. A recent literature including Knowles, Persico, and Todd (KPT 2001), Anwar and Fang (2006), Antinovics and Knight (2009), and Simoiu, Corbett-Davies, & Goel (2017) applies this logic to the criminal justice setting, especially traffic stops. KPT propose an outcome test to indirectly assess whether police use the same rules to search white and black motorists by comparing the rates at which they find contraband, conditional on choosing to search for it. Ayres (2002) points out that outcome tests of this form have infra-marginality problems. Police could search all motorists, regardless of race, who have a minimum probability of carrying contraband, but they will still fail an outcome test if black motorists tend to just barely exceed this threshold while white motorists exceed it by much more. KPT avoid this problem with strong assumptions about the information structure of the game played by police and motorists, which ultimately result in all drivers carrying contraband with equal probability. Later papers showed how supplementary data, such as information about arresting officers or datasets from several jurisdictions, can be used to relax these assumptions. Arnold, Dobbie, & Yang (2018) show that using a valid instrument for the decision can help to alleviate

1. Though the Bebchuk (1984) model is readily adapted to the criminal context, it was originally written to model civil settlements.

the infra-marginality problem.[2] I further add to the bias literature by applying a KPT-style outcome tests to a novel criminal justice outcome: felony review.

Finally, this study contributes to empirical studies of racial bias in criminal justice outcomes. Alesina & Ferrara (2014) find that capital sentences in cases with white victims and black defendants are more likely to be reversed on appeal. Rehavi & Starr (2014) find that race is a strong determinant of whether federal prosecutors file charges with a mandatory minimum, which in turn has a strong effect on final sentences. Several papers show that black defendants are less likely to plead guilty than white defendants (Albonetti 1990, Frenzel & Ball 2008, Metcalfe & Chiricos 2018), but none of them consider this outcome disparity through the lens of the economic discrimination literature.

2. This works because the set of compliers for the instrument is clustered around the decision threshold. If an instrument induces marginally more traffic searches, and the induced traffic searches are successful less often for black motorists, this implies that the decision threshold for black motorists was set below the one for white motorists.

# CHAPTER 3

# MODEL

A defendant (she) charged with a crime is brought before a prosecutor (he). After a non-strategic period of discovery and pretrial motions, both sides observe an identical signal of the probability that the defendant is convicted if the case goes to trial, $\theta \in (0,1)$. They then play the following game.

## 3.1 Technologies

The case may be resolved in one of three ways:

- **Trial:** The case may go to trial. The outcome of the trial is random: the defendant will be convicted with probability $\theta$ and not convicted with probability $(1-\theta)$. If the defendant is convicted, she is given sentence $S > 0$. If the defendant is not convicted, she is given sentence 0. Going to trial incurs a cost $c > 0$ for the prosecutor regardless of the outcome.

- **Plea Bargain:** The prosecutor may offer the defendant a plea bargain sentence of $s > 0$. $s$ is chosen by the prosecutor. This is a one-time take-it-or-leave-it offer. If the defendant accepts the offer, she is given sentence $s$. If the defendant rejects the offer, the prosecutor chooses to resolve the case either by trial or by dropping the charge. Plea bargains incur no additional cost to the prosecutor or the defendant.

- **Dropped Charge:** The prosecutor may drop all charges against the defendant. Neither party pays any costs, and the defendant is given sentence 0.

## 3.2 Preferences

### *Defendant*

The defendant belongs to an observable demographic group $j \in \{B,W\}$. Her payoff, regardless of demographic group, is decreasing in the sentence assigned, which I will represent with the placeholder variable $\varsigma$. In particular, I assume her utility is given by:

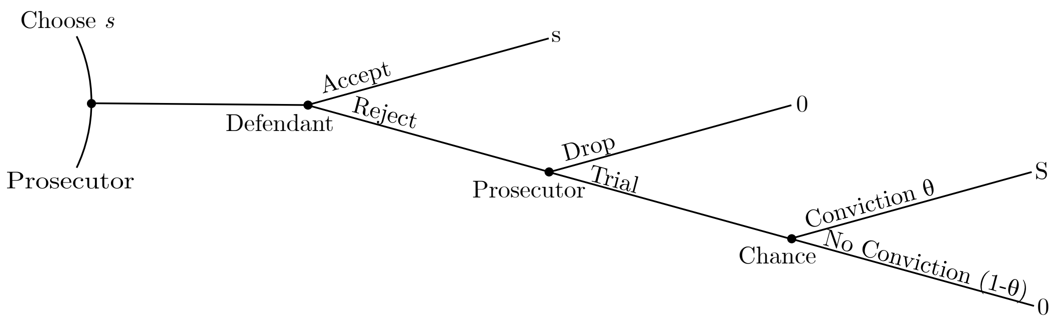
$$-\frac{\varsigma^{\rho}}{\rho}$$

The defendant's relative risk aversion is constant, and her coefficient of relative risk aversion is $1-\rho$. When $\rho = 1$, she is risk neutral, and her risk aversion increases as $\rho$ increases. I assume that $\rho$ is private information drawn from a continuously differentiable cdf $G(\rho)$ with support $[1,\infty)$ and associated pdf $g(\rho)$. $G(\rho)$ does not depend on demographic group and satisfies the increasing hazard property, i.e. that $\frac{g(\rho)}{1-G(\rho)}$ is weakly increasing for all $\rho > 1$. The prosecutor's marginal cost of increasing $s$ is controlled by the hazard of $G(\rho)$, so this assumption ensures that the prosecutor's choice of $s$ has a unique solution. The increasing hazard property holds for many common distributions such as normal, uniform, and gamma with shape parameter $> 1$. I further assume that $\lim_{x\to 1} g(\rho) = 0$, i.e. that there is not a mass of risk-neutral defendants. This assumption ensures that the prosecutor's optimal choice of $s$ does not collapse to the defendant's expected trial sentence due to a critical mass of defendants where that is the optimal offer.

### *Prosecutor*

The risk-neutral prosecutor has preferences that are decreasing in the cost of going to trial and increasing in the sentence assigned, $\varsigma$. His payout is scaled by a preference parameter,

**Figure 3.1**. Game Tree




$k_j$, that may depend on the demographic group $j$ the defendant belongs to. When $k_B > k_W$, I will say the prosecutor is biased against group $B$. If the prosecutor avoids trial, he receives:

$$k_j \varsigma$$

for each $j \in \{B, W\}$. If the prosecutor goes to trial, he receives:

$$k_j \varsigma - c$$

Neither $c$ nor $k_j$ is private information. The defendant may be encountering the prosecutor for the first time, but she is also advised by a defense attorney who has worked with the prosecutor before.

## 3.3 Timing and Choices

Figure 3.1 depicts the game played by prosecutor and defendant.

1. The prosecutor chooses a value $s$ to offer.

2. The defendant either rejects or accepts $s$. This may depend on the defendant's private information, $\rho$. I denote the defendant's choice by $\alpha(s,\rho) \in \{0,1\}$ where $\alpha(s,\rho) = 0$ is rejecting the offer, and $\alpha(s,\rho) = 1$ is accepting the offer.

3. If the defendant accepts $s$, the game is over.

4. If the defendant rejects $s$, the prosecutor must choose whether to go to trial or drop charges. I denote the prosecutor's choice by $\delta \in \{0,1\}$ where $\delta = 0$ is continuing to trial and $\delta = 1$ is dropping charges.

5. If the prosecutor chooses to drop charges, the game is over and the defendant receives a sentence of 0.

6. If the prosecutor chooses to go to trial, the trial proceeds, the conviction outcome is determined by chance, and the game is over.

## 3.4 Agent Problems

I next describe each of the optimization problems solved by the agents in my game, working backwards from the end.

### *Prosecutor's Choice to Drop*

I first define the problem for the last choice made in the game: the prosecutor's choice of whether or not to drop the charge. This problem takes as given his plea bargain offer, $s$, and is only made if the defendant has chosen not to accept the offer, $\alpha(s,\rho) = 0$.

$$\max_{\delta \in \{0,1\}} (1-\delta)\left(\theta k_j S - c\right) + \delta * 0$$

I assume that when the payout to dropping the charge is equal to that of pursuing the case, the prosecutor will drop the charge. The solution to this problem is immediate. The prosecutor drops the case if his expected payout from a trial, $\theta k_j S$, is less than or equal to the cost of a trial, $c$. If the expected payout from trial instead exceeds the cost, the prosecutor will go to trial.

### *Defendant's Problem*

I next define the problem for the second-to-last choice made in the game: the defendant's choice of whether accept the plea bargain. This problem takes as given the prosecutor's plea bargain offer, $s$, and anticipates his choice to drop, $\delta$:

$$\min_{\alpha \in \{0,1\}} (1-\alpha)\left[\delta 0 + (1-\delta)\left(\theta \frac{S^{\rho}}{\rho} + (1-\theta)\frac{0^{\rho}}{\rho}\right)\right] + \alpha \frac{s^{\rho}}{\rho}$$

I assume that when the payout to insisting upon a trial is equal to that of accepting the plea bargain, the defendant will insist on trial. I address the solution to this problem below.

### *Prosecutor's Choice of Plea Bargain*

Finally, I define the problem for the first choice made in the game. This is the prosecutor's choice of plea bargain offer $s$. This problem anticipates both the defendant's choice of $\alpha(s,\rho)$ and the prosecutor's choice of $\delta$ given the outcome of the game up to that point. The prosecutor does not know $\rho$, so he must integrate it out and consider the expectation of $\alpha(s,\rho)$ conditional on his choice of $s$:

$$\max_{s>0} \left(1 - E_{\rho}\left[\alpha(s,\rho)\,|s\right]\right)\left[\delta 0 + (1-\delta)\left(\theta k_j S - c\right)\right] + E_{\rho}\left[\alpha(s,\rho)\,|s\right] k_j s$$

### 3.5 Model Solution

*Strategies*

The prosecutor's strategy in this game is fully characterized by two choices. First, I define $s^*$ as his optimal choice of $s$ given the case characteristics ($\theta$, $S$, $k_j$, $c$, and $G(\rho)$). Second, I define as $\delta^*$ his optimal choice of whether to drop the case in the third step given the characteristics of the case and the defendant's behavior up to that point.

The defendant's strategy is characterized by a single choice: whether to insist upon a trial given the prosecutor's offer of a plea bargain sentence, $s$, her private type, $\rho$, and the case characteristics. I define her optimal choice as $\alpha^*(s,\rho)$.

Given case characteristics, a subgame perfect equilibrium of the game is any triple $(s^*, \alpha^*(s^*,\rho), \delta^*)$ where $\delta^*$ is optimal for the prosecutor, $\alpha^*(s^*,\rho)$ is optimal for the defendant given $\delta^*$, and $s^*$ is optimal for the prosecutor given the defendant's response function $\alpha^*(s^*,\rho)$ and his own $\delta^*$.[1]

*Dropped Cases*

Notice that $\delta^* = 1$ for *any* case where the prosecutor's expected trial payout is non-positive. Therefore $\theta k_j S - c \leq 0$ implies $\alpha^*(s,\rho) = 0$ for all $\rho$ and $s$. The defendant always rejects the plea bargain, and the prosecutor always drops the charges. This outcome arises because the prosecutor cannot credibly threaten to take the case to trial. His expected utility at trial does not exceed his utility from dropping the case. Knowing this, the defendant can always force the prosecutor to drop the case by rejecting any plea bargains.

1. The equilibrium $s^*$ will depend on the prosecutor's anticipation of $\alpha^*(s^*,\rho)$ and $\delta^*$, and the equilibrium $\alpha^*(s^*,\rho)$ will depend on the defendant's anticipation of $\delta^*$. For clarity, I do not include future decisions as arguments to any strategies.

For the remainder of this discussion, I will restrict attention to cases where $\theta k_j S - c > 0$. In this event, $\delta^* = 0$ in any subgame perfect equilibrium because the prosecutor's utility at trial will always be higher than his utility from dropping the case.

## *Defendant's Choice*

**Proposition 3.1:** Take $S$, $\theta$, and $\rho$ as given. Suppose that the prosecutor offers $s < S$. Then, the defendant's optimal strategy follows a cutoff rule: For each $s$, there is a unique value $\hat{\rho}(s) = \frac{\ln\theta}{\ln s - \ln S}$ such that $\alpha^*(s,\rho) = 0$ if $\rho \leq \hat{\rho}(s)$ and $\alpha^*(s,\rho) = 1$ if $\rho > \hat{\rho}(s)$.

**Proof**

See Appendix A

Defendants participate in plea bargaining because they are risk averse, and plea bargaining allows them to avoid an uncertain trial. Given values for $S$ and $\theta$ and an offer of $s$, only defendants with a sufficiently high aversion to risk will accept the offer. $\hat{\rho}(s)$ defines this critical value. If a defendant is at the margin of accepting an offer of $s$, increasing $S$ or $\theta$ makes the trial less attractive, decreases $\hat{\rho}(s)$, and induces her to accept the offer.

## *Prosecutor's Choice of s*

Given the defendant's strategy, I can rewrite the prosecutor's problem when $s < S$ as:

$$\max_s G(\hat{\rho}(s)) \left(\theta k_j S - c\right) + (1 - G(\hat{\rho}(s))) k_j s$$

**Proposition 3.2:** Take $S$, $\theta$, $c$, $G(\rho)$, $j$, and $k_j$ as given. Then the prosecutor's strategy is given by a unique $s^* \in (\theta S, S)$.

**Proof**

See Appendix A

The prosecutor never offers a plea bargain sentence greater than $S$ because the defendant will always reject that deal. This forces the prosecutor into a costly trial with expected payout of only $\theta S$. There is no cost to the prosecutor for offering a plea bargain in the range $(\theta S, S)$, and the worst that could happen is that the case goes to trial anyway. It therefore always benefits the prosecutor to offer a plea bargain that the defendant may accept, however unlikely that acceptance.

Likewise, the prosecutor never offers a plea bargain sentence less than $\theta S$ because the defendant will always accept that deal. The defendant is risk averse, and $\theta S$ is certainty equivalent of a risk neutral defendant. If the prosecutor offers an even lower sentence than $\theta S$, he gives up sentence length with no compensating increase in the probability that the defendant will accept the deal.

Within $(\theta S, S)$, the prosecutor trades longer plea bargain sentences off against greater risk of the defendant rejecting the deal. When choosing $s$, the prosecutor also implicitly chooses $\hat{\rho}(s)$, the risk tolerance of the defendant who is indifferent between accepting and rejecting the plea bargain. I define $\rho^* = \hat{\rho}(s^*)$.

The prosecutor's central tradeoff is encapsulated in the first order condition to his choice of $s$:

$$(1 - G(\rho^*)) = g(\rho^*) \frac{\partial \hat{\rho}(s)}{\partial s}|_{s=s^*} \left[s^* - (\theta S - c/k_j)\right]$$

The left hand side is the marginal benefit of increasing $s$. The prosecutor obtains a longer sentence for the $(1 - G(\rho^*))$ defendants who accept the plea bargain. The right hand side is the marginal cost of increasing $s$. The prosecutor shifts $g(\rho^*) \frac{\partial \hat{\rho}(s)}{\partial s}|_{s=s^*}$ defendants from accepting the plea bargain to demanding a trial, so he must trade off that many plea bargain payouts $(s^*)$ for trial payouts $(\theta S - c/k_j)$. Notice that $k_j$ only appears relative to the trial cost $c$. All other payoff components in the prosecutor's problem are scaled by $k_j$, so his problem would be completely neutral in $k_j$ without a trial cost that is constant in all cases.

### 3.6 Comparative Statics of $s^*$and $\rho^*$

I now describe how $s^*$ and $\rho^*$ change as underlying characteristics of the case change.

**Proposition 3.3:** As the prosecutor's bias increases, holding all else constant, plea sentence length increases and trial rate increases. That is, $\frac{\partial s^*}{\partial k_j} > 0$ and $\frac{\partial \rho^*}{\partial k_j} > 0$.

**Proof:** See Appendix A

An increase in $k_j$ leads to a corresponding decrease in the prosecutor's perceived cost of trial, $c/k_j$. If the prosecutor perceives trials as less costly, he will be willing to trade longer plea bargain sentences for an increased risk of going to trial. Meanwhile, changing $k_j$ has no effect on the defendant's cutoff rule, $\hat{\rho}(s)$. If a defendant would accept a certain plea deal from an unbiased prosecutor, she would accept exactly the same plea deal from a highly biased prosecutor. This means that the set of $(s^*, \rho^*)$ pairs available to the prosecutor does not change with $k_j$. If he wants longer plea bargain sentences (a higher $s^*$), he *must* accept more trials (a higher $\rho^*$).

**Proposition 3.4:** As the probability of conviction at trial increases, plea sentence length increases. That is, $\frac{\partial s^*}{\partial \theta} > 0$. When $\theta \geq e^{-\rho^*}$, as the probability of conviction at trial increases, trial rate decreases. That is, $\frac{\partial \rho^*}{\partial \theta} < 0$.

**Proof:** See Appendix A

In contrast to $k_j$, a change in $\theta$ works primarily through the defendant's incentives. As the probability of conviction at trial increases, the defendant becomes more willing to accept a longer plea bargain sentence in order to avoid that trial. This changes the set of $(s^*, \rho^*)$ pairs available to the prosecutor. As $\theta$ increases, he can hold $s^*$constant while decreasing $\rho^*$ or hold $\rho^*$ constant while increasing $s^*$. He will generally choose a convex combination of these two options, securing both longer sentences *and* fewer trials. Thus, a change in $\theta$ is not bound to the same tradeoff logic as a change in $k_j$. The latter is a change in preferences that does not grant the prosecutor any additional resources but merely shifts how he chooses to spend them. The former acts more like a windfall of income for the prosecutor that he may spend on both of the goods he likes.

The restriction that $\theta \geq e^{-\rho^*}$ is necessary to rule out the possibility that trial rate may be an inferior good. When $\theta$ is very low, the prosecutor's case is very weak. The defendant on the margin of accepting his plea bargain offer has a very low risk tolerance. This low marginal risk tolerance allows the prosecutor to increase $s^*$ a great deal and see only a small increase in the trial rate. Under these circumstances, granting the prosecutor greater bargaining leverage by increasing $\theta$ may cause him to increase $s^*$ very aggressively and accept the small compensating increase in $\rho^*$. The assumption that $\theta \geq e^{-\rho^*}$ rules out this scenario regardless of the exact distribution of $G(\rho)$. It is a sufficient condition, but not a necessary one. Depending on $G(\rho)$, $\frac{\partial \rho^*}{\partial \theta} < 0$ may hold for some $\theta < e^{-\rho^*}$, but it will not hold in general as $\theta \to 0$.[2]

A useful property of the $\theta \geq e^{-\rho^*}$ restriction is that it can be transformed, via $\rho^* = \hat{\rho}(s^*)$, into a form that is testable in data: $\frac{S}{s^*} < e$. The prosecutor's case must not be so weak that he offers plea sentence lengths that are very low compared to the defendant's potential punishment at trial. In Chapter 7, I test this form of the restriction in data from the Circuit Court of Cook County and find that it holds in 84% of cases. My results are not sensitive to the exclusion of the remaining cases.

Appendix A also calculates comparative statics for $c$ and $S$. Increasing $c$ directly increases perceived trial costs, $c/k_j$, so it has the opposite effects as an increase in $k_j$. A higher $S$ increases both the expected sentence at trial and the variance associated with a

2. If the prosecutor has log utility in $\varsigma$, $\frac{\partial \rho^*}{\partial \theta} < 0$ for all $\theta$.

trial. The increase in expected trial sentences makes all defendants more willing to accept long plea bargains. The increase in variance amplifies this effect for more risk averse defendants. The prosecutor capitalizes on this by greatly increasing the sentences he offers. Some risk-tolerant defendants will demand a trial, but the more risk-averse defendants will still accept. The overall effect is an increase in both plea bargain sentences and trial rates.

# CHAPTER 4

# EMPIRICAL IMPLICATIONS

The comparative statics derived in Chapter 3 suggest a method for distinguishing differences in $k_j$ from differences in $\theta$. Increasing either leads to more punitive plea bargain offers, but they will have opposite effects on the critical level of risk aversion. It may therefore be possible to learn something about how $k_j$ and $\theta$ differ across races by examining the joint differences in $s^*$ and $\rho^*$. Neither $s^*$ nor $\rho^*$ is observable, but I show in this chapter that their comparative statics are closely related to the comparative statics of average observed sentence length, $L$, and trial rate, $T$, in a population. I then explain how Figure 1.1 summarizes what can be learned from available data given the maintained assumptions of my model.

## 4.1 Distributions of $\theta$

Although $\theta$ is known to both the prosecutor and the defendant, the econometrician cannot observe it. I define $F(\theta|j)$ as the distribution of $\theta$ among defendants of race $j$ who reach the plea bargaining stage.[1] Unlike the bias in my model, where there is a single $k_B$ that can be directly compared to $k_W$, it is not always possible to order distributions like $F(\theta|B)$ and $F(\theta|W)$.[2] Therefore, I will restrict my attention to cases where $F(\theta|B)$ and $F(\theta|W)$ can be compared using the usual stochastic order. That is, either

1. These distributions may be shaped by the prosecutor's decision to drop cases. I consider the consequences of this in Chapter 7. This chapter and all of the empirical work guided by it consider the population of defendants *after* the prosecutor has dropped any cases he does not wish to pursue.

2. Throughout I will maintain the abstraction of a monotlithic prosecutor with a pair of scalar $k_j$ weights. The cases considered in my data were heard by many different prosecutors, but I do not know which prosecutor is assigned to which case. A dataset where this is known could plausibly learn about individual values for $k_j$.

$Pr\{\theta > x|B\} > Pr\{\theta > x|W\}\ \forall x \in (0,1)$, in which case I will say $F(\theta|B) >_{ST} F(\theta|W)$, or $Pr\{\theta > x|B\} < Pr\{\theta > x|W\}\ \forall x \in (0,1)$, in which case I will say $F(\theta|B) <_{ST} F(\theta|W)$.[3] If a group has the greater $\theta$ distribution, I will say that the cases against them are *stronger*, and if a group has the lesser $\theta$ distribution, I will say that the cases against them are *weaker*.

Stochastic order is a strong restriction, but it can encompass two key models about why $\theta$ may differ between black and white defendants. First, consider a model of structural discrimination where black defendants face different probabilities of conviction due simply to their race. All defendants draw $\tilde{\theta}$ from a shared distribution. White defendants have probability of conviction $\theta = \tilde{\theta}$, but black defendants have probability of conviction $\theta = b(\tilde{\theta})$ with $b(\tilde{\theta}) > \tilde{\theta}\ \forall \tilde{\theta}$. In this simple model, $F(\theta|B) >_{ST} F(\theta|W)$. This model captures the behavior of a judge or juror who would convict a black defendant under circumstances where they would not convict a white defendant.

Alternatively, consider a model of selection discrimination where the necessary $\theta$ to trigger arrest and criminal charges differs by race. That is, all potential defendants have the same distribution of $\theta$, but the *realized* population of black defendants is those with $\theta > \hat{\theta}_B$, the realized population of white defendants is those with $\theta > \hat{\theta}_W$, and $\hat{\theta}_B < \hat{\theta}_W$ . In this simple model, $F(\theta|W) >_{ST} F(\theta|B)$ . This model captures the behavior of a police officer who would arrest a black defendant under circumstances where they would not arrest a white defendant.

### 4.2 Analogues for $s^*$ and $\rho^*$

Neither $s^*$ nor $\rho^*$ is directly observable in typical court data. $s^*$ describes plea bargain *offers* and is only observed when the defendant accepts an offer. $\rho^*$ is private information

3. This order is also known as First-Order Stochastic Dominance.

of the defendant. In place of $s^*$, I will use a measure of average observed sentence length, including sentences from trials and counting not guilty verdicts as 0. I call this measure $L$ :

$$L = (1 - G(\rho^*))\, s^* + G(\rho^*)\, \theta S$$

I show in Appendix A that $L$ and $s^*$ have the same comparative statics with respect to $k_j$ and $\theta$. That is, $\frac{\partial L}{\partial k_j} > 0$ and $\frac{\partial L}{\partial \theta} > 0$.[4]

In place of $\rho^*$, I will use the rate at which defendants go to trial. I call this measure $T$:

$$T = G(\rho^*)$$

It is immediately apparent that for any parameter $x$, $\frac{\partial \rho^*}{\partial x} > 0 \Rightarrow \frac{\partial T}{\partial x} > 0$. Hence, $\frac{\partial T}{\partial k_j} > 0$ and $\frac{\partial T}{\partial \theta} < 0$.

Now consider sentence length and trial rate as functions of case strength: $L(\theta|j)$ and $T(\theta|j)$.[5] Within the set of non-dropped cases and if there are no cases that are too weak, the above comparative statics hold everywhere, and $L(\theta|j,c,s)$ is strictly increasing in $\theta$ while $T(\theta|j,c,S)$ is strictly decreasing in $\theta$. It is a general property of stochastic order that if $F(x) >_{ST} G(x)$, then for any strictly increasing (decreasing) and piecewise differentiable function $u(x)$: $E_F[u(x)]$ is greater than (less than) $E_G[u(x)]$. To fix ideas, I can temporarily assume that case strength differences are the only differences by race, so $k_B = k_W$. In this case, I can conclude $F(\theta|B) >_{ST} F(\theta|W) \Rightarrow E[L(\theta)|B] > E[L(\theta)|W]$ and $E[T(\theta)|B] < E[T(\theta)|W]$.

4. The average observed plea bargain sentence, despite being the more natural analogue, does not necessarily have this property. $k_j$ and $\theta$ also affect which plea bargains are rejected, so entirely excluding cases that go to trial interferes with properly measuring the effects of changing $k_j$ and $\theta$.

5. Trial cost $c$, trial sentence $S$, and risk aversion distribution $G(\rho)$ are being held constant throughout this analysis, but I suppress this notation.

If I focus instead on how sentence length and trial rate differ with prosecutor bias, I only need to order scalars rather than distributions. If $k_B > k_W$, then $L(\theta|B) > L(\theta|W)$ and $T(\theta|B) > T(\theta|W)\ \forall\theta$. Ignoring case strength differences for now,$F(\theta|B) = F(\theta|W)$, I can conclude: $k_B > k_W \Rightarrow E[L(\theta)|B] > E[L(\theta)|W]$ and $E[T(\theta)|B] > E[T(\theta)|W]$.

Finally, I find it convenient to define $\Delta L = E[L(\theta)|B] - E[L(\theta)|W]$ and $\Delta T = E[T(\theta)|B] - E[T(\theta)|W]$. For example, if black defendants have, on average, longer sentences and more trials, then $\Delta L > 0$ and $\Delta T > 0$. These are the y-axis and x-axis of Figure 1.1, respectively. My regression analysis in Chapter 6 estimates $\Delta L$ and $\Delta T$.

## 4.3 Results

The results above are informative about the data patterns I should expect to result from case strength differences or bias when everything else is held constant. When both bias and case strength are allowed to vary freely, their effects on $\Delta L$ or $\Delta T$ may be at odds. A state of the world with both prosecutor bias against black defendants and weak cases against black defendants will certainly see $\Delta T > 0$ because both forces tend to increase $\Delta T$. However, $\Delta L$ may be zero if the positive effect from bias offsets the negative effect from weak cases. Even so, if I were to observe data where both $\Delta L$ and $\Delta T$ can be clearly signed, I can definitely learn something either about case strength or about prosecutor bias. For example, if $\Delta L > 0$ and $\Delta T < 0$, I know there must be strong cases against black defendants because bias alone could not have produced that data. The propositions below formalize this intuition.

**Proposition 4.1:** Consider the set of cases where $\theta k_j S - c > 0$. Suppose that $c$, $S$, and $G(\rho)$ are the same for all defendants. Further suppose that, $\theta \geq e^{-\rho^*}\ \forall\{(\theta, j)\}$ in the support of $F(\theta|j)$. Lastly, assume $F(\theta|B)$ and $F(\theta|W)$ can be stochastically ordered. Then

$\Delta L < 0$ and $\Delta T > 0$ implies that $F(\theta|W) >_{ST} F(\theta|B)$. Likewise, if $\Delta L > 0$ and $\Delta T < 0$, then $F(\theta|B) >_{ST} F(\theta|W)$.

**Proof:** Because $c$, $S$ and $G(\rho)$ do not vary across group, the only candidates for explaining the cross-group differences in average plea bargain sentence length and average plea bargain acceptance rate are $F(\theta|j)$ and $k_j$.

Now, consider data where $\Delta L < 0$ and $\Delta T > 0$ and further suppose that $F(\theta|B) \geq_{ST} F(\theta|W)$. If $k_B = k_W$, this implies $\Delta L \geq 0$ and $\Delta T \leq 0$. Either constitutes a contradiction. Letting $k_B > k_W$ will only exacerbate the first contradiction because $L$ is increasing in $k_j$. Likewise, letting $k_B < k_W$ will only exacerbate the second contradiction because $T$ is increasing in $k_j$. It is therefore impossible to avoid a contradiction, and it must be the case that $F(\theta|W) >_{ST} F(\theta|B)$. The arm of the proof where $\Delta L > 0$ and $\Delta T < 0$ is similar.

**Proposition 4.2:** Consider the set of cases where $\theta k_j S - c > 0$. Suppose that $c$, $S$, and $G(\rho)$ are the same for all defendants. Further suppose that, $\theta \geq e^{-\rho^*}$ $\forall\{(\theta, j)\}$ in the support of $F(\theta|j)$. Lastly, assume $F(\theta|B)$ and $F(\theta|W)$ can be stochastically ordered. Then $\Delta L > 0$ and $\Delta T > 0$ implies that $k_B > k_W$. Likewise, $\Delta L < 0$ and $\Delta T < 0$ implies that $k_B < k_W$.

**Proof:** See Appendix A

## 4.4 Discussion

These theorems divide $(\Delta L, \Delta T)$ space into the four quadrants in Figure 1.1. It is important to note that, despite the appearance of Figure 1.1, this technique cannot provide information about the *magnitude* of any differences of bias or case strength, just about their presence. Proposition 4.1 says that if the data are anywhere in the top-left (bottom-right), I can conclude that cases against black defendants are stronger (weaker) than cases against their white counterparts. Data in these quadrants, however, do not permit any conclusion about prosecutor bias, nor does data farther away from the origin necessarily imply that the differences are larger. Proposition 4.2 says that if the data are in the top-right (bottom-left), I can conclude that prosecutors are biased against (for) black defendants. Data in these quadrants, however, do not permit any conclusion about case strength. The advantage to using these results to guide empirical work is that they do not require a research design that attempts to hold constant or structurally estimate $k_j$ or $\theta$. The disadvantage is that regression results will not always permit a conclusion about one of the parameters of interest. It it is also possible to see data where there are racial differences in *both* case strength and prosecutor bias, but their combined effect on $\Delta L$ and $\Delta T$ is such that one difference cannot be clearly signed, making it difficult to come to a clear conclusion.

The results in this chapter can cleanly associate racial differences in trial rate and sentence length with differences in case strength and prosecutor bias only by holding other parameters constant. In particular, prosecutor trial costs, potential sentences, and the distribution of risk aversion. In Chapter 7, I discuss the plausibility of those assumptions and which patterns of results could be explained by the failure of each.

# CHAPTER 5

# DATA

## 5.1 Institutional Setting

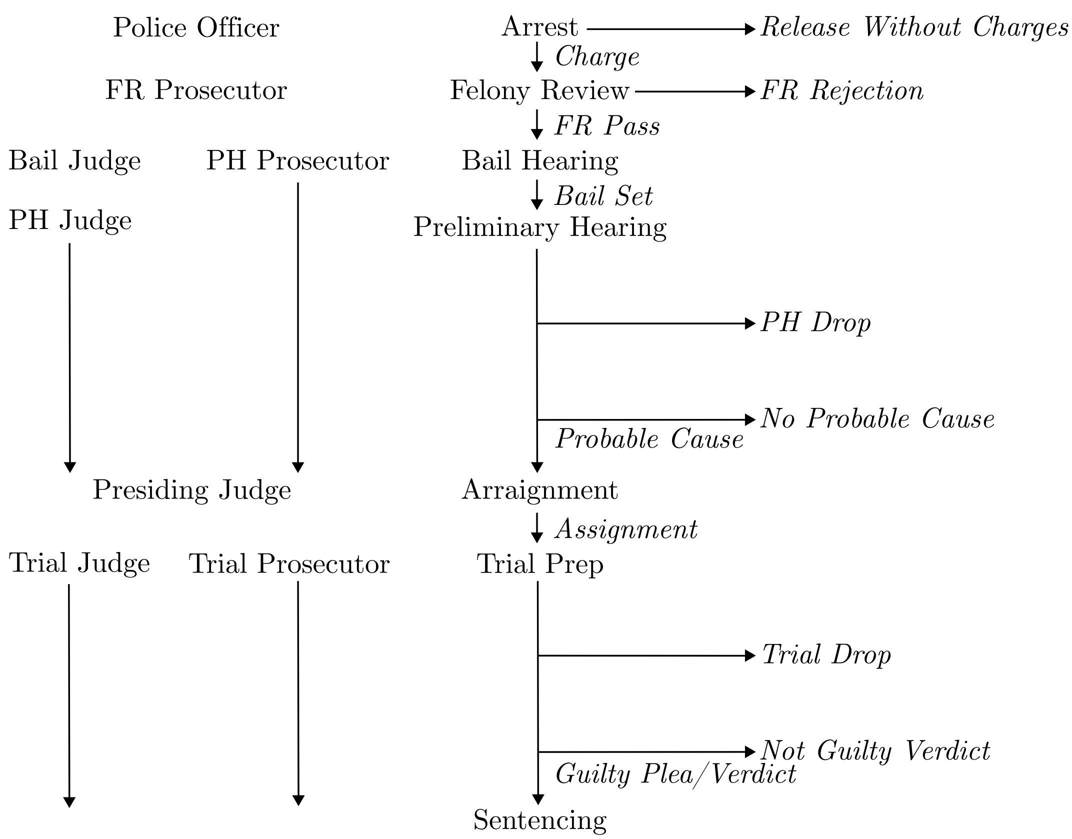
I will use two datasets in my analysis: Circuit Court data and State's Attorney data. Both of my datasets come from the criminal justice system of Cook County, IL. Figure 5.1 gives a visual representation of how a criminal case progresses through that system from arrest to sentencing. My court data begin at the arraignment stage, when a defendant is formally charged and assigned to a trial courtroom. My State's Attorney data is most useful for examining the felony review and preliminary hearing steps.

The left side of Figure 5.1 tracks key state actors at each stage in the criminal case. The prosecutor in my model is the trial prosecutor who receives the case post-arraignment, after the charges have been determined by the felony review and preliminary hearing prosecutors. The right side of Figure 5.1 tracks ways for the case to proceed. Arrows pointing downwards indicate cases that continue within the system. Arrows pointing to the right indicate cases that exit the system. Appendix B discusses Figure 5.1, and the Cook County criminal justice system as a whole, in more detail.

## 5.2 Circuit Court Data

My court data are electronic records of all unsealed cases heard by the Criminal Division of the Cook County Circuit Court from 1984 to 2019. I observe all charges filed in the case, including amended charges. I observe the full disposition history of each case, which records all official actions in the courtroom (e.g. pleas, motions, continuances, orders, verdicts, and sentences). I also observe identifying and demographic information for each

**Figure 5.1**. Felony Case Progression in Cook County



defendant.[1] The court stopped classifying defendants of Hispanic origin separately from white and black defendants around 2010, so I combine white and Hispanic origin defendants in my analysis. Most defendants have a unique, fingerprint-based ID number that I can use to follow them across cases and over time. Cases against the same defendant that were initiated within one week of each other and resolved on the same day are collapsed into a single case. I restrict my attention to defendants who were not already adults at the time my sample begins. This guarantees that I observe all of their felony cases in Cook County and can construct an accurate criminal history.

The Cook County Circuit Court data are administrative data. They required substantial cleaning and reformatting before they were ready to be used in statistical analysis. See Appendix C for details of this process. In some cases, essential fields could not be recovered because they were never entered by the Clerk or contain invalid data. Sometimes I am able to plausibly impute this information. When fingerprint ID is missing, I impute on similarity in name and demographic information between cases. Conversely, I can fill in missing demographic information between cases that share a fingerprint ID.[2] This leaves just 6.5% of my total dataset that must be dropped due to missing/invalid fingerprint ID, demographic information, or charge information.

My two outcomes of interest are whether a case ended in a trial and the length of incarceration imposed. I mark a case as NOT ending in a trial if I see a guilty plea or a Supreme Court Rule 402 conference followed by a trial and a guilty verdict.[3] I measure

1. The original data extract provided by the Clerk of Court did not include these fields for cases where the defendant was not convicted. I supplement the Clerk's extract with data obtained from scraping the Clerk's public computer system. This system is populated by the same database that generated my original extract.

2. When demographic fields disagree among cases that share a fingerprint ID, I use the information that appears in the greatest number of cases associated with that ID.

3. Illinois Supreme Court Rule 402 deals with plea bargain negotiations while the judge is present. This set of circumstances can signal a "stipulated bench trial." These can arise because the prosecutor is proce-

incarceration as the nominal incarceration length announced by the judge, topcoded at 80 years. In relation to my model, this is $s^*$ in the event of a plea bargain and $S$ or 0 in the event of a trial. Prisoners in Illinois routinely receive day-for-day good time credit, so actual expected time served is half the time announced by the judge.[4] Some short incarceration sentences return the defendant to jail, but most send them to a state prison. I do not distinguish between these two types of incarceration. Defendants who awaited trial in jail typically receive a time served credit that reduces their post-conviction sentence by the amount of time spent in jail. I consider below an alternative sentence length measure that applies this credit. I record a sentence of 0 if the defendant is sentenced to probation or some other non-incarceration punishment.

The type of charges faced by the defendant is an important conditioning variable in my empirical model. I divide the space of criminal charges into two dimensions. The first is felony class. Illinois has 5 felony classes: X, 1, 2, 3, and 4. Felony class determines the range of sentences a judge may give if they find the defendant guilty, with X being the most severe and 4 being the least. The second dimension of a criminal charge is category. Guided by the criminal code of Illinois, I split charges into 9 major categories: Murder, Sex, Robbery, Other Violent, Burglary, Theft, Drug, Weapons, and Other Nonviolent. Some charges fall outside these categories (e.g. contempt of court, escape from prison, and aggravated

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durally or politically unable to reduce charges in a way necessary to secure a satisfactory plea agreement. Alternatively, they can arise because defendant does not want to formally admit guilt despite having no defense against the charges. In a stipulated bench trial: all parties meet to agree upon an outcome, the defendant stipulates to certain facts, the case goes to trial, and the judge quickly convicts on a reduced charge. This adjustment applies to 1,533 cases (0.8%) in my final estimation sample.

4. Prisoners are not guaranteed this credit and may have it taken away if they misbehave. Illinois also has a Truth in Sentencing law that demand prisoners serve 85-100% of their nominal sentence for some serious crimes. Most of these are murder and sex crimes, which I exclude from my estimation sample.

DUI), and I do not include them in my estimation sample. A single case may carry multiple charges, but I condition on the most serious charge.[5]

I use the following selection rules to construct my final sample: (1) Fingerprint ID information is available or can be imputed. Without this, I cannot construct an accurate criminal history. (2) The case began between 1984 and 2016. Cases that began after 2016 have a much higher chance to still be ongoing. (3) No missing/invalid fingerprint ID, demographic, or charge data. (4) The defendant must have been at most 16 in 1984. This ensures that I can observe their full adult criminal history in Cook County. (5) The defendant is either black, white, or Hispanic. (6) The most serious charge is robbery, assault, burglary, theft, drug, weapon, or other nonviolent, and the defendant did not receive a life sentence or death sentence.[6] (7) The case was assigned to one of the primary courtrooms serving Chicago. (8) The case ended in conviction, acquittal at trial, or dismissal by a judge. This excludes cases abandoned because the defendant died or fled, not yet closed, or with otherwise unparse-able conclusions. It also excludes cases dropped by the prosecution, which matches the set of defendants considered by my model and by Propositions 4.1 and 4.2.

- I begin with 1,173,923 felony cases after aggregating cases with same defendant that were concluded on the same day.
- 81,263 (6.9%) cases were initiated outside of the period 1984-2016.
- An additional 64,899 (5.5%) cases had invalid/missing fingerprint, charge, or demographic data
- An additional 397,807 (33.9%) cases had defendants who were older than 16 in 1984.

5. I define seriousness first by felony class, then by category, then by the order that they appear in the charging document.

6. Life or death sentences for crimes other than murder and rape are extremely rare. My estimation sample without that restriction would include only 6 more cases.

Table 5.1: Court Data Summary Statistics

| Full Sample | Mean | SD | White | Mean | SD | Black | Mean | SD |
|---|---|---|---|---|---|---|---|---|
| Sentence (months) | 22.1 | 37.5 | Sentence (months) | 19.3 | 37 | Sentence (months) | 22.8 | 37.6 |
| % Plea Guilty | 87.6 | | % Plea Guilty | 89.1 | | % Plea Guilty | 87.1 | |
| % Black | 79.5 | | | | | | | |
| Age at Arrest | 24.4 | 6.4 | Age at Arrest | 24.8 | 6.3 | Age at Arrest | 24.3 | 6.4 |
| % Male | 90.8 | | % Male | 90.5 | | % Male | 90.9 | |
| Prior Convictions | 1.5 | 1.97 | Prior Convictions | 1 | 1.6 | Prior Convictions | 1.6 | 2 |
| % Public Defender | 62.4 | | % Public Defender | 48.4 | | % Public Defender | 66 | |
| % Held in Custody | 70.3 | | % Held in Custody | 63 | | % Held in Custody | 72.2 | |
| % Class X Felony | 14.8 | | % Class X Felony | 12.5 | | % Class X Felony | 15.5 | |
| % Class 1 Felony | 20.7 | | % Class 1 Felony | 13.4 | | % Class 1 Felony | 22.6 | |
| % Class 2 Felony | 27 | | % Class 2 Felony | 30.1 | | % Class 2 Felony | 26.2 | |
| % Class 3 Felony | 12.2 | | % Class 3 Felony | 14.6 | | % Class 3 Felony | 11.6 | |
| % Class 4 Felony | 25.2 | | % Class 4 Felony | 29.5 | | % Class 4 Felony | 24.2 | |

*Notes*: This table shows summary statistics, collectively and by race, for the 388,599 observations used in the analysis sample for the Cook County Court data.

- An additional 2,401 (0.2%) cases had defendants who were not black, white, or Hispanic.
- An additional 85,159 (7.3%) cases had some other lead charge or assigned a life/death sentence.
- An additional 118,419 (10.1%) cases were not assigned to a primary Chicago courtroom.
- An additional 35,379 (3%) cases had an unsuitable conclusion.
- This leaves 388,599 (33.1%) cases in my final estimation sample.

Table 5.1 presents summary statistics for my analysis sample in aggregate and separately by race. The average nominal sentence, including 0 month sentences, is about 1.75 years. This distribution is substantially skewed to the right. The median sentence is only 1.5 months. As in most criminal courts, the majority of defendants, 87.6%, plead guilty. My sample is 79.5% black, a higher proportion than the general population of Chicago, which is 33% black. Defendants in my sample are 90.8% male and generally young with an average age of 24.4. Only 3.1% of defendants in my sample are over 40. Many defendants do not have the resources to make cash bail or pay a private attorney. 62.4% have a public defender appointed to represent them, and 70.3% spend at least some time after arraignment in jail.[7] These statistics are driven by black defendants, though many white defendants also use public defenders and/or sit in jail. Felonies of all 5 classes are well-represented, and black defendants are more likely to be charged with more serious felony classes like 1 and X. 38% of black defendants are charged with a Class X or 1 felony, while only 26% of white defendants are. This will make any comparison between the groups that does not condition properly on felony class very misleading.

## 5.3 State's Attorney Data

My State's Attorney data include all cases brought to the attention of the Cook County State's Attorney from 2011 to the present. All cases include information on the defendant's race, sex, and age. I place each case into the same 9-category scheme as in the circuit court data, but I cannot assign a felony class to each case because class is not set until a case has passed felony review. I mark a case as failing felony review if it has a felony review outcome of: Rejected, Continued Investigation, Approved as Misdemeanor, or Not Charged. I mark a case as not passing the preliminary hearing stage if it is not in the preliminary hearing dataset or has a final disposition of: Finding No Probable Cause.

I use the following selection rules to construct my final sample: (1) No demographic or charge information is idiosyncratically missing. (2) The suspect was arrested between 2011 and 2016. Cases that began after 2016 have a much higher chance to still be ongoing. (3) The suspect is either black or white. (4) The suspect was arrested by the Chicago Police

7. Arraignment occurs at least a few days after the initial bail hearing, so all defendants would have had an opportunity to post bail by that time.

Table 5.2: State's Attorney Data Summary Statistics

| Full Sample | Mean | SD | White | Mean | SD | Black | Mean | SD |
|---|---|---|---|---|---|---|---|---|
| % Pass Felony Review | 90.3 | | % Pass Felony Review | 90.4 | | % Pass Felony Review | 90.3 | |
| % Probable Cause | 85.1 | | % Probable Cause | 84.9 | | % Probable Cause | 85.2 | |
| % Black | 89 | | | | | | | |
| Age at Arrest | 32.7 | 12.4 | Age at Arrest | 35.5 | 11.8 | Age at Arrest | 32.3 | 12.5 |
| % Male | 87.1 | | % Male | 81.7 | | % Male | 87.8 | |

*Notes*: This table show summary statistics, collectively and by race, for the 68,527 observations used in the analysis sample for the State's Attorney's data.

Department. This avoids including cases that will eventually be heard in suburban branch courts. (5) The suspect is not charged with a drug crime. Drug cases in Cook County are not subject to felony review.

- I begin with 357,268 cases brought in by the police.
- In 5,929 (1.7%) demographic or charge information is missing.
- An additional 90,797 (25.4%) cases were initiated outside of the period 2011-2016.
- An additional 51,186 (14.3%) cases had suspects who were neither white nor black.
- An additional 60,010 (16.8%) were not CPD arrests.
- An additional 80,819 (2.6%) were drug cases.
- This leaves 68,527 (19.2%) cases in my final estimation sample.

Table 5.2 presents summary statistics for my analysis sample in aggregate and separately by race. Approximately 10% of cases end at the felony review stage, and an additional 5% end because the State's Attorney cannot show probable cause. This sample is once again overwhelmingly black, 89%, and male, 87.1%. I do not condition on birth year, so this sample is older than my court sample with an average age at arrest of 32.7. Black and white arestees look broadly similar, though white arestees are about 6% more likely to be women.

# CHAPTER 6

# RESULTS

## 6.1 Regression Specification

In this chapter, I use the court data to investigate the correlation between defendant race and my two outcomes of interest using a linear regression specification:

$$Y_i = \alpha + \pi black_i + X_i\beta + \gamma_i^c\psi + \gamma_i^t\rho + \varepsilon_i$$

$Y_i$ is an outcome (either sentence length or an indicator for going to trial). $black_i$ is an indicator for whether the defendant is black. Thus, when $Y_i = L_i$, $\pi$ will estimate $\Delta L$, and when $Y_i = T_i$, $\pi$ will estimate $\Delta T$. $X_i$ is a vector of controls (dummies for age and number of priors, plus indicators for male, multiple charges brought in the case, multiple defendants on the case, public defender appointed, and any jail time). $\gamma_i^c$ is a vector of dummy variables that describe the charge. $\gamma_i^t$ is a vector of dummy variables for the timing and courtroom of case assignment. $\varepsilon_i$ is an error term that I assume is orthogonal to the other variables in my estimation model.

For my core results, I will present four iterative specifications. The first is a simple comparison of means between black and nonblack defendants. The second adds the vector of covariates $X_i$ and sets $\gamma_i^t$ to a vector of dummies for year of assignment. The third adds $\gamma_i^c$ as a vector of charge fixed effects that interact crime category and felony class.[1] The fourth changes $\gamma_t^t$ to a vector of dummies that interact year of assignment with courtroom of assignment.

1. Some of the resulting cells are sparse due to the criminal code. For example, there are almost no Class 4 robberies because most offenses classified under robbery are considered more serious than Class 4. In these cases, I combine adjacent classes into the same cell. In particular, I combine: robbery 2-4, burglary X-1, burglary 2-4, and theft X-1.

Table 6.1: Sentence Length

| | Sentence | Sentence | Sentence | Sentence |
|---|---|---|---|---|
| Black | 3.537*** | -2.058*** | -1.288*** | -1.484*** |
| | (0.233) | (0.209) | (0.173) | (0.171) |
| Male | | 6.522*** | 4.127*** | 4.166*** |
| | | (0.176) | (0.147) | (0.147) |
| Public Defender | | 0.539** | 1.509*** | 2.064*** |
| | | (0.184) | (0.152) | (0.142) |
| Ever in Jail | | 14.75*** | 8.153*** | 8.232*** |
| | | (0.193) | (0.134) | (0.135) |
| Multiple Defendants | | 5.002*** | -1.669*** | -1.640*** |
| | | (0.233) | (0.185) | (0.182) |
| Multiple Charges | | 13.44*** | 2.669*** | 2.687*** |
| | | (0.198) | (0.135) | (0.132) |
| Observations | 388599 | 388599 | 388599 | 388599 |
| Adjusted $R^2$ | 0.001 | 0.184 | 0.386 | 0.395 |
| Charge Cond. | None | None | ClassXCat FE | ClassXCat FE |
| Assignment Cond. | None | Year FE | Year FE | CtrmXYear FE |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes*: This table presents the results of regressions of an indicator for black defendants on nominal sentence length in months. Beginning with the second column, covariates also include dummy variables for age and number of prior convictions. Standard errors are clustered at the courtroom-year level. See Chapter 5 for details about sample selection.

All standard errors are heteroskedastically robust and clustered by assigned year and courtroom. I cluster at this level because courtroom assignment at a point in time determines both the specific judge and prosecutor who will handle the case. This may induce variation in $\theta$ and $k$ at the courtroom level that could cause defendants assigned to the same courtroom at the same time to have correlated errors.

Table 6.2: Trial

| | Trial | Trial | Trial | Trial |
|---|---|---|---|---|
| Black | 0.0200*** | 0.0300*** | 0.0175*** | 0.0166*** |
| | (0.00215) | (0.00202) | (0.00182) | (0.00165) |
| Male | | 0.0376*** | 0.0243*** | 0.0253*** |
| | | (0.00197) | (0.00192) | (0.00190) |
| Public Defender | | -0.0477*** | -0.0383*** | -0.0447*** |
| | | (0.00228) | (0.00217) | (0.00169) |
| Ever in Jail | | -0.00233 | -0.0139*** | -0.0150*** |
| | | (0.00185) | (0.00184) | (0.00175) |
| Multiple Defendants | | 0.0526*** | 0.0450*** | 0.0437*** |
| | | (0.00197) | (0.00189) | (0.00187) |
| Multiple Charges | | 0.0451*** | -0.0128*** | -0.0142*** |
| | | (0.00187) | (0.00179) | (0.00173) |
| Observations | 388599 | 388599 | 388599 | 388599 |
| Adjusted $R^2$ | 0.001 | 0.030 | 0.058 | 0.081 |
| Charge Cond. | None | None | ClassXCat FE | ClassXCat FE |
| Assignment Cond. | CtrmXYear FE | None | None | CtrmXYear FE |

Standard errors in parentheses

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

*Notes*: This table presents the results of regressions of an indicator for black defendants on whether the case ended in a trial. Beginning with the second column, covariates also include dummy variables for age and number of prior convictions. Standard errors are clustered at the courtroom-year level. See Chapter 5 for details about sample selection.

## 6.2 Aggregate Results

Table 6.1 shows the relationship between sentence length and race as I add conditioning variables. In a pure comparison of means, black defendants receive substantially longer sentences than white defendants. However, I find that after controlling for demographic and case characteristics, black defendants in my data receive sentences that are about 1.5 nominal months shorter than comparable white defendants. With typical good time credit, this is about 3 weeks of actual incarceration time.

Table 6.2 presents a similar progression for trial rate. It shows that black defendants are about 1.7% more likely to go to trial. This is a large difference in percentage terms because only 12.4% of cases go to trial overall. Given the low trial rate, a linear probability model may not be well specified, but Table D1 shows that a logistic model also finds that black defendants are more likely to go to trial.

In the language of my model, these results indicate that $\Delta L < 0$ and $\Delta T > 0$. According to Proposition 4.1, if we assume that the $\theta$ distributions can be stochastically ordered, then black defendants must be the ones facing cases with a lower probability of conviction. The finding that black defendants face weaker cases may be surprising. The fact that African Americans are extremely over-represented in prisons has motivated the search for some structural disadvantage at court that makes them *more* likely to be convicted. I find instead that over-representation in prison is driven primarily by the composition of defendants who reach court. In a city that is 33% black, nearly 80% of my sample of felony defendants is black. This disparity, coupled with the fact that black defendants face weaker cases than their white counterparts, suggests that black citizens may be charged with felonies on the basis of weaker evidence. In Chapter 9, I investigate the possibility that police apply a lower standard of case quality when arresting black defendants.

I also investigate the rate at which black defendants are actually convicted, though this analysis cannot speak directly to underlying $\theta$ distributions. The first column of Table 6.3 shows the racial difference in conviction rates for cases that reach trial. I find that black defendants are less likely to be convicted at trial, but the effect is not statistically significant. The second column of Table 6.3 looks at all defendants in my analysis sample, including the ones who accepted plea deals. I also find that black defendants in this sample are less likely to be convicted. These results are suggestive, but neither of these specifications are a direct test of the hypothesis that black defendants face weaker cases overall. The first focuses only on the selected sample of cases that proceed to trial, which may not be representative

Table 6.3: Conviction

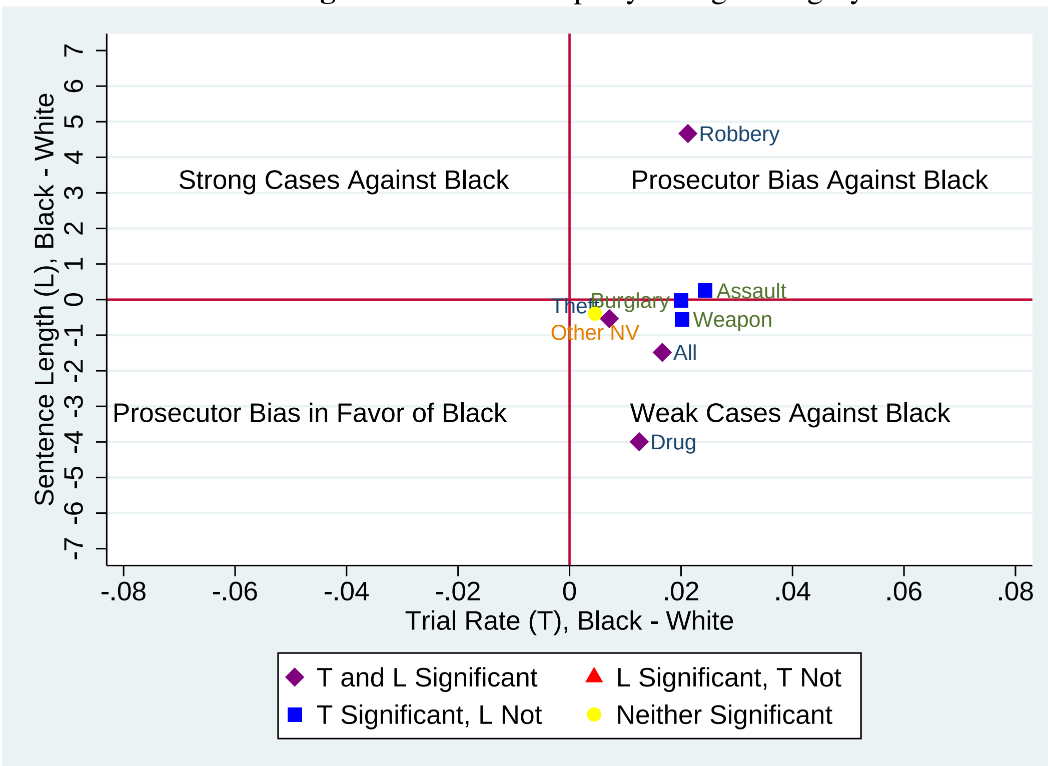
| | Conviction | Conviction |
|---|---|---|
| Black | -0.00634 | -0.00884*** |
| | (0.00664) | (0.00114) |
| Male | -0.0275** | -0.0146*** |
| | (0.00905) | (0.00128) |
| Public Defender | 0.0663*** | 0.0315*** |
| | (0.00539) | (0.00113) |
| Ever in Jail | 0.157*** | 0.0277*** |
| | (0.00618) | (0.00118) |
| Multiple Defendants | -0.118*** | -0.0377*** |
| | (0.00587) | (0.00140) |
| Multiple Charges | 0.0795*** | 0.0174*** |
| | (0.00566) | (0.000966) |
| Observations | 48379 | 388599 |
| Adjusted $R^2$ | 0.117 | 0.040 |
| Charge Cond. | ClassXCat FE | ClassXCat FE |
| Assignment Cond. | CtrmXYear FE | CtrmXYear FE |
| Sample | Trials | All Cases |

Standard errors in parentheses

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

*Notes*: This table presents the results of regressions of an indicator for black defendants on whether the case ended in a conviction. Covariates also include dummy variables for age and number of prior convictions. Standard errors are clustered at the courtroom-year level. The first column restricts to cases that went to trial. See Chapter 5 for details about sample selection.

**Figure 6.1**. Racial Gaps by Charge Category



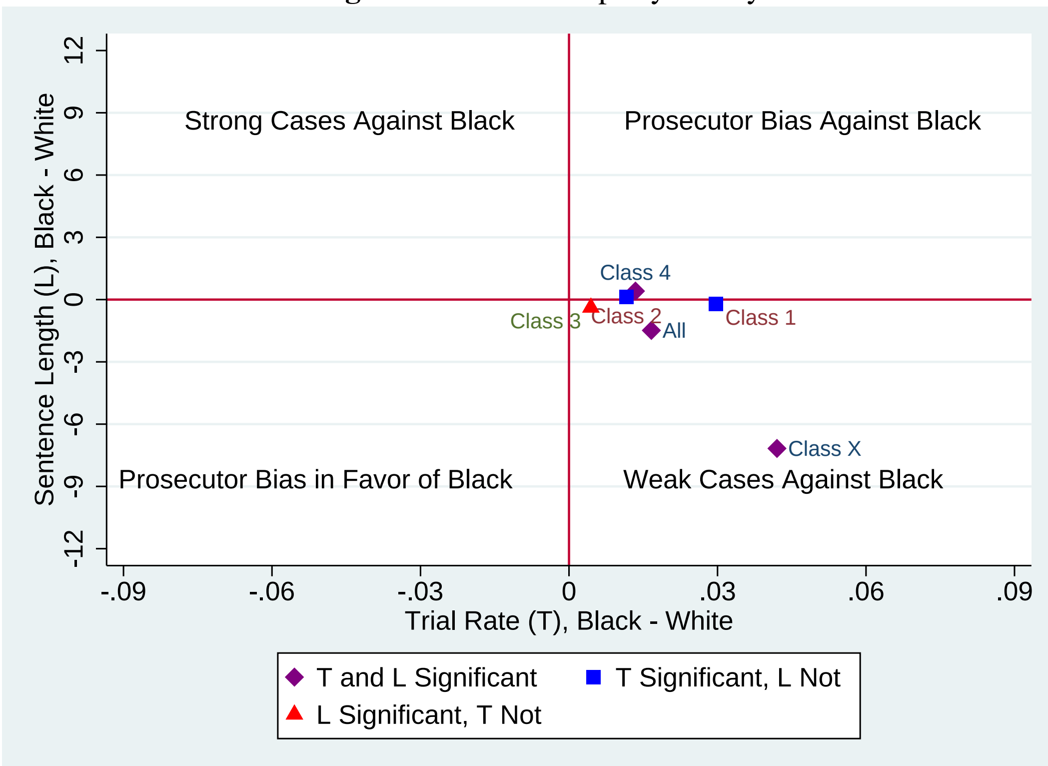

*Notes:* This figure plots the coefficients from regressions of an indicator for black defendants on whether the case ended in a trial (x-axis) and nominal sentence in months (y-axis). Each regression has covariates: dummy for quarter of case initiation, class of most seriouscharge, age, and number of prior convictions, plus indicators for whether the defendant is male, ever had a public defender, was ever held in custody awaiting trial, and whether the state filed multiple charges or included multiple defendants in the case. Standard errors are clustered at the courtroom-year level. See Chapter 5 for details about sample selection.

of the overall distribution. The second includes the fact that black defendants are less likely to accept plea bargains, which mechanically result in conviction.

## 6.3 Heterogeneity

The aggregate results above potentially mask substantial heterogeneity across defendant subgroups. Figure 6.1 presents the results of several crime-category-specific regressions in the same $(\Delta T, \Delta L)$ space used in Figure 1.1. Purple diamonds are categories with significant

**Figure 6.2**. Racial Gaps by Felony Class

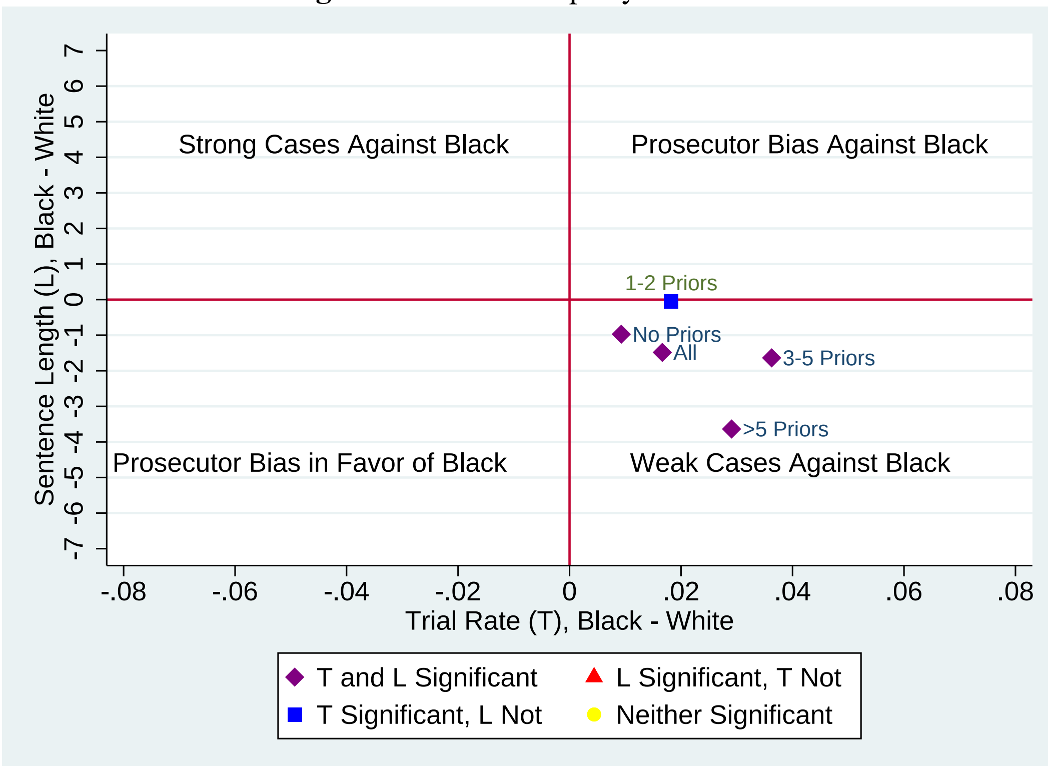



*Notes:* This figure plots the coefficients from regressions of an indicator for black defendants on whether the case ended in a trial (x-axis) and nominal sentence in months (y-axis), conditional on class of most serious charge. Each regression has covariates: dummy for quarter of case initiation, category of most serious charge, age, and number of prior convictions, plus indicators for whether the defendant is male, ever had a public defender, was ever held in custody awaiting trial, and whether the state filed multiple charges or included multiple defendants in the case. Standard errors are clustered at the courtroom-year level. See Chapter 5 for details about sample selection.

effects on both dimensions. Blue squares are significant on only the plea deal acceptance dimension. Red triangles are categories significant only on the sentence length dimension. Yellow circles are significant in neither dimension. My data cluster around the southeast, but only two individual crime categories show significant evidence of weaker cases against black defendants: drug and weapons offenses.

Figure 6.2 divides the data by felony class instead of charge category. The results are split between the southeast and northeast quadrants. The sentencing gap within Class X is

**Figure 6.3**. Racial Gaps by Prior Convictions




*Notes:* This figure plots the coefficients from regressions of an indicator for black defendants on whether the case ended in a trial (x-axis) and nominal sentence in months (y-axis), conditional on number of prior convictions. Each regression has covariates: dummy for quarter of case initiation, class of most serious charge, category of most serious charge, and age, plus indicators for whether the defendant is male, ever had a public defender, was ever held in custody awaiting trial, and whether the state filed multiple charges or included multiple defendants in the case. Standard errors are clustered at the courtroom-year level. See Chapter 5 for details about sample selection.

particularly large, which is not surprising given the fact that Class X felonies carry much longer sentences with no option of probation. Figure 6.3 divides the data by the number of prior convictions the defendant has. I find results that are in the southeast quadrant and stronger for defendants who have many prior convictions.

Recall that my theoretical results in Chapter 4 do not claim that data indicating one type of racial disparity preclude the existence of the other. Even uniform and overwhelming evidence that black defendants face weaker cases would not rule out the possibility of prosecutor bias. When the two states coexist, regression evidence can reveal at most one. It is worth noting that not a single data point in Figures 6.1, 6.2, and 6.3 suggests that black defendants face stronger cases or are favored by prosecutors. Furthermore, some subsamples, such as robbery and class 4 felonies, are in the region of $\Delta T, \Delta L$ space that implies prosecutor bias against black defendants.[2] I interpret this to mean that black defendants are probably subject to both weak sentences and prosecutor bias. However, the evidence for the former is stronger and more uniform. Furthermore, I do not have a clear theory as to why evidence of prosecutor bias would be concentrated in robberies and Class 4 felonies. These two samples do not even overlap. This evidence helps to motivate the structural estimation of my model in Chapter 8, which has the potential to reveal *both* prosecutor bias and differences in $\theta$.

Figure D1 presents heterogeneity by year. Both $\Delta T$ and $\Delta L$ are more volatile in early sample years. Defendants in later years are more likely to have fully observed felony conviction records, so this may simply be noise driven by smaller sample sizes. After 2000, black defendants consistently have shorter sentences and more trials. Overall, I conclude that the differences documented in the aggregate regressions were likely driven by persistent forces rather than extreme factors confined to just one era.

## 6.4 Robustness

My primary sentence length outcome is only one way of interpreting the sentence given at court. Table 6.4 recreates the last column Table 6.1 using alternative measures of sentence length. The first calculates the marginal sentence length by subtracting any time served credits awarded at sentencing. This is the amount of time the defendant will actually spend

2. These results remain statistically significant even after applying a Bonferroni correction for multiple hypothesis testing.

Table 6.4: Alternative Sentence Measures

| | Marginal | Total |
|---|---|---|
| Black | -1.474*** | -1.484*** |
| | (0.153) | (0.171) |
| Male | 3.121*** | 4.166*** |
| | (0.129) | (0.147) |
| Public Defender | 1.234*** | 2.064*** |
| | (0.126) | (0.142) |
| Ever in Jail | 5.385*** | 8.232*** |
| | (0.130) | (0.135) |
| Multiple Defendants | -2.093*** | -1.640*** |
| | (0.165) | (0.182) |
| Multiple Charges | 2.210*** | 2.687*** |
| | (0.119) | (0.132) |
| Observations | 388599 | 388599 |
| Adjusted $R^2$ | 0.334 | 0.395 |
| Charge Cond. | ClassXCat FE | ClassXCat FE |
| Assignment Cond. | CtrmXYear FE | CtrmXYear FE |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes*: This table presents the results of regressions of an indicator for black defendants on alternative sentence measures. Covariates also include dummy variables for age and number of prior convictions. Standard errors are clustered at the courtroom-year level. See Chapter 5 for details about sample selection.

in prison. The second calculates the total sentence length by including any time spent in jail even for defendants who were not eventually given an incarceration sentence. This is the amount of time the defendant spends incarcerated in any way, even if it is never labeled by the state as punishment. My measure of the black-white sentencing gap does not react much to the choice of sentencing measure.[3]

My data include some serious crimes and cases with many charges, which can sometimes lead to extremely long nominal sentence lengths. I topcode sentence lengths at 80 years because this is a practical limit on how long someone can actually be incarcerated. Table D2 shows my primary sentencing result for different choices about topcoding, including dropping observations with unusually high sentence lengths. My estimates of the black-white sentencing gap are robust to this choice.

3. I also considered a measure that treats a sentence to probation as a potential prison sentence that may or may not be realized depending on whether probation is violated. Thus, it measures a defendant who is sentenced to probation and later sent to prison for 2 years for a probation violation as having been given a 2 year sentence at trial. Under this measure, the black-white sentencing gap shrinks to 0.9 months, reflecting the fact that white defendants are disproportionately likely to be sentenced to probation.

# CHAPTER 7

# ALTERNATIVE EXPLANATIONS

## 7.1 Differences in Other Parameters

Propositions 4.1 and 4.2 depend on holding constant $c$, $S$, and $G(\rho)$. I hold prosecutor trial costs $c$ constant only for clarity. They are closely related to the bias term $k_j$, and my comparative statics could easily be rewritten in terms of the prosecutor's perceived trial cost $c/k_j$. Thus, my model will never be able to distinguish racial patterns in prosecutor bias from racial patterns in prosecutor trial costs. Importantly, these would have to be *real* differences in the cost to try black and white defendants. If prosecutors simply *perceive* a different cost to trying black defendants, than this is just a different way for the prosecutor's attitudes about race to enter the plea bargaining process. Lastly, the clearest pattern in the data suggests that black and white defendants differ most in their $\theta$ distributions, and this does not depend on the distinction between prosecutor bias and prosecutor trial cost.

I must also hold constant $S$, the punishment the defendant would face at trial. It is difficult to directly observe $S$ because so few cases go to trial, but it is still possible to condition on $S$ using information about the charges brought against the defendant. Illinois has determinate criminal sentencing. Its criminal code lays out specific sentencing rules for each charge that judges are obligated to follow. These rules typically permit a range of sentences. Judges retain some discretion, but they have far less discretion than judges and parole boards in indeterminate sentencing states. Furthermore, as with $c$, even if $S$ did vary by race, its comparative statics are such that racial differences in $S$ could not explain the pattern of sentence lengths and trial rates observed in the data.

In Appendix A, I discuss a variation on my model that allows the risk tolerance distribution, $G(\rho)$, to vary by race. I find that a group with higher overall risk tolerance will generate the same patterns in $\Delta T$ and $\Delta L$ as a group with lower values of $\theta$. This could be an alternative explanation for the patterns I observe in the data. I am not aware of any study that quantifies the relative risk tolerance of black defendants in the criminal justice context. However, empirical studies of risk attitudes in insurance and financial settings have not yielded clear evidence that African Americans are more tolerant of risk than their white counterparts (Halek and Eisenhauer 2001; Yao, Gutter, and Hanna 2005). It is possible that the process of selection into the criminal justice system could distort population characteristics, but the fact that relatively more black people end up in court suggests, if anything, that the risk tolerance distribution for black defendants will include not just thrill seekers but also people with more typical risk attitudes.

## 7.2 Trial Rate as an Inferior Good

Proposition 3.4 depends on the assumption that $\theta \geq e^{-\rho^*}$. If this assumption fails, the marginal defendant may be sufficiently inelastic that the prosecutor responds to an increase in $\theta$ by increasing $s^*$ so much that his trial rate also increases. In data where $\theta < e^{-\rho^*}$ for many cases, differences in $\theta$ may generate data that suggest differences in $k$ instead. My results in Chapter 6 provide only limited evidence for differences in $k$, so this ambiguity is not an immediate concern. However, I test the condition to assess whether my theoretical results may be useful in other settings. Using the definition $\rho^* = \hat{\rho}(s^*)$, I can rewrite the condition as $\frac{S}{s^*} < e$. Figure D2 displays a histogram of $\frac{S}{s^*}$ for all non-trial cases in my estimation sample that resulted in an incarceration sentence.[1] Only 14.1% of these cases

1. For any case in real data, either $S$ or $s^*$ is counterfactual; a defendant cannot both accept a plea bargain and receive a trial sentence. However, $S$ is a feature of the environment that is not dependent on any choices and closely tied to the charges brought against the defendant. Two cases with the same charge characteristics likely have close to the same value for $S$. Therefore, I impute $S$ within felony class as the median sentence among cases lost at trial. I try several other specifications, including the mean of observed S, joint condition-

have a value of $\frac{S}{s^*} > e$, and I suspect that this is driven by imputation error for $S$.[2] To test robustness, Table D3 replicates my core results for a sample that excludes any case with a measured $\frac{S}{s^*} > e$. The results are very similar to the last columns in Tables 6.1 and 6.2.

### 7.3 Prosecutor Selection of Cases

In my definition of the defendant θ distributions, $F(\theta|B)$ and $F(\theta|W)$, I was careful to note that these distributions are conditional on reaching the plea bargaining stage. Cases that do not meet the criterion $\theta S k_j - c > 0$ are dropped before this stage. This drop decision depends on $k_j$, so prosecutor bias has an opportunity to shape defendant θ distributions. What appears to be differences in case strength could instead be prosecutor bias operating through a different vector.[3] Table D4 shows that race seems to matter in the prosecutor's decision to drop a case. However, I can bound the importance of this for my core results by considering a sample that includes all dropped cases as if they were plea bargains with a sentence of 0. Table D5 recreates the last columns of Tables 6.1 and 6.2 under this new sample, and my results change very little.

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ing on felony class and category, and predicted values from a regression of observed S on covariates. These choices do not have a significant impact on my results.

2. I find that 27.9% of cases have a value of $\frac{S}{s^*} < 1$. It is unlikely that defendants in my model, or any model where $S$ is known before the trial, would ever accept a plea bargain for a longer sentence than what they would risk at trial. Likewise, of the cases for which $\frac{S}{s^*} > e$, more than half are extreme in that $\frac{S}{s^*} > 6$. These facts suggest that my imputation method for $S$ does not work well for some cells in my data and creates a spread both below 1 and above $e$.

3. Call the unconditional defendant θ distributions $\hat{F}(\theta|B)$ and $\hat{F}(\theta|W)$ and assume that $\hat{F}(\theta|B) = \hat{F}(\theta|W)$. If the prosecutor is biased against black defendants, he will be more willing to retain their cases rather than drop them. This will skew the defendant θ distributions such that $F(\theta|W) >_{ST} F(\theta|B)$. For this reason, Propositions 4.1 and 4.2 are not guaranteed to hold with $\hat{F}(\theta|B)$ and $\hat{F}(\theta|W)$ in the place of $F(\theta|B)$ and $F(\theta|W)$.

# CHAPTER 8

# STRUCTURAL ESTIMATION

My model permits me to interpret the regression evidence from Chapter 6, However, I have not yet presented direct evidence that my model is a useful tool for explaining the overall patterns in the court data or for making predictions about the likely impacts of policy changes. In this chapter, I use court data to structurally estimate the parameters of the model described in Chapter 3. I do this with the Simulated Method of Moments, following the suggestions in Eisenhaur et al (2015).

## 8.1 Parameterization and Moments

First, I must make distributional assumptions for $\theta$, $\rho$, and $S$. I assume that case strength, $\theta$, is drawn from $U\left(\underline{\theta}_j, 1\right)$. If $\underline{\theta}_B < \underline{\theta}_W$, the case strength distribution for white defendants will stochastically dominate the case strength distribution for black defendants. I assume that each defendant's risk tolerance, $\rho = 1 + \tilde{\rho}$, where $\tilde{\rho}$ is drawn from $Gamma\left(\alpha_\rho, \beta_\rho\right)$ with $\alpha_\rho > 1$.[1] This ensures the risk tolerance distribution will have the properties I assume about $G(\rho)$ in Chapter 3. I also assume that the trial sentence, $S$, is drawn from the $\mathcal{G}(\mu_S, \sigma_S, Q_S)$where $\mathcal{G}(\mu, \sigma, Q)$ is the 3-parameter generalized gamma function as parameterized in Prentice (1974).[2] I normalize the trial cost, $c$, to 1. My model can thus be described by the following 9 parameters:

- $k_B$: The prosecutor's utility multiplier for black defendants.

1. This $\alpha_\rho$ is distinct from the $\alpha$ function that denotes the defendant's choice of whether or not to accept a plea bargain.

2. Allowing $S$ to vary between defendants gives more flexibility than what is considered in my comparative statics, which holds $S$ constant across defendants. I find that this is necessary to match the empirical variance in sentencing outcomes, even when conditioning on charge characteristics.

- $k_W$: The prosecutor's utility multiplier for white defendants.

- $\underline{\theta}_B$: The lower bound of the black case strength distribution.

- $\underline{\theta}_W$: The lower bound of the white case strength distribution.

- $\alpha_\rho$: The shape parameter of the risk tolerance distribution.

- $\beta_\rho$: The scale parameter of the risk tolerance distribution.

- $\mu_S$: The location parameter of the trial sentence distribution.

- $\sigma_S$: The scale parameter of the trial sentence distribution.

- $Q_S$: The shape parameter of the trial sentence distribution.

I choose these parameters to target 12 moments in my data. Conditioning variables, especially information about charges and prior convictions, are important in my data but not modeled in my simulation. I therefore calculate all data moments after residualizing with respect to the control variables described in Chapter 6.[3] The 10 moments I target are:

- The percentage of cases against black defendants that are dropped.

- The percentage of cases against white defendants that are dropped.

- The percentage of non-dropped cases against black defendants that go to trial.

- The percentage of non-dropped cases against white defendants that go to trial.

- The average sentence handed down to black defendants in non-dropped cases.

3. I carry out the residualizing regressions within my full sample and include an indicator for black defendants as a covariate, but I do not residualize with respect to race or the overall mean of each outcome. This means that white and black first moments will be spaced by exactly the coefficient on black in the the residualizing regression, but the effect on higher moments is less obvious.

- The average sentence handed down to white defendants in non-dropped cases.
- The standard deviation of sentences handed down to black defendants in non-dropped cases.
- The standard deviation of sentences handed down to white defendants in non-dropped cases.
- The skewness of sentences handed down to black defendants in non-dropped cases.
- The skewness of sentences handed down to white defendants in non-dropped cases.
- The conviction rate of black defendants for cases that go to trial
- The conviction rate of white defendants for cases that go to trial.

Following Eisenhauer et al (2015), I create 200 bootstrap samples from my data, calculate the moments of interest within each, and store the joint distribution of the moments across these 200 samples. Then, for a given parameterization of my model, I simulate 20,000 white defendants and 75,000 black defendants and calculate the moments of interest within that population. I repeat this procedure 20 times and capture the mean of my moments across simulations. I then use a Nelder-Mead algorithm to minimize the difference between the simulated moments and the data moments. I weight these differences with the inverse of the variance-covariance matrix of the bootstrapped moments.

## 8.2 Estimation Results

Panel A of Table 8.1 shows the data moments, the standard deviation of the moment across bootstrap observations, and my fitted simulated moments. I provide the standard deviations to give a sense of the relative weight my optimization procedure placed on each moment.

Table 8.1: Structural Fit

| **Panel A** | Moment | Data | Model | Moment | Data | Model |
|---|---|---|---|---|---|---|
| | Black Drop Rate | 0.057 (0.0007) | 0.057 | White Drop Rate | 0.067 (0.002) | 0.068 |
| | Black Trial Rate | 0.127 (0.001) | 0.127 | White Trial Rate | 0.114 (0.002) | 0.115 |
| | Black Sentence | 21.9 (0.13) | 21.9 | White Sentence | 23.1 (0.2) | 22.7 |
| | Black Sen. SD | 28.9 (0.55) | 29.5 | White Sen. SD | 29 (0.74) | 29.9 |
| | Black Sen. Skew | 5.52 (0.58) | 5.58 | White Sen. Skew | 3.84 (0.7) | 5.35 |
| | Black Trial Convict | 0.573 (0.005) | 0.56 | White Trial Convict | 0.578 (0.008) | 0.59 |
| **Panel B** | Parameter | Value | SE | Parameter | Value | SE |
| | $k_B$ | 0.613 | (0.0002) | $k_W$ | 0.493 | (0.0003) |
| | $\underline{\theta}_B$ | 0.244 | (0.0002) | $\underline{\theta}_W$ | 0.314 | (0.0002) |
| | $\alpha_\rho$ | 2.789 | (1e-6) | $\mu_S$ | 2.8 | (4e-5) |
| | $\beta_\rho$ | 1.11 | (0.0009) | $\sigma_S$ | 1.017 | (2e-5) |
| | | | | $Q_S$ | 0.046 | (1e-5) |

*Notes:* This table displays the results of estimating the model in Chapter 3 using a Nelder-Mead algorithm to minimize the bootstrap-variance-weighted error in 10 moments between Cook County Court data and synthetic data created by 20 simulations of the model with 20,000 white defendants and 75,000 black defendants. Panel A compares the data moments to the simulated moments. Bootstrap standard errors for the data moments in parentheses. Panel B shows the parameter estimates obtained from the estimation. Standard errors of parameter estimates calculated from numerical derivatives with step length $\log n/n$.

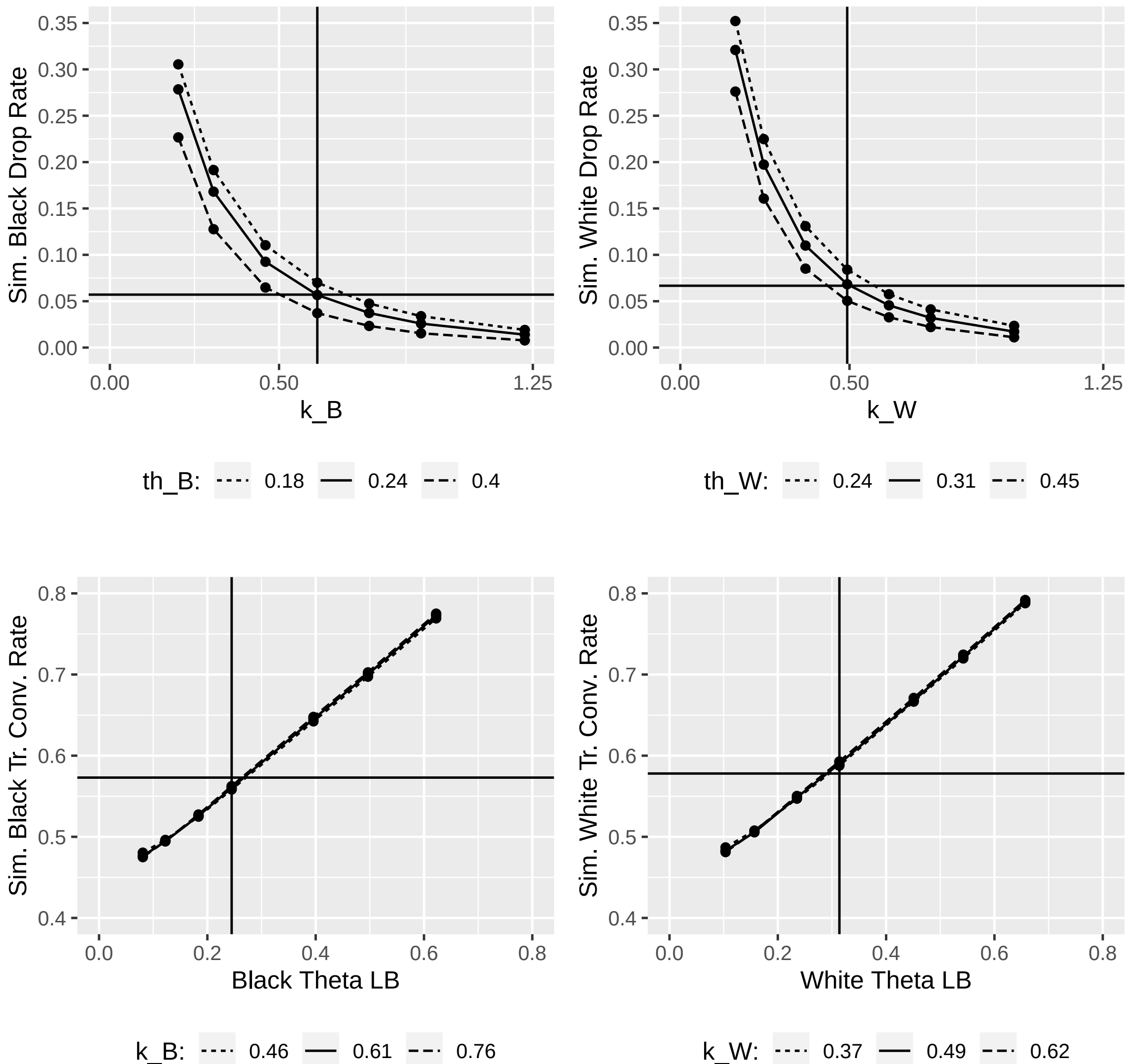
The standard deviations are quite small because the size of my dataset allows high precision when estimating the data moments. Overall the fit is satisfactory. I closely match empirical rates of dropped cases, rates of cases that proceed to trial, and average sentence length for both races. I slightly overestimate the variance of sentences for both white and black defendants. My model draws sentences for black and white defendants from the same distribution, so it is unable to reconcile the fact that the white sentencing distribution has substantially less skew than the black distribution. Conversely, my model wants to create a larger difference between black and white trial win rates than in the data. Intuitively, if unconditional black and white conviction rates vary (as I will find), one would expect conviction rates conditional on trial to vary at least a little. My model can rationalize some of the non-difference in the data with differential selection into trials, but it retains a gap of 3% in the simulated moments. Due partially to the high precision with which I estimate my bootstrapped moments, my model is rejected by a standard J test (3 degrees of freedom) with a test statistic of 26.7.

Panel B of Table 8.1 lists my estimated parameter values. Standard errors are calculated using numerical derivatives of the objective function with a stepsize equal to $n/\log n$. (Hong, Mahajan, and Nekipelov 2015) The parameter estimates confirm the conclusion of Chapter 6 by setting the lower bound of the black $\theta$ distribution, $\underline{\theta}_B$, at 0.244, below $\underline{\theta}_W$ at 0.314. This means black defendants draw from an overall weaker distribution of cases. Interestingly, the model also finds that black defendants were subject to substantially more prosecutor bias ($k_B = 0.613$) than white defendants ($k_W = 0.493$). The regression results in Chapter 6 found some evidence of this in particular subgroups, but the structural model was necessary to reveal the disparity in aggregate data.

Figures 8.1, 8.2, and 8.3 present the response of selected moments to changes in simulation parameters. Each line holds all other parameters constant and varies one parameter in the region around its estimated value. The solid lines set other parameters to their optimal values. The dotted and dashed lines set a related parameter to a value that is lower or higher than its optimal value, respectively. These figures select combinations of parameters and moments where changing the parameter has an obvious and monotonic effect on the simulated moment. This is not a formal proof of identification, but it provides intuition about the connections between particular moments and parameters in the model.

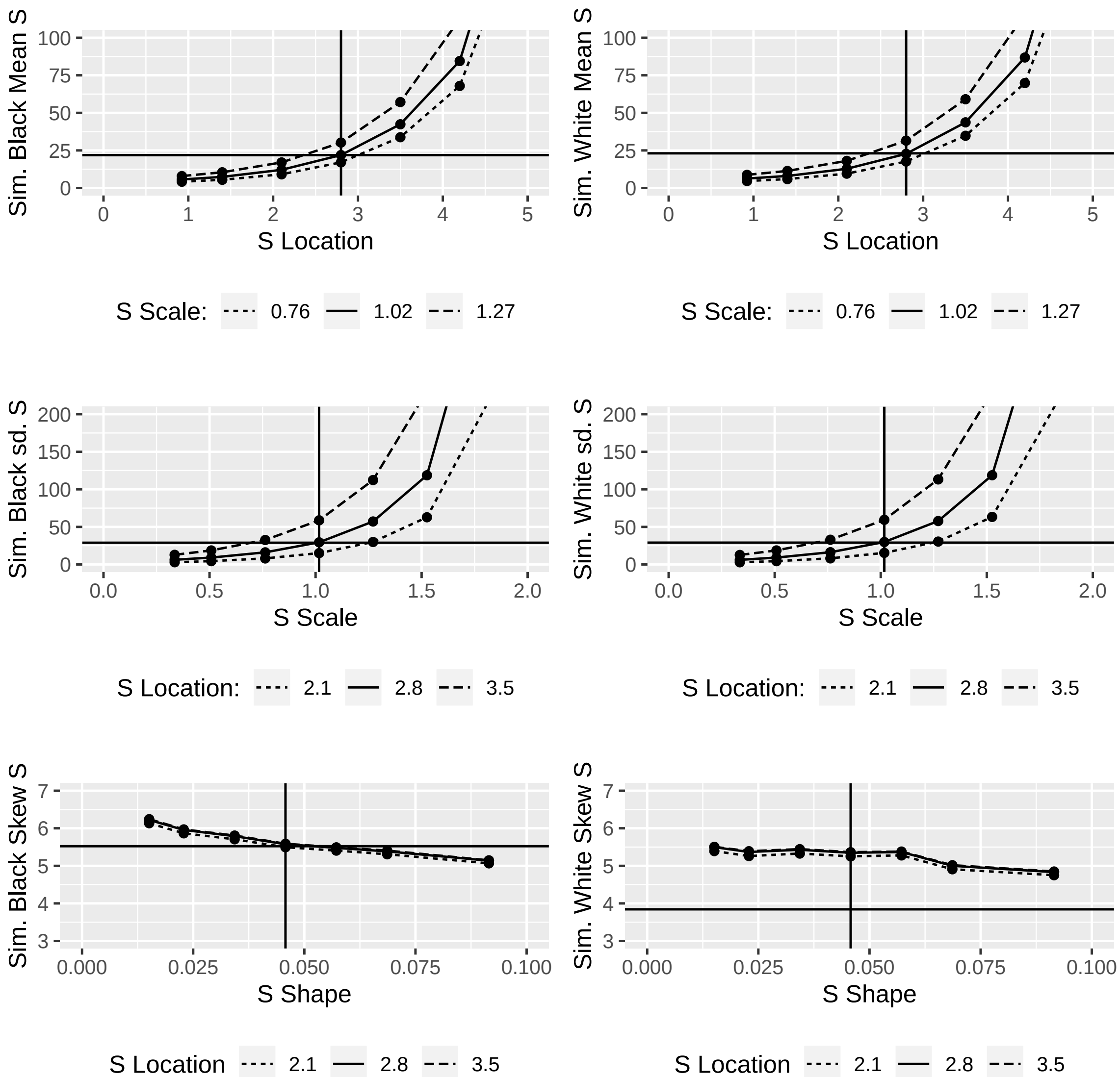
Figure 8.1 highlights the difficulty my model has fitting trial conviction probabilities. These probabilities (shown in the lower panel) seem to only be affected by $\underline{\theta}_B$ and $\underline{\theta}_W$ . Varying $k_B$ and $k_W$ has no effect. However, the model does not have unlimited leeway to vary $\underline{\theta}_B$ and $\underline{\theta}_W$ to match these moments, because they clearly affect drop rates (shown in the upper panel). Figure 8.2 sheds light on my model's failure to fit white sentencing skew. The sentencing shape parameter, $Q_S$, has a clear effect on black sentencing skew in

**Figure 8.1**. Simulated Moment Responses to Parameter Shifts Pt. 1



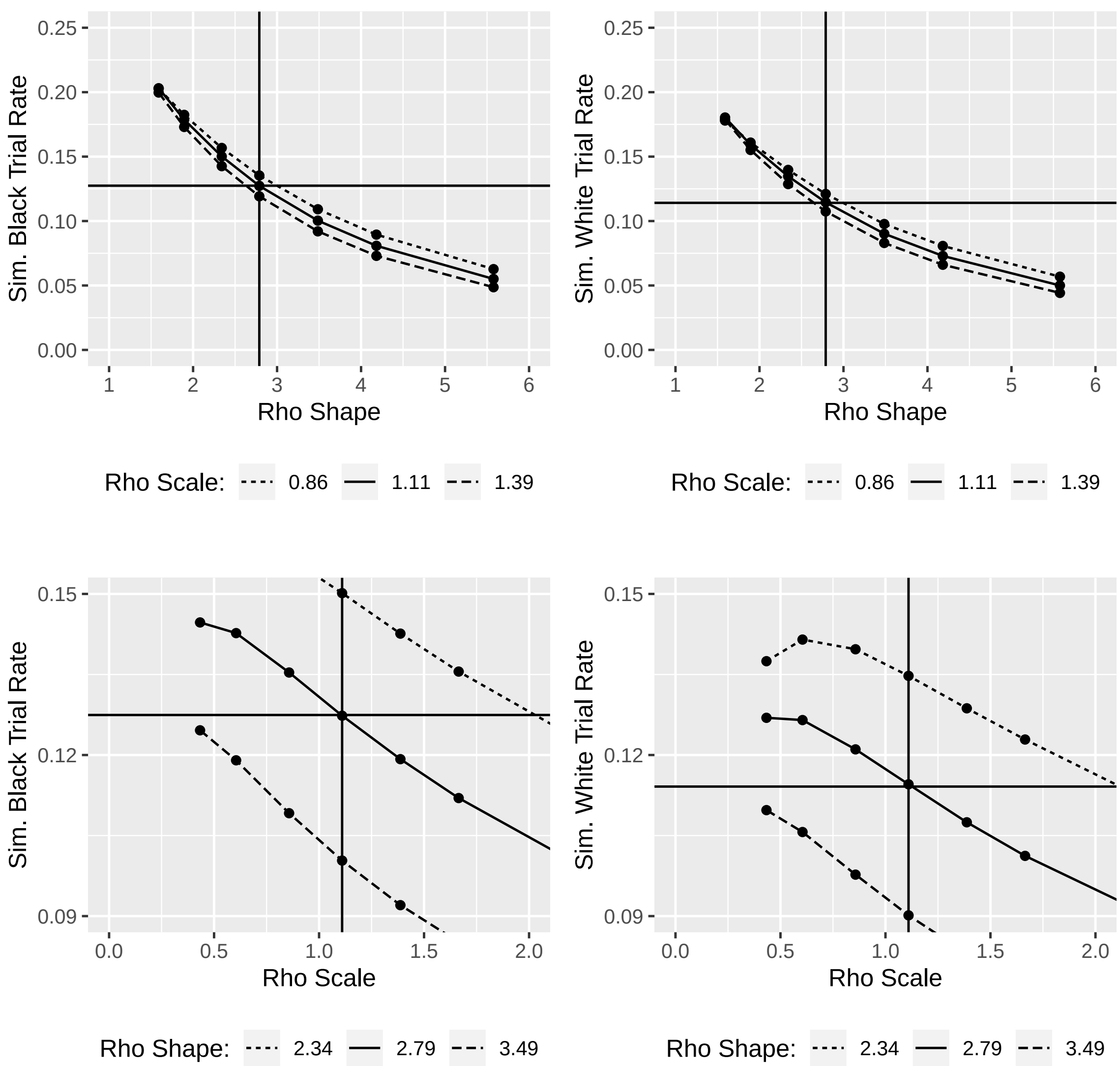

*Notes:* This figure shows the response of selected simulated moments to changes in the race-specific values of $k$ and distributions of $\theta$. The vertical line denotes the value of the parameter found by my estimation procedure. The horizontal line denotes the value of the moment in the data. The solid curve holds constant all other parameter values at those estimated in Table 8.1. The dotted and dashed curves set the value of a selected parameter above and below its optimal value, respectively.

**Figure 8.2**. Simulated Moment Responses to Parameter Shifts Pt. 2




*Notes:* This figure shows the response of selected simulated moments to changes in the distribution of *S*. The vertical line denotes the value of the parameter found by my estimation procedure. The horizontal line denotes the value of the moment in the data. The solid curve holds constant all other parameter values at those estimated in Table 8.1. The dotted and dashed curves set the value of a selected parameter above and below its optimal value, respectively.

**Figure 8.3**. Simulated Moment Responses to Parameter Shifts Pt. 3




*Notes:* This figure shows the response of selected simulated moments to changes in the distribution of ρ. The vertical line denotes the value of the parameter found by my estimation procedure. The horizontal line denotes the value of the moment in the data. The solid curve holds constant all other parameter values at those estimated in Table 8.1. The dotted and dashed curves set the value of a selected parameter above and below its optimal value, respectively.

the region observed, so my model cannot alter it to match white sentencing skew without failing to match black skew, a moment it gives more weight to.

## *Counterfactual Analysis*

Policies that attempt to directly influence or equalize θ distributions or values of $k$ have the appeal of being conceptually simple within my theoretical framework, but they may be prohibitively difficult to implement in a real court system. If the party responsible for enforcing the policy cannot observe θ with the same accuracy as the parties actually involved in the case, they will have difficulty determining if certain cases are too weak or certain plea bargains influenced by bias.

Instead I consider two straightforward policy changes that do not have obvious consequences for racial outcome disparities. The first is a policy that reduces sentencing severity across all crimes, which I parameterize as a 20% reduction in $\mu_S$. The second is a policy that forbids plea bargaining, forcing all cases to go to trial. While these policies cannot directly address underlying inequities in the courts, it may still be interesting to know what effect, if any, they have on disparities in outcomes.[4]

Table 8.2 presents black and white trial rate and sentencing distribution information for the baseline specification and my two counterfactual scenarios. To keep a consistent measure of trial rate and sentencing gaps across policies that change the levels of these measures, I also present the ratio of black to white in each. I find first that reducing the mean of the sentencing distribution, predictably, reduces average realized sentences and their variance. It also reduces the rate at which defendants demand trial by lowering the stakes of those trials. It has only a small effect on trial rate and sentencing gaps, increasing

4. It is also worth considering whether it is *desirable* to close an outcome gap, especially the sentencing outcome gap, with such a policy. Black defendants would continue to face weaker cases, but they would no longer be partially compensated for this with shorter expected sentences.

Table 8.2: Counterfactual Analysis

| Moment | Baseline | Red. Sentence | No Pleas |
|---|---|---|---|
| Black Trial Rate | 12.7% | 11% | 100% |
| White Trial Rate | 11.5% | 9.7% | 100% |
| Black Trial/White Trial | 1.11 | 1.13 | 1 |
| Black Sentence Mean | 21.9 | 13.5 | 17.6 |
| White Sentence Mean | 22.7 | 14.2 | 18.6 |
| Black Sent/White Sent | 0.96 | 0.95 | 0.94 |
| Black Sentence SD | 29.5 | 17.3 | 30.9 |
| White Sentence SD | 29.9 | 17.6 | 31.1 |

*Notes:* This table displays the impact of two counterfactual exercises on the trial rates and sentence distribution (in months) of black and white defendants. The reduced sentence counterfactual reduces the mean of the sentencing distribution by 20%. The no pleas counterfactual forces all cases to go to trial

(moving away from 1) both. When potential sentences are less extreme, it appears that outcomes for black defendants better reflect the fact that weaker cases are being brought against them.

In the third column of Table 8.2, I find that eliminating plea bargaining would decrease average sentences and increase sentencing variation. This is consistent with the basic mechanism of plea bargaining, where the defendant insures themselves against an uncertain outcome at the cost of a longer expected sentence. However, the effect is not uniform across black and white defendants. I find that sentences fall more for black defendants in the absence of plea bargaining, thus increasing the sentencing gap. This is because prosecutors in my model can only exercise their bias through plea bargaining. I estimate that $k_B > k_W$, so prosecutors in the baseline case exert relatively more upward pressure on sentences for black defendants. It is important to note, however, that by removing a choice for the defendant, a policy that forbids plea bargaining could only ever reduce their utility. Even if prosecutors were absurdly biased, defendants would retain the option to go to trial, so they would only accept a plea bargain if they preferred it to a trial.

# CHAPTER 9

# POLICE BIAS

The results in Chapters 6 and 8 indicate that black defendants tend to face cases with a lower probability of conviction at trial. This chapter considers the possibility that this finding is driven by decisions police make about which suspects become defendants. I first show that a standard model of police bias can generate the necessary differences in $\theta$ distributions for black and white defendants. I then use a simple outcome test to check for this kind of police bias. I apply the test to outcomes that occur prior to inclusion in my court sample: felony review and probable cause. These tests show that police may apply a lower threshold to arresting black suspects, which could contribute both to the relative abundance of black defendants and the relative weakness of the cases against them.

## 9.1 A Simple Model of the Arrest Decision

A police officer encounters a suspect and observes a noisy signal of probability of conviction, $\tilde{\theta} = \theta + \varepsilon$ where $\theta$ is drawn from a distribution $H(\theta)$ and $\varepsilon$ is a noise term drawn from the distribution $E(\varepsilon)$. Neither distribution depends on race. The officer must decide either to arrest the suspect, $a = 1$, or let them go, $a = 0$. If the officer arrests the suspect, they receive a reward of $R\theta$ with $R > 0$. However, to make the arrest, they must pay a cost $\lambda_j$ that may depend on the suspect's race $j$. The police officer's decision is characterized by the problem:

$$\max_{a \in \{0,1\}} E\left[a\left(R\left(\tilde{\theta} - \varepsilon\right) - \lambda_j\right)\right]$$

The solution to this problem is immediate:

$$a^* = \begin{cases} 0 & R\tilde{\theta} \leq \lambda_j \\ 1 & R\tilde{\theta} > \lambda_j \end{cases}$$

This solution implies a cutoff value $\theta_j^* = \lambda_j/R$ such that the police officer always arrests the suspect if $\tilde{\theta} > \theta_j^*$ and lets them go free if $\tilde{\theta} \leq \theta_j^*$. As the fixed cost of making an arrest decreases, the police officer will decrease their arrest threshold. Thus, if the police officer perceives a lower cost for arresting black suspects, $\lambda_B < \lambda_W$, they will set a lower arrest threshold for black suspects $\theta_B^* < \theta_W^*$. [1]

This difference in arrest thresholds is sufficient to produce the kind of variation in $\theta$ distributions that is detectable by my model. The $\theta$ distribution of suspects from group $j$ who are arrested and proceed to court is $H\left(\theta|\tilde{\theta} > \theta_j^*\right)$. When $\theta_B^* < \theta_W^*$, $H\left(\theta|\tilde{\theta} > \theta_W^*\right) >_{ST} H\left(\theta|\tilde{\theta} > \theta_B^*\right)$. If $k_B = k_W$, this will generate data where $\Delta T > 0$ and $\Delta L < 0$, as observed in the Cook County Courts.

In Appendix A, I develop a more complex model where an unbiased felony review prosecutor has an opportunity to intervene after the arrest decision. It shows that so long as police do not observe $\theta$ perfectly, police bias against black suspects will still cause the eventual $\theta$ distribution for white defendants to stochastically dominate that of black defendants. The intuition behind this result is that a police force that observes a noisy signal of $\theta$ will err in two ways. First, they will arrest suspects who actually have a low $\theta$. Second, they will decline to arrest suspects who actually have a high $\theta$.When the arrest threshold for black suspects is set below the arrest threshold for white suspects, police will arrest relatively more low-$\theta$ black suspects and release relatively more high-$\theta$ white suspects. An unbiased prosecutor who intervenes after the fact can correct the first error

1. A difference in costs that depends on the race of the suspect is frequently used to parameterize police bias (KPT 2001, Anwar and Fang 2006). An equivalent way to represent bias is a multiplicative shift in the reward function, such as allowing $R$ to depend on race.

by releasing all low-$\theta$ arrestees. However, he cannot correct the second error because the released high-$\theta$ suspects cannot be recalled.

## 9.2 Outcome Tests

I use the SAO data sample described in Chapter 5 and a linear probability model to conduct simple outcome tests. My outcomes of interest are passing felony review and meeting the probable cause standard. My regression includes age, sex, and dummy variables for year of arrest and offense category. My variable of interest is an indicator that the suspect is black. Under the assumptions of the simple model above, the coefficient on the black suspect indicator is informative about the relative choice of arrest threshold on the part of the police. If police set a lower arrest threshold for black suspects, the black cases they send to the SAO will be weaker and less likely to pass the felony review or probable cause filters.

I find in Table 9.1 that a case against a black suspect is about 1.1% less likely to pass felony review. 10% of cases overall fail felony review, so the State's Attorney's office rejects roughly 10 black cases for every 9 white cases. I next look at whether cases pass the standard of probable cause at a preliminary hearing, conditional on passing felony review. I find that cases against black suspects are about 0.8% less likely to meet this standard.

## 9.3 Infra-Marginality

The simple model in this chapter assumes away the infra-marginality problem in the literature by drawing $\theta$ and $\varepsilon$ from distributions that do not depend on race. If initial $\theta$ distributions are instead allowed to differ arbitrarily by race, one could generate data that yield the empirical results in this chapter even if police are unbiased. If white suspects tend to have $\theta$ values that are extremely above some unbiased threshold and black suspects tend

Table 9.1: Felony Review and Probable Cause

| | Felony Review | Probable Cause |
|---|---|---|
| Black | -0.0119*** | -0.00841** |
| | (0.00358) | (0.00310) |
| Age | -0.0000537 | -0.000747*** |
| | (0.000103) | (0.0000889) |
| Male | 0.0213*** | 0.0304*** |
| | (0.00390) | (0.00365) |
| Observations | 68527 | 61891 |
| Adjusted $R^2$ | 0.044 | 0.034 |
| Year FE | Yes | Yes |
| Charge Conditioning samp Sample | Cat FE | Cat FE |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes:* This table presents the results of regressions in the State's Attorney's data of an indicator for black suspects on indicators for whether the case passed felony review, met probable cause, and met probable cause conditional on passing felony review. Standard errors are robust to heteroskedasticity. See Chapter 5 for details about sample selection.

to have $\theta$ values that are only slightly above this threshold, the conditional $\theta$ distribution for white defendants can stochastically dominate the conditional $\theta$ distribution for black defendants.

I make this assumption because it is particularly difficult to address the infra-marginality problem around the arrest decision. KPT (2001) do so by having suspects and police play a game that causes *all* suspects offend with equal probability, but this would trivialize a setting where police base their decisions on the probability of conviction. What varies in my setting is precisely what KPT hold constant. Arnold, Dobbie, and Yang (2018) address the infra-marginality problem with an instrumental variables approach, but this technique is not readily applied to arrests because I do not observe people who were considered as suspects but not arrested.

Table 9.2: Trial Takeup and Conviction

| | Trial Takeup | Conviction |
|---|---|---|
| Black | -0.0106** | -0.0177*** |
| | (0.00339) | (0.00350) |
| Male | -0.00843* | -0.0113* |
| | (0.00405) | (0.00456) |
| Public Defender | 0.0350*** | 0.0398*** |
| | (0.00341) | (0.00346) |
| Ever in Jail | 0.0391*** | 0.0440*** |
| | (0.00498) | (0.00536) |
| Multiple Defendants | -0.00960* | -0.0182*** |
| | (0.00467) | (0.00474) |
| Multiple Charges | 0.0112** | 0.0325*** |
| | (0.00346) | (0.00317) |
| Observations | 39510 | 36761 |
| Adjusted $R^2$ | 0.044 | 0.080 |
| Charge Cond. | ClassXCat FE | ClassXCat FE |
| Assignment Cond. | CtrmXYear FE | CtrmXYear FE |

Standard errors in parentheses

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

This table presents the results of regressions in the Cook County Court data of an indicator for black suspects on indicators for whether the case was not dropped by the prosecution and whether the defendant was convicted. See Chapter 5 for details about sample selection. This sample further excludes drug cases and cases initiated before 2011.

Table 9.2, together with Table 9.1, provides some evidence that infra-marginality may not be a problem in my data. These regressions cover the four major decision points I can see across my data: felony review, probable cause hearing, taken up (not dropped) by trial prosecutor, and convicted. Each regression uses the sample of defendants who advanced past the prior decision point.[2] For comparability, I restrict the regressions that use the Circuit Court data to non-drug cases from 2011-2016. At every stage, black defendants are less likely to proceed. This shows that the disparity between white and black defendants is present at not just one margin but many. In the standard infra-marginality story, this relationship must eventually flip as the margin considered begins to infringe upon the mass of high-quality cases against white defendants. It is, however, possible that all of the margins I am able to study fall before this critical point.

2. I cannot track individual cases between the probable cause hearing and trial prosecutor take up because the latter occurs in the SAO data and the former in the Circuit Court data. However, cases in the Circuit Court data have, by definition, passed probable cause.

# CHAPTER 10

# CONCLUSION

In this paper I used a model of plea bargaining to understand more about bias in the criminal justice system. My model explores two unobservable reasons why criminal justice outcomes might differ: case strength and prosecutor bias. From the comparative statics of that model, I derived a method for distinguishing between the two using conventional court data. Greater case strength in a population allows prosecutors to secure both longer plea bargain sentences and fewer trials. Bias forces prosecutors to exchange longer sentences for more trials. I derived precise conditions under which this intuition applies.

I then investigated outcome patterns in felony court data from Chicago. I found that black defendants tend to receive shorter sentences and demand more trials. According to my model, this indicates that they face weaker cases overall. A structural estimation of my model confirmed the conclusion of the reduced form results. I conjectured that the weaker cases against black suspects could be driven by the rules police use to arrest suspects. If police set a lower arrest threshold for black suspects, this could simultaneously explain why black defendants face weaker cases and why they make up a much higher proportion of the defendant population. I found evidence that arrest decisions made by police are less likely to meet the felony review or probable cause standard if the suspect is black. By the logic of a conventional outcome test, this means that police do indeed set a lower threshold for black suspects. Future research should apply the framework of this paper to other court datasets to see if my findings about Chicago hold elsewhere. It should also pursue new data or techniques to better evaluate the arrest decisions made by police.

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# APPENDIX A: MATHEMATICAL ANALYSIS

## *Proof of Proposition 3.1*

Using the fact that $\delta^* = 0$, I can rewrite the defendant's problem as:

$$\min_{\alpha \in \{0,1\}} (1-\alpha)\left(\theta \frac{S^\rho}{\rho}\right) + \alpha \frac{s^\rho}{\rho}$$

Her objective is maximized by the following policy:

$$\alpha^* = \begin{cases} 0 & s^\rho > \theta S^\rho \\ 1 & s^\rho \leq \theta S^\rho \end{cases}$$

Rearranging to express this choice as a direct function of the defendant's risk tolerance type, I find the threshold value of:

$$\hat{\rho}(s) = \frac{\ln \theta}{\ln s - \ln S}$$

$\theta$ is a probability that lies in $(0,1)$, so $\ln \theta < 0$ and $\ln s - \ln S < 0$ by assumption. Therefore, $\hat{\rho}(s) > 0$ and $\hat{\rho}(s)$ is strictly increasing in $s$. Therefore, $\rho < \hat{\rho}(s)$ is equivalent to $s^\rho > \theta S^\rho$ and leads the defendant to reject the plea deal. $\rho \geq \hat{\rho}(s)$ is equivalent to $s^\rho \leq \theta S^\rho$ and leads the defendant to accept the plea deal.

## *Proof of Proposition 3.2*

First, suppose the prosecutor chooses an $\tilde{s} > S$. The defendant will never accept this plea bargain, so the prosecutor will always receive $\theta k_j S - c$. However, for any $\hat{s} \in (\theta S, S)$, the prosecutor's objective evaluated at $\hat{s}$ is a convex combination of $\theta k_j S - c$ and $k_j \hat{s} > \theta k_j S - c$. Therefore, a choice of $\tilde{s} > S$ is not optimal for the prosecutor.

Second, suppose the prosecutor chooses an $\tilde{s} < \theta S$. Note that $\hat{\rho}(\theta S) = 1$ and $\hat{\rho}(\tilde{s}) < 1$, so $G(\hat{\rho}(\theta S)) = G(\hat{\rho}(\tilde{s})) = 0$ . Therefore, the value of the prosecutor's objective when he offers $\tilde{s}$ is $k_j \tilde{s}$, but if he were to offer $\theta S$ instead, the value of his objective would be $k_j \theta S > k_j \tilde{s}$. Therefore, offering $\tilde{s} < \theta S$ can never be optimal.

Using the fact that $\delta^* = 1$ and incorporating the defendant's cutoff strategy, I can rewrite the prosecutor's choice of plea bargain when $s < S$ as:

$$\max_{s \in (\theta S, S)} G(\hat{\rho}(s)) \left(\theta k_j S - c\right) + (1 - G(\hat{\rho}(s))) k_j s$$

The FOC of this optimization problem defines an optimal choice $s^*$ and the critical $\rho$ induced by this choice $\rho^* = \hat{\rho}(s^*)$:

$$(1 - G(\rho^*)) k_j - g(\rho^*) \frac{\partial \hat{\rho}(s)}{\partial s}|_{s=s^*} k_j s^* + g(\rho^*) \frac{\partial \hat{\rho}(s)}{\partial s}|_{s=s^*} \left(\theta k_j S - c\right) = 0$$

Where $\frac{\partial \hat{\rho}(s)}{\partial s}|_{s=s^*} = \frac{-\ln\theta}{(\ln(s^*) - \ln S)^2 s^*} = \frac{-\rho^*}{(\ln(s^*) - \ln S) s^*}$. Moving the second two terms to the right of 0 and cross-multiplying yields:

$$\frac{s^*(\ln S - \ln(s^*))}{s^* - \theta S + c/k_j} = \frac{g(\rho^*)}{1 - G(\rho^*)} \rho^*$$

Notice that the RHS of this expression is non-negative for all $\rho^*$ and increasing in $\rho^*$. Because $\rho^*$ is increasing in $s^*$, the RHS is increasing in $s^*$.

Next, observe that:

$$\frac{\partial LHS}{\partial s^*} = \frac{\left(s^* - \theta S + c/k_j\right)\left(\ln S - \ln\left(s^*\right) - 1\right) - s^*\left(\ln S - \ln\left(s^*\right)\right)}{\left(s^* - \theta S + c/k_j\right)^2}$$
$$= \frac{\left(c/k_j - \theta S\right)\left(\ln S - \ln\left(s^*\right)\right) - \left(s - \theta S + c/k_J\right)}{\left(s^* - \theta S + c/k_j\right)^2}$$

Recall that due to the prosecutor's ability to drop the case, $\theta S k_j - c > 0$, which implies $c/k_j - \theta S < 0$. Therefore, the LHS is is strictly decreasing in $s^*$.

When $s^* = \theta S$, the RHS smoothly approaches 0, and the LHS is positive. Furthermore when $s^* = S$, the LHS is 0. In conclusion, the LHS begins above the RHS and descends monotonically to 0 while the RHS rises monotonically from 0. Therefore, the two must intersect once and only once in the interval $(\theta S, S)$ at the prosecutor's unique, optimal choice of plea bargain sentence.

## *Sentencing Comparative Statics (Proofs of Propositions 3.3 and 3.4)*

When calculating effects on $s^*$ and $\rho^*$ it will be convenient to explicitly write the LHS and RHS each in terms of exclusively $\rho^*$ or $s^*$:

$$LHS_s = \frac{s^*\left(\ln S - \ln\left(s^*\right)\right)}{\left(s^* - \theta S + c/k_j\right)}$$

$$RHS_s = \frac{g\left(\frac{\ln\theta}{\ln(s^*) - \ln S}\right)}{1 - G\left(\frac{\ln\theta}{\ln(s^*) - \ln S}\right)} \frac{\ln\theta}{\ln\left(s^*\right) - \ln S}$$

$$LHS_\rho = \frac{-\theta^{1/\rho^*} S \ln\theta/\rho*}{\left(\theta^{1/\rho^*} S - \theta S + c/k_j\right)}$$

$$RHS_\rho = \frac{g\left(\rho^*\right)}{1 - G\left(\rho^*\right)}\rho^*$$

The main text establishes that $\frac{\partial LHS_s}{\partial s^*} < 0$. Observe that:

$$\left(\theta^{1/\rho^*}S - \theta S + {}^{c}\!/_{k_j}\right)^2 \frac{\partial LHS_\rho}{\partial \rho^*} = \left(\theta^{1/\rho^*}S - \theta S + {}^{c}\!/_{k_j}\right)\left(\theta^{1/\rho^*}S\frac{(\ln\theta)^2}{(\rho^*)^3} + \theta^{1/\rho^*}S\frac{\ln\theta}{(\rho^*)^2}\right)$$
$$+\theta^{1/\rho^*}S\frac{(\ln\theta)^2}{(\rho^*)^3}\theta^{1/\rho^*}S$$

which simplifies to:

$$\theta^{1/\rho^*}S\frac{\ln\theta}{(\rho^*)^2}\left[\left({}^{c}\!/_{k_j} - \theta S\right)\frac{\ln\theta}{\rho^*} + {}^{c}\!/_{k_j} - \theta S + \theta^{1/\rho^*}S\right] < 0$$

Using the facts that ${}^{c}\!/_{k_j} - \theta S + \theta^{1/\rho^*}S > 0$ from the FOC and that ${}^{c}\!/_{k_j} - \theta S < 0$ from the condition on cases the prosecutor does not drop.

### $\hat{\rho}(s)$

First I establish basic facts about the function that defines the cutoff value of $\rho$. Note that $\theta \in (0,1)$, so $\ln\theta < 0$, and recall that $s^* < S$.

$$\frac{\partial\hat{\rho}(s)}{\partial s} = \frac{-\ln\theta}{(\ln(s) - \ln S)^2}\frac{1}{s} > 0$$

$$\frac{\partial\hat{\rho}(s)}{\partial S} = \frac{\ln\theta}{(\ln(s) - \ln S)^2}\frac{1}{S} < 0$$

$$\frac{\partial\hat{\rho}(s)}{\partial\theta} = \frac{1}{(\ln(s) - \ln S)}\frac{1}{\theta} < 0$$

## Relative Prosecutor Trial Cost ${}^{c}\!/_{k_j}$

Taking derivatives

$$\frac{\partial LHS_s}{\partial c/k_j} = \frac{s^*\left(\ln\left(s^*\right) - \ln S\right)}{\left(s^* - \theta S + c/k_j\right)^2} < 0$$

$$\frac{\partial RHS_s}{\partial c/k_j} = 0$$

$$\frac{\partial LHS_\rho}{\partial c/k_j} = \frac{\theta^{1/\rho^*} S \ln\theta/\rho^*}{\left(\theta^{1/\rho^*}\left(S+\gamma\right) - \theta S + c/k_j\right)^2} < 0$$

$$\frac{\partial RHS_\rho}{\partial c/k_j} = 0$$

Then by the implicit function theorem, noting that the denominators are negative:

$$\frac{\partial s^*}{\partial c/k_j} = \frac{-\left(\frac{\partial LHS_s}{\partial c/k_j} - \frac{\partial RHS_s}{\partial c/k_j}\right)}{\left(\frac{\partial LHS_s}{\partial s^*} - \frac{\partial RHS_s}{\partial s^*}\right)} < 0$$

$$\frac{\partial \rho^*}{\partial c/k_j} = \frac{-\left(\frac{\partial LHS_\rho}{\partial c/k_j} - \frac{\partial RHS_\rho}{\partial c/k_j}\right)}{\left(\frac{\partial LHS_\rho}{\partial \rho^*} - \frac{\partial RHS_\rho}{\partial \rho^*}\right)} < 0$$

A clear consequence of this is that $\frac{\partial s^*}{\partial k_j} > 0$ and $\frac{\partial \rho^*}{\partial k_j} > 0$.

## Probability of Conviction θ

Taking derivatives

$$\frac{\partial LHS_s}{\partial \theta} = \frac{s^*\left(\ln S - \ln\left(s^*\right)\right) S}{\left(s^* - \theta S + c/k_j\right)^2} > 0$$

$$\frac{\partial RHS_s}{\partial \theta} = \frac{\partial RHS_\rho}{\partial \rho^*}\frac{\partial \hat{\rho}\left(s\right)}{\partial \theta} < 0$$

$$\frac{\partial LHS_\rho}{\partial \theta} = \frac{\theta^{1/\rho^*}\frac{S}{\rho^*}\left[\left(\theta S - {}^{c}\!/_{k_j}\right)\frac{1}{\theta}\left(1+\frac{\ln\theta}{\rho^*}\right) - \theta^{\frac{1-\rho^*}{\rho^*}} S - S\ln\theta\right]}{\left(\theta^{1/\rho^*} S - \theta S + {}^{c}\!/_{k_j}\right)^2} < 0$$

When $\theta \geq e^{-\rho^*}$. To see this, change variables to $\theta = e^{-y}$ and call the expression in the brackets in the numerator $\Phi(y)$:

$$\Phi(y) = S\left[y - e^{y\left(1-\frac{1}{\rho^*}\right)} + 1 - \frac{y}{\rho^*}\right] - \frac{c}{k_j}\frac{e^y}{\rho^*}(\rho^* - y)$$

Notice that the last term is non-positive for any $y \leq \rho^*$ (which is analogous to $\theta \geq e^{-\rho^*}$). The first term is 0 when evaluated at $y = 0$, and its derivative with respect to $y$ is:

$$\left(1 - e^{y\left(1-\frac{1}{\rho^*}\right)}\right)\left(1 - \frac{1}{\rho^*}\right) < 0$$

Therefore, $\Phi(0) < 0$, and increasing $y$ from 0 cannot turn $\Phi(y)$ positive, at least so long as $y \leq \rho^*$. Finally, the sign of $\frac{\partial LHS_\rho}{\partial \theta}|_{\theta=e^{-y}}$ is determined by $\Phi(y)$.

$$\frac{\partial RHS_\rho}{\partial \theta} = 0$$

Then by the implicit function theorem, noting that the denominators are negative:

$$\frac{\partial s^*}{\partial \theta} = \frac{-\left(\frac{\partial LHS_s}{\partial \theta} - \frac{\partial RHS_s}{\partial \theta}\right)}{\left(\frac{\partial LHS_s}{\partial s^*} - \frac{\partial RHS_s}{\partial s^*}\right)} > 0$$

$$\frac{\partial \rho^*}{\partial \theta} = \frac{-\left(\frac{\partial LHS_\rho}{\partial \theta} - \frac{\partial RHS_\rho}{\partial \theta}\right)}{\left(\frac{\partial LHS_\rho}{\partial \rho^*} - \frac{\partial RHS_\rho}{\partial \rho^*}\right)} < 0$$

## Statutory Sentence $S$

Taking derivatives

$$\frac{\partial LHS_s}{\partial S} = \frac{\left(s^* - \theta S + c/k_j\right)\frac{s^*}{S} + s^*\left(\ln S - \ln\left(s^*\right)\right)\theta}{\left(s^* - \theta S + c/k_j\right)^2} > 0$$

$$\frac{\partial RHS_s}{\partial S} = \frac{\partial RHS_\rho}{\partial \rho^*}\frac{\partial \hat{\rho}(s)}{\partial S} < 0$$

$$\frac{\partial LHS_\rho}{\partial S} = \frac{-\left(\theta^{1/\rho^*} S - \theta S + c/k_j\right)\theta^{1/\rho^*}\ln\theta/\rho^* + \theta^{1/\rho^*}\ln\theta/\rho^* S\left(\theta^{1/\rho^*} - \theta\right)}{\left(\theta^{1/\rho^*} S - \theta S + c/k_j\right)^2} > 0$$

$$\frac{\partial RHS_\rho}{\partial S} = 0$$

Then by the implicit function theorem, noting that the denominators are negative:

$$\frac{\partial s^*}{\partial S} = \frac{-\left(\frac{\partial LHS_s}{\partial S} - \frac{\partial RHS_s}{\partial S}\right)}{\left(\frac{\partial LHS_s}{\partial s^*} - \frac{\partial RHS_s}{\partial s^*}\right)} > 0$$

$$\frac{\partial \rho^*}{\partial S} = \frac{-\left(\frac{\partial LHS_\rho}{\partial S} - \frac{\partial RHS_\rho}{\partial S}\right)}{\left(\frac{\partial LHS_\rho}{\partial \rho^*} - \frac{\partial RHS_\rho}{\partial \rho^*}\right)} > 0$$

# *Comparative Statics of Observed Sentences*

## Probability of Conviction $\theta$

Observe that the derivative of observed sentences with respect to $\theta$ is:

$$\frac{\partial L}{\partial \theta} = (1 - G(\rho^*)) \frac{\partial s^*}{\partial \theta} + G(\rho^*) S - (s^* - \theta S) g(\rho^*) \frac{\partial \rho^*}{\partial \theta}$$

Using the fact that $s^* \geq \theta S$ and $\frac{\partial \rho^*}{\partial \theta} < 0$, this is always positive.

## Prosecutor Bias $k_j$

Define the prosecutor's value function as:

$$V = G\left(\frac{\ln \theta}{\ln s^* - \ln S}\right)\left(\theta S k_j - c\right) + \left(1 - G\left(\frac{\ln \theta}{\ln s^* - \ln S}\right)\right) s^* k_j$$

So by the Envelope Theorem:

$$\frac{\partial V}{\partial k_j} = G(\rho^*) \theta S + (1 - G(\rho^*)) s^*$$

Then note that observed sentences relate to $V$ as:

$$L = \frac{V + G\left(\frac{\ln \theta}{\ln s^* - \ln S}\right) c}{k_j} = \frac{\partial V}{\partial k_j}$$

Therefore

$$\frac{\partial L}{\partial k_j} = \frac{k_j \left(\frac{\partial V}{\partial k_j} + g\left(\frac{\ln \theta}{\ln s^* - \ln S}\right) \frac{\partial \rho^*}{\partial k_j} c\right) - \left(V + G\left(\frac{\ln \theta}{\ln s^* - \ln S}\right) c\right)}{k_j^2} = g(\rho^*) \frac{\partial \rho^*}{\partial k_j} \frac{c}{k_j} > 0$$

## *Proof of Proposition 4.2*

Because $c$, $S$, and $G(\rho)$ do not vary across group, the only candidates for explaining the cross-group differences in average plea bargain sentence length and average plea bargain acceptance rate are $F(\theta | j)$ and $k_j$.

First, suppose that $F(\theta|B)$ first-order stochastic dominates $F(\theta|W)$. Assume that $k_B = k_W$. Then, $\Delta L > 0$. Likewise, because $\rho^*$ is decreasing in $\theta$, $\Delta T < 0$. This yields a contradiction. Letting $k_B < k_W$ will only exacerbate the contradiction because $T$ is increasing in $k_j$. However, for $k_B$ sufficiently larger than $k_W$, the effect of prosecutor bias on $T$ can offset that of case strength, giving $\Delta T > 0$. Meanwhile, the effect of prosecutor bias on $L$ would only reinforce the effect of case strength.

Next, suppose that $F(\theta|W)$ first-order stochastic dominates $F(\theta|B)$. Assume that $k_B = k_W$. Then, $\Delta L < 0$ and $\Delta T > 0$. This yields a contradiction. Letting $k_B < k_W$ will only exacerbate the contradiction because $L$ is increasing in $k_j$. However, for $k_B$ sufficiently larger than $k_W$, the effect of prosecutor bias on $L$ can offset the effect of case strength, giving $\Delta L > 0$. Meanwhile, the effect of prosecutor bias on $T$ would only reinforce the effect of case strength.

The second arm of the proof is similar.

## *Differences in Risk Aversion*

Consider a simple parameterization that captures race-specific differences in the risk aversion distribution $G(\rho)$. Let $G_j(\rho) = G(\rho + \psi_j)$ so that groups with a higher value of $\psi_j$ are more likely to draw a low value of $\rho$, which corresponds to higher risk tolerance. Notice that the defendant's cutoff rule does not depend on $\psi_j$, so the only difference in equilibrium behavior comes through the prosecutor's choice of $s^*$, which is determined by:

$$\frac{s^*(\ln S - \ln(s^*))}{s^* - \theta S + c/k_j} = \frac{g(\rho^* + \psi_j)}{1 - G(\rho^* + \psi_j)}\rho^*$$

Using the comparative static framework from earlier in this appendix, clearly $\frac{\partial LHS_s}{\partial \psi_j} = \frac{\partial LHS_\rho}{\partial \psi_j} = 0$. From the assumption that $G(\rho)$ has an increasing hazard rate, I can conclude that $\frac{\partial RHS_s}{\partial \psi_j} > 0$ and $\frac{\partial RHS_\rho}{\partial \psi_j} > 0$. Consequentially, $\frac{\partial s^*}{\partial \psi_j} < 0$ and $\frac{\partial \rho^*}{\partial \psi_j} < 0$. The first comparative static is intuitive. As the typical defendant in a given group becomes more tolerant of risk, the prosecutor must moderate the sentences he offers or else face a higher rate of expensive trials. The second comparative static states that the marginal defendant is now more risk tolerant, and therefore that some types of defendants who would have ordinarily demanded a trial no longer do.

This does not, however, imply that the *trial rate*, $T$, is decreasing in $\upsilon_j$. The acceptance margin has shifted, but the distribution of $\rho$ to compare it against has shifted as well. Using that $T = G\left(\rho^* + \psi_j\right)$, I can calculate:

$$\frac{\partial T}{\partial \psi_j} = g\left(\rho^* + \psi_j\right)\left(\frac{\partial \rho^*}{\partial \psi_j} + 1\right)$$

I next argue that $0 > \frac{\partial \rho^*}{\partial \psi_j} > -1$. That is, the shift in $\rho^*$ induced by changing $\psi_j$ is dominated by the direct change to the risk tolerance distribution and hence to the trial rate.

$$\frac{\partial \rho^*}{\partial \psi_j} = \frac{\frac{\partial RHS_\rho}{\partial \psi_j}}{\frac{\partial LHS_\rho}{\partial \rho^*} - \frac{\partial RHS_\rho}{\partial \rho^*}}$$

The numerator can be written as:

$$\frac{\partial}{\partial x}\left[\frac{g(x)}{1 - G(x)}\right]\rho^*$$

And the denominator as

$$\frac{\partial LHS_\rho}{\partial \rho^*} - \frac{\partial}{\partial x}\left[\frac{g(x)}{1 - G(x)}\right]\rho^* - \frac{g\left(\rho^* + \psi_j\right)}{1 - G\left(\rho^* + \psi_j\right)} < -\frac{\partial}{\partial x}\left[\frac{g(x)}{1 - g(x)}\right]\rho^*$$

The inequality holds because $\frac{\partial LHS_\rho}{\partial \rho^*} < 0$. These facts imply that $0 > \frac{\partial \rho^*}{\partial \psi_j} > -1$. Thus $\frac{\partial T}{\partial \psi_j} = g\left(\rho^* + \psi_j\right)\left(\frac{\partial \rho^*}{\partial \psi_j} + 1\right) > 0$.

Intuitively, the change in $\rho^*$ induced by an increase in $\psi_j$ is moderated by other forces in the prosecutor's problem. Therefore, he only partially counteracts the increase in overall risk tolerance for that group. The overall effect is still to increase trials, albeit less than if the prosecutor had not reacted at all.

Given that $\frac{\partial T}{\partial \psi_j} > 0$ and $\frac{\partial s^*}{\partial \psi_j} < 0$ and recalling $s^* > \theta S$, it is straightforward that

$$\frac{\partial L}{\partial \psi_j} = \frac{\partial T}{\partial \psi_j}\theta S - \frac{\partial T}{\partial \psi_j}s^* + (1-T)\frac{\partial s^*}{\partial \psi_j} = \frac{\partial T}{\partial \psi_j}(\theta S - s^*) + (1-T)\frac{\partial s^*}{\partial \psi_j} < 0$$

This shows that shifts in the risk tolerance distribution must move trial rates and sentence lengths in opposite directions. Therefore, cross-race differences of this form could serve as an alternative explanation to empirical results related to differences in $\theta$ but not differences in $k_j$.

### *Arrest-Driven Differences in $\theta$ with Unbiased Felony Review*

Consider the same model of the police arrest decision presented in Chapter 8. After the arrest decision, the case is sent to a prosecutor who is omniscient and fair. This prosecutor applies the same standard to all cases, dropping them if $\theta \leq \hat{\theta}$. The resulting distribution of defendants is described by $F(\theta|j) = H\left(\theta|\theta + \varepsilon > \tilde{\theta}^*_j \ \&\ \theta > \hat{\theta}\right)$. Observe:

$$F(x|j) = \frac{\int_{-\infty}^{\infty}\int_{\tilde{\theta}^*_j-\varepsilon}^{x} 1\left\{\theta > \hat{\theta}\right\} dh(\theta)\, de(\varepsilon)}{\int_{-\infty}^{\infty}\int_{\tilde{\theta}^*_j-\varepsilon}^{\infty} 1\left\{\theta > \hat{\theta}\right\} dh(\theta)\, de(\varepsilon)}$$

From this, I can write $F(x|B) - F(x|W)$ as:

$$\frac{\left(\int_{-\infty}^{\infty}\int_{\tilde{\theta}^*_B-\varepsilon}^{\tilde{\theta}^*_W-\varepsilon} 1\left\{\theta > \hat{\theta}\right\} dh(\theta)\, de(\varepsilon)\right)\left(\int_{-\infty}^{\infty}\int_{x}^{\infty} 1\left\{\theta > \hat{\theta}\right\} dh(\theta)\, de(\varepsilon)\right)}{\left(\int_{-\infty}^{\infty}\int_{\tilde{\theta}^*_B-\varepsilon}^{x} 1\left\{\theta > \hat{\theta}\right\} dh(\theta)\, de(\varepsilon)\right)\left(\int_{-\infty}^{\infty}\int_{\tilde{\theta}^*_W-\varepsilon}^{x} 1\left\{\theta > \hat{\theta}\right\} dh(\theta)\, de(\varepsilon)\right)} \geq 0$$

Where the inequality comes from the fact that $\tilde{\theta}_B^* < \tilde{\theta}_W^*$. This shows that the $\theta$ distribution of white defendants will first-order stochastic dominate the $\theta$ distribution of black defendants so long as $\int_{-\infty}^{\infty} \int_{\tilde{\theta}_B^* - \varepsilon}^{\tilde{\theta}_W^* - \varepsilon} 1\left\{\theta > \hat{\theta}\right\} dh(\theta)\, de(\varepsilon) > 0$. This condition will hold if there is a non-zero probability of drawing values for $\theta$ and $\varepsilon$ where: the police would arrest a black suspect, the police would not arrest a white suspect, and the prosecutor would accept the case. It is guaranteed to hold if the support of $E(\varepsilon)$ is $\mathbb{R}$.

# APPENDIX B: FELONY COURT IN COOK COUNTY

The information in this appendix is drawn from private conversations with defense attorneys, prosecutors, and judges with extensive experience in the Criminal Division of the Cook County Circuit Court, supplemented with information in IICLE (2017).

## *Arrest and Charging*

Felony cases begin when the suspect is arrested by police. This is shown in the first row of Figure 3. Many agencies have arresting authority within Cook County, including the Chicago Police Department, the police departments of suburban areas within Cook County, the Cook County Sheriff's Office, and the Illinois State Police. Following an arrest, if the police wish to press charges, the arresting officer completes an arrest report that lays out the evidence against the suspect. This arrest report can be thought of as a first draft of the charges against the defendant.

Before becoming a formal felony charge, the case must first be approved by the Cook County State's Attorney (SA). This is shown in the second row of Figure 3. The SA maintains a dedicated Felony Review Unit for this purpose, comprised of a relatively small group of Assistant State's Attorneys (ASAs). Felony Review ASAs are on call 24 hours a day to review and approve charges. In simple cases, they may do this over the phone, but in more complex cases, they will travel to the relevant police station to examine the case directly. Though the police may technically override the decision of the Felony Review ASA, this is a rare occurrence. A felony case that lacks the support of the State's Attorney's Office will almost certainly founder later on. One can think of the Felony Review ASA as responsible for editing the draft charges brought in the police report, bringing them in line with the law and throwing them out when the evidence is too weak.

### *Bail and Preliminary Hearings*

Following felony review, the case moves through two hearings. The first is a bail hearing, which takes place as soon as possible. This is shown in the third row of Figure 3. At this hearing, a bail judge listens to arguments for whether a defendant should be permitted to post a bail bond, and if they are, the amount of that bond. Bail bonds call for the defendant to give the court a specified amount of money as collateral. In return, the defendant is permitted to leave jail while awaiting trial. If the defendant does not return to court when required, they forfeit the collateral and may face additional charges. At the conclusion of court proceedings, the bond is refunded to the defendant, though some fines and costs may be deducted directly from this amount. Illinois only permits individuals to post bail. A defendant may be bailed out by a friend of family member but not by a commercial enterprise like a bail bondsman.

The second hearing is a preliminary hearing where the state shows probable cause. It may be held up to 2 months after arrest. This is shown in the fourth row of Figure 3. The purpose of this hearing is for the SA to show probable cause that the defendant committed a crime. This is a standard of proof well below the "shadow of a doubt" standard used at trial. Probable cause can be shown either in a preliminary hearing or in a grand jury. A preliminary hearing is adversarial; the defendant or their attorney is given the opportunity to present their side of the case to a judge. Preliminary hearings produce a charging document known as an information. A grand jury is not adversarial, so it is typically easier for the SA to establish probable cause. However, grand juries produce a charging document known as an indictment. Unlike an information, an indictment cannot be readily altered by the prosecutor, though the prosecutor can still convict a defendant of a "lesser included offense" of the charges listed in the indictment. At this stage, the prosecutor may also opt to abandon the case. This is not the drop decision I observe in my court data, though it is observable in the State's Attorney's data.

Bail and preliminary hearings are the responsibility of the SA's Preliminary Hearings Unit. One can think of the Preliminary Hearing ASA as responsible for publishing the charges that were drafted by the Felony Review ASA.

### *Arraignment and Assignment*

After the SA has established probable cause, the case proceeds to the office of the Presiding Judge of the Criminal Division for arraignment and assignment. This is shown in the fifth row of Figure 3. At the arraignment, the Presiding Judge reads the charging document produced in the probable cause stage and asks the defendant how they plead. At this stage, nearly all defendants plead not guilty.

If the crime was committed in one of the suburban areas surrounding Chicago but still part of Cook County, the case is sent to the Municipal courthouse for that area. If the crime was committed in Chicago proper, the case is next assigned to a judge in the Criminal Division. This is shown in the sixth row of Figure 3. Typically, this assignment is made by a randomization program maintained by the Clerk of Court. This program randomly assigns the case to one of the permanent judges on the court. Exceptions to this assignment mechanism include: defendants already on probation are assigned to the judge who gave them probation; certain defendants may be diverted to problem solving courts (e.g. drug treatment, mental health, and veterans); some judges handle exclusively drug cases; some particularly difficult or sensitive cases may be diverted to more experienced judges.

Defendants have the right to make one Motion to Substitute Judge within 10 days of the initial judge assignment. The court automatically grants this first motion but will only grant subsequent motions if the defendant is able to prove that the judge assigned to their case showed "animosity, hostility, ill will, or distrust" towards them. I observe all SOJ motions in my data. Anecdotally, this automatic SOJ motion is typically used to avoid judges that are considered to be particularly harsh.

Simultaneously with its assignment to a judge, the case is assigned to an ASA in the Criminal Prosecutions Bureau who will oversee it until its completion. This ASA is typically the prosecutor posted to the courtroom where the assigned judge hears cases. This is the prosecutor whose problem is captured in my model. Importantly, by the time the case reaches the hands of the Criminal Prosecutions prosecutor, three other actors have contributed to the charging document (the arresting officer, Felony Review ASA, and Preliminary Hearing ASA), and if that charging document is an indictment, it belongs to the grand jury in the sense that the prosecutor may not freely alter it. Thus, I model my prosecutor as taking the charges against the defendant as given.

### *Discovery*

Illinois has strong discovery rules intended to "promote the search for the truth and to eliminate surprise as a trial tactic." Upon the request of the defense, prosecutors are required to disclose:

- The identities and criminal records of all intended witnesses and their statements
- All statements made by the defendant
- Minutes from any grand jury proceedings
- Expert witness reports and medical/scientific test results
- Documentary, physical, and surveillance evidence

- Any material favorable to the defense, even if the prosecution does not intend to present it at trial

Meanwhile, the defense is required to give access to the defendant for medical and other tests, disclose the results of medical and scientific reports, and announce all intended defenses (e.g. an alibi).

### *Trial and Pleas*

From this point on, the prosecution and defense will meet periodically in court. This is shown in the space between the sixth and seventh rows of Figure 3. It is not unusual for these meetings to consist solely of a request for postponement. Defendants have a constitutional right to a speedy trial, though it is rarely binding because any postponement requested or agreed to by the defense does not count against the speedy trial clock. During the trial preparation, both sides file motions, review case materials, and prepare their arguments for trial. The prosecutor may opt to abandon the case; this is the drop decision captured in my model. The defendant has the right to demand a jury trial, though the vast majority of trials carried out in Cook County are bench trials presided over only by the judge. During the trial, the prosecutor presents the state's case, followed by the defense, followed by a ruling of guilty or not guilty on each charge.

At any point during this process, the defendant may change their plea to guilty, almost always after having arranged an informal deal with the prosecutor to drop or amend certain charges and arrange a specific sentence for the remaining charges. No plea deal can be carried out without the assent of the judge. They must ultimately be the one to enact the agreed-upon sentence. However, judges rarely object to the terms of a deal that the prosecution and defense both agree on.

*Sentencing and Punishment*

If the defendant pleads or is found guilty, the case proceeds to a sentencing hearing. This is shown in the seventh row of Figure 3. The purpose of this hearing is for both sides of the case to present evidence towards various factors in aggravation and factors in mitigation that may influence the length of the sentence. In the case of a plea bargain, this hearing is typically waived by the defendant as both sides have already agreed on a sentence. At the conclusion of the hearing, the judge passes a sentence that may include prison time, probation, alternative punishments (e.g. boot camp), and/or fines.

If the defendant is sentenced to probation, she must meet regularly with a probation officer and hold to the terms of their probation. These terms vary from case to case (e.g. remaining within the state or county, staying away from criminal associates, submitting to regular drug tests). During this period, the probation officer may allege to the court that the defendant has violated the terms of her probation, at which point the case is returned to the judge who assigned the initial sentence of probation. If the defendant is found to have indeed violated the terms of her probation, the judge may send her to prison for the original charge. The proceedings of this hearing to determine violation of probation are recorded as an extension of the original case.

If the defendant is sentenced to prison, she is transferred to a state facility to serve the sentence. Effective sentences may be shorter than recorded sentences both because prisoners receive credit for time served in prison while awaiting trial and because of the system of good time credits in Illinois. Prior to 1998, prisoners in Illinois received sentence credit for good behavior at a rate of one day per day, meaning that a well-behaved prisoner served an effective sentence that was 50% of the nominal sentence (absent further adjustments for time served awaiting trial). Once in prison, defendants may receive additional credit for completing rehabilitation and training programs, educational degrees, and up to 6 months discretionary credit from the warden. In 1998, Illinois passed a Truth in Sentencing law that reduced good time credits for sentences related to certain charges. Prisoners serving a sentence for murder are now required to serve 100% of the nominal sentence, and prisoners for a number of other crimes (primarily sex crimes and violent crime resulting in great bodily harm to the defendant) are required to serve 85% of the nominal sentence.

Following completion of a prison sentence, defendants are subject to 2-3 years of Mandatory Supervised Release (MSR). Much like probation, a person under MSR must adhere to certain conditions and may be returned to prison if they are found to have violated them. Illinois does not have a parole system. Prisoners serve a sentence of a determinate length (albeit with many ways to reduce the length of this sentence), and there is no mechanism to release them before this sentence is over.

# APPENDIX C: COOK COUNTY CIRCUIT COURT DATA

## *The Structure of the Raw Data*

The files provided by the Cook County Clerk of Court are a snapshot of the court's felony case database as of June 2019. The data were saved as fixed-width text files, which I converted to the Stata .dta format using provided record layout files. Some of the raw data files contained non-ASCII characters that impeded Stata from properly reading and interpreting the data. Before processing, I removed these characters with sed.

The Clerk's data are structured as a relational database. This database has three tables: Root, Charge, and Disposition. The tables are linked by unique case ID numbers, and in the case of Charge and Disposition, charge numbers. The Root table contains exactly one record per case. It stores information that does not vary over time, such as the defendant's name and address, demographic information, case initiation date, and various identification numbers.[1] It also contains some information that may vary over time (attorney, custody status, court dates, etc.). These fields were likely updated as the case proceeded in order to provide "current" information as necessary. Thus, these fields will generally reflect the status of cases at the time of their conclusion. I do not use any time-varying information from the Root table.

The Charge table contains one record per charge, and hence potentially many records per case. Within a case, each charge is identified by a unique charge number. The information in this file is based on the charging document (indictment or information) that initiated the felony case. Charges are described in three ways. First, a reference to the Criminal Code of Illinois. For example, "18-2 (A) (2)" refers to Article 18 (Robbery), Chapter 2

1. In addition to the unique case ID number, most records also contain a finger-print based "Internal Rapsheet" or "IR" number, which I use to link records belonging to the same person. "Central Booking" or "CB" numbers link cases to arrests. "Records Division" or "RD" numbers link cases to police reports. Some cases also have Illinois Department of Investigation or Federal Department of Investigation identifiers.

(Armed Robbery), Part A (Definition), Subpart 2 (Weapon other than firearm). Second, a written description of the charge. These typically paraphrase the code section quoted, e.g. "ARMED ROBBERY WEAP OTH FIREARM." The length of these descriptions is constrained, and they do not follow a consistent abbreviation scheme. Third, a "charge sequence code" assigning a number to the charge, though this mapping is not one-to-one. The felony class of each charge, though technically implied by the criminal code citation, is listed in a separate field. Each charge record also indicates whether a charge was a amended, and if so what the new charge was. The Clerk includes information about the disposition of each charge (e.g. dropped by the prosecution, sentenced to prison, etc.), but I found their method of creating those variables flawed, and I do not use those fields.[2]

The Disposition table contains one record per disposition, and hence almost always many records per case. Within a case, each disposition is identified by a unique disposition number. These numbers proceed in chronological order. "Disposition" in this context refers to anything the judge records on the "half sheet" provided to the Clerk after each court session. These include: any official actions, rulings, verdicts, or orders made by the judge, motions filed by attorneys, and pleas made by defendants.[3] Most dispositions are routine and so can be represented with a numerical "disposition code." When the judge makes a special order or needs to provide additional information, this is recorded in the "free description" field of the data. Disposition histories in my data begin when the defendant is arraigned (See Appendix B for details). They may contain dispositions made after the initial judgment and sentence if any such dispositions were made (for example in probation hearings or appeals).

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2. The clerk bases their measure on the last disposition in the Disposition table related to each charge. This produces spurious or nonsensical data in the (common) event that a case records significant activity after the initial sentencing, for example due to a probation violation hearing or an appeal.

3. "Disposition" more commonly refers exclusively to how a criminal charge is resolved.

Each disposition also includes fields indicating which judge recorded the disposition and in which courtroom. Both judges and courtrooms are represented by numerical codes, and the Clerk did not provide any correspondence between these codes and actual judges and courtrooms. Disposition records include fields to record sentence lengths and fines for dispositions dealing with sentencing.[4] When a disposition record references a record in some other table, most often a charge or a bond, the exact record is indicated by the "CB reference" field. For example, a verdict finding the defendant guilty of charge 1 but not charge 2 would read as a guilty disposition referring to "C001" and a not guilty disposition referring to "C002." When a disposition refers to all charges, the CB reference field reads "CALL." This allows me to link records in the Charge table directly to records in the Disposition table. Finally, any dispositions where the case is being transferred or court business has concluded for the day has a separate field that indicates the courtroom that the case will next appear in. This is most useful for identifying initial case assignment.

### *Deciphering Fields*

Many aspects of the court data are doubly encoded in the sense that the raw data stores them only as numbers, but even after the numbers are interpreted, specific legal knowledge is required to fully understand them. I focus first on the process of deciphering numerical encodings. The Clerk provided explicit data dictionaries for some numerical encodings: race, charging document type, disposition code. The Clerk also confirmed that the final two digits of the ID variable enumerate defendants in a multi-defendant case. Thus, two records that match ID up to this point are associated with codefendants. The code section field of the Charge table can be deciphered using the IL Criminal Code itself. The charge

4. Confusingly, the fine field is sometimes used to encode information about bond amounts and hence must be analyzed carefully.

sequence field can be deciphered by careful comparison to the code section and written description fields, but this process does not scale well. Judge numbers can be matched to judge names by comparing the electronic version of the case given to me by the Clerk to the representations of the same case available in the Clerk's office (either on paper or via a dedicated computer terminal), which use judge names in place of the numerical code. Courtroom numbers can be matched to physical courtrooms via a similar process, though the courtroom numbers in the electronic data actually refer to "calls." Calls are groups of cases that are typically associated with a single judge and may have some other distinguishing feature, like being scheduled in the evenings or diverted towards drug treatment. When a judge changes physical courtrooms, their call typically follows them. This means that the courtroom/call numbers in the Clerk's electronic files are generally more informative than physical courtroom numbers.

The two major legal deciphering tasks are categorizing dispositions and charges. With the aid of a lawyer with criminal defense experience in Chicago, I grouped dispositions into categories based on the descriptions associated with the codes. Examples of categories include: sentenced to incarceration, case dismissed, and public defender appointed. My goal was to identify only dispositions relevant to various data processing steps described below, so I did not categorize every disposition. I do attempt to exhaustively categorize charges in a manner approximating the FBI's UCR charge categorization scheme. This could primarily be done at the Article level in the IL Criminal Code, with a few categories requiring me to make distinctions at the Chapter level. Furthermore, I did not need to extract felony class information from the detailed charge information because it was already provided separately by the Clerk.Thus, my crime categorization algorithm works by parsing the code section strings in the Charge data to extract Article and Chapter information and recombining that information to form UCR-like categories.

### *Supplementing Defendant Information*

The electronic data files provided by the Clerk of Court redacted defendant personal and demographic information in cases that, in the estimation of the Clerk, ended in a non-conviction. Other information, such as charges and dispositions, was unaffected. Nevertheless, this meant that a large and very selected subset of my initial dataset was lacking race information and thus could not be included in my analysis. I addressed this problem by supplementing the Clerk's electronic data files with information collected by the Chicago Data Collaborative (CDC). The CDC data were scraped from web forms populated by the same database given to me by the Clerk. However, the Clerk did not redact any information in this setting. Among records where both my data and the CDC data have defendant information, they match perfectly, even on name and address. This is why I am confident that the two datasets don't just carry the same *information* but are in fact drawing from precisely the same source database. I ultimately use defendant information provided by the CDC for N records in my final estimation sample.

### *Aggregation to Case-Level Records*

The complex structure of the raw data as provided by the Clerk is not suitable to most forms of statistical analysis, which assume that each observation in the data can be written as a single vector of a constant length. This requires me to aggregate the Charge and Disposition tables from several records per case to a single record per case. I aggregate the Charge table by recording information about the most serious charge (as described in Chapter 5 of the text) and noting whether the defendant faced more than one charge.

In most cases, I aggregate the Disposition table by searching for *events* within the disposition histories from arraignment to initial sentencing. For example, to construct the indicator variable for public defender, I search the disposition history for disposition code

901, which decodes to “Public Defender Appointed.” Any case with that code has the public defender indicator set to 1, and all other cases have it set to 0. Some defendants with the public defender indicator set to 1 may have, at some other time, hired a private attorney to handle their case. I do not attempt to differentiate defendants on that basis. I use a similar strategy to construct my indicators for guilty pleas, dismissal, defendant flight/death, and awaiting trial in jail.[5]

## Sentencing Information

The sentencing information contained in disposition histories is too complex to allow for aggregation using an event-based strategy. It must be carefully aggregated across both time and charges. Disposition histories frequently include sentencing information from hearings that occurred after the initial sentencing, most often probation violation hearings. I therefore restrict my attention to the *first* day that I observe any sentencing disposition for any charge. Initial sentences are almost always handed down on a single day, and this strategy avoids erroneously including later sentencing dispositions.[6] This initial sentencing date is the endpoint of the case for most of my purposes, and my event-based aggregation strategy ignores most events that occur after this date.

I gather all sentencing dispositions made on the initial sentencing date, as well as dispositions indicating that the defendant is to get sentencing credit for time served in jail while awaiting trial and any dispositions indicating that sentences are to be served consecutively. I aggregate probation sentences as if they are to be served concurrently. I aggregate incar-

5. In light of the fact that disposition histories begin at arraignment, often at least a month after the initial arrest, I am not concerned about picking up any defendants who were jailed only before their bail hearing.

6. In probation hearings, sentences are often passed on charge numbers that are unrelated to the initial charging document. A defendant who initially convicted of only the second charge in his charging document, may be sentenced to prison in a probation violation hearing based on a placeholder “charge 1.” An approach that treated each charge separately would conflate the two sentences.

ceration sentences as if they are to be served concurrently unless I observe a disposition that says they are to be served consecutively. When a defendant is given both a probation sentence and an incarceration sentence, I treat the incarceration sentence as their primary sentencing outcome, but I make a note of the probation sentence.

This information is sufficient to construct my main sentencing outcome, which I call "nominal incarceration." I can also construct "marginal incarceration" by subtracting any sentencing credit from the nominal incarceration sentence. I construct total incarceration by treating measured jail time as incarceration time when a defendant did *not* get an incarceration sentence.[7] Finally, I construct "realized incarceration" by considering cases with probation violation hearings and repeating my sentencing information procedure on the disposition histories following the initial sentencing date, then treating any resulting incarceration as if had been given at the initial sentencing.

## Related Cases

The state sometimes wishes to charge a person with a set of crimes that cannot be contained in a single charging document, most frequently because some of the crimes are not part of the same "course of action." This can generate sets of criminal cases that are, for all practical purposes, treated as a single case. They are assigned to the same judge, negotiated as a unit, and sentenced at the same time. However, the cases have distinct ID numbers and are not explicitly linked in the Clerk's electronic records. If I ignored this feature of the data, I would risk mismeasuring case outcomes, especially when a plea bargain calls for a defendant to plead guilty to charges in only one case, causing the other cases to be dropped

7. When sentencing credit is not available, I measure jail time as the sum of the time between dispositions where the defendant was observed to be in jail. Most court appearances include a disposition indicating whether the defendant was held in custody or on bond at the time.

entirely. This is properly measured as a single plea bargain, but a naive approach would measure it as a plea bargain and a dropped case.

To address this problem, I first assemble sets of cases for combination. I combine cases if they share a defendant and an initial sentencing date and were initiated within 7 days of each other. I must then condense the information contained in this set of cases into a single vector of information. For some variables, primarily dates and event indicators, I assign to the combined case the minimum or maximum value across the set of cases, as appropriate. For all event indicators, I take the maximum. If a defendant has a public defender disposition in one case, the indicator should be turned on for the combined case. All other variables I treat as sets. For example, *all* of the sentencing information in the combined case comes from the case that has the most severe sentence. All charge information comes from the case with the most severe charge, etc. This prevents nonsensical combinations of information while still accounting for scenarios where a defendant's plea bargain in one case was influenced by charges brought in a different case, even when those charges are eventually dropped.

### *Judge Assignment*

It is possible to use the information in the Clerk's electronic files both to determine which judge most cases were assigned to and to restrict to a subset of cases that were assigned randomly. This fact plays a small role in my plea bargain analysis but is generally important for future work, so I document it here.

## Assignment to Judges

As noted above, when a disposition indicates that a case is to be transferred or concludes court business for a day, the record for that disposition includes information about the call under which it is scheduled to resume. This is also true of all dispositions that assign a case to a particular call. This is the best available measure of *assignment* and is superior to simply observing the call of future dispositions in the case. It is not uncommon for defendants to immediately respond to judge assignment with a Substitution of Judge motion.[8] Defendants who do so are immediately reassigned. This means that the defendant's initial assignment, the true point of randomization, sometimes *only* exists as an assignment disposition and cannot be observed from future calls.

This property of the data makes the relationship between cases and calls obvious, and I rely on it alone when forming my clustering variable in Chapter 6. To use a judge stringency measure, however, it is also necessary to establish which calls receive random assignments as well as the relationship between calls and judges. According to Lawrence Fox, a retired judge in the court, an established judge typically has only one call throughout their career, even if they move physical courtrooms. However, new judges frequently begin their careers as "floaters" who tend to the calls of other judges when they are absent from the court. Judges may also change calls if they make a major career change (e.g. moving from the Chicago courthouse to one in the suburbs). A small number of judges (Judge Fox included) also maintain a separate call for specialty courts, such as those for drug abusers or veterans. I focus on a set of primary calls. These are the calls located at the main court building that are most frequently assigned cases at arraignment. They take numbers 17XX where XX is between 02 and 34.[9] Judge Fox confirmed that these are the relevant calls and the ones receiving assignments from the general pool of cases.

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8. Defendants in Illinois are afforded one such motion "by right," meaning that they do not have to provide any reason for the substitution. Multiple sources familiar with the courts in Chicago have confirmed that defense attorneys use this right strategically and file Substitution of Judge motions when their case is assigned to a particularly harsh judge.

9. 1701 is the Presiding Judge's call. 1749 is another administrative call. 1735-48 are used for various ancillary calls, most often dedicated drug courts.

The relationship between judges and calls is stable, but it is not one-to-one. Retiring judges hand off their calls to acceding judges. Judges who take a long leave of absence yield their call to another judge for that time. Fortunately, the disposition histories themselves can be treated as a dataset that establishes which call (if any) a judge was hearing on any given day. I first count the number of dispositions each judge heard on each call and assign a judge to a call if they made the most dispositions on that call in that day. It is rare in practice to see a call with dispositions from more than one judge within a single day, so this step is straightforward. Then, to account for very brief absences, in which a floater judge may fill in for a permanent judge, I use information from other days to assign a permanent judge to each day. If a judge: (1) Held the call for the most days in the surrounding four week period (two before and two after); (2) Held the call for at least one day in the prior two weeks and at least one day in the subsequent two weeks; and (3) Held the call for a majority of days in the surrounding year (calculated *either* January to December *or* July to June), then I assign them to that call in that day. This produces a result that aligns with what insiders have told me about call assignment: judges hold their calls for a contiguous period of several years before handing them off to another judge. In rare cases, these tenures are interrupted for a period of a few months.

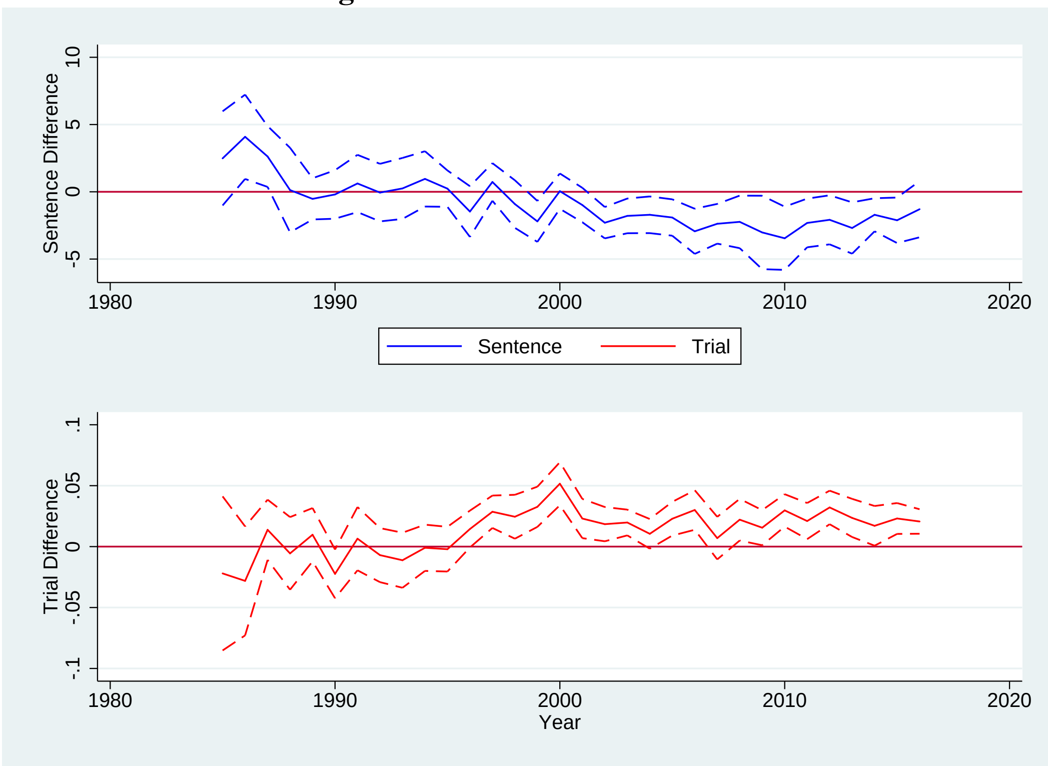
## Random Assignment

Just because a case was assigned to a call that *may* receive random assignment does not mean that a case was randomly assigned. In conversations with court insiders, they listed 3 primary reasons why a case may not be randomly assigned: (1) The defendant already had a pending matter before the court. (2) The case was assigned to a drug or specialty treatment court. (3) The case was a high-profile "heater" intentionally assigned to a more experienced judge. The first reason is by far the most common. If the defendant in any new case was already awaiting trial or on probation, the case is automatically assigned to the judge overseeing the pending case. I address this problem by excluding from my randomized sample any case that was initiated as its defendant was awaiting trial or within the probation period of a prior case. As added insurance, I exclude *any* cases where a defendant is re-assigned to the same judge within 4.5 years of his last assignment to that judge. Specialty courts are managed from a list of calls distinct from the primary calls considered above. If news materials or interviews with court insiders indicate that a judge managed a specialty court at any time, I exclude all of their cases for good measure.[10] My sample does not include murder or sexual assault cases, which likely eliminates most heaters from my dataset. Large cases may be sufficiently complex or public to be designated a heater, so I also do not consider a case randomly assigned if it had more than 4 defendants.

10. It is not practical to exclude judges who headed drug courts at any time in their career. Throughout the 1990s, almost all new judges spent 1-2 years in night narcotics courts before being promoted to a permanent call.

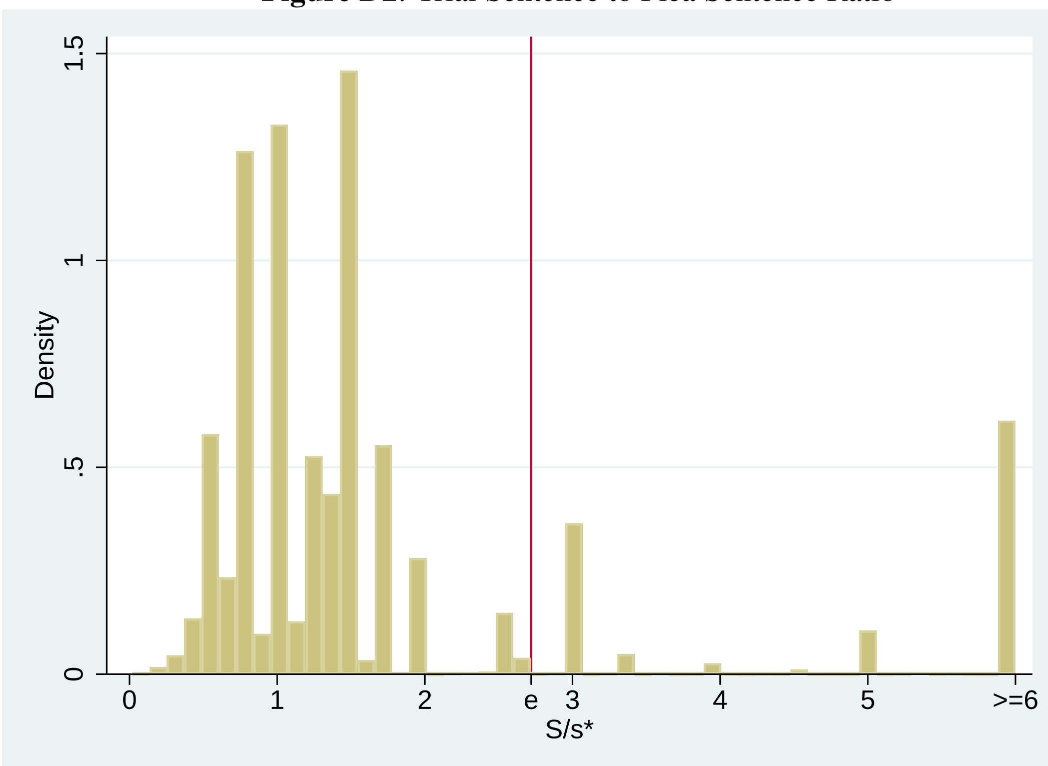
# APPENDIX D: ADDITIONAL EMPIRICAL RESULTS

**Figure D1**. Racial Differences Over Time




*Notes:* This figure plots the coefficients from regressions of an indicator for black defendants on nominal sentence length (upper panel) and whether a case ended in trial (lower panel), conditional on year of case initiation. Each regression has covariates: class of most serious charge, category of most serious charge, age, and number of prior convictions, plus indicators for whether the defendant is male, ever had a public defender, was ever held in custody awaiting trial, and whether the state filed multiple charges or included multiple defendants in the case. Dashed lines present 95% confidence intervals clustered at the courtroom-year level. I exclude years with fewer than 500 observations, which affects only 1984. See Chapter 5 for more details about sample selection.

**Figure D2**. Trial Sentence to Plea Sentence Ratio




*Notes:* This figure shows a histogram of estimated values for $S/s^*$ among cases that ended with a plea bargain. For these cases, $S$ is estimated within felony class cells as the median sentence given to defendants convicted at trial.

Table D1: Trial Logit

| | Trial | Trial | Trial | Trial |
|---|---|---|---|---|
| reg_trial | | | | |
| Black | 0.192*** | 0.292*** | 0.182*** | 0.162*** |
| | (0.0126) | (0.0132) | (0.0138) | (0.0142) |
| Male | | 0.402*** | 0.274*** | 0.290*** |
| | | (0.0197) | (0.0203) | (0.0204) |
| Public Defender | | -0.435*** | -0.355*** | -0.378*** |
| | | (0.0104) | (0.0107) | (0.0110) |
| Ever in Jail | | -0.0320** | -0.148*** | -0.156*** |
| | | (0.0123) | (0.0128) | (0.0129) |
| Multiple Defendants | | 0.448*** | 0.396*** | 0.391*** |
| | | (0.0113) | (0.0119) | (0.0120) |
| Multiple Charges | | 0.431*** | -0.100*** | -0.111*** |
| | | (0.0102) | (0.0122) | (0.0123) |
| Observations | 388599 | 388599 | 388599 | 388597 |
| Charge Cond. | None | None | ClassXCat FE | ClassXCat FE |
| Assignment Cond. | None | None | None | Ctrm and Year FE |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes*: This table presents the results of logistic models using an indicator for black defendants as the independent variable and whether the case ended in a trial as the outcome variable Beginning with the second column, covariates also include dummy variables for age and number of prior convictions. See Chapter 5 for details about sample selection.

Table D2: Alternative Topcodes

| | 60 Months | 40 Months | 20 Months | Censored at 80 |
|---|---|---|---|---|
| Black | -1.501*** | -1.530*** | -1.548*** | -1.541*** |
| | (0.170) | (0.168) | (0.155) | (0.170) |
| Male | 4.166*** | 4.157*** | 4.097*** | 4.170*** |
| | (0.145) | (0.143) | (0.136) | (0.143) |
| Public Defender | 2.056*** | 2.053*** | 2.033*** | 2.035*** |
| | (0.142) | (0.140) | (0.127) | (0.141) |
| Ever in Jail | 8.237*** | 8.248*** | 8.291*** | 8.240*** |
| | (0.134) | (0.134) | (0.130) | (0.134) |
| Multiple Defendants | -1.629*** | -1.614*** | -1.466*** | -1.619*** |
| | (0.181) | (0.176) | (0.157) | (0.179) |
| Multiple Charges | 2.678*** | 2.658*** | 2.587*** | 2.665*** |
| | (0.132) | (0.130) | (0.122) | (0.131) |
| Observations | 388599 | 388599 | 388599 | 388578 |
| Adjusted $R^2$ | 0.400 | 0.412 | 0.439 | 0.404 |
| Charge Cond. | ClassXCat FE | ClassXCat FE | ClassXCat FE | ClassXCat FE |
| Assignment Cond. | CtrmXYear FE | CtrmXYear FE | CtrmXYear FE | CtrmXYear FE |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes*: This table presents the results of regressions of an indicator for black defendants on nominal sentences in months under different topcoding rules. Covariates also include dummy variables for age and number of prior convictions. Standard errors are clustered at the courtroom-year level. See Chapter 5 for details about sample selection.

Table D3: No High $s^*/S$

| | Sentence | Trial |
|---|---|---|
| Black | -1.571*** | 0.0178*** |
| | (0.174) | (0.00172) |
| Male | 4.086*** | 0.0259*** |
| | (0.151) | (0.00199) |
| Public Defender | 2.050*** | -0.0475*** |
| | (0.148) | (0.00178) |
| Ever in Jail | 8.660*** | -0.0125*** |
| | (0.141) | (0.00181) |
| Multiple Defendants | -1.694*** | 0.0454*** |
| | (0.188) | (0.00195) |
| Multiple Charges | 2.699*** | -0.0158*** |
| | (0.136) | (0.00178) |
| Observations | 369309 | 369309 |
| Adjusted $R^2$ | 0.405 | 0.084 |
| Charge Cond. | ClassXCat FE | ClassXCat FE |
| Assignment Cond. | CtrmXYear FE | CtrmXYear FE |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes*: This table presents the results of regressions of an indicator for black defendants on both nominal sentences in months and whether the case ended in a trial. Covariates also include dummy variables for age and number of prior convictions. Standard errors are clustered at the courtroom-year level. Cases with an estimate of $s^*/S > e$ are excluded. of See Chapter 5 for details about sample selection.

Table D4: Dropped Cases

| | Case Dropped |
|---|---|
| Black | -0.0120*** |
| | (0.00124) |
| Male | 0.00715*** |
| | (0.00132) |
| Public Defender | -0.0389*** |
| | (0.00117) |
| Ever in Jail | -0.0304*** |
| | (0.00129) |
| Multiple Defendants | 0.0151*** |
| | (0.00121) |
| Multiple Charges | -0.0178*** |
| | (0.00101) |
| Observations | 412992 |
| Adjusted $R^2$ | 0.032 |
| Charge Cond. | ClassXCat FE |
| Assignment Cond. | CtrmXYear FE |

Standard errors in parentheses

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

*Notes*: This table presents the results of a regression of an indicator for black defendants on whether the case was dropped by the prosecution. Covariates also include dummy variables for age and number of prior convictions. Standard errors are clustered at the courtroom-year level. See Chapter 5 for details about sample selection. This sample does not apply the standard restriction against cases dropped by the proseuction.

Table D5: Imputing Dropped Cases

| | Sentence | Trial |
|---|---|---|
| Black | -1.430*** | 0.0167*** |
| | (0.164) | (0.00153) |
| Male | 3.747*** | 0.0224*** |
| | (0.140) | (0.00179) |
| Public Defender | 2.662*** | -0.0356*** |
| | (0.139) | (0.00154) |
| Ever in Jail | 8.173*** | -0.00973*** |
| | (0.131) | (0.00159) |
| Multiple Defendants | -1.833*** | 0.0384*** |
| | (0.178) | (0.00176) |
| Multiple Charges | 2.892*** | -0.0102*** |
| | (0.126) | (0.00165) |
| Observations | 412992 | 412992 |
| Adjusted $R^2$ | 0.362 | 0.072 |
| Charge Cond. | ClassXCat FE | ClassXCat FE |
| Assignment Cond. | CtrmXYear FE | CtrmXYear FE |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Notes*: This table presents the results of regressions of an indicator for black defendants on both nominal sentences in months and whether the case ended in a trial. The both outcomes are set to 0 for cases dropped by the prosecution. Covariates also include dummy variables for age and number of prior convictions. Standard errors are clustered at the courtroom-year level. See Chapter 5 for details about sample selection. This sample does not apply the standard restriction against cases dropped by the prosecution.