# BARGAINING WITH ASYMMETRIC INFORMATION: AN EMPIRICAL STUDY OF PLEA NEGOTIATIONS

BERNARDO S. DA SILVEIRA

OLIN BUSINESS SCHOOL
WASHINGTON UNIVERSITY IN ST. LOUIS

NOVEMBER, 2014

Abstract. This paper empirically investigates how sentences to be assigned at trial impact plea bargaining. The analysis is based on a variation of a bargaining model with asymmetric information due to Bebchuk (1984). I provide conditions for the non-parametric identification of the model, propose a consistent non-parametric estimator, and implement it using data on criminal cases from North Carolina. Employing the estimated model, I evaluate how different sentencing reforms affect the outcome of criminal cases. My results indicate that lower mandatory minimum sentences could greatly reduce the total amount of incarceration time assigned by the courts, but may increase conviction rates. In contrast, the broader use of non-incarceration sentences for less serious crimes reduces the number of incarceration convictions, but has a negligible effect over the total assigned incarceration time. I also consider the effects of a ban on plea bargains. Depending on the case characteristics, over 20 percent of the defendants who currently receive incarceration sentences would be acquitted if plea bargains were forbidden. Nevertheless, the option of settling their cases makes defendants ex-ante substantially better off.
*Keywords:* Settlement models, plea bargaining, non-parametric identification, non-parametric estimation, bargaining models, structural estimation.

---

I am grateful to Alessandro Lizzeri for invaluable support, encouragement and advice. I also benefited from guidance by and insightful conversations with John Asker and Quang Vuong. I would like to thank Andrew Daughety, Sandy Gordon, Barton Hamilton, Jakub Kastl, Fernanda de Leon, Konrad Menzel, Isabelle Perrigne, Nicola Persico, Luigi Pistaferri, Jennifer Reinganum and seminar and conference participants at Caltech, Carnegie Mellon, Cornell, FGV-EESP, ITAM, Microsoft Research, Princeton, UCLA, Maryland, Minnesotta, NYU, PUC-Rio, Stanford, Toronto, USC, Wisconsin, Vanderbilt, WUSTL, the 2013 American Law and Economics Association Meeting, the 2013 Econometric Society Summer Meeting, the 2013 Southern Economic Association Meeting and the 2013 New Directions in Applied Economics Meeting. I would also like to thank Brad Fowler, from the North Carolina Administrative Office for the Courts, and Cathy Moss, from the Publications Division at the North Carolina Secretary of State's Office, for help in obtaining the data.
Address: One Brookings Drive, Campus Box 1133, St. Louis, MO 63130, silveira@wustl.edu .

## 1. Introduction

This paper analyzes how the harshness of sentences to be assigned at trial affects plea bargaining. I build upon a model by Bebchuk (1984) and establish sufficient conditions under which the model is non-parametrically identified. I then propose a non-parametric estimator and implement it using data on criminal cases from North Carolina state courts. The estimates allow me to evaluate the impact of commonly proposed sentencing reforms on the final result of cases. In particular, I consider a reduction in minimum mandatory sentences, and the wider use of non-incarceration sentences for mild offenses. I also assess the proportion of cases that are currently settled for incarceration sentences but that would result in an acquittal at trial if plea bargains were banned.

The results presented here are relevant for the debate on sentencing reform. Due mainly to the high incarceration rates in the United States, a discussion has developed over whether current sentencing guidelines should be made more lenient. Prior to considering what the optimal guidelines should be, however, a better understanding is required of the effects of different sentencing reforms on the outcomes of prosecuted cases. This task is complicated by the prevalence of plea bargaining in the American justice system. Indeed, the vast majority of criminal cases in the United States are settled without a trial.[1] Thus it is likely that the impact of any sentencing policy depends largely on how it affects plea-bargaining, rather than on the outcome of cases actually brought to trial. In order to contemplate the effects of changes in the sentencing guidelines on the final outcome of cases, it is necessary to account for plea bargaining.

In the model, a prosecutor and a defendant bargain over the outcome of a case. The prosecutor offers the defendant to settle for a sentence. If there is no agreement, the case proceeds to trial, which is costly to both parties. The defendant is better informed than the prosecutor about the probability of being found guilty at trial, so that bargaining takes place under asymmetric information. The sentence to be assigned in the event of a trial conviction is common knowledge.

Although the defendant's private information is continually distributed, her action space consists simply of accepting or rejecting the prosecutor's offer. The lack of a one-to-one mapping between defendants' types and actions poses a challenge to the

[1] In 2001, 94% of Federal cases were resolved by plea bargain (Fischer, 2003). Numbers for state cases are similar. In 2000, 95% of all felony convictions in state courts were the result of a plea agreement (Durose and Langan, 2003).

identification of the model. To overcome that challenge, I exploit information on the distribution of defendants' types conveyed by the prosecutor's offers. Specifically, there is a one-to-one mapping between the the trial sentence and the prosecutor's optimal offer. If such a mapping is known by the econometrician, the distribution of defendants' types can be recovered. The identification of the prosecutor's optimal offer as a function of the trial sentence, however, is complicated by a selection problem. Indeed, the prosecutor's offer is observed only if plea bargaining is successful, while the trial sentence is available only in cases resulting in a trial conviction trial. Nevertheless, I show that the prosecutor's optimal offer function satisfies an equation relating the (observed) distributions of accepted settlement offers and assigned trial sentences. I present sufficient conditions for that functional equation to be solved. These conditions amount to the existence of a source of variation in the distribution of trial sentences that does not affect the other model primitives model. My application uses cross-judge heterogeneity in sentencing patterns as such a source of variation.

The estimation of the model closely follows the identification strategy. First, I compute kernel density estimates for the observed distributions of trial and settlement sentences. I then use sieve methods to solve an empirical analogue to the functional equation defined above and to obtain an estimator for the prosecutor's optimal offer function, which I show to be uniformly consistent. Employing this function, I recover the model's primitives..

I implement the estimator using data on cases filed in the North Carolina Superior Courts, the main general-purpose trial courts in that state, between 1996 and 2009. The estimated model fits the main features of the data well. It accurately reproduces the observed settlement and conviction rates, as well as the average length of assigned sentences. I find that the asymmetric information between prosecutors and defendants is quantitatively relevant and that the prosecutors incur high costs for bringing a case to trial. Defendants, however, behave as if their costs of going to trial were negligible. Such differences in trial costs, together with the informational asymmetry, help to explain why sentences assigned in settled cases are shorter than those assigned in trial convictions.

I employ the estimated model to evaluate the effects of a number of policy interventions on the final outcome of criminal cases. My results indicate that a decrease in mandatory minimum sentences, which I express in the model by shortening the potential trial sentences in all cases, greatly reduces the total amount of incarceration time assigned, but raises the proportion of cases that result in a conviction. Because

of the latter effect, such intervention may actually raise incarceration rates in the short run. Another intervention, the broader use of non-incarceration sentences for mild cases, has little effect on the total assignment of incarceration time, but may reduce conviction rates significantly. In a third experiment, I eliminate the asymmetric information between prosecutors and defendants. Besides serving as a reference for evaluating policies such as the enhancement of discovery rules, the results of this experiment quantify the informational rents obtained by the defendants in the process of plea bargaining. I estimate such rents to be substantial. In my last experiment, I assess the impact of eliminating plea bargains. I find that a large proportion of the defendants that currently settle their cases for incarceration sentences would be acquitted at trial if bargaining was forbidden. Depending on the characteristics of the case, such proportion is well above 20 percent. Insofar as trials accurately convict the guilty and acquit the innocent, these numbers suggest that plea bargaining leads a disturbing number of defendants to be unjustly incarcerated. Nevertheless, my results indicate that, in expectation, defendants would be considerably worse off if settlements were not allowed, relative to the present situation.

The identification and estimation strategies proposed here are adaptable to contexts that extend beyond the resolution of legal disputes. Many important situations in economics can be modeled as bargaining games in which one party is privately informed on the consequences of bargaining failure. An example is the acquisition of public companies, where the board of the target firm must decide whether to accept the acquirer's proposal for a friendly takeover. If negotiations fail, the acquirer may proceed with a hostile takeover, but the target's board has private information on the quality of the company's takeover defenses or on the likelihood of winning a proxy fight. Another example is debt renegotiation, where the debt holder is privately informed on the likelihood of going into bankruptcy if the renegotiation fails. To widen the applicability of my empirical strategy, I generalize the identification result to settings in which more than two outcomes are possible, after bargaining failure.

The paper is organized as follows: Section 2 discusses the contribution of this study to the literature. Section 3 describes the North Carolina Superior Courts, as well as the data used in the paper. In Section 4, I present the theoretical model on which the empirical analysis is based. The structural model is then presented in Section 5, followed by the empirical results, in Section 6. Section 7 contains the policy experiments and Section 8 concludes. In the Appendix, I show proofs omitted from the main text, details concerning the estimation procedure and a more detailed

comparison between my analysis and the previous literature. In an online Appendix, I present a reduced form analysis supporting key assumptions of the model, details on the manipulation of the data and extensions of my identification strategy to more general settings.

## 2. Related Literature

This paper contributes to a vast Law and Economics literature on settlement.[2] Most papers in that literature use game-theoretic models to investigate the litigation and resolution of civil disputes, but the same framework is readily adaptable to the analysis of plea bargaining.[3] Several studies explore the empirical implications of settlement models using data on criminal cases, with a particular interest in how the severity of sentences to be assigned at trial affects plea bargaining outcomes. For example, Elder (1989) provides evidence that factors that may aggravate a trial punishment (e.g., the possession of a firearm by the defendant at the moment of the alleged offense) reduce the probability of settlement. LaCasse and Payne (1999), examining federal court cases, show a positive correlation between plea and trial sentences of cases under the responsibility of the same judge. Boylan (2012) finds similar results. Kuziemko (2006) analyzes homicide cases and finds that defendants subject to the death penalty tend to accept harsher settlements. Taken ogether these results serve as strong evidence that plea bargaining takes place in the shadow of a trial.

My investigation differs from the existing plea-bargaining literature in that I develop and implement a framework for the structural analysis of data on judicial cases. This approach has several advantages over those of previous studies. First, I quantify the relationship between potential trial sentences and plea-bargaining results. Also, I recover objects that are not directly observable, such as the full distribution of sentences to be assigned at trial. Most importantly, I am able to conduct policy experiments to evaluate the impact of different interventions on the justice system.

[2]The literature offers two basic explanations for why settlements fail, resulting in a costly trial. One theory is that agents bargain under asymmetric information (classic contributions include Bebchuk (1984); Reinganum and Wilde (1986); Nalebuff (1987); and Kennan and Wilson (1993)). The other is that agents have divergent priors on the distribution of trial outcomes (see, for example, Priest and Klein, 1984). It is beyond the scope of my paper to compare the merits of these two branches of literature. See Daughety and Reinganum (2012) for a detailed review.

[3]Theoretical papers that apply settlement models to the criminal context include Rubbinfeld and Sappington (1987), Reinganum (1988), Kobayashi (1992), Miceli (1996), Baker and Mezzetti (2001) and Bjerk (2007).

In that sense, my study is related to a group of papers that conduct the structural estimation of settlement models using data on civil cases—notably, Waldfogel (1995), Sieg (2000) and Watanabe (2009). My paper differs from those in three important aspects: First, my focus is on criminal, rather than civil, cases. Second, I conduct a careful identification analysis, showing what can be learned from the data using only restrictions derived from the theoretical model, and imposing minimal parametric assumptions on the model's primitives. The non-parametric approach is particularly valuable in the empirical investigation of legal disputes since, due to the endogenous selection of cases for trial, the raw data provide little guidance about the adequacy of different parametric specifications for the model. Accordingly, my estimation procedure is non-parametric. Third, and due mainly to my focus on plea bargaining, the model estimated here departs from the ones used in previous papers. Waldfogel (1995) does not account for variation across cases in the size of trial awards, which would be the civil cases' equivalent to trial sentences. Such lack of variation prevents the investigation of how awards affect settlement decisions, which is the centerpiece of my analysis. Watanabe (2009) is interested primarily in dynamic aspects of the bargaining process, such as the costs of bargaining delays, which are more relevant in the context of tort cases than in that of criminal ones. His model, for example, emphasizes the differences between cases settled with and without the filing of a lawsuit, whereas the latter group of cases has no clear equivalent in the criminal justice system. The model estimated by Sieg (2000) is probably the closest to the one studied here. However, some features of Sieg's model make it inappropriate for the analysis of criminal cases. Specifically, that model does not allow changes in the distribution of potential trial sentences to affect conviction rates, which are of great interest in the discussion of sentencing reform. As Section 4 makes clear, the model estimated in my paper does not have such a limitation. I present a detailed comparison between Sieg's paper and mine in Appendix A.3.

More generally, my paper proposes a new strategy for the non-parametric identification and estimation of bargaining games with asymmetric information, which can, in principle, be applied to settings other than the settlement of judicial cases. Models of bargaining with asymmetric information are used in several fields of Economics, and recent years have seen a renewed interest in the empirical analysis of such models. Besides the papers on settlement mentioned above, recent studies by Merlo, Ortalo-Magné and Rust (2008), Keniston (2011) and Larssen (2014) estimate models of bargaining over the sale of a good in which agents have private information about

their valuations. Using rich data on offers and counteroffers, these papers analyze dynamic aspects of bargaining. However, data on many relevant topics are rarely available at such a level of detail. The techniques developed here are useful in the far more common scenario, where only the final outcome of bargaining is observable.

My paper also contributes to a growing empirical literature on political incentives in the justice system. Studies such as Huber and Gordon (2004), Gordon and Huber (2007) and Lim (2013) evaluate how elections affect the sentencing behavior of trial judges. But measuring such behavior based only on observed sentences is challenging since numerous cases are resolved by plea bargain. Lim (2013) treats trial and settlement sentences equally, which may lead to overestimation of the differences in the sentencing patterns across different judges. Indeed, according to most settlement models, including the one I consider, harsher trial sentences make it more difficult to settle cases. Moreover, settled sentences are normally considerably shorter than the ones assigned at trial. Therefore, if one specific judge tends to be harsher than another, the difference between the observed sentencing patterns of these two judges may be explained not only because the former assigns longer sentences than the latter, but also because cases under the responsibility of the former judge are more likely to be resolved at trial. Huber and Gordon (2004) and Gordon and Huber (2007) use indicators of whether a case is resolved by plea bargain as a control variable in their estimation procedures, but that does not account for the endogeneity of settlement. The empirical framework presented recovers the full distribution of trial sentences, which could be used to assess the harshness of different judges.

## 3. Data and Institutional Details

I use data on criminal cases prosecuted in the North Carolina Superior Courts—the highest of the general trial courts in North Carolina's justice system. The Superior Courts have exclusive jurisdiction over all felony cases, as well as over civil cases involving large amounts of money and misdemeanor and infraction cases appealed from a decision in the lower District Courts.[4] The state is divided into eight Superior Court divisions, and each division is further divided into districts for electoral and administrative purposes.[5] There are 46 such districts statewide.

[4]Felonies are the most serious offenses in the criminal code, whereas misdemeanors are less serious crimes. Whether the main charge in a case is a felony or a misdemeanor often depends on several circumstances. In assault cases, for example, a felony may be characterized by the use of a lethal weapon, the intention to seriously injure, or the actual injuries suffered by the victim.

[5]Until 1999, there were only four Superior Court Divisions statewide. In that year, each division was split in two.

A unique feature of the North Carolina Superior Courts is the rotation of judges. About 90 judges are elected for eight-year terms by voters in their districts, and may be re-elected indefinitely.[6] Although each judge belongs to a district, the state constitution mandates judges to rotate among the districts within their divisions on a regular basis. The rotation schedule for judges in the whole state is determined by the Administrative Office for the Courts. According to such schedule, judges rotate from one district to another every six months.

All Superior Court cases brought to trial are decided by a jury of 12, who decides whether the defendant is guilty or not guilty of the charged offenses. If the defendant is convicted, the judge decides on a sentence. The judge must follow a set of structured sentencing guidelines—i.e., a sentence is selected from a predetermined range of options, which depends on the severity of the crime and on the defendant's previous criminal record.[7] The sentence may include incarceration time and alternative punishments, such as fines, community service and probation.

I use case-level data provided by the North Carolina Administrative Office of the Courts.[8] Such data comprise all criminal cases filed at the Superior Courts from 1996 to 2009 and include detailed information on case disposition, charged offenses and characteristics of the defendants. The data also identify the judge hearing each case. I match judges with their respective judicial district using the annual editions of the North Carolina Manual.[9]

The structural analysis to be presented in Section 5 requires a degree of homogeneity across cases in the sample. Such homogeneity cannot be achieved with samples that comprise offenses too different from each other. It is likely, for example, that the prosecution of a traffic offense is far different than that of a drug-related crime. Therefore, I use a reduced sample of cases, comprising offenses that do not vary much in nature. The chosen sub-sample cannot be too small, in practice, since the non-parametric estimation procedure, described in Section 5, demands a relatively large number of observations to be implemented. I consider a sample of cases in which the main offense is a non-homicide violent crime—a category that consists of assault,

[6]A few judges may be appointed by the Governor for five-year terms.

[7]The judge sets only the minimum sentence length. The maximum length is determined according to a formula. There is no parole under the structured sentencing system in North Carolina. Offenders must serve at least their entire minimum sentence in incarceration and may serve up to the maximum length. Whether the offender serves more than the minimum sentence is determined by the Department of Corrections, not by the judge. For convenience, in the remainder of the paper, I refer to the assigned minimum sentence simply as the assigned sentence.

[8]Dyke (2007) uses the same data to analyze prosecutors' political incentives.

[9]See Appendix B.3 for details.

sexual assault and robbery.[10] Drug-related offenses are not included. Non-homicide violent crimes are, at the same time, homogeneous and numerous enough to allow the estimation of the model.[11] Unless otherwise specified, the tables and results presented throughout the paper are based on this sub-sample.

For each case, I observe the following defendant's characteristics: Gender, race, ethnicity, age and previous criminal record. The latter variable is reported in terms of points, which the North Carolina justice system assigns for the purposes of setting sentencing guidelines. In my sample, these points range from zero to 98. I also observe the type of defense counsel employed in the case. Counsel services are provided by a public defender or, alternatively, by a privately-retained or court-appointed attorney.[12]

Table 1 contains descriptive statistics of the defendant's characteristics. Over half of the defendants in the data are African-American, and the vast majority of the remaining defendants are non-Hispanic white. Less than four percent of the defendants are Hispanic and around to two percent are from other race or ethnicity. More than 90 percent of the defendants are male, and the mean defendant's age is approximately 29 years. Public defenders and court-appointed attorneys represent about 23 percent and 50 percent of the defendants, respectively. In roughly 22 percent of the cases, the defendants are represented by a privately-retained attorney. Less than 3 percent of the defendants either employ others types of counsel services or waive counsel.

The focus of this study is on incarceration sentences. In many of the cases in the data, the defendant receives an alternative punishment, such as probation, community service or the payment of a fine. Unfortunately, such punishments cannot be incorporated into my analysis since every criterion for representing incarceration and

[10]Robbery is defined as the taking or attempted taking of personal property, either by force, or by threat of force. It is, therefore, both a property crime and a crime against the person.

[11]The Federal Bureau of Investigation employs the larger category of violent crimes (comprising also homicides) in its Uniform Crime Reporting Program. I exclude homicides from the sample because of the prevalence of death and life sentences assigned to defendants convicted of such crimes. There would be no clear way of incorporating death sentences in my analysis. See Appendix B.3 for details on the classification of the offenses in the data.

[12]Public defenders are full-time state employees who represent indigent defendants accused of crimes that may result in incarceration. Public defender offices are only present in 16 judicial districts in North Carolina. In the absence of such an office, indigent defendants are entitled to be represented by a court-appointed private attorney. Notice that these counsel services are provided at a subsidized rate, but not free of charge to the defendant. In the event of a conviction, the defendant is ordered to reimburse the state for the value of the counsel services provided either by public defenders or court-appointed attorneys.

TABLE 1. Descriptive statistics – defendant's characteristics

| Race, ethnicity, gender and counsel type | | |
|---|---|---|
| Characteristic | Observations | Frequency |
| Race/ethnicity | | |
| African-American | 66755 | 56.12% |
| Non-Hispanic White | 45618 | 38.35% |
| Hispanic | 4126 | 3.47% |
| Other | 2449 | 2.06% |
| Total | 118948 | 100.00% |
| Gender | | |
| Male | 110495 | 92.89% |
| Female | 8453 | 7.11% |
| Total | 118948 | 100.00% |
| Counsel type | | |
| Court-appointed | 62325 | 52.40% |
| Public defender | 27331 | 22.98% |
| Privately-held | 25769 | 21.66% |
| Other | 3523 | 2.96% |
| Total | 118948 | 100.00% |
| **Defendant's age and previous criminal record** | | |
| Characteristic | Mean | Variance |
| Age (years) | 28.88 | 10.64 |
| Criminal record points | 3.93 | 5.03 |

non-incarceration sentences on the same space would be arbitrary.[13] Thus, in my empirical analysis, I treat any alternative sentence as no sentence whatsoever.

Table 2 presents descriptive statistics of the case outcomes. 88.69 percent of the cases in the sample are solved by plea agreements—the majority of which result in an alternative sentence. The share of cases that settle for a incarceration sentence is 32.83 percent. Of the 9.91 percent of cases that reach trial, slightly more than half result in an acquittal. 3.91 percent of all cases result in a conviction with incarceration time at trial. In 83.00 percent of the cases, the main charge is a felony. In the other cases, the charge is either a misdemeanor or not known. Trial sentences tend to be

[13]Moreover, in many cases where an alternative sentence is assigned, the data do not report the exact nature or the severity of such a sentence. Thus, in order to take alternative sentences into account in my analysis, I would either have to treat all such sentences as equivalent to each other, or I would have to deal with a severe missing-variables problem.

TABLE 2. Descriptive statistics – non-homicide violent crimes

| Distribution of cases by outcome | | |
|---|---|---|
| Case outcome | Observations | Frequency |
| Settlement | | |
| Incarceration | 39048 | 32.83% |
| Alternative sentence | 66443 | 55.86% |
| Total | 105491 | 88.69% |
| Trial conviction | | |
| Incarceration | 4654 | 3.91% |
| Alternative sentence | 779 | 0.65% |
| Total | 5433 | 4.56% |
| Trial acquittal / dismissed | | |
| Absolved by jury | 5049 | 4.24% |
| Dismissed by judge | 1319 | 1.11% |
| Total | 6368 | 5.35% |
| Dismissed by prosecutor | 1656 | 1.39% |
| Total | 118948 | 100.00% |
| **Distribution of cases by severity of the charge** | | |
| Main charged offense | Observations | Frequency |
| Felony | 98726 | 83.00% |
| Other | 20222 | 17.00% |
| Total | 118948 | 100.00% |
| **Sentences' length** | | |
| Conviction method | Mean | Standard deviation |
| Trial convictions† | 100.73 | 106.41 |
| Settlement convictions† | 38.98 | 47.92 |
| † : Measured in months. | | |

longer than those of settled cases. The average length of the former is 100.73 months, while that for the latter is 38.98 months. Sentence dispersion is high. The standard deviations of trial and settlement sentences are 106.41 and 47.92, respectively.

## 4. The Model

4.1. **Setup.** In this section, I briefly describe Bebchuk's (1984) settlement model, which will guide my analysis in subsequent sections.[14] Two agents—the prosecutor and the defendant—bargain over the outcome of a case. The agents' utility functions are linear in the sentence assigned to the defendant. Specifically, the defendant wants to minimize the sentence, whereas the prosecutor wants to maximize it.[15]

If bargaining fails, the case is brought to trial, where the defendant is found guilty with probability $\Theta$. This probability represents the strength of the case against the defendant and is drawn at the beginning of the game from a distribution $F$. I make the following technical assumptions:[16] $F$ is distributed over an interval $(\underline{\theta}, \bar{\theta}) \subseteq (0, 1)$ and is twice differentiable. The associated density function $f$ is strictly positive on $(\underline{\theta}, \bar{\theta})$ and is non-increasing in a neighborhood of $\bar{\theta}$. Moreover, to rule out multiple equilibria, I assume that the hazard rate $f/[1-F]$ is strictly increasing in $\theta$.

Bargaining takes place under asymmetric information. Specifically, only the defendant knows the realization $\theta$ of $\Theta$. The assumption that the defendant has private information on the probability of being convicted at trial is motivated by noticing that most defendants know whether they are guilty. As Scott and Stuntz (1992) point out, such knowledge may assume several forms. A defendant may, for example, not be involved in the crime at all. Alternatively, the defendant may be involved, but may have committed the offense without the requisite criminal intent. Regardless of guilt, the defendant may have more information than the prosecutor on the quality of the evidence that may be used at trial (e.g., what, exactly, a given witness knows).[17]

[14] Bebchuk's game was originally proposed for the study of civil cases. Since I use the model for analyzing plea bargaining, the names of the agents and certain variables are changed in order to better suit the criminal-law context. For example, the plaintiff in the original model is named the prosecutor, the judgment to which a winning plaintiff is entitled is named a trial sentence, etc.

[15] Alschuter (1968) provides several pieces of anecdotal evidence that prosecutors mostly play the role of advocates in the process of plea bargaining. The author explains that "... in this role, the prosecutor must estimate the sentence that seems likely after a conviction at trial, discount this sentence by the possibility of an acquittal, and balance the "discounted trial sentence" against the sentence he can ensure through a plea agreement." The assumption that the prosecutor's utility is linear in the assigned sentence captures such behavior in a simple way. Landes (1971) uses a similar utility function for the prosecutor.

[16] These assumptions ensure that, without conditioning in $\Theta$, the probability of settlement is strictly between zero and one.

[17] Ideally, I should allow for private information on the prosecutor's side, as well. Such an extension, however, would make the empirical analysis of the model impractical. See Schweizer (1989), Sobel (1989), Daughety and Reinganum (1994) and Friedman and Wittman (2007) for models of settlement with two-sided asymmetric information.

In the event of a conviction at trial, a common knowledge sentence $t$ is assigned. The assumption that $t$ is common knowledge may be interpreted as follows: At the bargaining stage, the prosecutor and the defendant know enough about the case to determine exactly what sentence the judge will assign if the defendant is found guilty at trial. Such information comes, for example, from the charged offenses, the defendant's criminal record, sentencing guidelines, the judge's previous sentencing patterns, etc. The prosecutor and the defendant, respectively, pay costs $c_p$ and $c_d$ for reaching the trial stage. I interpret the costs for the prosecutor as the opportunity costs of taking a case to trial. For the defendant, the costs are associated with attorney fees and court fees in general. Similarly to $t$, I assume that $c_p$ and $c_d$ are common knowledge to both players.

The bargaining protocol is take-it-or-leave-it, so that the model constitutes a standard screening game. The prosecutor offers the defendant to settle for a sentence $s$. If the defendant accepts it, the game ends. Payoffs are then $s$ for the prosecutor and $-s$ for the defendant. If the defendant rejects the offer, the case reaches the trial stage. The trial payoffs for the prosecutor are $t - c_p$ if the defendant is found guilty, and $-c_p$ otherwise. For the defendant, the trial payoffs are $-t - c_d$ in the case of a conviction, and $-c_d$ otherwise. Whereas imposing a take-it-or-leave-it bargaining protocol is not without loss of generality, notice that, under fairly general conditions, that procedure is optimal from the prosecutor's perspective (Spier, 1992). Since the prosecutor is a recurrent player in the plea-bargaining game, reputational incentives make the commitment with a take-it-or-leave-it offer plausible.

For now, I assume that the prosecutor cannot withdraw the case. Therefore, the case may be brought to trial even if the expected value of doing so is negative for the prosecutor. Such an assumption is justified in the criminal-law context since prosecutors often have incentives to stay in a case—either due to career concerns or for the sake of their reputation.[18]. Later, in my empirical analysis, I clarify how dropped cases are dealt with.

4.2. **Equilibrium.** The relevant equilibrium concept is subgame perfection, and the game is solved by backward induction. The defendant accepts a prosecutor's offer $s$ if and only if $s \leq \theta t + c_d$. Therefore, for every value $s$ chosen by the prosecutor, the

[18]Bebchuk (1984) assumes that $\underline{\theta} t \geq c_p$ holds, so that it is always better for the prosecutor to go to trial than to drop the case. See Nalebuff (1987) for a game in which the prosecutor cannot commit to bringing a case to trial if, by doing that, the expected payoff becomes negative.

defendant's strategy is characterized by a cutoff

$$\theta(s) = \frac{s - c_d}{t} \tag{4.1}$$

such that the defendant accepts the prosecutor's offer if and only if the probability of conviction at trial is greater then or equal to $\theta(s)$.

The prosecutor then solves the following problem:

$$\max_s \quad \{1 - F[\theta(s)]\} s + F[\theta(s)] \left\{ -c_p + t \frac{\int_{\underline{\theta}}^{\theta(s)} x f(x) dx}{F[\theta(s)]} \right\}.$$

Bebchuk (1984) shows that the optimal prosecutor's offer $s^*$ satisfies $\theta(s^*) \in (\underline{\theta}, \bar{\theta})$, so that the prosecutor's first-order condition, presented below, holds with equality

$$\frac{t}{c_p + c_d} = \frac{f[\theta(s^*)]}{\{1 - F[\theta(s^*)]\}}. \tag{4.2}$$

Equations (4.1) and (4.2) characterize the equilibrium. Without conditioning on $\Theta$, the equilibrium probability that the prosecutor's offer is rejected is given by $F[\theta(s^*)]$ and is strictly between zero and one. The probability of conviction is the sum of the probabilities of settlement and conviction at trial, and is given by

$$1 - F[\theta(s^*)] + \int_{\underline{\theta}}^{\theta(s^*)} x f(x) dx \quad = \quad 1 - \int_{\underline{\theta}}^{\theta(s^*)} (1 - x) f(x) dx. \tag{4.3}$$

4.3. **Empirical implications.** Keeping the trial costs $c_p$ and $c_d$ constant, I perform a comparative static analysis by letting the trial sentence $t$ vary and verifying how that affects the equilibrium outcome. Define the functions $\tilde{s}(\cdot)$ and $\tilde{\theta}(\cdot)$, which, for any trial sentence $t$, respectively return the equilibrium prosecutor's offer and the equilibrium cutoff point for the defendant. The domain of both functions is $\Re_{++}$. Bebchuk (1984) shows that both $\tilde{s}(\cdot)$ and $\tilde{\theta}(\cdot)$ are strictly increasing, and $\tilde{s}(\cdot)$ is strictly convex.[19]

Since $\tilde{\theta}(\cdot)$ is strictly increasing and the density $f$ is strictly positive over the whole support of $\Theta$, the probability that the defendant rejects the prosecutor's offer decreases strictly with the trial sentence $t$. Furthermore, it is clear from the right-hand side of (4.3) that the probability of conviction also decreases strictly with $t$.

In Appendix B.1, I present reduced-form results indicating that the data are consistent with these empirical implications of the model. In particular, I show evidence

[19]That $\tilde{\theta}(\cdot)$ is strictly increasing follows from (4.2) and the assumption that the hazard rate for the defendants' type is strictly increasing. The strict monotonicity and convexity of $\tilde{s}(\cdot)$ are then obtained from (4.1).

that the settlement of a case becomes less likely as the sentence to be assigned in the event of a trial conviction increases.

## 5. Structural analysis

This section contains the structural analysis of the data, based on the model outlined in Section 4. I first describe the data-generating process, which adapts the model to the institutional setting presented in Section 3. Then, I show sufficient conditions for the model to be identified and propose an estimator for it.

### 5.1. **Data-generating process.**

5.1.1. *Primitives.* For every case $i$, let the (possibly vector valued) random variable $Z_i$, defined on the space $\Delta$, describe case-level characteristics that are observable to the econometrician. Such characteristics include variables related to the charged offense, the defendant, the judge responsible for the case, the time and the location where prosecution takes place, etc. The other primitives of the structural model, which are presented below, are defined conditional on $Z_i$.

To each case $i$ corresponds a potential incarceration sentence, which is assigned if the defendant is convicted at trial. Note that such a sentence exists even for cases settled by a plea bargain or for cases in which there is a trial, but the defendant is found not guilty. The potential trial sentence is described by the random variable $T_i$, which, conditional on $Z_i$, is assumed to be i.i.d. across cases. $T_i$ follows a conditional mixture distribution. With probability $\nu(Z_i)$, it is equal to zero, which means that, in the event of conviction at trial, a non-incarceration sentence is assigned. With probability $1-\nu(Z_i)$, $T_i$ is distributed according to the CDF $G(\cdot|Z_i)$, defined on the interval $[\underline{t},\bar{t}]$, where $\underline{t}>0$.[20] Assume that $G(\cdot|Z_i)$ is continuous, and denote by $g(\cdot|Z_i)$ the associated conditional pdf. Moreover, assume that $g(t|Z_i)>0$ for all $t\in[\underline{t},\bar{t}]$.

The defendant's probability of conviction at trial also varies across cases. For case $i$, such a probability is described by the random variable $\Theta_i$, with support $(\underline{\theta},\bar{\theta})\subseteq(0,1)$. Assume that, conditional on $Z_i$, $\Theta_i$ is i.i.d. across cases, and let $F(\cdot|Z_i)$ be its conditional distribution. Assume, also, that $\Theta_i$ and $T_i$ are independent, conditional on $Z_i$.[21] Make the following technical assumptions: $F(\cdot|Z_i)$ is twice differentiable, and the associated conditional density, denoted by $f(\cdot|Z_i)$, is strictly positive over

[20] I could, in principle, allow the support $[\underline{t},\bar{t}]$ to vary with $Z_i$. In the estimation of the model, which is discussed below, I chose not to do so due to sample size limitations. Accordingly, here I assume a constant support, in order to keep the notation as clear as possible.

[21] Relaxing the independence assumption I partially identify the model. See Appendix B.2.

the whole support and non-increasing on a neighborhood of $\bar{\theta}$. Moreover, assume that the conditional hazard rate $f(\cdot|Z_i)/[1-F(\cdot|Z_i)]$ is strictly increasing.

Let $c_d(Z_i)$ and $c_p(Z_i)$ be the trial costs for the defendant and the prosecutor, respectively. Notice that, conditional on $Z_i$, such variables are deterministic. At this point, two observations are in order. First, $c_d(Z_i)$ and $c_p(Z_i)$ are just the costs expected by the agents at the moment of plea bargaining. It is possible that the actual trial costs vary across cases. Second, as shown below, the model is overidentified under the assumption that, conditional on $Z_i$, the trial costs are constant. Indeed, I still identify the model after allowing the trial costs for the defendant and the prosecutor to vary deterministically with $T_i$. In the estimation of the model, I assume that $c_d(Z_i)$ and $c_p(Z_i)$ are linear functions of the trial costs.

The primitives of the structural model are then: (i) the conditional distribution of potential trial sentences, characterized by the functions $\nu(Z_i)$ and $G(\cdot|Z_i)$; (ii) the conditional distribution of defendants' types, given by the $F(\cdot|Z_i)$; (iii) the trial costs $c_d(Z_i)$ and $c_p(Z_i)$; and (iv) the distribution of $Z_i$.

5.1.2. *Observables.* For every case $i$, given realizations $z_i$ of $Z_i$, $t_i$ of $T_i$ and $\theta_i$ of $\Theta_i$, as well as $F(\cdot|Z_i = z_i)$, $c_d(z_i)$ and $c_p(z_i)$, the prosecutor and defendant play the game described in Section 4. A prosecutor's settlement offer to the defendant corresponds to each case. As in Section 4, use equations (4.1) and (4.2) to define the functions $\tilde{\theta}(t,z)$ and $\tilde{s}(t,z)$. Such functions, respectively, return the defendant's equilibrium cutoff point and the prosecutor's equilibrium offer, given a trial sentence $t$ and case characteristics $z$[22]. Assume that $\tilde{\theta}(0,z) = 0$ and $\tilde{s}(0,z) = 0$ for every $z$. Hence, if a non-incarceration sentence is to be assigned following a conviction at trial, then the prosecutor offers to settle for a non-incarceration sentence. In equilibrium, the defendant always takes such offer, so that the case settles with certainty.[23]

The prosecutor's offer for case $i$, therefore, is described by the random variable $S_i = \tilde{s}(T_i, Z_i)$. Conditional on $Z_i$, $S_i$ is i.i.d. across cases, and, similarly to $T_i$, follows a mixed distribution. With probability $\nu(Z_i)$, it equals zero. With probability $1-\nu(Z_i)$, $S_i$ is conditionally distributed according to the CDF $B(\cdot|Z_i)$, which has

[22]Notice that $\tilde{\theta}(t,z)$ and $\tilde{s}(t,z)$ depend on $z$ through $F(\cdot|Z_i = z)$, $c_d(z)$ and $c_p(z)$.

[23]In my analysis, I consider all non-incarceration sentences as no sentence whatsoever. Thus, I make no distinction between cases that settle for an alternative sentence and cases that the prosecutor drops. Notice that the model does not allow for the assignment of alternative sentences at trial. As shown in table 2 that is a rare event. Accommodating it would make the identification of the model considerably more difficult.

support $[\tilde{s}(\underline{t}, z), \tilde{s}(\bar{t}, z)]$. Notice that $B(\cdot|Z_i)$ is continuous, and let $b(\cdot|Z_i)$ be the associated density.[24]

The model implies a selection process that complicates identification. The realization $t_i$ of $T_i$ is observable to the econometrician only in the event of a conviction at trial. Similarly, the realization $s_i$ of $S_i$ is available only for settled cases. Formally, let $\Psi_i$ be a discrete random variable describing the way case $i$ is resolved. Define

$$\Psi_i = \begin{cases} 0 & \text{if the case is dropped by the prosecutor or settled for an alternative sentence} \\ 1 & \text{if the case is settled for a incarceration sentence} \\ 2 & \text{if the case results in a incarceration conviction at trial} \\ 3 & \text{if the defendant is found not guilty at trial.} \end{cases}$$

The observables for each case are (i) the realization $\psi_i$ of $\Psi_i$; (ii) the realization $z_i$ of $Z_i$; (iii) the realization $t_i$ of $T_i$, if and only if $\psi_i = 2$; and (iv) the realization $s_i$ of $S_i$, if and only if $\psi_i = 1$. To identify the model's primitives, I must account for such a selection problem.

In the remainder of this section, I refer to a settlement or a successful plea bargain only if $\Psi_i = 1$. Similarly, by a trial conviction, I mean $\Psi_i = 2$. Moreover, for ease of notation, I omit the index $i$ when I refer to a specific case.

5.2. **Identification.** Since $\Theta$ is distributed continuously on $(\underline{\theta}, \bar{\theta})$, and the defendants' action space consists of merely accepting or rejecting the prosecutor's offer, there is no one-to-one mapping between the defendants' types and actions. As a consequence, techniques often employed by the auctions literature for the identification of private types cannot be used here.[25] However, the prosecutor's equilibrium offer conveys information on the distribution $F$. As shown below, such information can be explored to recover all the model's primitives.

The strategy described here provides the identification of the model's primitives, conditional on a realization $z$ of $Z$. It consists of two main parts. First, I identify the prosecutor's optimal offer function $\tilde{s}(\cdot, z)$. Then, using $\tilde{s}(\cdot, z)$, I show how to recover $G(\cdot|Z = z)$, $F(\cdot|Z = z)$, $c_d(z)$ and $c_p(z)$. Remember that the case characteristics, represented by $Z$, are distributed over the space $\Delta$. Since $Z$ is always observable, the identification of its distribution is straightforward, and I do not discuss it here. The same observation holds for $\nu(z)$, as $P[\Psi = 0|Z = z]$ is observable.

[24] To see that $B(\cdot|Z_i)$ is, indeed, continuous, notice that both $G(\cdot|Z_i)$ and $\tilde{s}(t, z)$ are continuous.
[25] See Athey and Haile (2007) for an introduction to the identification of auction models.

5.2.1. *Conditions A and B.* I begin by defining the following two conditions, which pose restrictions on subsets of the space of case characteristics $\Delta$. Together with the technical assumptions stated in the definition of the primitives, such conditions are sufficient for the identification of the model.

DEFINITION 1. *A subset $\Delta_\rho$ of $\Delta$ satisfies* ***condition* A** *if, for every pair $z', z''$ in $\Delta_\rho$, the following equalities hold*

$$\begin{aligned} & c_d(z') = c_d(z'') \\ & c_p(z') = c_p(z'') \\ \textit{and} \qquad & F(\theta|Z = z') = F(\theta|Z = z'') \end{aligned}$$

*for all $\theta \in (\underline{\theta}, \bar{\theta})$.*

The trial costs and the distribution of defendants' types are, thus, constant across all $z$ within a subset $\Delta_\rho$ that satisfies condition $A$. Notice that $\Delta_\rho$ satisfying condition $A$ implies that $\tilde{s}(\cdot, z') = \tilde{s}(\cdot, z'')$ and $\tilde{\theta}(\cdot, z') = \tilde{\theta}(\cdot, z'')$ for all $z', z''$ in $\Delta_\rho$. Notice, also, that the condition does not restrict the distribution of potential trial sentences within $\Delta_\rho$. Condition $A$ is not vacuous since it is trivially valid for every singleton subset of $\Delta$. It is also plausible to assume that the condition holds for subsets of $\Delta$ that present little variation in the nature of the main offense, as well as in the characteristics of potential jury members, prosecutors and defendants—the main determinants of trial costs and the probability of convictions at trial.

Before I state the next definition, notice that a partition of an interval $[a, b]$ is a finite sequence of the form

$$a = x_0 < x_1 < \cdots < x_N = b$$

I now define the second identification condition.

DEFINITION 2. *Consider the function*

$$\phi(t, z', z'') \equiv \frac{g(t|Z = z')}{g(t|Z = z'')}.$$

*A subset $\Delta_\rho$ of $\Delta$ satisfies* ***condition* B** *on a bounded interval $X \subseteq [\underline{t}, \bar{t}]$ if there is a partition $\{x_0, x_1, \cdots, x_N\}$ of $X$ such that, for all $n \in \{1, \cdots, N\}$, there are elements $z', z'' \in \Delta_\rho$ such that the function $\phi(\cdot, z', z'')$ is strictly monotonic in $t$ on the interval $[x_{n-1}, x_n]$.*

The function $\phi(\cdot, z', z'')$ consists of the ratio of the trial sentence densities $g(\cdot|Z = z')$ and $g(\cdot|Z = z'')$. If $\Delta_\rho$ contains only the two elements $z'$ and $z''$, then it satisfies

condition $B$ on an interval $X$ if and only if $\phi(\cdot, z', z'')$ is piecewise monotone on $X$. If $\Delta_\rho$ has more than two elements, condition $B$ is easier to satisfy. It is enough that $X$ can be partitioned in a finite number of intervals, and, on each of such intervals, $\phi(\cdot, z', z'')$ is piecewise monotone for some pair $z'$, $z''$ of elements of $\Delta_\rho$.

Conditions $A$ and $B$ can be regarded as exclusion and inclusion restrictions, respectively, similar to the conditions for an instrumental variable. They require that variation in some dimension of $Z$ affects the conditional distribution of potential trial sentences, but not the other primitives in the model. However, for $\Delta_\rho$ to satisfy condition $B$, there must be enough variation within $\Delta_\rho$, so that the distribution of trial sentences is affected along its whole support.[26]

The selection of a subset $\Delta_\rho$ that simultaneously satisfies conditions $A$ and $B$ involves a trade-off. The fewer elements $\Delta_\rho$ has, the more plausible condition $A$ is. But condition $B$ becomes harder to satisfy as $\Delta_\rho$ gets small.[27] I propose the following choice of $\Delta_\rho$: To satisfy condition $A$, I restrict $\Delta_\rho$ according to the the nature of the charged offense and to the defendant's gender, race and previous criminal background. Moreover, I restrict $\Delta_\rho$ by the place where the case is prosecuted, which helps controlling for characteristics of the prosecutor and the jury members. I then obtain the variation in the conditional distributions of trial sentences, which is necessary for condition $B$ to be satisfied, by allowing judge-specific characteristics to vary within $\Delta_\rho$. Specifically, I divide the judges in the data into two groups—lenient and harsh—based on their observed sentencing behavior. Section 6 presents the details of such a classification of judges. Each $\Delta_\rho$ considered has, thus, two elements—one for each of the groups of judges mentioned above. The judge rotation system in North Carolina ensures that, throughout a long enough time period, different judges decide on similar cases in the same location. In Appendix B.1 I present evidence indicating that the distributions of cases under the the responsibility of lenient and harsh judges are, indeed, indistinguishable from one another—making it valid, for the purposes of my analysis, to employ differences in the sentencing patterns between these two groups as a source of variation in the distribution of trial sentences.

5.2.2. *Prosecutor's settlement offer function.* Remember that $g(\cdot|Z)$ is the pdf of potential trial sentences, and $b(\cdot|Z)$ is the pdf of prosecutors' settlement offers, conditional on $Z$. The following lemma is useful for the identification of $\tilde{s}(\cdot, z)$:

[26]Like the exclusion condition for an instrumental variable, condition $A$ cannot be tested. The validity of condition $B$, however, can be verified empirically. See footnote 30 below.

[27]The estimation of the model for a small $\Delta_\rho$ may also be impractical, given a limited sample size.

LEMMA 1. *Assume that* $(b[s|Z=z']/b[s|Z=z''])$ *and* $(g(t|Z=z')/g(t|Z=z''))$ *are known for every* $z', z'' \in \Delta_\rho$, $s \in [\tilde{s}(\underline{t}, z), \tilde{s}(\bar{t}, z)]$ *and* $t \in [\underline{t}, \bar{t}]$. *Assume, also, that condition B holds on* $[\underline{t}, \bar{t}]$, *and that there exists* $\check{z} \in \Delta_\rho$ *such that*

$$\frac{b[\tilde{s}(t, \check{z})|Z=z']}{b[\tilde{s}(t, \check{z})|Z=z'']} = \frac{g(t|Z=z')}{g(t|Z=z'')}$$

*for all* $z', z'' \in \Delta_\rho$ *and* $t \in [\underline{t}, \bar{t}]$. *Then, the function* $\tilde{s}(\cdot, \check{z})$ *is identified over* $[\underline{t}, \bar{t}]$.

See Appendix A for the proof.

The functional equation in the statement of Lemma 1 relates ratios of densities for two different elements of $\Delta_\rho$. On the right-hand side is a ratio of trial sentence densities, evaluated at $t$. On the left-hand side is a ratio of settlement offer densities, evaluated at $\tilde{s}(t, \check{z})$. The lemma shows that, if such a functional equation is valid for all $t$, then the left-hand side can be inverted to recover the function $\tilde{s}(\cdot, \check{z})$. Condition $B$ ensures that the left-hand side of the functional equation is piecewise invertible.

My first main result states that, under conditions $A$ and $B$, the prosecutor's optimal offer function is identified.

PROPOSITION 1. *Assume that the set* $\Delta_\rho \subseteq \Delta$ *satisfies conditions A and B on* $[\underline{t}, \bar{t}]$. *Then, for all* $z \in \Delta_\rho$, *the prosecutor's optimal offer function* $\tilde{s}(\cdot, z)$ *is identified over the whole interval* $[\underline{t}, \bar{t}]$.

Condition $A$ allows me to write a functional equation for $\tilde{s}(t, z)$, equivalent to the one that appears in the statement of Lemma 1. I use the same condition to recover the two sides of the equation from the observables. Using condition $B$, I can then apply Lemma 1 and identify $\tilde{s}(t, z)$ for all $z \in \Delta_\rho$. I present the proof of the proposition in the main text since it is important for understanding the estimation procedure proposed later in the paper.

*Proof.* Since, for all $z \in \Delta$, $\tilde{s}(\cdot, z)$ is strictly increasing in $t$, I can write

$$b(s|Z=z) = g\left(\tilde{s}^{-1}(s, z)|Z=z\right) \frac{d\tilde{s}^{-1}(s, z)}{ds} \tag{5.1}$$

for all $s \in [\tilde{s}(\underline{t}, z), \tilde{s}(\bar{t}, z)]$ and all $z \in \Delta$

Therefore, for every pair $z', z'' \in \Delta_\rho$ and all $t \in [\underline{t}, \bar{t}]$, I have that

$$\frac{b\left[\tilde{s}(t,z')|Z=z'\right]}{b\left[\tilde{s}(t,z'')|Z=z''\right]} = \frac{g\left(\tilde{s}^{-1}\left[\tilde{s}(t,z'),z'\right]|Z=z'\right)\frac{d\tilde{s}^{-1}(\tilde{s}(t,z),z')}{ds}}{g\left(\tilde{s}^{-1}\left[\tilde{s}(t,z''),z''\right]|Z=z''\right)\frac{d\tilde{s}^{-1}(\tilde{s}(t,z),z'')}{ds}}$$

$$= \frac{g\left(t|Z=z'\right)}{g\left(t|Z=z''\right)},$$

where the derivatives of the right-hand side of the first equality cancel out due to condition $A$. Now consider any $\breve{z} \in \Delta_\rho$, and notice that, again by condition $A$, $\tilde{s}(\cdot,\breve{z}) = \tilde{s}(\cdot,z') = \tilde{s}(\cdot,z'')$. The equation above then implies

$$\frac{b\left[\tilde{s}(t,\breve{z})|Z=z'\right]}{b\left[\tilde{s}(t,\breve{z})|Z=z''\right]} = \frac{g\left(t|Z=z'\right)}{g\left(t|Z=z''\right)} \tag{5.2}$$

for all $z', z'' \in \Delta_\rho$ and $t \in [\underline{t}, \bar{t}]$.

If the full distribution of offers and potential trial sentences were observed, I would be able to apply Lemma 1 to equation (5.2) in order to recover $\tilde{s}(t,z)$ for all $z \in \Delta_\rho$. However, due to selection, I do not observe such distributions, so that (5.2) cannot be used directly. Still, I can employ the censored versions of the distributions of settlement offers and trial sentences to obtain the density ratios in (5.2). Consider, first, the settlement offers. Although $b(\cdot|Z=z)$ is not available, I observe $b(\cdot|\Psi=1, Z=z)$, the distribution of accepted settlement offers. Given any $z$ and any value $s$, the equilibrium conditional probability of a successful plea bargain is

$$P\left[\Psi=1|S=s,Z=z\right] = 1 - F\left[\tilde{\theta}\left(\tilde{s}^{-1}(s,z),z\right)|Z=z\right]. \tag{5.3}$$

From Bayes' rule, I have that

$$b(s|\Psi=1,Z=z) = \frac{P[\Psi=1|S=s,Z=z]b(s|Z=z)}{P[\Psi=1|Z=z]}. \tag{5.4}$$

Notice that the support of $b(s|\Psi=1,Z=z)$ is still $[\tilde{s}(\underline{t},z'),\tilde{s}(\bar{t},z')]$.[28] Since $\Delta_\rho$ satisfies condition $A$, $P\left[\Psi=1|S=s,Z=z'\right] = P\left[\Psi=1|S=s,Z=z''\right]$ for all $s$ and every $z'$ and $z''$ in $\Delta_\rho$. Hence, I can write

$$\frac{b(s|\Psi=1,Z=z')}{b(s|\Psi=1,Z=z'')}\,\frac{P[\Psi=1|Z=z']}{P[\Psi=1|Z=z'']} = \frac{b(s|Z=z')}{b(s|Z=z'')} \tag{5.5}$$

for every $s \in [\tilde{s}(\underline{t},z'),\tilde{s}(\bar{t},z')]$ and all $z', z'' \in \Delta_\rho$. Therefore, I recover the density ratio on the left-hand side of equation (5.2), using the (observable) censored distribution of accepted settlement offers.

[28] That is because the defendant's equilibrium cutoff $\tilde{\theta}\left(\tilde{s}^{-1}(s,z),z\right)$ belongs to the interval $(0,1)$ for all values of $s$, so that $P\left[\Psi=1|S=s,Z=z\right]$ is always strictly positive.

Turning to the potential trial sentences, I do not observe the full conditional density $g(\cdot|Z=z)$. However, its censored counterpart, $g(\cdot|\Psi=2,Z=z)$, is available for all $z$. Given any sentence value $t$ and any $z\in\Delta$, the probability of conviction at trial is

$$P[\Psi=2|T=t,Z=z]=\int_{\underline{\theta}}^{\tilde{\theta}(t,z)} x\; f(x|Z=z)\,dx. \tag{5.6}$$

Using Bayes' rule once more, I have that

$$g(t|\Psi=2,Z=z)=\frac{P[\Psi=2|T=t,Z=z]g(t|Z=z)}{P[\Psi=2|Z=z]}. \tag{5.7}$$

The support of $g(t|\Psi=2,Z=z)$ is still $[\underline{t},\bar{t}]$.[29] Condition $A$ implies that, for all $t$ and every $z'$ and $z''$ in $\Delta_\rho$, $P\left[\Psi=2|T=t,Z=z'\right]=P\left[\Psi=2|T=t,Z=z''\right]$. Hence,

$$\frac{g(t|\Psi=2,Z=z')}{g(t|\Psi=2,Z=z'')}\,\frac{P[\Psi=2|Z=z']}{P[\Psi=2|Z=z'']}=\frac{g(t|Z=z')}{g(t|Z=z'')} \tag{5.8}$$

for all $t\in[\underline{t},\bar{t}]$ and all $z',z''$ in $\Delta_\rho$. I thus use the (observable) censored distribution of potential trial sentences for cases where the defendant is convicted at trial in order to identify the density ratio on the right-hand side of equation (5.2).[30] The proof of the proposition then follows from Lemma 1. □

5.2.3. *Completing the identification of the model.* I now show that, once $\tilde{s}(\cdot,z)$ is identified for a given value $z$, the model's primitives can be recovered, conditional on $Z=z$. Intuitively, the prosecutor's optimal offer function conveys information about the distribution of defendants' private types, which allows the identification of the whole model. The next proposition formalizes this idea.

Proposition 2. *Assume that, for all $z\in\Delta_\rho$, the prosecutor's optimal offer function $\tilde{s}(\cdot,z)$ is identified over the whole interval $[\underline{t},\bar{t}]$. Then, for all $z\in\Delta_\rho$, the following objects are identified: (i) the distribution function $G(\cdot|Z=z)$, over the whole interval $[\underline{t},\bar{t}]$; (ii) the distribution of defendants' types $F(\cdot|Z=z)$, over the interval $[\tilde{\theta}(\underline{t},z),\tilde{\theta}(\bar{t},z)]$; and (iii) the trial costs $c_d(z)$ and $c_p(z)$.*

See the Appendix A for the proof.

The proposition is based on the insight that, knowing $\tilde{s}(\cdot,z)$, I can employ the first-order condition of the prosecutor's optimization problem to recover the hazard function for the distribution of defendants' types. Using the hazard function, I am

[29] Indeed, $\tilde{\theta}(t,z)\in(0,1)$ for all $t$, and $f(\theta|Z=z)>0$ for all $\theta\in(\underline{\theta},\bar{\theta})$, so that $P[\Psi=2|T=t,Z=z]$ is always strictly positive.

[30] Equation (5.8) points to how condition $B$ can be verified using the data, although a formal test would require the computation of confidence bands for the density ratios.

able to identify the distribution itself, followed by all the other primitives of the model. The distribution of defendants' types $F(\cdot|Z=z)$ is identified only over the interval $[\tilde{\theta}(\underline{t},z),\tilde{\theta}(\bar{t},z)]$. The proof of the proposition shows that the model is overidentified under the assumption that $c_d(z)$ and $c_p(z)$ are constant. It is trivial to extend the analysis to the case in which the trial costs are parametric functions of the trial sentence $T$. In the estimation of the model, I let $c_d(z)$ and $c_p(z)$ vary linearly with $T$. This result concludes the identification of the model.

5.3. **Estimation.** I propose an estimation procedure that closely follows my identification strategy. It consists of two parts. First I estimate $\tilde{s}(\cdot,z)$. Then, I use the estimated function $\tilde{s}(\cdot,z)$ to obtain estimators for the model's primitives.

5.3.1. *Estimation of* $\tilde{s}(\cdot,z)$. Let $\Delta$ contain case-specific variables that affect $F(\cdot)$, $c_d(\cdot)$ and $c_p(\cdot)$, as well as judge-specific variables that affect sentencing. I choose a subset $\Delta_\rho \subseteq \Delta$ in which the case-specific variables are constant (so that condition $A$ holds), but where the judge-specific characteristics vary.

For every $z \in \Delta_\rho$, I obtain the estimates

$$\begin{aligned} & \hat{P}[\Psi=\psi|Z=z] \quad \text{for} \quad P[\Psi=\psi|Z=z] \quad ,\psi\in\{0;1;2\} \\ & \hat{g}(t|\Psi=2,Z=z) \quad \text{for} \quad g(t|\Psi=2,Z=z) \\ \text{and} \quad & \hat{b}(s|\Psi=1,Z=z) \quad \text{for} \quad b(s|\Psi=1,Z=z). \end{aligned}$$

The estimates for the distribution of $\Psi$ are trivially computed. The estimation of the densities $g(t|\Psi=2,Z=z)$ and $b(s|\Psi=1,Z=z)$ can be conducted by a kernel density estimator (KDE). There are two challenges to the estimation of these densities. First, I must deal with the boundedness of $[\underline{t},\bar{t}]$. When the standard KDE is applied to distributions with bounded support, it tends to underestimate the density near the boundaries, resulting in inconsistent estimates. To overcome this problem, I employ a boundary-correction method recently developed by Karunamuni and Zhang (2008).[31] Broadly speaking, the method generates artificial data beyond the boundaries of the original distribution's support. A kernel estimator applied to this enlarged data is uniformly consistent on the entire support of the original distribution.[32] The rate

[31]The Karunamuni and Zhang correction is an improvement on the correction proposed by Zhang, Karunamuni and Jones (1999). It is applied to the non-parametric estimation of first-price auction models by Hickman and Hubbard (2012).

[32]The bandwidth for most of the support is chosen by Silverman's "rule-of-thumb" (Silverman, 1986). Near the boundaries, a modified bandwidth is employed. See Karunamuni and Zhang (2008) for details. I use the Epanechnikov kernel kernel function.

of convergence is the same as the one obtained away from the boundaries using the standard KDE. The second challenge arises because the dimensionality of $Z$ may be large. The curse of dimensionality can prevent the estimation of $g(t|\Psi = 2, Z = z)$ and $b(s|\Psi = 1, Z = z)$ using conventional KDE methods, even for large sample sizes. I deal with this problem by, first, assuming that all variables in $\Delta$ are discrete and, then, employing smoothing techniques proposed by Li and Racine (2007) for the estimation of conditional densities. This procedure divides the space of case-level characteristics into a finite number of subsets and estimates the densities for each one of these subsets. As opposed to a naive implementation of this idea, which would employ only observation satisfying $Z = z$ for the estimation of $g(t|\Psi = 2, Z = z)$ and $b(s|\Psi = 1, Z = z)$, Li and Racine's estimator uses all the available data, assigning to each observation $i$ a weight based on the realization of $Z_i$. See Appendix A.2 for more details about this procedure and how it is implemented in the present study.

Equation (5.2) implies that

$$\int_{\underline{t}}^{\bar{t}} \left\{ \left\{ \frac{b\left[\tilde{s}(t,z)|\Psi=1,Z=z'\right]}{b\left[\tilde{s}(t,z)|\Psi=1,Z=z''\right]} \frac{P[\Psi=1|Z=z']}{P[\Psi=1|Z=z'']} - \frac{g\left(t|\Psi=2,Z=z'\right)}{g\left(t|\Psi=2,Z=z''\right)} \frac{P[\Psi=2|Z=z']}{P[\Psi=2|Z=z'']} \right\}^2 \right\} dH(t) = 0$$

for any measure $H$ over $[\underline{t}, \bar{t}]$. Denote the lowest and highest observed trial sentences for $z \in \Delta_\rho$ by $\hat{\underline{t}}$ and $\hat{\bar{t}}$, respectively, and notice that such values are consistent estimates for $\underline{t}$ and $\bar{t}$. Similarly, denote by $\hat{\underline{s}}$ and $\hat{\bar{s}}$, respectively, the lowest and highest observed plea-bargained sentences for $z \in \Delta_\rho$, and notice that these are consistent estimates for $\tilde{s}(\underline{t}, z)$ and $\tilde{s}(\bar{t}, z)$. Remember that $\tilde{s}(\cdot, z)$ is increasing and convex, and let $\Upsilon$ be the space of increasing and convex functions $s(\cdot)$ over $[\underline{t}, \bar{t}]$ such that $s(\hat{\underline{t}}) = s(\hat{\underline{s}})$ and $s(\hat{\bar{t}}) = s(\hat{\bar{s}})$. Also, let $\mathcal{C}$ be the set of all pairwise combinations of points in $\Delta_\rho$. The estimator $\hat{s}(\cdot, z)$ for the function $\tilde{s}(\cdot, z)$ can be found by solving

$$\min_{s\in\Upsilon} \sum_{(z',z'')\in\mathcal{C}} \int_{\underline{t}}^{\bar{t}} \left\{ \frac{\hat{b}\left[s(t,z')|\Psi=1,Z=z'\right]}{\hat{b}\left[s(t,z'')|\Psi=1,Z=z''\right]} \frac{\hat{P}[\Psi=1|Z=z']}{\hat{P}[\Psi=1|Z=z'']} - \frac{\hat{g}\left(t|\Psi=2,Z=z'\right)}{\hat{g}\left(t|\Psi=2,Z=z''\right)} \frac{\hat{P}[\Psi=2|Z=z']}{\hat{P}[\Psi=2|Z=z'']} \right\}^2 dH(t), \tag{5.9}$$

where $H$ is an arbitrary measure over $[\underline{t}, \bar{t}]$.[33] In order to solve this infinite-dimensional optimization problem, I approximate the space $\Upsilon$ using splines—functions that are

[33] In the application described below, I set such a measure to be $\hat{g}\left(t|\Psi=2,Z=z''\right)$.

piecewise polynomial and have a high degree of smoothness at the points where the polynomials meet.[34] Splines can be conveniently represented as the linear combination of a finite set of basis functions, which allow me to treat problem (5.9) as a finite-dimension non-linear regression problem. A popular family of basis functions is B-splines. Here, instead, I use C-splines, a set of basis functions recently proposed by Meyer (2008). C-splines differ from B-splines in that the basis functions in the former are strictly increasing and strictly convex. Because of such properties of the basis functions, monotonicity and convexity can be easily imposed to the approximate solution of (5.9), by restricting the regression coefficients to be non-negative.

To state the result showing the consistency of the estimator described above, define the functions

$$\tilde{b}_r(s, z', z'') \equiv \frac{b\left[s|\Psi = 1, Z = z'\right]}{b\left[s|\Psi = 1, Z = z''\right]} \frac{P[\Psi = 1|Z = z']}{P[\Psi = 1|Z = z'']}$$

$$\text{and} \qquad \tilde{g}_r(t, z', z'') \equiv \frac{g\left(t|\Psi = 2, Z = z'\right)}{g\left(t|\Psi = 2, Z = z''\right)} \frac{P[\Psi = 2|Z = z']}{P[\Psi = 2|Z = z'']}$$

for $(z', z'') \in \mathcal{C}$. I can now state the following proposition:

PROPOSITION 3. *Assume that, for every pair $(z', z'') \in \mathcal{C}$, the following conditions hold: (i) the function $\bar{b}_r(\cdot, z', z'')$ is differentiable and the absolute value of its derivative is bounded by $\mathring{b}_r(z', z'')$; and (ii) the functions $\bar{b}_r(\cdot, z', z'')$ and $\bar{g}_r(\cdot, z', z'')$ are positive and bounded by $\bar{B}_r(z', z'')$ and $\bar{G}_r(z', z'')$, respectively. Then, the estimator of the prosecutor's settlement offer function $\tilde{s}(\cdot, z)$ for $z \in \Delta_\rho$ is uniformly consistent.*

See Appendix A for the proof.

The estimation of $\tilde{s}(\cdot, z)$ has two steps. First, I obtain $\hat{P}[\Psi = \psi|Z = z]$, $\hat{g}(t|\Psi = 2, Z = z)$ and $\hat{b}(s|\Psi = 1, Z = z)$, and then these estimates are used in the construction of the objective function shown in (5.9). The proof of Proposition 3 is facilitated by noticing that, given the first-step estimates, the objective function is non-random. The restrictions on the density ratios $\bar{b}_r(\cdot, z', z'')$ and $\bar{g}_r(\cdot, z', z'')$ ensure the continuity of the objective function. Such continuity allows me to apply standard techniques for achieving the consistency of two-step estimators.

5.3.2. *Estimation of the model's primitives.* Using $\hat{s}(\cdot, z)$, I am able to recover the model's primitives. I extend the basic model by allowing the trial costs to vary linearly with the potential trial sentence $T$. Formally, I assume that the trial costs for the defendant and the prosecutor are given, respectively, by $c_d(t, z) \equiv \alpha_d(z) + \beta_d(z)t$ and

[34] See Eubank (1999) for an excellent introduction to spline approximation.

$c_p(t,z) \equiv \alpha_p(z) + \beta_p(z)t$. The primitives to be estimated are then the cost parameters $\alpha_d(z)$, $\beta_d(z)$, $\alpha_p(z)$ and $\beta_p(z)$, the distribution of defendant's types $F(\cdot|Z=z)$ and the distribution of trial sentences, characterized by $\nu(z)$ and $g(\cdot|Z=z)$.

For all $z \in \Delta_\rho$, I trivially estimate $\nu(z)$ by using the empirical probabilities that $\Psi = 0$, conditional on $Z = z$. In the proof of proposition 2, I show that, given the offer function $\tilde{s}(\cdot, z)$, I am able to write $F(\cdot|Z=z)$ and $g(\cdot|Z=z)$ in terms of the following parameters: The cost parameters $\alpha_d(z)$, $\beta_d(z)$, $\alpha_p(z)$ and $\beta_p(z)$, as well as the auxiliary parameters $\mu(z)$ and $\pi(z)$.[35] The proof of the proposition also makes it clear that these six parameters are overidentified. Therefore, to obtain estimates of the model primitives, I estimate $\alpha_d(z)$, $\beta_d(z)$, $\alpha_p(z)$, $\beta_p(z)$ and $\mu(z)$ by maximum likelihood. I present details of the estimation procedure in Appendix A.2.

## 6. Empirical Results

In implementing the estimator above, I use differences in sentencing patterns across judges as a source of variation in the distribution of trial sentences, which is necessary for condition $B$ to hold. Precisely, I obtain OLS estimates of the following specification

$$sentence_i = \vartheta_1 X_i + \zeta_{\mathbf{1}}\, \mathbf{Judge_i} + \epsilon_{1i}, \tag{6.1}$$

where $sentence_i$ is the length of the incarceration sentence assigned in case $i$, $\mathbf{Judge_i}$ is a vector of dummies identifying the judge responsible for case $i$, $X_i$ is a vector of control variables and $\epsilon_{1i}$ is an error term.[36] I consider the estimated judge fixed effects from specification (6.1). Table 3 contains information on the distribution of such estimates. The mean fixed effect is 31.58 months, and the median is 31.51 months. The heterogeneity across judges is substantial. The standard deviation and interquartile range of the fixed effects are, respectively, 6.26 and 8.06 months.

[35] The auxiliary parameters capture information about the distribution $F(\cdot|Z=z)$ for points of the support outside of the interval $[\tilde{\theta}(\underline{t}, z), \tilde{\theta}(\bar{t}, z)]$. Specifically,

$$\mu(z) = \exp\left(-\int_{\underline{\theta}}^{\tilde{\theta}(\underline{t},z)} \lambda(x,z)\,dx\right)$$

$$\text{and} \quad \pi(z) = \int_{\underline{\theta}}^{\tilde{\theta}(\underline{t},z)} x\, f(x|Z=z)\,dx.$$

See the proof of proposition 2 for details.

[36] The reduced form analysis presented in Appendix B.1 reports the OLS results of the specification above. The vector of control variables includes the defendant's gender, racial / ethnic group, previous criminal record, age and squared age, as well as dummies indicating the type of attorney representing the defendant. See Appendix B.1 for more details.

TABLE 3. Variation of sentencing behavior across judges

| Estimated judge fixed effects† | | | | | | |
|---|---|---|---|---|---|---|
| mean | std. dev. | min. | 1st quart. | median | 3rd quart. | max. |
| 31.58 | 6.26 | 16.28 | 27.56 | 31.51 | 35.62 | 64.63 |
| Number of judges: 169 | | | | | | |
| †: Measured in months. | | | | | | |

I divide the 169 judges in the data into two groups, depending on whether their estimated fixed effects are smaller or larger than the median judge fixed effect reported in table 3. Judges whose fixed effects are strictly smaller than the median are classified as lenient, while the others are classified as harsh.[37] Averaging across judges within each group, the estimated fixed effects for lenient and harsh judges are 25.97 and 36.21, respectively. In Appendix B.1, I present evidence that the variation in the distribution of trial sentences arising from differences in sentencing behavior across judges is uncorrelated with other variables that may affect the outcome of the case.

I focus on cases that are relatively homogeneous, so that condition $A$ is plausible. I restrict the analysis to cases in which the main charged offense is a non-homicide violent crime. Also, to control for observed heterogeneity across cases in my estimation, I separate the observations in the sample into covariate groups, according to the following variables: The Superior Court division where the case is prosecuted, the type of defense counsel employed in the case and the defendant's gender, race and previous criminal record. I then estimate the model separately across these groups.

The motivation for separating cases by the Superior Court division is twofold: First, doing so helps controlling for any case-specific characteristic that may be correlated with the place of prosecution. Importantly, these characteristics include the district of the prosecutor in charge of the case.[38] Second, the judge rotation mandated by the state constitution takes place at the division level. Thus, over the period of 14 years

[37]In principle, I could implement the estimator employing a finer classification of the judges in the data. The advantage of a binary classification is that it maximizes the number of judges within each group. Therefore, given the non-parametric nature of the estimator and the limited sample size, the use of a binary classification of judges, such as the one considered here, is justified.

[38]North Carolina is divided into prosecutorial districts that roughly correspond to the Superior Court districts described in Section 3. Sample size limitations prevent me from undertaking the analysis at the Superior Court district level. Dividing the cases in the data by the Superior Court division is a feasible alternative.

covered by my data set, it is reasonable to assume that cases decided by different judges within a division are drawn from the same pool.

I further separate the cases according to the type of defense attorney. I consider the following three categories of counsel: privately-retained, public defender and court-appointed. This classification is motivated by the empirical literature linking the type of defense counsel and the outcome of criminal cases.[39] Lastly, I divide cases by defendant's gender, race (African-Americans vs. others) and previous criminal record. To avoid dividing the data into too many sparsely populated groups, I consider two categories of criminal record: short (four points or less) and long (more than four points).[40] According to this definition, approximately one-fourth of the defendants in the data have a long criminal record.

Separating the observations in the data according to the eight Superior Court divisions, three defense attorney types, two gender groups, two race groups and two categories of previous criminal records results in 192 covariate bins. Some of these bins contain relatively few observations. In particular, female defendants are only represented in 7.11% of all cases. The estimation of the model based on such few observations would be inappropriate, due to the non-parametric nature of my estimator. Therefore, I focus on covariate groups in which the defendant is male. Still, there are 96 such groups. Estimating the model separately for each one of them would be computationally too costly. I thus restrict my analysis to cases prosecuted at the 5th Superior Court division, which comprises counties located in the northwestern part of the state and is the division with the largest sample size in my data set.[41] These restrictions leave me with a total of 12 covariate groups, which are summarized in table 4. The table also shows how many cases are observed in the data for each one of the groups.[42] Notice that, even though I do not recover the model primitives for

[39]See, for example, Iyengar (2007) and Anderson and Heaton (2012). The former paper examines Federal District Court cases, while the latter analyzes homicide cases in Philadelphia. Both studies find evidence that cases assigned to public defenders tend to result in more lenient sentences than those assigned to court-appointed attorneys.

[40]To put this classification into perspective, notice that four points are equivalent to having a previous conviction for setting fire to an unoccupied building (second-degree arson) or breaking and entering an unoccupied residency with the intent to commit another crime (second-degree burglary).

[41]The 5th division has 22,658 cases overall. The 1st, 2nd, 3rd, 4th, 6th, 7th and 8th divisions have, respectively, 11,084, 10,110, 19,906, 13,743, 13,047, 19,033 and 9,364 cases.

[42]Previous criminal records are only available for defendants who are convicted—either at trial or by plea bargain. Therefore, I do not observe directly the number of cases by covariate group. To compute the numbers reported in table 4, I first calculate the proportion of cases matching each covariate group among all cases that result in a conviction. Then I multiply this proportion by the

TABLE 4. Covariate groups

| Group | Covariates | | | | | Obs. |
|---|---|---|---|---|---|---|
| | Defendant's race | Defendant's gender | Defense counsel | Defendant's record | Sup. Court division | |
| 1 | other | Male | appointed | short | 5 | 2141 |
| 2 | Afr. American | Male | appointed | short | 5 | 2727 |
| 3 | other | Male | appointed | long | 5 | 1989 |
| 4 | Afr. American | Male | appointed | long | 5 | 2868 |
| 5 | other | Male | public | short | 5 | 956 |
| 6 | Afr. American | Male | public | short | 5 | 2049 |
| 7 | other | Male | public | long | 5 | 915 |
| 8 | Afr. American | Male | public | long | 5 | 2547 |
| 9 | other | Male | private | short | 5 | 1922 |
| 10 | Afr. American | Male | private | short | 5 | 1308 |
| 11 | other | Male | private | long | 5 | 882 |
| 12 | Afr. American | Male | private | long | 5 | 707 |

female defendants and divisions other than the 5th, I still employ observations corresponding to these groups for the estimation of conditional densities of trial sentences and settlement offers. See Section 5 and Appendix A.2 for details.

In the interest of space, I only report in the main text estimation results for covariates groups one and two. Both groups comprise defendants with short criminal history and who are represented by court-appointed attorneys. Defendants in group two are African-American, while those in group one are not. Appendix B.4 reports the results for covariate groups three to 12. The differences in the estimation results across groups one and two, presented below, suggest a non-trivial variation across races in the outcome of criminal cases. The results for groups three to 12 largely point in the same direction.[43]

Figure 1 depicts estimates of the trial sentence densities, conditional on a conviction at trial, for lenient and harsh in covariate groups one and two.[44] All distributions

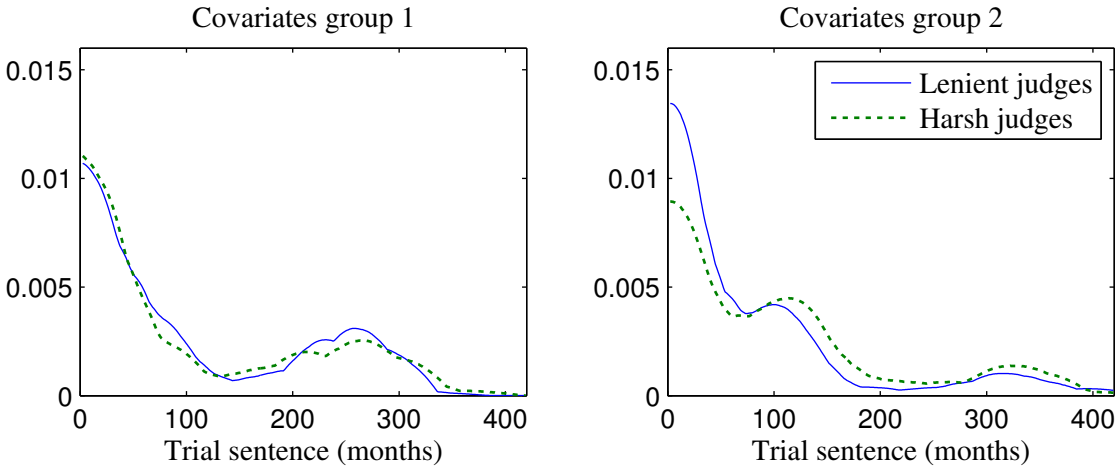
number of cases in the data matching the following reduced list of covariates: Race/ethnicity and gender of the defendant, defense counsel type and the Superior Court division of prosecution.

[43]Notice that the covariates group classification in table 4 attributes even numbers to groups in which the defendant is African-American and odd numbers to groups in which the defendant is not. It is possible to assess the differences between African-American and non-African-American defendants by comparing the estimation results for subsequent odd and even-numbered groups. Groups seven and eight are the only groups for which the estimation results differ considerably from those of groups one and two. See Appendix B.4 for more details.

[44]Bandwidths are reported in Appendix A.2, together with other estimation details.

show signs of multi-modality—with most of their mass concentrated at sentences shorter than 100 months. The densities for group two vary as expected across lenient and harsh judges. Indeed, the density associated with lenient judges has more mass at short sentences, relative to that associated with harsh judges. For group one the pattern is less clear. Although a formal test of condition $B$ is beyond the scope of the present study, the figures suggest that there is enough variation in the sentencing behavior across judges to implement the estimator described in Section 5.

FIGURE 1. Conditional trial sentence densities – lenient and harsh judges



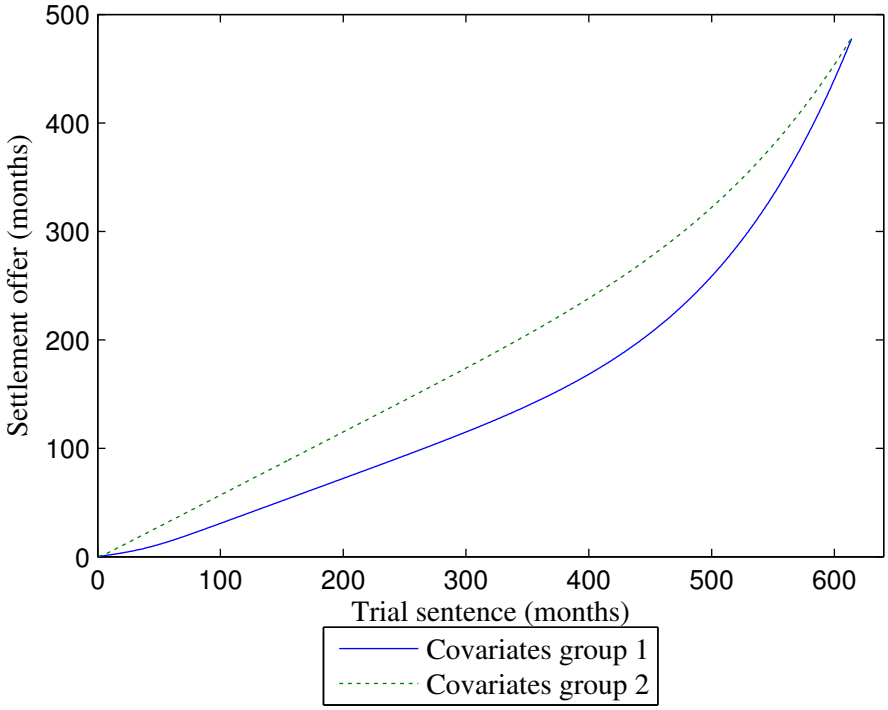

See table 4 for a description of the covariate groups.

To estimate the prosecutor's settlement offer function, I implement the spline regression procedure described previously. I do so independently for each covariate group. An important step in any spline regression is the selection of knots—the points in the domain of the function to be estimated where the polynomial pieces that constitute the spline connect. I set such knots at the 25th, 50th and 75th percentiles of the entire sample of trial sentences, irrespective of the covariate group. The chosen knots are 21, 70 and 125 months. Notice that, because I constrain the estimated offer function to be increasing and convex, the selection of knots is not as critical in my analysis as it is in other spline regression applications (Meyer, 2008).

Figure 2 presents the estimated settlement offer functions. The variation of the estimates across groups one and two is substantial. Specifically, the estimated offer functions is more convex for group one than for group two. Remember that the only difference between these groups is that defendants in group two are African-American.

The result thus indicates that prosecutors tend to offer longer sentences to African-American defendants than to their non-African-American counterparts, conditional on the length of the trial sentence. This is not a rigorous result, however, since I do not formally test whether one offer function is more convex than the other.

FIGURE 2. Settlement offer function




See table 4 for a description of the covariate groups.

Once estimates for the settlement offer functions are obtained, I proceed with the estimation of the model's primitives. For each judicial division group, that consists of estimating five scalar parameters: $\alpha_p$ and $\beta_p$, which characterize the prosecutor's trial costs; $\alpha_d$ and $\beta_d$, which characterize the defendant's trial costs; and $\mu$, which captures the behavior of the distribution of defendants' types for values of $\theta$ smaller than $\tilde{\theta}(\underline{t}, z)$. Let $\hat{\alpha}_p$, $\hat{\beta}_p$, $\hat{\alpha}_d$, $\hat{\beta}_d$ and $\hat{\mu}$ be the respective estimates, which are obtained separately for each covariate group.

Table 5 reports the estimation results, together with bootstrap standard errors.[45] Trial costs are measured in terms of months. Accordingly, the trial cost intercepts $\hat{\alpha}_d$ and $\hat{\alpha}_p$ are expressed in months, while $\hat{\beta}_d$ and $\hat{\beta}_p$ are coefficients. For both covariate

[45]See Appendix A.2 for details on the computation of the standard errors.

TABLE 5. Parameter Estimates by Covariate Group

| Group | Parameters | | | | |
|---|---|---|---|---|---|
| | $\hat{\alpha}_d$ | $\hat{\beta}_d$ | $\hat{\alpha}_p$ | $\hat{\beta}_p$ | $\hat{\mu}$ |
| 1 | 0.02 | 0.00 | 0.00 | 0.97 | 1.00 |
| | (0.01) | (0.00) | (0.00) | (0.41) | (0.00) |
| 2 | 0.00 | 0.00 | 0.00 | 1.06 | 1.00 |
| | (0.01) | (0.00) | (0.00) | (0.26) | (0.00) |

Bootstrap standard errors in parenthesis.

See table 4 for a description of the covariate groups.

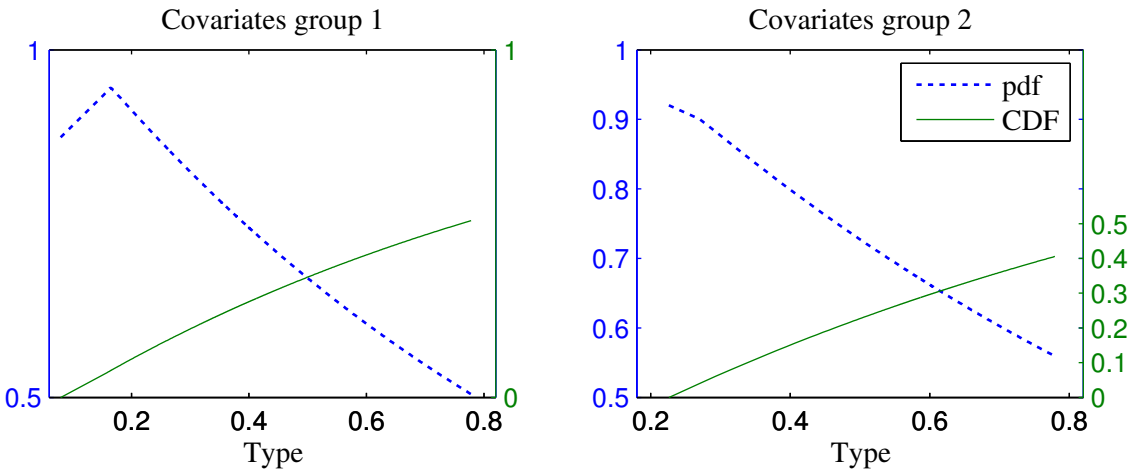
groups, both $\hat{\alpha}_d$ and $\hat{\beta}_d$ are very small. The former parameter varies from 0.00 to 0.02, depending on the group, and the latter is always 0.00. These numbers suggest that defendants barely take the costs of going to trial into consideration when deciding whether or not to accept the prosecutor's offer. One possible interpretation of this result is that, for the defendant, the costs of serving time in prison are so high that every expenditure associated with the trial procedure is of second order.

For both groups, $\hat{\alpha_p}$ is equal to zero and $\hat{\alpha_p}$ is roughly one, suggesting that trial costs for the prosecutor increase rapidly as the trial sentence gets longer. The differences between the estimated trial costs for the defendant and the prosecutor may, at first glance, seem striking. Notice, however, that the model does not allow for the comparison of cardinal utility between the prosecutor and the defendant—which implies that the trial cost estimates for the two parties are not directly comparable either.[46] Estimates of $\mu$ are one for both groups. Notice that $F(\tilde{\theta}(\underline{t})) = 1 - \mu$ (see footnote 35). My results thus indicate that defendants whose type belongs to the interval $[0, \tilde{\theta}(\underline{t})]$ are very rare.

After the estimation of the remaining parameters, I am able to compute estimates for the distribution of defendants' types. Figure 3 depicts these distributions. For each covariate groups, the figure shows both the estimated density function and the estimated cumulative distribution function. All distributions have a mode at a type lower than 0.3. The densities then sharply decrease, giving the impression that the distributions of defendants' types are unimodal. However, from Section 5, we know

[46]Indeed, the equilibrium outcome of the bargaining game is invariant to any monotone linear transformation affecting both the parameters $\alpha_p$ and $\beta_p$ and the utility derived by the prosecutor from the assignment of a given incarceration sentence.

FIGURE 3. Distribution of defendants' types – density and CDF




See table 4 for a description of the covariate groups.

that these distributions are only identified over part of their support—specifically, the interval $[\tilde{\theta}(\underline{t}), \tilde{\theta}(\bar{t})]$. For both covariate groups, this interval comprises a large portion of the unit line. The lower bound of the identified range of the support varies from zero to just above 0.2, depending on the covariate group, and the upper bound is roughly 0.8 for both groups. But both distributions have substantial mass outside of this range. For group one, the estimated cumulative distribution function evaluated at the upper bound of the identified range is approximately 0.5, while for group two this value is roughly 0.4. Such numbers suggest that the distributions of defendants' types have at least one more mode, located at a relatively high type. In particular, my results are consistent with distributions that concentrate mass at types located near the boundaries of the unit line. Interestingly, these bimodal distributions of types are precisely the ones that would arise if trials were generally, but not always, successful at convicting the guilty defendants and acquitting the innocent ones.

The distributions shown in figure 3 help rationalizing the differences between the estimated settlement offer functions of African-American and non-African-American defendants, which were pointed-out in the discussion of figure 2. The estimate of $F(\tilde{\theta}(\bar{t}))$ is greater for group one than for group two, indicating that the distribution of types for African-American defendants concentrates more mass at high types than the distribution for other defendants. Thus, controlling for the other covariates considered in my analysis, the results suggest that African-Americans are more likely than others to to be convicted by the jury in the event of a trial. According to the model, these differences in the distributions of types are considered by the

prosecutors in the process of making settlement offers. Specifically, given an African-American and a non-African-American defendant who face the same trial sentence, a prosecutor offers to the former a longer sentence. Relatively generous offers made to non-African-American defendants result in a more convex settlement offer function, which is precisely the finding in figure 2. Two comments are in order here: First, as pointed out in the discussion of the offer function estimates, a rigorous comparison between the distribution of types of African-American and non-African-American defendants would require formal tests that I do not carry out in this paper. Second, even assuming that the likelihood of trial convictions is indeed higher for African-Americans than for other defendants, it is not clear whether this difference is due to the discretion of the jury or to variation in other case characteristics across groups of defendants. These are interesting topics for further research. The final step in the estimation of the model primitives is to obtain the full distribution of potential trial sentences for each covariate group—i.e., the distribution without conditioning on a trial conviction. In the interest of space, I report such distributions in Appendix B.4.

Table 6 presents information on the fit of the model. It separately shows the probabilities of conviction to incarceration by plea bargain and at trial for each covariate group. The model fits well the probability of a plea bargain, while it slightly under-estimates the probability of a conviction at trial (by approximately 2 to 3 p.p., depending on the group). As a result, the model under-estimates the total probability of a conviction to incarceration by roughly the same amount. The table also shows three versions of the average assigned sentences: (i) The overall average—i.e,, the average sentence, conditional on either a conviction at trial or on a plea bargain; (ii) the average sentence, conditional on a plea bargain; and (iii) the average sentence, conditional on a trial conviction. The model fits the the overall average sentence well. However, it substantially over-estimates the average trial sentence for group one. It is useful to put such over-estimation into perspective by comparing it to the standard deviation of the observed trial sentences reported in table 2. The fitted model predicts the average trial sentence of group one to be 0.59 standard deviations longer than observed. A possible explanation for that is the small number of trial conviction observations in my sample, which leads the maximum likelihood procedure used for completing the estimation of the model to prioritize reproducing other features of the data. For the exact same reason, the overestimation of the average trial sentences has a very weak effect on the general fit of the model—as shown by the other moments on table 6. As long as one is not particularly interested in the distribution of outcomes

TABLE 6. Fitted values versus data

| Group | | Conviction probability | | |
|---|---|---|---|---|
| | | Any ($\Psi \in \{1,2\}$) | Settlement ($\Psi = 1$) | Trial ($\Psi = 2$) |
| 1 | Data | 38.35% | 34.60% | 3.75% |
| | Model | 36.59% | 34.86% | 1.73% |
| 2 | Data | 44.11% | 36.66% | 7.45% |
| | Model | 42.22% | 37.50% | 4.71% |

| Group | | Average sentence, conditional on method of resolution† | | |
|---|---|---|---|---|
| | | All ($\Psi \in \{1,2\}$) | Settlement ($\Psi = 1$) | Trial ($\Psi = 2$) |
| 1 | Data | 63.13 | 54.93 | 138.73 |
| | Model | 57.12 | 49.97 | 201.18 |
| 2 | Data | 48.14 | 41.51 | 80.73 |
| | Model | 45.08 | 40.63 | 80.50 |

† : Measured in months.
See table 4 for a description of the covariate groups.

for the small minority of cases that reach the trial stage, the model is able to replicate the key aspects of the data very well for both covariate groups.

## 7. Policy Experiments

Sentencing reform has been at the center of the recent public policy discussion, thanks to the growing consensus that the United States incarcerates too many people for too long. About 0.7 percent of Americans were in prison or jail at the end of 2010 (Glaze, 2011)—the highest incarceration rate in the world (Walmsley, 2009). Besides drastically affecting the lives of millions of inmates and their families, the correctional system constitutes a major component of public spending. Nationwide direct expenditures on corrections surpassed $70 billion in every year between 2000 and 2007 (Kyckelhahn, 2011). That, combined with the fiscal crisis in the past years, has led policy makers to consider reforms intended to reduce the number of prisoners. In particular, there have been an increasing number of proposals for reversing some of the "tough on crime" sentencing reforms of the 1980s and 1990s.

Two of the proposals that have recently gained political currency are the reduction of mandatory minimum sentence lengths, and the broader use of alternative punishments for less serious offenses.[47] In this section, I use the estimated model to conduct counterfactual policy experiments on such reforms. Specifically, I consider a decrease in trial sentences, capturing the effect of an across-the-board reduction in the mandatory minimum sentence lengths. Also, I analyze the scenario in which relatively short trial sentences are set to zero. Such a scenario simulates the effect of abolishing incarceration sentences for the mildest offenses.

The focus of my counterfactual analysis is on the number of defendants who receive incarceration sentences, as well as on the total time of incarceration assigned. The outcomes of interest are: (i) the average probability that a case results in a incarceration conviction, either at trial or due to a settlement; (ii) the average observed incarceration sentence length; and (iii) the expected incarceration sentence length at the beginning of the prosecution process, which is simply the product of outcomes (i) and (ii). The total number of months of incarceration assigned in any given period is determined by the number of defendants prosecuted over that period times the expected sentence length. Outcome (iii) is, thus, the main variable of interest if, for example, one is mostly concerned about the total incarceration costs of current sentencing decisions.[48] However, a decrease in the expected sentence length that is solely due to shorter sentences may have no immediate effects on the incarceration rate. To see that, consider the short-term impact of reducing a convicted defendant's sentence from 40 to 20 years. Changes in the probability of conviction are more likely to capture short-term effects of sentencing reforms.

My counterfactual analysis ignores important outcomes of sentencing reform, such as crime deterrence and recidivism. A more complete exercise would need to simultaneously account for these effects and plea bargaining. My analysis is one of partial equilibrium, and can be thought of as a step towards the better understanding of policy interventions in the criminal justice system. Endogenizing crime rates in a model similar to the one considered here is an exciting avenue for further research.

[47]The following are examples of reforms adopted in 2010 alone: New Jersey reduced the mandatory minimum sentence for defendants convicted of drug-related offenses committed within 1000 feet of school property or a school bus. South Carolina equalized penalties for offenses involving crack and powder cocaine. In the same state, the minimum sentence for non-violent second-degree burglary was reduced from 15 to ten years. Tennessee enhanced alternative sentences for several non-violent property offenses, including felony theft. See Porter (2011) for other policy reforms.

[48]Of course, that assumes the linearity of costs on incarceration time.

I also consider two counterfactual experiments unrelated to sentencing reform. In one of them I eliminate asymmetries of information between prosecutors and defendants. In principle, better discovery rules could reduce such asymmetries, although at the cost of longer and more burdensome negotiations. Therefore, this counterfactual analysis serves as a reference for assessing the potential effects of more detailed discovery. More importantly, the experiment allows me to assess the magnitude of the defendant's informational rents by comparing the average length of the incarceration sentences assigned in the scenarios with and without asymmetric information.

The last counterfactual analysis addresses the scenario in which plea bargaining is not allowed, so that every case is decided at trial. Admittedly, given that roughly 90 percent of all criminal cases are currently settled, completely eliminating plea bargaining is likely to be too radical an intervention. But considering this extreme scenario allows me to measure the loss of information that arises due to settlements. Specifically, I compute the proportion of defendants who are currently convicted to incarceration sentences, but who would be acquitted if their cases were decided at trial. Insofar as trials correctly convict the guilty and acquit the innocent, this proportion reveals the extent to which plea bargaining results in the conviction of innocent defendants. I am also able to calculate the losses incurred by defendants who are prohibited from settling their cases. In debating the merits of plea bargaining, legal scholars make a distinction between its private and social benefits. A plea bargaining is a voluntary contractual arrangement between the prosecutor and the defendant. If both parties are rational, they will only agree to settle a case if such an arrangement is mutually beneficial (Scott and Stuntz, 1992). But the conviction of innocent individuals imposes a negative externality to society—as attested, for example, by the requirement that judges find factual basis before accepting guilty pleas (Schulhofer, 1992). Although my analysis does not provide direct estimates of this externality, it allows me to assess how often innocent defendants agree to settle their cases. This result, along with my measure of the private costs of forbidding settlements, contributes to a better understanding of the welfare implications of plea bargaining.

7.1. **Reducing mandatory minimum sentences.** Table 7 shows the effects of a twenty percent reduction in the length of potential trial sentences for all cases in the sample.[49] The top half of the table reports the effect on the probability of an

[49]This policy experiment assumes that an across-the-board reduction in mandatory minimum sentences would lower the sentences to be assigned in the event of a trial conviction for all cases. While it is true that a case's potential trial sentence is determined by a conjunction of factors, mandatory minimums are likely to serve as a reference for the determination of sentences by the judges, and

incarceration conviction, either by plea bargain or at trial. The results indicate that shorter potential trial sentences increase the probability of a settlement, which raises the total probability of conviction. The latter probability increases by 1.89 percent for group one and 0.64 percent for group two.

The bottom half of the table shows the impact on the expected length of the assigned sentences. For both covariate groups, the elasticity of the expected sentence with respect to the potential trial sentence is roughly one, indicating that this intervention may be highly effective in reducing the total incarceration time assigned by the courts. This magnitude is not surprising, considering the results in figure 2, which show that the prosecutor's offer functions are quite steep. Since most cases are resolved by plea bargain, the main effect of a reduction in the potential trial sentences is a decrease in the settlement sentences. Thus, a reduction in the length of potential trial sentences is likely to increase incarceration rates slightly in the short run. But in the long run, the same intervention may lead to a major decrease in these rates.

7.2. **Assigning alternative punishments for mild cases.** Now I replace the ten percent of cases with the lowest positive potential trial sentence with cases in which the potential trial sentence is zero.[50] Table 7 shows the results. The impact of the intervention on the probability of conviction is high. A ten percent decrease in the number of cases with positive trial sentence reduces the total probability of conviction by roughly ten percent for all covariate groups. This effect is due to the types of cases affected by the intervention. Cases with short potential trial sentences are very likely to be settled before trial, which results in a guaranteed conviction. The elimination of such cases, therefore, has a direct impact on the probability of conviction.

Nevertheless, the impact of the intervention on the expected sentence is relatively low. A ten percent decrease in the number of cases with positive potential trial sentence reduces the expected sentence by less than one percent for both covariate groups. The policy intervention considered here is rather extreme, and it is surprising that its effect on the expected sentence is so modest. An explanation for such a low magnitude is that the current expected sentences are largely influenced by the length

even be a binding constraint in a considerable number of cases. The results presented here can be interpreted as the effects of changes in mandatory minimum sentences insofar as such changes actually affect the punishments to be assigned at trial.

[50]The 20th percentiles in the distribution of positive potential trial sentences for groups one and two are 48.23 and 21.75 months, respectively. It is arguably more plausible that an actual reform would affect all cases below a specific threshold (say one year) statewide. Still, the results presented here serve as an illustration of the potential effects of a broader use of alternative sentences.

TABLE 7. Counterfactual results – Sentencing reform

| Group | | Conviction probability | | |
|---|---|---|---|---|
| | | Any | Settlement | Trial |
| 1 | Current | 36.59% | 34.86% | 1.73% |
| | -20% trial sentence length | 37.28% | 35.91% | 1.37% |
| | -10% incarceration cases | 32.74% | 31.04% | 1.70% |
| 2 | Current | 42.22% | 37.50% | 4.71% |
| | -20% trial sentence length | 42.49% | 37.94% | 4.55% |
| | -10% incarceration cases | 37.94% | 33.38% | 4.56% |

| Group | | Expected sentence† | |
|---|---|---|---|
| | | $\Psi \in \{1, 2\}$ | Unconditional on $\Psi$ |
| 1 | Current | 57.12 | 20.90 |
| | -20% trial sentence length | 41.23 | 15.37 |
| | -10% incarceration cases | 63.64 | 20.84 |
| 2 | Current | 45.08 | 19.03 |
| | -20% trial sentence length | 35.63 | 15.14 |
| | -10% incarceration cases | 49.95 | 18.95 |

† : Measured in months.
See table 4 for a description of the covariate groups.

of the most severe sentences. Even the complete elimination of the mildest cases has a small effect on the average outcome.

The results of the two policy simulations undertaken so far suggest that the broader use of alternative sentences and the reduction of mandatory minimum sentences complement each other. Assigning alternative sentences more often reduces the total probability of conviction, which immediately affects incarceration rates. Lowering the mandatory minimum sentences, particularly for severe offenses, greatly reduces the total incarceration time assigned. However, the latter policy is not likely to decrease incarceration rates in the short run.

7.3. **Eliminating asymmetric information.** With complete information, given a trial sentence $t$, defendant's trial costs $c_d$ and a defendant of type $\theta$, the prosecutor offers to settle for $\theta t + c_d$. This offer leaves the defendant just indifferent between accepting it and facing a trial. As a consequence, every case is settled. A natural outcome of eliminating informational asymmetries is thus an increase in the conviction rate. Such an increase can be easily measured using the estimated model.

TABLE 8. Counterfactual results – No asymmetric information

| Group | | Outcome | | |
|---|---|---|---|---|
| | | Probability of conviction | Expected sentence† (given $\Psi \in \{1, 2\}$) | Expected sentence† (unconditional) |
| 1 | Current | 36.59% | 57.12 | 20.90 |
| | No asym. info. | 43.61% | [84.41 , 100.57] | [36.81 , 43.86] |
| 2 | Current | 42.22% | 45.08 | 19.03 |
| | No asym. info. | 50.26% | [48.47 , 58.15] | [24.36 , 29.22] |

† : Measured in months
See table 4 for a description of the covariate groups.

A more difficult computation is that of the distribution of sentences. The challenge here is that I only identify the distribution of defendant's types for values within the interval $[\tilde{\theta}(\underline{t}), \tilde{\theta}(\bar{t})]$. Recovering the full distribution of settlement offers in the complete information scenario would require me to know the distribution of types outside of this range. Nevertheless, I am able to compute bounds for the mean settlement offer. To do so, I consider two extreme cases. In the first one, which leads to a lower bound for the mean settlement offer, I assume that all defendants with type $\theta$ lesser than $\tilde{\theta}(\underline{t})$ have type equal to zero, and all defendants with type greater or equal to $\tilde{\theta}(\bar{t})$ have type exactly equal to $\tilde{\theta}(\bar{t})$. In the second extreme case, I obtain an upper bound for the mean settlement offer by assuming that all defendants with type lesser or equal to $\tilde{\theta}(\underline{t})$ have type exactly equal to $\tilde{\theta}(\underline{t})$, and all defendants with type above $\tilde{\theta}(\bar{t})$ have type equal to one.

Table 8 shows the results of this analysis. The probability of a conviction to incarceration increases by roughly 19 percent for both groups. The lower bounds for the expected sentence, conditional on an incarceration conviction, are estimated to be longer than the current level for both covariate groups. My findings indicate that eliminating the asymmetric information between the prosecutor and the defendant would lead to more incarceration convictions and, conditional on such a conviction, longer assigned sentences. Therefore, it is not a surprise that the unconditional expected sentence increases considerably. The lower bounds for this increase are 76.17 and 28.01 percent for groups one and two, respectively. The upper bounds are 109.86 and 53.55 percent. These results suggest that, on average, defendants greatly benefit from informational rents in the process of plea bargaining.

TABLE 9. Counterfactual results – No plea bargaining

| Group | | Outcome |
|---|---|---|
| | | Probability of conviction |
| 1 | Current | 36.59% |
| | No plea bargaining | [25.31% , 30.21%] |
| 2 | Current | 42.22% |
| | No plea bargaining | [33.09% , 39.69%] |

See table 4 for a description of the covariate groups.

7.4. **Eliminating plea bargaining.** If no plea bargaining is allowed and every case reaches the trial stage, each defendant is convicted with a probability equal to her type. Given a trial sentence $t$ and a defendant of type $\theta$, the expected sentence is $\theta t$. Here, both the computation of the overall probability of incarceration conviction and that of the expected sentence are complicated by the lack of identification of the distribution of types $F(\cdot)$ over its whole support. I can only calculate bounds for these values. To obtain the bounds, I follow the same criteria as in the previous counterfactual exercise.

Table 9 presents the results. Relative to current levels, the probability of an incarceration conviction falls substantially for both covariate groups. The differences between the current probabilities and the estimated lower bounds are 11.28 p.p. for group one and 9.13 p.p. for group two. When, instead, the upper bounds are considered, the differences are 6.38 p.p. and 2.53 p.p., respectively. These magnitudes are large, especially considering that the current rates of incarceration convictions are roughly 40 percent. For group one, eliminating plea bargaining leads to a decrease of 17.44 to 30.83 percent in the incarceration conviction rate. For group two, the decrease is between 5.99 and 21.62 percent. The explanation for these large effects is that the estimated distributions of defendants' types, depicted in figure 3, place a considerable portion of their probability mass at relatively low values. These estimates indicate that, despite facing low probabilities of being convicted at trial, many defendants currently accept to settle their cases for short incarceration sentences.

Notice that, for each defendant, the expected sentences in the scenarios without plea bargaining and without asymmetric information are given by $\theta t$ and $\theta t + c_d$, respectively. That is, the difference between the sentences in each scenario consists of the defendants' trial costs. As shown in table 5, I estimate such costs to be essentially zero for all covariate groups. Thus, for each group, the expected sentence without

plea bargaining is the same as the one reported in the third column of table 8, for the case of no asymmetric information. These values are considerably longer than the current expected sentences. Therefore, a large proportion of the defendants would be acquitted at trial after a ban on plea bargains. But my results suggest that, in expectation, defendants would be considerably worse off in such a scenario.

## 8. Conclusion

I develop a framework for the empirical analysis of plea bargaining, which allows me to evaluate how sentences to be assigned at trial affect the result of criminal cases. I adapt a model of bargaining with asymmetric information due to Bebchuk (1984), and I present conditions for it to be non-parametrically identified. I then propose a consistent estimator for the model, which I apply to data on criminal cases prosecuted in the North Carolina. My findings suggest that, while the opportunity costs of going to trial are high for prosecutors, defendants behave as if trials were costless.

Using the estimated model, I evaluate the impact of different sentencing reforms on the outcome of prosecuted cases. My experiments suggest that lowering mandatory minimum sentences may greatly reduce the total amount of incarceration time assigned by the courts. However, the same intervention would increase the proportion of cases resulting in incarceration convictions, which, in the short run, may have unintended effects on the incarceration statistics. A different reform, the wider use of alternative sentences in less serious cases, leads to a decrease in conviction rates but has little effect on the total incarceration time assigned. Hence, these two interventions have the potential to complement each other. I also evaluate the impact of two other policy experiments: Eliminating the asymmetric information between the prosecutor and the defendant and prohibiting cases from being settled. The results from these analysis suggest that a large proportion of defendants who presently receive incarceration convictions by plea bargaining would be acquitted if their cases reached the trial stage. Nevertheless, in expectation, defendants are considerably worse off in the scenario without plea bargaining than in the current one.

## References

**Alschuter, Albert W.**, "The Prosecutor's Role in Plea Bargaining," *University of Chicago Law Review*, 1968, *36*, 50–112.

**Anderson, James M. and Paul Heaton**, "How Much Difference Does the Lawyer Make? The Effect of Defense Counsel on Murder Case Outcomes," *Yale Law Journal*, 2012, *122* (1), 154–2694.

**Athey, Susan. and Philip.A. Haile**, "Nonparametric Approaches to Auctions," in James J. Heckman and Edward E. Leamer, eds., *Handbook of Econometrics*, Vol. 6A, Elsevier, 2007, pp. 3847–3965.

**Baker, Scott and Claudio Mezzetti**, "Prosecutorial Resources, Plea Bargaining and the Decision to Go to Trial," *Journal of Law, Economics and Orgainzation*, 2001, *17*, 149–167.

**Bebchuk, Lucian Arye**, "Litigation and Settlement under Imperfect Information," *RAND Journal of Economics*, 1984, *15*, 404–415.

**Bjerk, David**, "Guilt Shall Not Escape or Innocence Suffer: the Limits of Plea Bargaining When Defendant Guilt is Uncertain," *American Law and Economics Review*, 2007, *9*, 305–329.

**Boylan, Richard T.**, "The Effect of Punishment Severity on Plea Bargaining," *Journal of Law and Economics*, 2012, *55* (3), pp. 565–591.

**Buescher, Paul A. and Ziya Gizlice**, "Healthy Life Expectancy in North Carolina, 1996-2000," SCHS Studies 129, State Center for Health Statistics, 1908 Mail Service Center, Raleigh, N.C. January 2002.

**Chen, Xiaohong**, "Large Sample Sieve Estimation of Semi-nonparametric Models," in James J. Heckman and Edward E. Leamer, eds., *Handbook of Econometrics*, Vol. 6B, Elsevier, 2007, pp. 5549–5632.

**Daughety, Andrew F. and Jennifer F. Reinganum**, "Settlement Negotiations with Two Sided Asymmetric Information: Model Duality, Information Distribution, and Efficiency," *International Review of Law and Economics*, 1994, *14*, 283–298.

_____ **and** _____, "Settlement," in Chris W. Sanchirico, ed., *Encyclopedia of Law and Economics*, second ed., Vol. 8 - Procedural Law and Economics, Cheltenham, UK: Edward Elgar Publishing Co, 2012.

**Durose, Matthew R. and Patrick A. Langan**, "Felony Sentences in State Courts 2000," Bulletin NCJ 198821, U.S. Department of Justice, Bureau of Justice Statistics, Washington, DC: U.S. Department of Justice June 2003.

**Dyke, Andrew**, "Electoral Cycles in the Administration of Criminal Justice," *Public Choice*, 2007, *133*, 417–437.

**Elder, Harold W.**, "Trials and Settlement in the Criminal Courts: an Empirical

Analysis of Dispositions and Sentencing," *Journal of Legal Studies*, 1989, *18*, 191–208.

**Eubank, Randall L.**, *Nonparametric Regression and Spline Smoothing*, second ed., New York: Marcel Dekker, 1999.

**Fischer, George**, *Plea Bargain's Triumph: A History of Plea Bargaining in America*, Palo Alto: Stanford University Press, 2003.

**Friedman, Daniel and Donald Wittman**, "Litigation with Symmetric Bargaining and Two-Sided Incomplete Information," *Journal of Law, Economics and Organization*, 2007, *23*, 98–126.

**Glaze, Lauren E.**, "Correctional Population in the United States, 2010," Bulletin NCJ 236319, U.S. Department of Justice, Bureau of Justice Statistics, Washington, DC: U.S. Department of Justice December 2011.

**Gordon, Sanford C. and Gregory A. Huber**, "The Effect of Electoral Competitiveness on Incumbent Behavior," *Quarterly Journal of Political Science*, 2007, *2*, 107–138.

**Hickman, Brent R. and Timothy P. Hubbard**, "Replacing Sample Trimming with Boundary Corrections in Nonparametric Estimation of First-price Auctions," 2012. Mimeo, Northwestern University.

**Huber, Gregory A. and Sanford C. Gordon**, "Accountability and Coercion: Is Justice Blind when it Runs for Office?," *American Journal of Political Science*, 2004, *48*, 247–263.

**Iyengar, Radha**, "An Analysis of the Performance of Federal Indigent Defense Counsel," *NBER Working Paper Series*, 2007, *13187*.

**Karunamuni, Rohana J. and Shunpu Zhang**, "Some Improvements on a Boundary Corrected Kernel Density Estimator," *Statistics and Probability Letters*, 2008, *78*, 499–507.

**Keniston, Daniel E.**, "Bargaining and Welfare: a Dynamic Structural Analysis," 2011. Mimeo, Massachusetts Institute of Technology.

**Kennan, John and Robert Wilson**, "Bargaining with Private Information," *Journal of Economic Literature*, 1993, *31*, 45–104.

**Kobayashi, Bruce H.**, "Deterrence with Multiple Defendants: an Explanation for 'Unfair' Plea Bargaining," *RAND Journal of Economics*, 1992, *23*, 507–517.

**Kuziemko, Ilyana**, "Does the Threat of the Death Penalty Affect Plea Bargaining in Murder Cases? Evidence from New York's 1995 Reinstatement of Capital Punishment," *American Law and Economics Review*, 2006, *8* (1), 116–142.

**Kyckelhahn, Tracey E.**, "Justice Expenditures and Employment, FY 1982-2007 - Statistical Tables," Bulletin NCJ 236218, U.S. Department of Justice, Bureau of Justice Statistics, Washington, DC: U.S. Department of Justice December 2011.

**LaCasse, Chantele L. and A. Abigail Payne**, "Federal Sentencing Guidelines and Mandatory Minimum Sentences: Do Defendants Bargain in the Shadow of the Judge?," *Journal of Law and Economics*, 1999, *42*, 245–270.

**Landes, William M.**, "An Economic Analysis of the Courts," *Journal of Law and Economics*, 1971, *14*, 61–107.

**Larssen, Bradley**, "The Efficiency of Dynamic, Post-Auction Bargaining: Evidence from Wholesale Used-Auto Auctions," 2014. Mimeo, Stanford University.

**Li, Qi and Jeffrey S. Racine**, *Nonparametric Econometrics: Theory and Practice*, first ed., New Jersey: Princeton University Press, 2007.

**Lim, Claire S. H.**, "Preferences and Incentives of Appointed and Elected Public Officials: Evidence from State Trial Court Judges," *American Economic Review*, 2013, *103* (4), 1360–1397.

**Merlo, Antonio, François Ortalo-Magné, and John Rust**, "The Home Selling Problem: Theory and Evidence," 2008. Mimeo, University of Maryland.

**Meyer, Mary C.**, "Inference Using Shape-restricted Regression Splines," *Annals of Applied Statistics*, 2008, *2*, 1013–1033.

**Miceli, Thomas J.**, "Plea Bargaining and Deterrence: an Institutional Approach," *European Journal of Law and Economics*, 1996, *3*, 249–264.

**Nalebuff, Barry**, "Credible Pretrial Negotiation," *RAND Journal of Economics*, 1987, *18*, 198–210.

**Newey, Whitney K. and Daniel L. McFadden**, "Large Sample Estimation and Hypothesis Testing," in Robert F. Engle and Daniel L. McFadden, eds., *Handbook of Econometrics*, Vol. 4, Elsevier, 1994, pp. 2113–2245.

**Politis, Dimitris N., Joseph P. Romano, and Michael Wolf**, *Subsampling*, first ed., New York: Springer, 1999.

**Porter, Nicole D.**, "The State of Sentencing 2010 – Developments in Policy and Practice," Technical Report, The Sentencing Project February 2011.

**Priest, George and Benjamin Klein**, "The Selection of Disputes for Litigation," *Journal of Legal Studies*, 1984, *13*, 1–56.

**Reinganum, Jennifer F.**, "Plea Bargaining and Prosecutorial Discretion," *American Economic Review*, 1988, *78*, 713–728.

——— **and Louis L. Wilde**, "Settlement, Litigation, and the Allocation of Litigation Costs," *RAND Journal of Economics*, 1986, *17*, 557–566.

**Rubbinfeld, Daniel L. and David E. M. Sappington**, "Efficient Awards and Standards of Proof in Judicial Proceedings," *RAND Journal of Economics*, 1987, *18*, 308–315.

**Schulhofer, Stephen J**, "Plea bargaining as disaster," *Yale Law Journal*, 1992, *101* (8), 1979–2009.

**Schweizer, Urs**, "Litigation and Settlement under Two Sided Incomplete Information," *Review of Economic Studies*, 1989, *56*, 163–177.

**Scott, Robert E. and William J. Stuntz**, "Plea Bargaining as Contract," *The Yale Law Journal*, 1992, *101* (8), pp. 1909–1968.

**Sieg, Holger**, "Estimating a Bargaining Model with Asymmetric Information: Evidence from Medical Malpractice Disputes," *Journal of Political Economy*, 2000, *108*, 1006–1021.

**Silverman, Bernard W.**, *Density Estimation for Statistics and Data Analysis*, London, UK: Chapman and Hall, 1986.

**Sobel, Joel**, "An Analysis of Discovery Rules," *Law and Contemporary Problems*, 1989, *52*, 133–160.

**Spier, Kathryn E.**, "The dynamics of pretrial negotiation," *The Review of Economic Studies*, 1992, *59* (1), 93–108.

**Waldfogel, Joel**, "The Selection Hypothesis and the Relationship between Trial and Plaintiff Victory," *Journal of Political Economy*, 1995, *103*, 229–260.

———, "Reconciling Asymmetric Information and Divergent Expectations Theories of Litigation," *Journal of Legal Studies*, 1998, *41*, 451–476.

**Walmsley, Roy**, "World Prison Population List – Eigth Edition," Technical Report, International Centre for Prison Studies January 2009.

**Watanabe, Yasutora**, "Learning and Bargaining in Dispute Resolution: Theory and Evidence from Medical Malpractice Litigation," 2009. Mimeo, Northwestern University.

**Zhang, Shunpu, Rohana J. Karunamuni, and M. Chris Jones**, "An Improved Estimator of the Density Function at the Boundary," *Statistics and Probability Letters*, 1999, *94*, 1231–1241.

## Appendix A

### A.1. **Proofs.**

A.1.1. *Proof of Lemma 1:* By condition $B$, I can divide $[\underline{t}, \bar{t}]$ into $N$ sub-intervals of the form $I_1^T = [\underline{t}, t_1)$ , $I_2^T = [t_1, t_2)$ , $\cdots$ , $I_{N-1}^T = [t_{N-2}, t_{N-1})$ , $I_N^T = [t_{N-1}, \bar{t}]$, and, for each $n = 1, \cdots, N$, choose elements $z_n', z_n''$ of $\Delta_\rho$ such that the function $\phi(t, z_n', z_n'') \equiv g(t|Z = z_n')/g(t|Z = z_n'')$ is strictly monotonic on $I_n^T$. Without loss of generality, I assume that, for all $n$, if $\phi(t, z_n', z_n'')$ is strictly increasing on $I_n^T$, then $\phi(t, z_{n+1}', z_{n+1}'')$ is strictly decreasing on $I_{n+1}^T$; and, if $\phi(t, z_n', z_n'')$ is strictly decreasing on $I_n^T$, then $\phi(t, z_{n+1}', z_{n+1}'')$ is strictly increasing on $I_{n+1}^T$.

That, together with equation (5.2) and the strict monotonicity of $\tilde{s}(\cdot, \breve{z})$, implies that the interval $[\tilde{s}(\underline{t}, \breve{z}), \tilde{s}(\bar{t}, \breve{z})]$ can be divided into sub-intervals $I_1^S, \cdots, I_N^S$ with the following property: for all $n = 1, \cdots, N$, I have that (i) if $\phi(t, z_n', z_n'')$ is strictly increasing on $I_n^T$, then the function $\phi_b(s, z_n', z_n'') \equiv b(s|Z = z_n')/b(s|Z = z_n'')$ is strictly increasing on $I_n^S$; and (ii) if $\phi(t, z_n', z_n'')$ is strictly decreasing on $I_n^T$, then $\phi_b(s, z_n', z_n'')$ is strictly decreasing on $I_n^S$. Notice that $I_1^S = [\tilde{s}(\underline{t}, \breve{z}), \tilde{s}(t_1, \breve{z}))$ , $I_2^S = [\tilde{s}(t_1, \breve{z}), \tilde{s}(t_2, \breve{z}))$ , $\cdots$ ,$I_{N-1}^S = [\tilde{s}(t_{N-2}, \breve{z}), \tilde{s}(t_{N-1}, \breve{z}))$ and $I_N^S = [\tilde{s}(t_{N-1}, \breve{z}), \tilde{s}(\bar{t}, \breve{z})]$.

Finally, for all $n = 1, \cdots, N$, I identify the function $\tilde{s}(\cdot, \breve{z})$ on the interval $I_n^T$ by the following equation

$$\tilde{s}(t, \breve{z}) = \phi_b^{-1}(\phi(t, z_n', z_n''), z_n', z_n'')$$

for all $t \in I_n^T$. $\square$

A.1.2. *Proof of Proposition 2.* Using the defendant's cutoff point in equation (4.1), I have that

$$\tilde{\theta}(t, z) = \frac{\tilde{s}(t, z) - c_d(z)}{t} \tag{A.1}$$

for all $t \in [\underline{t}, \bar{t}]$, so that $\tilde{\theta}(\cdot, z)$ is identified up to the constant $c_d(z)$. I later discuss how to recover such a constant.

I can now rewrite the prosecutor's first-order condition in equation (4.2) as

$$\frac{t}{c_p(z) + c_d(z)} = \frac{f\left[\tilde{\theta}(t, z)|Z = z\right]}{\left\{1 - F\left[[\tilde{\theta}(t, z)|Z = z\right]\right\}}.$$

Denote by $\lambda(\theta, z)$ the hazard function of $F(\cdot|Z = z)$ evaluated at $\theta$. The right-hand side of the expression above is $\lambda(\tilde{\theta}(t, z), z)$. Since $\tilde{\theta}(\cdot, z)$ is strictly increasing, I have

that

$$\lambda(\theta, z) = \frac{\tilde{\theta}^{-1}(\theta, z)}{c_p(z) + c_d(z)} \tag{A.2}$$

for every $\theta$ in the interval $[\tilde{\theta}(\underline{t}, z), \tilde{\theta}(\bar{t}, z)]$. I can then write

$$F(\theta|Z = z) = 1 - \mu(z) \exp\left(-\int_{\tilde{\theta}(\underline{t},z)}^{\theta} \lambda(x, z)\, dx\right) \tag{A.3}$$

for all $\theta \in [\tilde{\theta}(\underline{t}, z), \tilde{\theta}(\bar{t}, z)]$, where

$$\mu(z) = \exp\left(-\int_{\underline{\theta}}^{\tilde{\theta}(\underline{t},z)} \lambda(x, z)\, dx\right).$$

Together, (A.1), (A.2), (A.2) and (A.3) identify $F(\cdot|Z = z)$ for the whole image of $\tilde{\theta}(\cdot, z)$, up to the constants $c_p(z)$, $c_d(z)$ and $\mu(z)$.[51]

The full density of potential trial sentences, $g(t|Z = z)$, can then be recovered, up to $c_p(z)$, $c_d(z)$ and $\mu(z)$, using the functions $\tilde{s}(\cdot, z)$ and $F(\cdot|Z = z)$—as well as equations (5.1), (5.3) and (5.4). To complete the identification of the model's primitives, I must show how to recover the scalars $c_p(z)$, $c_d(z)$ and $\mu(z)$. But first I need to introduce a new parameter. Given $z$ and a potential trial sentence $t$, the equilibrium probability that a defendant is convicted at trial is

$$\int_{\underline{\theta}}^{\tilde{\theta}(t,z)} x\ f(x|Z = z)\, dx.$$

Thus,

$$\begin{aligned} P[\Psi = 2|Z = z] &= \int_{[\underline{t},\bar{t}]} \int_{\underline{\theta}}^{\tilde{\theta}(t,z)} x\ f(x|Z = z) g(t|Z = z)\, dx\, dt \\ &= \pi(z) + \int_{[\underline{t},\bar{t}]} \int_{\tilde{\theta}(\underline{t},z)}^{\tilde{\theta}(t,z)} x\ f(x|Z = z) g(t|Z = z)\, dx\, dt. \end{aligned} \tag{A.4}$$

where $\pi(z) = \int_{\underline{\theta}}^{\tilde{\theta}(\underline{t},z)} x\ f(x|Z = z)\, dx$.[52] Like $\mu(z)$, the parameter $\pi(z)$ captures the behavior of the distribution $F(\cdot|Z = z)$ for $\theta$ lower than $\tilde{\theta}(\underline{t}, z)$.

The identification of $c_p(z)$, $c_d(z)$, $\mu(z)$ and $\pi(z)$ may proceed as follows. Using equations (5.3), (5.4) and (A.1) to (A.3), I write the density $b(\cdot|Z = z)$ in terms of $c_p(z)$, $c_d(z)$, $\mu(z)$ and the conditional density $b(\cdot|\Psi = 1, Z = z)$. Integrating both sides over $[\tilde{s}(\underline{t}), \tilde{s}(\bar{t})]$, I recover $\mu(z)$ as a function of $c_p(z)$ and $c_d(z)$. As a consequence, I

[51] The term $\mu(z)$ depends on the behavior of $F(\cdot|Z = z)$ for values of $\theta$ lower than $\tilde{\theta}(\underline{t}, z)$. It can be rewritten as $\mu(z) = 1 - F(\tilde{\theta}(\underline{t}, z)|Z = z)$.

[52] Notice that $\pi(z)$ must belong to the interval $[0, (1 - \mu(z))\tilde{\theta}(\underline{t}, z)]$.

can recover the densities $b(\cdot|Z=z)$ and $f(\cdot|Z=z)$, up to $c_p(z)$ and $c_d(z)$ only. Using equation (A.4), I am then able to recover $\pi(z)$, up to $c_p(z)$ and $c_d(z)$. Finally, using equations (5.4) and (5.7), I have that

$$\frac{b(\tilde{s}(t,z)|\Psi=1,Z=z)}{g(t|\Psi=2,Z=z)} = \left(\frac{1}{\frac{d\tilde{s}(t,z)}{dt}}\right)\frac{P[\Psi=1|S=\tilde{s}(t,z),Z=z]}{P[\Psi=1|Z=z]}\frac{P[\Psi=2|Z=z]}{P[\Psi=2|T=t,Z=z]} \tag{A.5}$$

for all $t \in [\underline{t},\bar{t}]$. Notice that the left-hand side of the equation above depends only on $c_d(z)$ and $c_p(z)$, since $\mu(z)$ and $\pi(z)$ are known, up to the trial costs. The right-hand side is observable. Since the equation holds for all $t$ in the support, it implies a system of infinitely many equations. In such a system, the variables $c_d(z)$ and $c_p(z)$ are independent from each other, since only the former affects $\tilde{\theta}(\cdot,z)$. Intuitively, $c_d(z)$ and $c_p(z)$ jointly determine the distribution of the defendant's type—and, thus, the probability of bargaining failure. Given this probability, $c_d(z)$ is separately identified by the probability of a conviction at trial. Hence, evaluating equation (A.5) at two different values of $t$ (say $\underline{t}$ and $\bar{t}$), I can solve for $c_d(z)$ and $c_p(z)$.[53] $\square$

A.1.3. *Proof of Proposition 3.* The estimator of $\tilde{s}(\cdot,z)$ proposed in Section 5 has two stages. First, I estimate conditional densities of trial sentences and settlement offers. Then I use such sentences for constructing a functional equation whose solution is

[53] As mentioned above, I estimate an extended version of the model, in which I allow the trial costs to vary linearly with the trial sentence. More precisely, I assume that the trial costs for the defendant and the prosecutor are given, respectively, by $c_d(t,z) \equiv \alpha_d(z) + \beta_d(z)t$ and $c_p(t,z) \equiv \alpha_p(z) + \beta_p(z)t$, where $\alpha_d(z)$, $\beta_d(z)$, $\alpha_p(z)$ and $\beta_p(z)$ are constants and $t$ is the realization of $T$. The identification of these four parameters follows the argument above—except that equation (A.5) must be evaluated at four different values of $t$, in order to form a system of four equations and four unknowns. Notice that the model imposes bounds for $\alpha_d(z)$ and $\beta_d(z)$. Indeed, since the support of $\Theta$ is $(\underline{\theta},\bar{\theta}) \subseteq (0,1)$, it must be the case that $\tilde{\theta}(t,z) \in (0,1)$ for all $t$. From equation A.1, I conclude that, for all $[\underline{t},\bar{t}]$,

$$\alpha_d(z) + \beta_d(z)t < \tilde{s}(t,z)$$
$$\text{and} \qquad \alpha_d(z) + \beta_d(z)t > \tilde{s}(t,z) - t.$$

Also, as shown in Section 4, the function $\tilde{\theta}(\cdot,z)$ is strictly increasing in $t$. Therefore, the following inequality must hold:

$$\alpha_d(z) > \tilde{s}(t,z) - \tilde{s}'(t,z)\,t,$$

where $\tilde{s}_t(\cdot,z)$ is the partial derivative of $\tilde{s}(\cdot,z)$ w.r.t. $t$. Some algebra shows that the following conditions are sufficient for the three inequalities above to hold: (i) $\tilde{s}(t,z)$ is convex in $t$, (ii) $\tilde{s}(t,z) < t$ for all $t \in [\underline{t},\bar{t}]$, (iii) $\alpha_d(z) \in [\text{Max}\{0, \tilde{s}(\underline{t},z) - \tilde{s}'(\underline{t},z)\underline{t}\}, \tilde{s}(\underline{t},z)]$ and (iv) $\beta_d(z) \in [0, \tilde{s}'(\underline{t},z)]$. As argued in Section 4, condition (i) is true. Condition (ii) is strongly supported by the estimates of $\tilde{s}(\cdot,z)$ reported later in the paper. Conditions (iii) and (iv) are then enough to guarantee that the function $\tilde{\theta}(\cdot,z)$ behaves as predicted by the theory. These conditions will be useful for the estimation of the model.

the estimate for $\tilde{s}(\cdot, z)$. In order to show the consistency of this estimator, I now state and prove a lemma, offering sufficient conditions for the consistency of two-steps estimators in which the second step employs sieve methods. The lemma is adapted from the well known results on consistency of two-steps estimators by Newey and McFadden (1994), and from the results on the consistency of sieve estimators by Chen (2007). After that, I show that its conditions are satisfied by the estimator of $\tilde{s}(\cdot, z)$ from Section 5.

LEMMA 2. *Let $\Xi$ and $\Gamma$ be two (possibly infinite-dimensional) parameter spaces endowed with metrics $d_\xi$ and $d_\gamma$, respectively. Consider a data-generating process that can be described by the true parameters $\xi_0 \in \Xi$ and $\gamma_0 \in \Gamma$. An estimate $\hat{\gamma}_n$ of $\gamma_0$ is available from a previous estimation procedure. Let $\hat{Q}_n : \Xi \times \Gamma \to \Re$ be an empirical criterion, and $\Xi_k$ be a sequence of approximating spaces to $\Xi$. Also, let*

$$\hat{\xi}_n = \underset{\xi \in \Xi_k}{argmax}\ Q_n(\xi, \hat{\gamma}_n).$$

*Assume that the following conditions are true:*

*(a) (i) Under the metric $d_\xi$: $\Xi$ is compact; and $Q(\xi, \gamma_0)$ is continuous on $\xi_0$ and upper semi-continuous on $\Xi$*

*(ii) $\xi_0 = \underset{\xi \in \Xi}{argmax}\ Q(\xi, \gamma_0)$ and $Q(\xi_0, \gamma_0) > -\infty$*

*(b) (i) For any $\xi \in \Xi$ there exists $\pi_k \xi \in \Xi_k$ such that $d_\xi(\xi, \pi_k \xi) \to 0$ as $k \to \infty$*

*(ii) Under $d_\xi$, and for all $k \geq 1$: $\Xi_k$ is compact and $Q_n(\xi, \gamma_0)$ is upper semi-continuous on $\Xi_k$*

*(c) For all $k \geq 1$, $\underset{n \to \infty}{plim} \underset{(\xi, \gamma) \in \Xi_k \times \Gamma}{sup} |Q_n(\xi, \gamma) - Q(\xi, \gamma)| = 0$*

*(d) (i) $\hat{\gamma}_n \to^P \gamma_0$ under $d_\gamma$*

*(ii) $\underset{\xi \in \Xi}{sup}\ |Q(\xi, \gamma) - Q(\xi, \gamma')| \to 0$ as $\gamma \to \gamma'$ under $d_\gamma$*

*Then $\hat{\xi} \to^P \xi_0$ under $d_\xi$.*

*Proof.* Consider any $\epsilon > 0$, and notice that, by assumption $(a)$, $d_\xi(\hat{\xi}_n, \xi_0) > \epsilon$ implies $Q(\hat{\xi}_n, \gamma_0) - Q(\xi_0, \gamma_0) < -2\eta$ for some $\eta > 0$. By assumptions (a.i) and (b), for $k$ high enough, there is $\pi_k \xi_0 \in \Xi_k$ such that $Q(\xi_0, \gamma_0) - Q(\pi_k \xi_0, \gamma_0) < \eta$.

$$\begin{aligned} d_\xi(\hat{\xi}_n, \xi_0) > \epsilon \quad &\Rightarrow \quad Q(\hat{\xi}_n, \gamma_0) - Q(\pi_k \xi_0, \gamma_0) + Q(\pi_k \xi_0, \gamma_0) - Q(\xi_0, \gamma_0) < -2\eta \\ &\Leftrightarrow \quad Q(\hat{\xi}_n, \gamma_0) - Q(\pi_k \xi_0, \gamma_0) < -2\eta + Q(\xi_0, \gamma_0) - Q(\pi_k \xi_0, \gamma_0) \\ &\Rightarrow \quad Q(\hat{\xi}_n, \gamma_0) - Q(\pi_k \xi_0, \gamma_0) < -\eta. \end{aligned}$$

Define $A_n \equiv \left\{ Q(\hat{\xi}_n, \gamma_0) - Q(\pi_k \xi_0, \gamma_0) < -\eta \right\}$. Clearly, $P\left[ d_\xi(\hat{\xi}_n, \xi_0) \right] \leq P\left[ A_n \right]$. To complete the proof, I just need to show that $A_n = o_p(1)$. Define

$$\begin{aligned} B_n &\equiv \{ |Q(\pi_k \xi_0, \hat{\gamma}_n) - Q_n(\pi_k \xi_0, \hat{\gamma}_n)| > \eta/5 \} \\ C_n &\equiv \{ |Q(\pi_k \xi_0, \gamma_0) - Q(\pi_k \xi_0, \hat{\gamma}_n)| > \eta/5 \} \\ D_n &\equiv \left\{ |Q(\hat{\xi}_n, \hat{\gamma}_n) - Q_n(\hat{\xi}_n, \hat{\gamma}_n)| > \eta/5 \right\} \\ E_n &\equiv \left\{ |Q(\hat{\xi}_n, \gamma_0) - Q(\hat{\xi}_n, \hat{\gamma}_n)| > \eta/5 \right\}. \end{aligned}$$

Notice that $B_n = o_p(1)$ and $D_n = o_p(1)$ (by assumption (c)). Similarly, $C_n = o_p(1)$ and $E_n = o_p(1)$ (by assumption (d.ii)).

Now I argue that $A_n \cap B_n^C \cap C_n^C \cap D_n^C \cap E_n^C = \emptyset$. Indeed,

$$\begin{aligned} D_n^C \quad &\Rightarrow \quad Q_n(\hat{\xi}_n, \hat{\gamma}_n) \leq Q(\hat{\xi}_n, \hat{\gamma}_n) + \eta/5 \\ E_n^C \quad &\Rightarrow \quad Q(\hat{\xi}_n, \hat{\gamma}_n) \leq Q(\hat{\xi}_n, \gamma_0) + \eta/5 \\ A_n \quad &\Rightarrow \quad Q(\hat{\xi}_n, \gamma_0) < Q(\pi_k \xi_0, \gamma_0) - \eta \\ C_n^C \quad &\Rightarrow \quad Q(\pi_k \xi_0, \gamma_0) \leq Q(\pi_k \xi_0, \hat{\gamma}_n) + \eta/5 \\ B_n^C \quad &\Rightarrow \quad Q(\pi_k \xi_0, \hat{\gamma}_n) \leq Q_n(\pi_k \xi_0, \hat{\gamma}_n) + \eta/5. \end{aligned}$$

Hence, $A_n \cap B_n^C \cap C_n^C \cap D_n^C \cap E_n^C$ implies

$$\begin{aligned} Q_n(\hat{\xi}_n, \hat{\gamma}_n) &\leq Q(\hat{\xi}_n, \gamma_0) + 2(\eta/5) < Q(\pi_k \xi_0, \gamma_0) + 2(\eta/5) - \eta \\ &\leq Q(\pi_k \xi_0, \hat{\gamma}_n) + 3(\eta/5) - \eta \leq Q_n(\pi_k \xi_0, \hat{\gamma}_n) + 4(\eta/5) - \eta \\ &= Q_n(\pi_k \xi_0, \hat{\gamma}_n) - \eta/5. \end{aligned}$$

That contradicts $\hat{\xi}_n = \underset{\xi \in \Xi_k}{\text{argmax}} \; Q_n(\xi, \hat{\gamma}_n)$.

Finally, notice that

$$\begin{aligned} P\left[A_n\right] &\leq P\left[A_n \cup \left(B_n \cup C_n \cup D_n \cup E_n\right)\right] \\ &= P\left[A_n \cap \left(B_n \cup C_n \cup D_n \cup E_n\right)^C\right] + P\left[B_n \cup C_n \cup D_n \cup E_n\right] \\ &= P\left[\emptyset\right] + P\left[B_n\right] + P\left[C_n\right] + P\left[D_n\right] + P\left[E_n\right]. \end{aligned}$$

Therefore, $A_n = o_p(1)$. □

I can now show that the estimator for $\tilde{s}(\cdot, z)$ proposed in Section 5 is consistent. A feature of the second estimation stage is that, given the first-stage estimates for the conditional distribution of $\Psi$ and the censored densities of trial sentences and settlement offers, the objective function is not random. In the notation of Proposition 3, $Q_n(\cdot,\cdot) = Q(\cdot,\cdot)$. As a consequence, in order to apply Lemma 2, I do not need to verify condition $(c)$.

The estimator is defined for a set $\Delta_\rho \subseteq \Delta$. Remember that $\mathcal{C}$ is the set of all pairwise combinations of elements in $\Delta_\rho$. In the notation of Lemma 2, the true parameter $\xi_0$ is the function $\tilde{s}(\cdot, z)$, for $z \in \Delta_\rho$. The true parameter $\gamma_0$ consists of the two finite sequences of functions $\left\{\tilde{b}_r(\cdot, z', z'')\right\}_{(z',z'')\in\mathcal{C}}$ and $\{\tilde{g}_r(\cdot, z', z'')\}_{(z',z'')\in\mathcal{C}}$. In order to avoid burdensome notation, I'll present the proof for the case where $\Delta_\rho$ has only two elements, so that $\mathcal{C} = (z', z'')$. I denote $\tilde{s}(\cdot, z')$ and $\tilde{s}(\cdot, z'')$ by $\tilde{s}(\cdot)$; $\tilde{b}_r(\cdot, z', z'')$ by $\tilde{b}_r(\cdot)$; and $\tilde{g}_r(\cdot, z', z'')$ by $\tilde{g}_r(\cdot)$. The generalization for any finite $\Delta_\rho$ is conceptually trivial.

Remember that, by the assumptions in the statement of Proposition 2: (i) the function $b_r(\cdot)$ is differentiable and the absolute value of its derivative is bounded by $\mathring{b}_r$; and (ii) the functions $b_r(\cdot)$ and $g_r(\cdot)$ are positive and bounded by $\bar{B}_r$ and $\bar{G}_r$, respectively. Also, from equation 4.1 and the boundedness of $[\underline{t}, \bar{t}]$ , I can assume without loss of generality that the function $\tilde{s}(\cdot)$ is bounded from above by $\bar{s}$, and its derivative is bounded from above by a constant $\mathring{s}$.

Using the boundary correction discussed in Section 5, the kernel density estimators of $b\left[s|\Psi = 1, Z\right]$ and $g\left(t|\Psi = 2, Z\right)$ are uniformly consistent. The estimators of $P[\Psi = 1|Z]$ and $P[\Psi = 2|Z]$ are consistent, as well. From Slutsky's theorem, therefore, the first stage of the estimation procedure returns uniformly consistent estimates of $\tilde{b}_r(s)$ and $\tilde{g}_r(t)$.

The objective function in the second stage of estimation is given by

$$Q\left(s(\cdot), b_r(\cdot), g_r(\cdot)\right) = E\left\{\left[b_r(s(t)) - g_r(t)\right]^2\right\}$$

where $s(\cdot)$ is an element from the space of increasing and convex functions on $[\underline{t}, \bar{t}]$, and $g_r(\cdot)$ and $b_r(\cdot)$ are positive valued functions.

In order to show that the estimator in the second step is consistent, I need to prove that $Q\left(s(\cdot), b_r(\cdot), g_r(\cdot)\right)$ satisfies conditions (a) and (d) from Lemma 2. That is what I do in the following lemmas.

LEMMA 3. *Under the assumptions in the statement of Proposition 3, the estimator described in Section 5 satisfies condition (a) from Lemma 2, where $d_\xi$ is the sup norm*

*Proof.* Using equation (5.2), it is easy to verify that

$$Q\left(\tilde{s}(\cdot), \tilde{b}_r(s), \tilde{g}_r(t)\right) = 0$$

and that the objective function is strictly positive for any other continuous function $s(\cdot)$. Condition (a.ii) is then trivially verified.

Let $\Xi$ be the space of functions defined on $[\underline{t}, \bar{t}]$ that are increasing and convex, uniformly bounded by zero and $\bar{s}$, and whose derivative is uniformly bounded by zero and $\mathring{b}_r$. To verify condition (a.i), notice first that, by the Arzela-Ascoli theorem, the space of differentiable functions on $[\underline{t}, \bar{t}]$ that are uniformly bounded and have a uniformly bounded derivative is compact under the sup norm. The space $\Xi$ is the intersection of that space and the space of increasing and convex functions on $[\underline{t}, \bar{t}]$, which is closed. Hence, $\Xi$ is compact.

It remains to verify the upper semi-continuity of the objective function on $\Xi$ and the continuity at $\tilde{s}(\cdot, z)$. Here, I show that the objective function is continuous on $\Xi$ under the sup norm. Let $s(\cdot)$ and $\breve{s}(\cdot)$ be two functions in $\Xi$ such that

$$\sup_{t \in [\underline{t}, \bar{t}]} |s(t) - \breve{s}(t)| \leq \eta.$$

I can write

$$\begin{aligned}
&\left| E\left\{ \left[ \tilde{b}_r(s(t)) - \tilde{g}_r(t) \right]^2 \right\} - E\left\{ \left[ \tilde{b}_r(\breve{s}(t)) - \tilde{g}_r(t) \right]^2 \right\} \right| \\
&\quad = \left| E\left[ b_r(s(t))^2 - b_r(\breve{s}(t))^2 \right] + 2E\left\{ g_r(t) \left[ b_r(s(t)) - b_r(\breve{s}(t)) \right] \right\} \right| \\
&\quad \leq \left| E\left\{ \left[ b_r(s(t)) - b_r(\breve{s}(t)) \right] \left[ 2\, g_r(t) + b_r(s(t)) + b_r(\breve{s}(t)) \right] \right\} \right|.
\end{aligned}$$

Some algebra shows that the right-hand side of the last inequality is lower than $2\ \mathring{b}_r \left[ \bar{B}_r + \bar{G}_r \right] \eta$, so that the objective function is continuous on the whole space $\Xi$. □

LEMMA 4. *Under the assumptions in the statement of Proposition 3, the estimator described in Section 5 satisfies condition (d) from Lemma 2, where $d_\gamma$ is the sup norm.*

*Proof.* Since I have uniformly consistent estimates from the first stage, condition (d.i) holds under the sup norm. To verify condition (d.ii), assume that $b_r(\cdot)$, $\breve{b}_r(\cdot)$, $g_r(\cdot)$ and $\breve{g}_r(\cdot)$ are such that

$$\begin{aligned} & \sup_s \left| b_r(s) - \breve{b}_r(s) \right| \leq \eta \\ \text{and} \qquad & \sup_t \left| g_r(t) - \breve{g}_r(t) \right| \leq \eta \end{aligned} \tag{A.6}$$

for some $\eta > 0$. I can write

$$\begin{aligned} & \left| E\left\{ [b_r(s(t)) - g_r(t)]^2 \right\} - E\left\{ \left[ \breve{b}_r(s(t)) - \breve{g}_r(t) \right]^2 \right\} \right| \\ & \quad = \left| E\left[ b_r(s(t))^2 - \breve{b}_r(s(t))^2 \right] + E\left[ g_r(t)^2 - \breve{g}_r(t)^2 \right] + 2E\left[ \breve{b}(s(t))\breve{g}(t) - \underline{(}s(t))g(t) \right] \right| \\ & \quad \leq E_1(t) + E_2(t) + E_3(t), \end{aligned}$$

where

$$\begin{aligned} E_1(t) &\equiv \left| E\left[ b_r(s(t))^2 - \breve{b}_r(s(t))^2 \right] \right| \\ E_2(t) &\equiv \left| E\left[ g_r(t)^2 - \breve{g}_r(t)^2 \right] \right| \\ \text{and} \qquad E_3(t) &\equiv \left| 2E\left[ \breve{b}(s(t))\breve{g}(t) - b(s(t))g(t) \right] \right|. \end{aligned}$$

Some algebra shows that, for all functions $s(\cdot)$, the following inequalities hold

$$\begin{aligned} E_1(t) \leq & \max\left\{ \sup_{t \in t \in [\underline{t}, \bar{t}]} 2\,\eta\, b_r(s(t)) + \eta^2 \,;\, \sup_{t \in t \in [\underline{t}, \bar{t}]} 2\,\eta\, \breve{b}_r(s(t)) + \eta^2 \right\} \\ & \leq \eta^2 + 2\,\eta\,\bar{B}_r, \\ E_2(t) \leq & \max\left\{ \sup_{t \in t \in [\underline{t}, \bar{t}]} 2\,\eta\, g_r(t) + \eta^2 \,;\, \sup_{t \in t \in [\underline{t}, \bar{t}]} 2\,\eta\, \breve{g}_r(t) + \eta^2 \right\} \\ & \leq \eta^2 + 2\,\eta\,\bar{G}_r, \\ E_3(t) \leq & 2\ \max\left\{ \sup_{t \in t \in [\underline{t}, \bar{t}]} \eta\left[ b_r(s(t)) + g_r(t) \right] + \eta^2 \,;\, \sup_{t \in t \in [\underline{t}, \bar{t}]} \eta\left[ \breve{b}_r(s(t)) + \breve{g}_r(t) \right] + \eta^2 \right\} \\ & \leq 2\,\eta^2 + 2\,\eta\left[ \bar{B}_r + \bar{G}_r \right]. \end{aligned}$$

Since neither $\bar{B}_r$ nor $\bar{G}_r$ depends on $s(\cdot)$, condition (d) is satisfied. □

That concludes the proof of Proposition 3. □

## A.2. **Estimation appendix.**

A.2.1. *Estimation of the model primitives.* The primitives to be estimated are the cost parameters $\alpha_d(z)$, $\beta_d(z)$, $\alpha_p(z)$ and $\beta_p(z)$, the distribution of defendant's types $F(\cdot|Z=z)$ and the distribution of trial sentences, characterized by $\nu(z)$ and $g(\cdot|Z=z)$.

Notice that, for all $z \in \Delta_\rho$, I can trivially estimate $\nu(z)$ by using the empirical probabilities that $\Psi = 0$, conditional on $Z = z$. To recover the other primitives, I follow the steps outlined in the proof of proposition 2 (appendix A), which show that $F(\cdot|Z=z)$ and $g(\cdot|Z=z)$ can be written in terms of the cost parameters $\alpha_d(z)$, $\beta_d(z)$, $\alpha_p(z)$ and $\beta_p(z)$, as well as the auxiliary parameters $\mu(z)$ and $\pi(z)$. Since equation (A.5) holds for all $t \in [\underline{t}, \bar{t}]$, the model is overidentified. In order to recover the primitives, therefore, I estimate $\alpha_d(z)$, $\beta_d(z)$, $\alpha_p(z)$, $\beta_p(z)$ and $\mu(z)$ by maximum likelihood.[54]

More precisely, consider guesses $\ddot{\alpha}_p$, $\ddot{\beta}_p$, $\ddot{\alpha}_d$, $\ddot{\beta}_p$ and $\ddot{\mu}$ for $\alpha_p(z)$, $\beta_p(z)$, $\alpha_d(z)$, $\beta_d(z)$ and $\mu(z)$, respectively. From $\hat{s}(\cdot, z)$ and equation (A.1), I numerically obtain $\ddot{\theta}(\cdot, z, \ddot{\alpha}_d, \ddot{\beta}_d)$, the function $\tilde{\theta}(\cdot, z)$ consistent with the guesses $\ddot{\alpha}_d$ and $\ddot{\beta}_d$. Using equations (A.2) and (A.3), I then obtain $\ddot{f}(\cdot|Z=z, \ddot{\alpha}_d, \ddot{\beta}_d, \ddot{\alpha}_p, \ddot{\beta}_p, \ddot{\mu})$, the density function $f(\cdot|Z=z)$ consistent with $\ddot{\alpha}_d$, $\ddot{\beta}_d$, $\ddot{\alpha}_p$, $\ddot{\beta}_p$ and $\ddot{\mu}$. Employing $\hat{s}(\cdot, z)$, the estimated conditional density $\hat{b}(\cdot|\Psi=1, Z=z)$, and equations (5.3), (5.4) and (A.1) to (A.3), I can numerically compute $\ddot{g}(\cdot|Z=z, \ddot{\alpha}_d, \ddot{\beta}_d, \ddot{\alpha}_p, \ddot{\beta}_p, \ddot{\mu})$, the density $g(\cdot|Z=z)$ consistent with $\ddot{\alpha}_d$, $\ddot{\beta}_d$, $\ddot{\alpha}_p$, $\ddot{\beta}_p$ and $\ddot{\mu}$. From equation (A.4), I calculate $\ddot{\pi}(z, \ddot{\alpha}_d, \ddot{\beta}_d, \ddot{\alpha}_p, \ddot{\beta}_d, \ddot{\mu})$, the value of $\pi(z)$ consistent with $\ddot{\alpha}_d$, $\ddot{\beta}_d$, $\ddot{\alpha}_p$, $\ddot{\beta}_p$ and $\ddot{\mu}$. Using $\ddot{g}(\cdot|Z=z, \ddot{\alpha}_d, \ddot{\beta}_d, \ddot{\alpha}_p, \ddot{\beta}_p, \ddot{\mu})$, $\ddot{f}(\cdot|Z=z, \ddot{\alpha}_d, \ddot{\beta}_d, \ddot{\alpha}_p, \ddot{\beta}_p, \ddot{\mu})$ and $\ddot{\pi}(z, \ddot{\alpha}_d, \ddot{\beta}_d, \ddot{\alpha}_p, \ddot{\beta}_p, \ddot{\mu})$, I can numerically compute the likelihood that $\Psi = 3$, given $Z$, and consistently with $\ddot{\alpha}_d$, $\ddot{\beta}_d$, $\ddot{\alpha}_p$, $\ddot{\beta}_p$ and $\ddot{\mu}$. Such likelihood is

$$\ddot{P}[\Psi = 3|Z=z, \ddot{\alpha}_d, \ddot{\beta}_d, \ddot{\alpha}_p, \ddot{\beta}_p, \ddot{\mu}]$$
$$= \int_{[\hat{\underline{t}}, \hat{\bar{t}}]} \int_{\underline{\theta}}^{\ddot{\theta}(t,z,\ddot{\alpha}_d,\ddot{\beta}_d)} (1-x)\ \ddot{f}(x|Z=z, \ddot{\alpha}_d, \ddot{\beta}_d, \ddot{\alpha}_p, \ddot{\beta}_p, \ddot{\mu})\ddot{g}(t|Z=z, \ddot{\alpha}_d, \ddot{\beta}_d, \ddot{\alpha}_p, \ddot{\beta}_p, \ddot{\mu})\, dx\, dt.$$

[54] In principle, I could also allow $\pi(z)$ to be a free parameter. But doing so, in practice, would have a negligible effect on the fit of the model if the bounds on $\pi(z)$ discussed in footnote 52 were to be respected.

From equation (5.3), I can numerically compute the likelihood that $\Psi = 1$, given $Z$, and consistently with $\ddot{\alpha}_d$, $\ddot{\beta}_d$, $\ddot{\alpha}_p$, $\ddot{\beta}_p$ and $\ddot{\mu}$. This likelihood is given by

$$\begin{aligned}\ddot{P}[\Psi = 1|Z = z, \ddot{\alpha}_d, \ddot{\beta}_d, \ddot{\alpha}_p, \ddot{\beta}_p, \ddot{\mu}] \\ = \int_{[\underline{\hat{t}}, \bar{\hat{t}}]} 1 - \ddot{F}\left[\ddot{\theta}(t, z, \ddot{\alpha}_d, \ddot{\beta}_d)|Z = z\right] \ddot{g}(t|Z = z, \ddot{\alpha}_d, \ddot{\beta}_d, \ddot{\alpha}_p, \ddot{\beta}_p, \ddot{\mu})\, dt,\end{aligned}$$

where $\ddot{F}[\cdot|Z = z]$ is a CDF obtained from $\ddot{f}(\cdot|Z = z, \ddot{\alpha}_d, \ddot{\beta}_d, \ddot{\alpha}_p, \ddot{\beta}_p, \ddot{\mu})$. From equations (5.6) and (5.7), the likelihood that $T = t$ and $\Psi = 2$, given $Z$, and consistently with $\ddot{\alpha}_d$, $\ddot{\beta}_d$, $\ddot{\alpha}_p$, $\ddot{\beta}_p$ and $\ddot{\mu}$, is

$$\begin{aligned}\ddot{P}[\Psi = 2|Z = z, \ddot{\alpha}_d, \ddot{\beta}_d, \ddot{\alpha}_p, \ddot{\beta}_p, \ddot{\mu}]\ \ddot{g}(t|\Psi = 2, Z = z, \ddot{\alpha}_d, \ddot{\beta}_d, \ddot{\alpha}_p, \ddot{\beta}_p, \ddot{\mu}) \\ = \int_0^{\ddot{\theta}(t,z,\ddot{\alpha}_d,\ddot{\beta}_d)} x\ \ddot{f}(x|Z = z, \ddot{\alpha}_d, \ddot{\beta}_d, \ddot{\alpha}_p, \ddot{\beta}_p, \ddot{\mu})\, dx\, \ddot{g}(\cdot|Z = z, \ddot{\alpha}_d, \ddot{\beta}_d, \ddot{\alpha}_p, \ddot{\beta}_p, \ddot{\mu}).\end{aligned}$$

I am now ready to define the likelihood contribution of an observation $i$. I consider the likelihood conditional on $\Psi \neq 0$.[55] Let $W_i$ be the data corresponding to observation $i$.[56] Given $\ddot{\alpha}_d$, $\ddot{\beta}_d$, $\ddot{\alpha}_p$, $\ddot{\beta}_p$ and $\ddot{\mu}$, the likelihood contribution of an observation $i$, conditional on $\Psi_i \neq 0$, is

$$\begin{aligned}l(\ddot{\alpha}_d, \ddot{\beta}_d, \ddot{\alpha}_p, \ddot{\beta}_p, \ddot{\mu}, W_i) = \ddot{P}[\Psi = 1|Z = z, \ddot{\alpha}_d, \ddot{\beta}_d, \ddot{\alpha}_p, \ddot{\beta}_p, \ddot{\mu}]^{\mathbb{1}\{\Psi_i=1\}} \\ \times \left\{\ddot{P}[\Psi = 2|Z = z, \ddot{\alpha}_d, \ddot{\beta}_d, \ddot{\alpha}_p, \ddot{\beta}_p, \ddot{\mu}]\ \ddot{g}(t_i|\Psi = 2, Z = z, \ddot{\alpha}_d, \ddot{\beta}_d, \ddot{\alpha}_p, \ddot{\beta}_p, \ddot{\mu})\right\}^{\mathbb{1}\{\Psi_i=2\}} \\ \times \ddot{P}[\Psi = 3|Z = z, \ddot{\alpha}_d, \ddot{\beta}_d, \ddot{\alpha}_p, \ddot{\beta}_p, \ddot{\mu}]^{\mathbb{1}\{\Psi_i=3\}}.\end{aligned}$$

Estimates $\hat{\alpha}_d(z)$, $\hat{\beta}_d(z)$, $\hat{\alpha}_p(z)$, $\hat{\beta}_p(z)$ and $\hat{\mu}(z)$ for $\alpha_d(z)$, $\beta_d(z)$, $\alpha_p(z)$, $\beta_p(z)$ and $\mu(z)$ can then be obtained by performing a numerical search to find the parameters that maximize the sum of the logarithms of $l(\ddot{\alpha}_d, \ddot{\beta}_d, \ddot{\alpha}_p, \ddot{\beta}_p, \ddot{\mu}, W_i)$ over all observations for which $\psi \neq 0$. I constrain $\ddot{\alpha}_d$, $\ddot{\beta}_d$, $\ddot{\alpha}_p$ and $\ddot{\beta}_p$ to be positive, and $\ddot{\mu}$ to belong to the unit interval.[57] Finally, estimates for $g(\cdot|Z = z)$ and $f(\cdot|Z = z)$ are defined by $\ddot{g}(\cdot|Z =$

[55] I do so because the empirical probability that $\Psi = 0$ is useful only for identifying $\nu(z)$.

[56] That is, if $\Psi_i \in \{1, 3\}$, $W_i$ consists of $z_i$ and $\psi_i$, the realizations of $Z_i$ and $\Psi_i$. If $\Psi_i = 2$, $W_i$ also consists of $t_i$, the realization of $T_i$. Notice that I do not take into account the realization $s_i$ of $S_i$, which is observed when $\Psi_i = 1$. That is because the likelihood of $S = s$, given $\Psi = 1$ and $Z = z$ is simply $\hat{b}(z|\Psi = 1, Z = z)$, which does not depend on $\ddot{c}_p$, $\ddot{c}_d$ or $\ddot{\mu}$.

[57] I further constrain $\ddot{\alpha}_d$ and $\ddot{\beta}_d$ to satisfy conditions (iii) and (iv) described in footnote 53, where $\tilde{s}(\cdot, z)$ is replaced by the estimate $\hat{s}(\cdot, z)$. Restricting the trial cost coefficients to be positive is consistent with the notion that it is is more costly to bring relatively serious cases to trial. Notice that assuming $\alpha_d(z) > 0$ and $\alpha_p(z) > 0$ also ensures that the hazard rate of the distribution of defendant's type is strictly increasing, as can be shown by applying the implicit function theorem on equation (4.2).

$z, \hat{\alpha}_d(z), \hat{\beta}_d(z), \hat{\alpha}_p(z), \hat{\beta}_p(z), \hat{\mu}(z))$ and $\ddot{f}(\cdot|Z = z, \hat{\alpha}_d(z), \hat{\beta}_d(z), \hat{\alpha}_p(z), \hat{\beta}_p(z), \hat{\mu}(z))$, respectively.

A.2.2. *Observed heterogeneity.* I incorporate observed heterogeneity across cases to my estimation procedure by dividing the observations in the data into a finite number of covariate groups and implementing the estimator described in Section 5 separately for each one of them. The first step of the estimator consists of computing two types of conditional densities: that of trial sentences, conditional on a conviction at trial, and that of settlement offers, conditional on a successful plea bargain. These two types of conditional densities must be estimated both for cases under the responsibility of lenient judges and for those under the responsibility of harsh ones. Therefore, for each one of the 12 covariate groups under consideration in my analysis, I must estimate four conditional densities. I estimate these conditional densities using the smoothing method developed by Li and Racine (2007), which I briefly describe below. Notice that the notation employed in this part of the Appendix differs from that of the rest of the paper.

Let $Y$ be an univariate continuous random variable and $X$ an $r$-dimensional discrete random variable. Denote by $f(\cdot)$, $g(\cdot)$ and $\mu(\cdot)$ the joint density of $(X, Y)$ and the marginal densities of $Y$ and $X$, respectively. For each dimension $s$ of $X$, let $c_s$ be the number of values in the support of $X_s$ and $\lambda_s$ be a real number between zero and $(c_s - 1)/c_s$. Define the vector $\lambda = (\lambda_1, \ldots, \lambda_r)$ and consider the following estimates of $f(\cdot)$ and $\mu(\cdot)$:

$$\hat{f}(x, y) = n^{-1} \sum_{i=1}^{n} L(x, X_i, \lambda) k_{h_0}(y - Y_i)$$

$$\text{and} \qquad \hat{\mu}(x) = n^{-1} \sum_{i=1}^{n} L(x, X_i \lambda),$$

where $n$ is the sample size, $k_{h_0}(\cdot)$ is a kernel function with bandwidth $h_0$ and

$$L(x, X_i \lambda) = \prod_{s=1}^{r} \left[\lambda_s/(c_s - 1)\right]^{\mathbb{1}(X_{is} \neq x_s)} (1 - \lambda_s)^{\mathbb{1}(X_{is} = x_s)}.$$

Finally, define the the estimate of the conditional density $g(y|x)$ as

$$\hat{g}(y|x) = \hat{f}(x, y)/\hat{\mu}(x).$$

Notice that $\hat{g}(y|x)$ is obtained using all observations in the data—i.e., even those in which $X \neq x$. These observations, however, are weighted down, relative to the ones

satisfying $X = x$. The weights are given by the vector $\lambda = (\lambda_1, \ldots, \lambda_r)$. In one extreme case, $\lambda_s$ is zero for all $s$, and $\hat{g}(y|x)$ is calculated employing only observations such that the realization of $X$ is $x$. In the other extreme case, $\lambda_s = (c_s - 1)/c_s$ for all $s$, and $\hat{g}(y|x)$ becomes the estimate of $g(\cdot)$, the unconditional density of $Y$. The vector $\lambda$ can be regarded as a collection of smoothing parameters—one for each dimension of $X$. Together, $\lambda$ and $h_0$ determine the extent to which points away from $(y, x)$ affect $\hat{g}(y|x)$. As argued by Li and Racine (2007), positive values of $\lambda$ increase the finite sample bias of $\hat{g}(y|x)$ but also reduce its variance. Depending on the magnitudes of these two effects, the net result of increasing $\lambda$ can be a decrease in the mean squared error associated with $\hat{g}(y|x)$.

The greatest challenge in implementing this estimator, therefore, is the choice of the smoothing parameters $\lambda$ and $h_0$. In my application, I follow Li and Racine (2007) and select $\lambda$ by cross-validation.[58] For any given sample size and any covariate dimension $c$, this method aims to select relatively large values of $\lambda_c$ if the distribution of $Y$ is not largely affected by variations in $X_c$, and small values of $\lambda_c$ if the distribution of $Y$ varies considerably with $X_c$. Moreover, the selected values of $\lambda_c$ tend to decrease as the sample size increases.

For each covariate group in my analysis, I estimate four conditional densities. Using the notation of Li and Racine's estimator presented above, $Y$ may represent four random variables: Trial sentences assigned by lenient judges, trial sentences assigned by harsh judges, settlement offers made under lenient judges and settlement offers made under harsh judges. The discrete random variable $X$ refers to the covariates used to divide the data into groups.[59] This random variable has the following five dimensions: (i) defendant's gender (male or female), (ii) defendant's race (African American or non-African American), (iii) the type of defense counsel (public defender, court-assigned attorney or privately-held attorney), (iv) the length of the defendant's criminal record (short or long, as defined in Section 5) and (v) Superior Court division (numbers one to eight). The function $k_{h_0}(\cdot)$ is the Epanechnikov kernel.

[58] Li and Racine (2007) propose two basic approaches for the selection of smoothing parameters: least squares cross-validation and maximum likelihood cross-validation. The former method is too computationally costly for me to employ it, given the sample sizes that I deal with in my application. I therefore use maximum likelihood cross-validation in the present paper.

[59] To be sure, I estimate four conditional densities. The densities of trial sentences are conditional on a conviction at trial, and those of settlement offers are conditional on a plea bargain. Besides conditioning on the case outcome, I estimate these densities conditioning on five covariates. In the notation of this Appendix, $X$ refers only to these covariates.

TABLE 10. Smoothing parameters

| Covariate | Conditional density estimator† | | | | |
|---|---|---|---|---|---|
| | Trial sentences (lenient) | Trial sentences (harsh) | Offers (lenient) | Offers (harsh) | Upper endpoint |
| Gender | 0.39 | 0.11 | 0.03 | 0.03 | 0.50 |
| Race | 0.12 | 0.05 | 0.09 | 0.09 | 0.50 |
| Counsel | 0.23 | 0.18 | 0.20 | 0.25 | 0.67 |
| Record | 0.02 | 0.03 | 0.01 | 0.00 | 0.50 |
| Division | 0.41 | 0.33 | 0.44 | 0.41 | 0.88 |

† : Trial sentence densities, conditional on a conviction at trial and on covariates. Settlement offer densities, conditional on a plea bargain and on covariates.

Table 10 contains the smoothing parameters $\lambda$ obtained by maximum-likelihood cross-validation for each of the four conditional densities of my analysis. Notice that, for every covariate $c$, lambda must belong to the interval $[0, (c_s - 1)/c_s]$, where $c_s$ is the covariate's support. The upper endpoints of this interval are shown in the last column of the table. All the selected smoothing parameters are far away from these endpoints, suggesting that the covariates under consideration are important in explaining the distributions of trial sentences and settlement offers. In particular, the smoothing parameters associated with the defendant's previous criminal record are very close to zero. The parameters associated with race are also relatively low—ranging from 0.05 to 0.12. The gender parameters are larger for the densities of trial sentences than for those of settlement offers, which can be explained by the larger sample sizes used to compute the latter.

As explained in Section 5, the supports of trial sentences and settlement offers are bounded, which complicates the estimation of the conditional densities described above. To deal with this problem, I use a boundary correction proposed by Karunamuni and Zhang (2008). Using the notation of this Appendix, the approach consists of reflecting a transformation of the data near the boundary of $Y$. The reflected data points have the same $x$ as the corresponding observations in the original data set, but $y$ is modified. The estimator uses separate bandwidths $h_0$ for points near the boundary and away from it. Differently from the naive reflection of the untransformed data, this method allows the partial derivative of $g(y|x)$ with respect to $y$ to be different from zero at the boundary of the support. See Karunamuni and Zhang (2008) for details.

TABLE 11. Kernel bandwidths for trial sentences and settlement offers†

| | Trial sentences (lenient) | Trial sentences (harsh) | Settlement offers (lenient) | Settlement offers (harsh) |
|---|---|---|---|---|
| Bandwidth | 21.83 | 25.31 | 6.59 | 7.37 |
| †: Measured in months | | | | |

Table 11 reports the bandwidths $h_0$ for points away from the boundary, which are computed using Silverman's "rule-of-thumb" (Silverman, 1986). The bandwidths for trial sentences are 21.83 months (lenient judges) and 25.31 months (harsh judges). Those for settlement offers are 6.59 months (lenient judges) and 7.37 months (harsh judges). The larger bandwidths for trial sentences reflect the relative scarcity of cases that result in an incarceration conviction at trial.

A.2.3. *Standard errors.* I use bootstrap methods to compute standard errors for the parameters reported in table 5. Specifically, I consider 1200 bootstrap samples for each covariate group. For each of these samples, I estimate the densities of trial sentences and settlement offers using the same bandwidths an smoothing parameters employed in the main data. I then estimate the offer function and, finally, the model parameters.

There are two main issues with this procedure. The first one is that I do not offer a proof of the validity of the bootstrap for my estimator. Subsampling methods (Politis, Romano and Wolf, 1999) are more robust than the bootstrap, but, to apply these methods, the convergence rate of the estimator must be known. The development of suitable inference methods in the context of my estimator is an interesting topic for further research. The second issue is that, for part of the bootstrap samples, the last step of the estimation procedure—i.e., obtaining maximum likelihood estimates for $\alpha_d$, $\beta_d$, $\alpha_p$, $\beta_p$ and $\mu$—becomes computationally too costly. This is the case whenever the estimated settlement offer function is too convex. I do not implement the last estimation step for these samples.[60] As a consequence, the standard deviations

[60]More precisely, I drop from my analysis every bootstrap sample in which the coefficient associated with the last C-spline basis is greater than four. As a reference, using the main data, I estimate this coefficient to be 2.43 for covariate group one, 1.27 for group two, 2.04 for group three and 0.00 for group four. This procedure eliminates 13.83% of the 1200 bootstrap samples for group one, 32.50% for group two, 12.58% for group three, 37.00% for group four, 3,33% for group five, 4.83% for group six, 20.25% for group seven, 14.50% for group eight, 11.25% for group nine, 10.83% for group ten, 36.08% for group 11 and 14.75% for group 12.

reported in table 5 may underestimate the actual standard deviation of the model parameters.

A.3. **Comparison with Sieg (2000).** The model estimated by Sieg (2000), which is based on an earlier contribution due to Nalebuff (1987), is closely related to the one studied here. There are, however, important differences between Sieg's paper and mine. First, I identify and estimate my model without assuming any parametric specification, whereas Sieg's analysis is totally parametric. Also, I analyze data on criminal cases, whereas Sieg uses data on medical malpractice disputes. Not surprisingly, the different applications lead to distinctions between the models used in the two papers, which turn out to have substantial implications. I now discuss these differences.

In Sieg's model, the defendant is privately informed about the merit of the case, and the damages suffered by the plaintiff are commonly known by the two parties. If the case reaches the trial stage, the plaintiff is, with probability one, awarded the product of the damages and the merit. In such a setup, the defendant is found not liable if and only if the case has no merit at all. A direct implication is that changes in the distribution of damages across cases have no impact on the proportion of cases won by the plaintiff. That is not a shortcoming in Sieg's application since, in the context of medical malpractice disputes, the plaintiff win rate is not an outcome of major interest to policy makers. But the same setup in the context of criminal cases would imply that changes in the distribution of potential trial sentences do not affect the probability that the defendant is found guilty. That would prevent the evaluation of how changes in sentencing guidelines influence conviction rates, a topic of great interest in the discussion on sentencing reform. In the model estimated in my paper, the defendant is privately informed—not about the merit of the case, but about the probability of being found guilty at trial. Changes in the distribution of potential trial sentences affect conviction rates by altering the types of defendants who, in equilibrium, choose to go to trial.

Another difference between the model used by Sieg and the one analyzed here concerns the prosecutor's outside option. There, the plaintiff cannot bring a case to trial if doing so implies a negative expected payoff. In other words, the prosecutor's outside option is set to zero, which makes perfect sense in the context of tort cases. Here, in contrast, I assume that, for cases with positive potential trial sentence, the prosecutor's outside option is low enough that such cases are never withdrawn. This assumption is arbitrary. However, as argued in previous sections, prosecutors often

face career-concern incentives to not withdraw even cases that are very difficult. Although it is theoretically appealing to consider the prosecutor's outside option, setting it to zero in the analysis of criminal cases is at least as arbitrary as setting it to any negative number. Future research can incorporate the estimation of the prosecutor's outside option into the empirical analysis of criminal proceedings.

## Appendix B. Online Appendix

B.1. **Reduced form analysis.** In this appendix I present the results of a reduced-form analysis that has two main objectives: The fist one is to verify whether the data are consistent with basic predictions of the model. I do so by presenting evidence that the settlement of a case becomes less likely as the sentence to be assigned in the event of a trial conviction increases. The second objective is to validate the division of the judges in the data into lenient and harsh as a valid source of heterogeneity in the distribution of trial sentences, given the identifying assumptions of the structural model. Specifically, I show evidence that the distribution of cases assigned to lenient and harsh judges are indistinguishable from from each other.

B.1.1. *Reduced-form evidence for the model.* An important prediction of the bargaining model discussed in Section 4 is that the probability of a successful settlement is decreasing in the length of the trial sentence. It is useful to present evidence supporting this prediction. A simple way of doing so is by comparing the likelihoods of settlement across cases in which the main offenses differ in nature. Table 12 presents settlement rates and average incarceration sentences for several categories of crimes in the data. The table separately reports the average sentence lengths for cases resolved at trial and by plea bargain. The offense categories considered are homicide, non-homicide violent crimes, property crimes, drug-related crimes and other offenses.[61] Here, I consider as settled all cases decided by plea bargain—independent of whether the sentence includes incarceration time. That is because, otherwise, the settlement rates would largely capture differences in the the probabilities of incarceration across crime categories. The table shows that, as expected, sentences assigned to defendants convicted of homicide are very long.[62] Among the categories displayed in the table, non-homicide violent crimes have the second longest average sentences, followed by drug-related crimes and property crimes. More interestingly, the table suggests a negative relationship between average sentences and the likelihood of settlement. The settlement ratios for homicides, non-homicide violent crimes, drug-related crimes and property crimes are, respectively, 81.83 percent, 89.94 percent, 96.95 percent and 98.26 percent. It is also worth noticing that cases in which the average trial sentences

[61]Property crimes include burglary, larceny and arson. Drug-related crimes comprise both trafficking and possession.

[62]The numbers in table 12 underestimate the average homicide sentence since death sentences are not accounted for in the computation.

TABLE 12. Settlement rates and sentences by type of offense

| Distribution of cases by outcome | | | | |
|---|---|---|---|---|
| Nature of the offense | Obs. | % Settled | Average sentence (settled)† | Average sentence (trial)† |
| Violent (non-homicide) | 118948 | 89.94% | 38.98 | 100.73 |
| Homicide | 6611 | 81.83% | 134.71 | 236.76 |
| Property | 215505 | 98.26% | 13.36 | 49.68 |
| Drugs | 199692 | 96.95% | 18.63 | 51.44 |
| Other | 313622 | 96.09% | 18.47 | 37.03 |
| Total | 854378 | 95.86% | 25.05 | 81.30 |

† : Measured in months.

are long tend to settle for relatively long sentences. This observation provides further evidence that settlement negotiations take place in the shadow of the trial.

Another method of testing whether cases with long potential trial sentences are settled less often is to explore the correlation between settlement ratios and the sentencing patterns of different judges. There are several reasons why some judges can be harsher than others. North Carolina Superior Court judges are elected, and the electorate's preferences can vary across districts. Also, judges in different stages in their careers may have distinct incentives to pander to voters. For example, it is possible that young judges want to establish a reputation as tough on crime and, thus, tend to assign harsher punishments than their senior counterparts. Moreover, since electoral accountability is unlikely to be perfect, judges' personal preferences probably explain much of the heterogeneity in their sentencing behavior.

As previously mentioned, an important feature of the North Carolina justice system is the rotation of judges across districts within the same Superior Court divisions. The rotation schedule is centrally determined by the state administration, which makes it plausible to assume that cases are randomly assigned to judges.[63] That allows me to treat the caseloads of different judges as identical and to attribute any variation in the sentencing patterns to judges' characteristics. I can then verify whether the settlement ratios of cases decided by harsher judges are smaller than those of cases decided by more lenient ones.

[63]Later in this section I present empirical evidence supporting the random assignment hypothesis.

TABLE 13. Regression Outcomes

| | (1) | (2) | (3) |
|---|---|---|---|
| | Dependent Variable | | |
| | *sentence*† | *settled* | *harsh* |
| *settled* | -39.67 | _ | _ |
| | (1.31) | | |
| *age* | -0.05 | -0.01 | 0.00 |
| | (0.20) | (0.00) | (0.00) |
| $age^2$ | 0.00 | -0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) |
| $female$ | -4.31 | - 0.06 | -0.01 |
| | (0.76) | (0.00) | (0.01) |
| *black* | 0.93 | 0.00 | -0.01 |
| | (0.68) | (0.00) | (0.01) |
| *hispanic* | -1.42 | 0.19 | -0.01 |
| | (1.26) | (0.01) | (0.01) |
| *private attorney* | -3.78 | -0.09 | 0.00 |
| | (0.75) | (0.00) | (0.01) |
| *public defender* | -3.54 | -0.02 | -0.03 |
| | (0.74) | (0.01) | 0.03 |
| Judge dummies | Yes | Yes | No |
| County dummies | Yes | Yes | No |
| Superior Court division dummies | No | No | Yes |
| Observations | 36644 | 97942 | 97942 |
| $R^2$ | 0.51 | 0.27 | 0.28 |

Other controls: Year of disposition, offense severity and defendant's criminal record.
Reference category for counsel type: Court-assigned attorney.
Standard errors (robust to clustering at the judge level) in parenthesis.

†: Measured in months.

More precisely, consider the following regression model:[64]

$$sentence_i = \vartheta_1 X_i + \zeta_{\mathbf{1}} \, \mathbf{Judge_i} + \epsilon_{1i}, \tag{B.1}$$

[64]For an analogous exercise using data on federal criminal cases, see Boylan (2012). Waldfogel (1998) undertakes a similar analysis using data on civil cases. The results of both papers are similar to the ones presented in this section.

where $sentence_i$ is the length of the incarceration sentence assigned in case $i$, $\mathbf{Judge_i}$ is a vector of dummies identifying the judge responsible for case $i$, $X_i$ is a vector of control variables and $\epsilon_{1i}$ is an error term. Consider, also, the following model

$$settled_i = \vartheta_2 X_i + \boldsymbol{\zeta_2}\, \mathbf{Judge_i} + \epsilon_{2i}, \tag{B.2}$$

where $settled_i$ is a dummy indicating whether case $i$ is resolved by plea bargain, $\mathbf{Judge_i}$ and $X_i$ are defined as before, and $\epsilon_{2i}$ is another error term.[65] I estimate the two equations above by OLS, using only cases in which the main offense is a non-homicide violent crime. In both specifications, the vector of control variables $X_i$ includes the defendant's gender, racial / ethnic group, previous criminal record, age and squared age, as well as dummies indicating the type of attorney representing the defendant.[66] I also include as controls dummies indicating the county where the case is prosecuted, the year of disposition and the severity of the main charged offense, as defined by the North Carolina sentencing guidelines. Finally, I add the dummy *settled* as a control variable in specification B.1. The results of each regression are presented in columns (1) and (2) of table 13. Here, I am directly interested in the relation between $\hat{\boldsymbol{\zeta}}_\mathbf{1}$ and $\hat{\boldsymbol{\zeta}}_\mathbf{2}$, the vectors of estimated coefficients for the judge-specific dummies in equations (B.1) and (B.2), respectively. A negative correlation between such two vectors suggests that cases decided by harsh judges are less likely to be resolved by a plea bargain, as predicted by the model in Section 4. I find the Pearson's correlation coefficient to be -0.23 and significant at the ten percent level.[67]

There are evident problems with the OLS estimation of equation (B.1). Indeed, the regression includes only cases in which the defendant receives a incarceration sentence, which may generate sample selection. Also, it is not plausible to assume that $E(\epsilon_1\epsilon_2) = 0$, so that the variable $settled_i$ is endogenous in (B.1). Unfortunately, there is no clear instrument available for that variable. Therefore, one should be careful in interpreting the above results. Still, together with the variation in settlement ratios

[65] Here, and in all the empirical analysis in the remainder of this paper, I define a case as settled only if the prosecutor and the defendant agree on a incarceration sentence.

[66] The defendant's previous criminal record is incorporated as follows in specifications (B.1) and (B.2): Based on the criminal record points reported for each defendant and on the criteria employed by the North Carolina justice system for the determination of sentencing guidelines, I divide the cases in the data into six criminal record levels. I then add to the specifications dummies indicating the level to which the case belongs.

[67] The standard deviation of the correlation coefficient, calculated from 1000 bootstrap samples, is 0.1242. The associated p-value is 0.067. Replicating the exercise with the entire data set (i.e., not only non-homicide violent crimes), I find a correlation coefficient of -0.18 that is significant at all conventional levels.

from table 12, the negative correlation between $\hat{\zeta}_{\mathbf{1}}$ and $\hat{\zeta}_{\mathbf{2}}$ provides support for the model discussed in Section 4.

B.1.2. *Comparing cases of lenient and harsh judges.* One of the main identifying assumptions of the model, condition $A$, implies that the variation in the distribution of trial sentences arising from differences in sentencing behavior across judges must be uncorrelated with other variables that may affect the outcome of the case. This is an assumption that, unfortunately, cannot be tested. Notice, however, that the assumption holds if the cases in the data are indeed randomly assigned to the judges. It is possible to provide some support for the random assignment hypothesis by verifying whether the distribution of observable case characteristics varies substantially across lenient and harsh judges. I consider the following specification:

$$harsh_i = \vartheta_3 X_i + \epsilon_{3i}, \tag{B.3}$$

where $harsh_i$ is a dummy indicating whether the judge responsible for case $i$ is a harsh one, $X_i$ is a vector of case characteristics and $\epsilon_{3i}$ is an error term. The variables included in $X_i$ are the defense attorney type and the defendant's gender, race/ethnicity, previous criminal record, age and age squared. I also include, as controls, dummies indicating the year of disposition of the case, the severity of the offense and the Superior Court division where the case is prosecuted. All these variables are arguably out of the judge's control. Column (3) in table 13 contains OLS estimates of this specification. All of the point estimates are very close to zero and only the coefficient associated with the defendant's gender is significant at the ten precent level. These results suggest that the cases in the data do not differ considerably across the two judge categories.

B.2. **Extensions.**

B.2.1. *Relaxing the independence between $T$ and $\Theta$.* In the empirical model described in Section 5, I assume that the potential trial sentences and the defendants' types are independently distributed, conditional on the case characteristics $Z$. Below, I relax this assumption and show that it is still possible to obtain partial identification of the model. In fact, the optimal settlement offer function is exactly identified and can be estimated by the procedure proposed in Section 5. Therefore, the estimates of settlement offer functions presented in this paper are robust to the dependence between defendants' types and potential trial sentences, in the way defined below.

Let $F(\cdot|Z,T)$ be the distribution function of defendants' types, conditional on the potential trial sentence $T$ and on case characteristics $Z$. Assume that, for all $t \in [\underline{t}, \bar{t}]$ and $z \in \Delta$, the function $F(\cdot|Z,T)$ satisfies the technical assumptions outlined in section 4. Denote the density and the hazard functions associated with $F(\cdot|Z,T)$ by $f(\cdot|Z,T)$ and $\lambda(\theta,t,z)$, respectively. Assume that $\lambda(\theta,t)$ is differentiable in both its arguments, and that

$$\frac{\partial}{\partial\theta}\lambda(\theta,t,z) > 0 \quad \text{and} \quad \frac{\partial}{\partial t}\lambda(\theta,t,z) < \frac{1}{c_p(z)+c_d(z)} \tag{B.4}$$

for all $t \in [\underline{t}, \bar{t}]$, $\theta \in (\underline{\theta}, \bar{\theta})$ and $z \in \Delta$. The first inequality ensures that the hazard function associated with $F(\cdot|Z,T)$ is increasing in $\theta$. The second one limits the amount of mass $F(\cdot|Z,T)$ can redistribute towards low defendants' types as the potential trial sentence increases.

Given realizations $t$ of $T$, $z$ of $Z$, the equilibrium of the bargaining game can be found in the same way as in Section 4. It is characterized by equation (4.1) and by the first-order condition for the prosecutor, which is given by

$$\frac{t}{c_p + c_d} = \frac{f\left[\theta(s^*)|T=t, Z=z\right]}{1 - F\left[\theta^*|T=t, Z=z\right]}. \tag{B.5}$$

As before, I define the equilibrium settlement offer and defendant's threshold type as functions of $t$, and denote them by $\tilde{s}(\cdot,s)$ and $\tilde{\theta}(\cdot,s)$, respectively. Using condition (B.4), and applying the implicit function theorem to equation (B.5), I have that $\tilde{s}(\cdot,s)$ and $\tilde{\theta}(\cdot,s)$ are strictly increasing in $t$, and $\tilde{s}(\cdot,z)$ is strictly convex. The argument in Section 5 can then be easily adapted to show that, under condition $B$ and an analogue to condition $A$, the function $\tilde{s}(\cdot,z)$ is identified. Notice that the estimator of $\tilde{s}(\cdot,z)$ proposed in the same section does not make direct use of the distribution of defendants' types. That means that it can be applied under the more general conditions described here, and the estimates of $\tilde{s}(\cdot,z)$ presented in Section 6 are still valid.

Although I am able to recover the optimal offer function after relaxing the independence assumption between $T$ and $\Theta$, the exact identification of the model's primitives does not hold. I now outline a strategy for the partial identification of such primitives. I begin by noticing that I can still recover $\tilde{\theta}(t,z)$ and the hazard function $\lambda(\tilde{\theta}(t),t,z)$ for all $t \in [\underline{t}, \bar{t}]$, up to the scalars $c_d(z)$ and $c_p(z)$. I now strengthen condition (B.4), by assuming that

$$\frac{\partial}{\partial\theta}\lambda(\theta,t,z) > 0 \quad \text{and} \quad \frac{\partial}{\partial t}\lambda(\theta,t,z) < 0. \tag{B.6}$$

The second inequality in this condition implies that $F(\cdot|Z,T)$ places more mass on high defendants' types as the potential trial sentence increases. A consequence of this inequality is that $\lambda(\theta,t,z) \leq \lambda(\theta,\tilde{\theta}^{-1}(\theta),z)$ for all $\tilde{\theta}(\underline{t}) \leq \theta \leq \tilde{\theta}(t)$. Therefore, I have that

$$\begin{aligned} F(\theta|Z,T) &= 1 - \exp\left(-\int_0^{\theta} \lambda(x,t,z)\,dx\right) \\ &\leq 1 - \underline{\mu}(z)\exp\left(-\int_{\tilde{\theta}(\underline{t})}^{\theta} \lambda(x,\tilde{\theta}^{-1}(x),z)\,dx\right) \end{aligned}$$

for all $\tilde{\theta}(\underline{t}) \leq \theta \leq \tilde{\theta}(t)$ and $z \in \Delta$, where $\underline{\mu}(z) = \exp\left(-\int_0^{\tilde{\theta}(\underline{t})} \lambda(x,\underline{t},z)\,dx\right)$. Define the function

$$\ddot{F}(t,z) = 1 - \underline{\mu}(z)\exp\left(-\int_{\tilde{\theta}(\underline{t})}^{\tilde{\theta}(t)} \lambda(x,\tilde{\theta}^{-1}(x),z)\,dx\right).$$

I then have that $\ddot{F}(t,z) \geq F(\tilde{\theta}(t)|Z=z,T=t)$ for all $t \in [\underline{t},\bar{t}]$. Now consider the function

$$\ddot{g}(t,z) = \left[1-\ddot{F}(t,z)\right]^{-1}\left[\frac{\partial}{\partial t}\tilde{s}(t,z)\right] b\left(\tilde{s}(t)|\Psi=1,Z=z\right) P[\Psi=1|Z=z].$$

Notice that

$$\ddot{g}(t,z) \geq \left[1-F(t|Z=z)\right]^{-1}\left[\frac{\partial}{\partial t}\tilde{s}(t,z)\right] b\left(\tilde{s}(t)|\Psi=1,Z=z\right) P[\Psi=1|Z=z] = g_j(t)$$

for all $t \in [\underline{t},\bar{t}]$ and $z \in \Delta$, where the equality comes from (5.1), (5.3) and (5.4). That allows me to write

$$1 - \int_{[\underline{t},\bar{t}]} \ddot{F}(t,z)\ddot{g}(t,z)\,dt \geq 1 - \int_{[\underline{t},\bar{t}]} F(\tilde{\theta}(t)|Z=z,T=t)g(t|Z=z)\,dt \tag{B.7}$$

for all $t \in [\underline{t},\bar{t}]$ and $z \in \Delta$.

The expression on the right-hand side of (B.7) is the probability that a case is settled, conditional on $Z=z$ and $\Psi \neq 0$ (i.e., on it not being withdrawn by the prosecutor). That probability is observed by the econometrician. The expression on the left-hand side is known only up to the scalars $c_d(z)$, $c_p(z)$ and $\underline{\mu}(z)$. Thus, equation (B.7) establishes a non-linear bound for such scalars. If a subset $\Delta_\rho \subset \Delta$ satisfies condition $A$, then $c_d(z') = c_d(z'')$, $c_p(z') = c_p(z'')$ and $\underline{\mu}(z') = \underline{\mu}(z'')$ for all $z'$ and $z''$ in $\Delta_\rho$. Therefore, (B.7) establishes multiple bounds on the model's parameters—one for each $z \in \Delta_\rho$. Those can be combined with the bounds for $c_d$ described in footnote 53, in order to partially identify the model's primitives. Implementing such a strategy is an interesting topic for future research.

B.2.2. *Allowing for multiple outcomes following bargaining failure.* My identification and estimation strategies can be adapted to the analysis of settings other than the resolution of criminal cases. However, in the model presented above, a disagreement between the bargaining parties may lead to only two possible outcomes: A trial conviction or an acquittal. That assumption may be unrealistic in some applications. I now extend my identification strategy to allow for multiple possible outcomes in the event of a disagreement. Unfortunately, to do that, I must impose a parametric relationship between the private information received by one of the bargaining parties and the distribution of outcomes, conditional on a bargaining failure.

Assume that there are two agents, which I denote by $p$ and $d$. The game has two stages. Bargaining takes place in the first stage, and, if both parties reach an agreement, the game ends. Otherwise, the game proceeds to a second stage. Payoffs in the second stage depend on a random variable $O$, distributed over the finite support $\{1, \cdots, N\}$. Specifically, the second stage payoffs are given by

$$\begin{aligned} & -c_p + \sum_{n \in \{1,\cdots,N\}} \mathbb{1}\{o = n\}\kappa_{p,n} t \quad \text{, for agent } p \\ \text{and} \qquad & -c_d + \sum_{n \in \{1,\cdots,N\}} \mathbb{1}\{o = n\}\kappa_{d,n} t \quad \text{, for agent } p, \end{aligned}$$

where $o \in \{1, \cdots, N\}$ is the realization of $O$, and $c_d$ and $c_p$ are strictly positive real numbers. The value $t$, which is assumed to be strictly positive, measures the stake of the game and is common knowledge to both agents at the moment of bargaining.

Before bargaining begins, agent $d$ receives a signal about $O$. That signal is represented by a random variable $\Theta$, which is distributed according to the CDF $F$ over the support $[\underline{\theta}, \bar{\theta}]$. The distribution of $O$, conditional on the signal $\Theta$, is characterized by the functions $\{\mathcal{Y}_n(\cdot)\}_{i \in \{1,\cdots,N\}}$, so that

$$P\left[O = n | \Theta = \theta\right] = \mathcal{Y}_n(\theta)$$

for all $n \in \{1, \cdots, N\}$ and $\theta \in [\underline{\theta}, \bar{\theta}]$. My identification strategy assumes that the functions $\{\mathcal{Y}_n(\cdot)\}_{i \in \{1,\cdots,N\}}$ are known by the econometrician. For example, such functions may be implied by assuming that $\Theta$ follows a parametric distribution over $\{1, \cdots, N\}$, such as a binomial or a truncated Poisson distribution with parameter $\theta$.

Assume that $\mathcal{Y}_n(\theta)$ is twice differentiable for every $n \in \{1, \cdots, N\}$. Assume, also, that the technical conditions on $F$ listed in Section 4 also hold here—i.e., $F$ is twice

differentiable and has an associated density function $f$; the density $f$ is strictly positive on an interval $(\underline{\theta}, \bar{\theta})$, and is zero outside of such interval; $f$ is non-increasing in a neighborhood of $\bar{\theta}$; and the hazard rate $f/[1-F]$ is strictly increasing in $\theta$.

Bargaining follows a take-it-or-leave-it protocol. At stage one, agent $p$ makes a proposal $s$ to agent $d$. If the proposal is rejected, the game reaches the second stage described above. Conversely, if the proposal is accepted, the game ends, and the payoffs are

$$\begin{aligned} & \kappa_{p,1}t + (\kappa_{p,N} - \kappa_{p,1})s \quad \text{, for agent } p \\ \text{and} \qquad & \kappa_{d,1}t + (\kappa_{d,N} - \kappa_{d,1})s \quad \text{, for agent } d. \end{aligned}$$

Assume that the payoffs are symmetric, in the following sense: Let $\kappa_{p,1} < \cdots < \kappa_{p,N}$, and $\kappa_{d,1} > \cdots > \kappa_{d,N}$, so that, if bargaining fails, high realizations of $O$ benefit agent $p$ at the expense of agent $d$. Assume, also, that

$$\tilde{\kappa}_n \equiv \frac{\kappa_{p,n} - \kappa_{p,1}}{\kappa_{p,N} - \kappa_{p,1}} = \frac{\kappa_{d,1} - \kappa_{d,n}}{\kappa_{d,1} - \kappa_{d,N}}$$

for all $n \in \{1, \cdots, N\}$. Lastly, assume that

$$\begin{aligned} & \sum_{n \in \{1,\cdots,N\}} \tilde{\kappa}_n \mathcal{Y}_n'(\theta) > 0 \\ \text{and} \qquad & \sum_{n \in \{1,\cdots,N\}} \tilde{\kappa}_n \mathcal{Y}_n''(\theta) < \frac{\tilde{c}_p + \tilde{c}_d}{\bar{t}} \lambda'(\theta) \end{aligned}$$

for all $\theta \in [(\underline{\theta}, \bar{\theta}]$, where $\lambda(\cdot)$ is the hazard fuction associated with the distribution $F$. The two last conditions ensure the uniqueness of the equilibrium. They hold, for example, if $(\underline{\theta}, \bar{\theta}) \in [0,1]$; $\mathcal{Y}_1(\theta) = 1 - \sum_{n \in \{2,\cdots,N\}} a_n \theta$; and $\mathcal{Y}_n(\theta) = a_n \theta$ for $n \in \{2, \cdots, N\}$; where $\sum_{n \in \{2,\cdots,N\}} a_n \leq 1$, and $a_n \geq 0$ for all $n \in \{2, \cdots, N\}$.

The payoffs may be conveniently normalized, so that the second-stage payoffs are now given by

$$\begin{aligned} & -\tilde{c}_p + \sum_{n \in \{1,\cdots,N\}} \mathbb{1}\{o = n\} \tilde{\kappa}_n t \quad \text{, for agent } p \\ \text{and} \qquad & -\tilde{c}_d - \sum_{n \in \{1,\cdots,N\}} \mathbb{1}\{o = n\} \tilde{\kappa}_n t \quad \text{, for agent } p, \end{aligned}$$

and the payoffs in the event of an agreement in the first stage are

$$\begin{aligned} & s \quad \text{, for agent } p \\ \text{and} \qquad & -s \quad \text{, for agent } d, \end{aligned}$$

where $\tilde{c}_p = c_p/(\kappa_{p,N} - \kappa_{p,1})$, and $\tilde{c}_d = c_d/(\kappa_{d,1} - \kappa_{d,N})$.

I solve for the subgame perfect equilibria of this game. Agent $d$, after receiving the signal $\theta$, accepts an offer $s$ made by agent $p$ if and only if

$$s \leq \tilde{c}_d + \sum_{n \in \{1,\cdots,N\}} \tilde{\kappa}_n \mathcal{Y}_n(\theta) t.$$

Thus, an offer $s$ is accepted if and only if the signal $\theta$ received by agent $d$ is greater than or equal to the cutoff

$$\theta(s) = T^{-1}\left(\frac{s - \tilde{c}_d}{t}\right), \tag{B.8}$$

where $T(x) \equiv \sum_{n \in \{1,\cdots,N\}} \tilde{\kappa}_n \mathcal{Y}'_n(x)$.

Agent $p$ then chooses $s$ in order to solve

$$\max_s \quad \{1 - F[\theta(s)]\} s + F[\theta(s)] \left\{ -\tilde{c}_p + t \frac{\int_{\underline{\theta}}^{\theta(s)} \sum_{n \in \{1,\cdots,N\}} \tilde{\kappa}_n \mathcal{Y}_n(\theta) f(x) dx}{F[\theta(s)]} \right\}.$$

Under the assumptions above, the optimal offer $s^*$ satisfies $\theta(s^*) \in (\underline{\theta}, \bar{\theta})$. The first-order condition for agent $p$'s problem is then given by

$$\frac{t \sum_{n \in \{1,\cdots,N\}} \tilde{\kappa}_n \mathcal{Y}'_n(\theta)}{\tilde{c}_p + \tilde{c}_d} = \frac{f[\theta(s^*)]}{\{1 - F[\theta(s^*)]\}}. \tag{B.9}$$

The equilibrium is characterized by equations B.8 and B.9. From the assumptions above, it follows that the equilibrium is unique. Holding $\tilde{c}_p$ and $\tilde{c}_d$ constant, I can define the equilibrium offer $s^*$ and cutoff point $\theta(s^*)$ as functions of $t$, and denote such functions by $\tilde{s}(\cdot)$ and $\tilde{\theta}(\cdot)$, respectively.

Given a data-generating process similar to the one in Section 5, the identification of the model's primitives would proceed exactly as described in that section. As before, it is necessary to observe $s$ whenever bargaining is successful. Also, notice that, to achieve identification, it is necessary only to observe $t$ in the event of a single realization $o$ of $O$.

## B.3. **Data appendix.**

B.3.1. *Reducing multiple-counts cases to a single count.* My unit of analysis is a case. Some cases in the data are associated with multiple counts. To reduce such cases to a single count, I employ the following procedure: If sentences are assigned to more than one count of the same case, I consider only the count with the longest sentence.

[68] If no sentence is assigned to any count in a case, I classify the charged offenses for each count according to their severity (using the same classification adopted by the structured sentencing guidelines in North Carolina) and consider only the count with the most severe charged offense.

B.3.2. *Classification of offenses.* Each count in the data is associated with an offense code assigned by the North Carolina Justice System. The offense codes employed in North Carolina are based on the Uniform Offense Classifications, organized by the National Crime Information Center (NCIC). Like in the NCIC code system, the first two digits of the North Carolina codes classify the offenses into relatively broad categories (e.g., robbery, fraud, vehicle theft, etc). Based on these two digits, I determine whether each count in my data qualifies as a robbery, an assault or a sexual assault—the offense categories that I use in my structural analysis.

B.3.3. *Identification of judges.* In the main data, judges are identified only by their initials. In most cases, three initials are used. I match the initials to the full names of the judges as reported annually in the North Carolina Manual. In the period comprised by the sentencing data, only two pairs of judges have the same three initials. Cases decided by these judges were excluded from the data. I also excluded all the cases in which the judge was either identified by fewer than three initials or not identified at all.

B.3.4. *Life sentences.* To convert life sentences into a length of incarceration time, I consider the life expectancy in North Carolina for individuals of age 29.04, which is the average defendant's age in my sample. This life expectancy is 77.14 years (Buescher and Gizlice, 2002). I want to make sure that any life sentence is at least as long as the longest non-life sentence, which, in North Carolina, is forty years. I then define the length of a life sentence as Max {defendant's age - 77.14 ; 40}. Cases resulting in a death sentence are excluded from the analysis.[69] Cases whose sentence

[68] I observe in the data set whether a sentence consists of incarceration time, intermediate punishment (such as probation) or community service. In order to classify the sentences, I use a lexicographic order, so that any time in incarceration is considered a higher sentence than any intermediate punishment. Similarly, any intermediate sentence is considered higher than any type of community service. Notice that I only take intermediate or community punishments into consideration in order to organize the data set by case. As discussed in the main text,the empirical analysis in this paper only accounts for incarceration sentences, and treats cases where only alternative punishments are assigned as cases with no sentence whatsoever.

[69] Cases of non-homicide crimes against the person, which constitute the subsample considered in the structural analysis, never result in a capital sentence.

length is missing in the data are treated as cases in which only an alternative sentence is assigned.

B.4. **Extra empirical results.** This section contains estimation and counterfactual results for covariates groups three to 12. In the interest of space, I do not report these results in the main text.

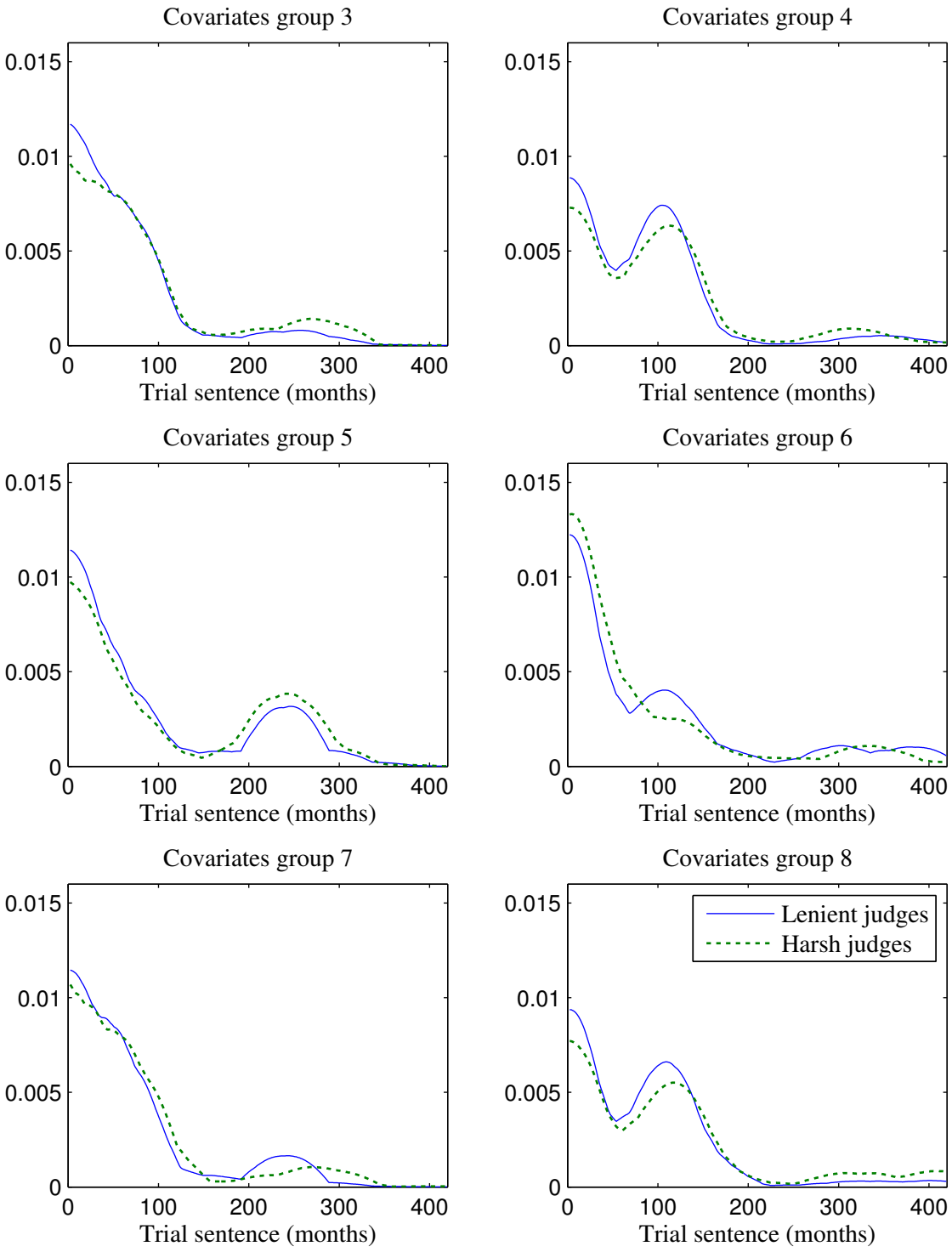
TABLE 14. Parameter Estimates by Covariate Group

| Group | Parameters | | | | |
|---|---|---|---|---|---|
| | $\hat{\alpha}_d$ | $\hat{\beta}_d$ | $\hat{\alpha}_p$ | $\hat{\beta}_p$ | $\hat{\mu}$ |
| 3 | 0.01 | 0.00 | 0.00 | 0.64 | 1.00 |
| | (0.01) | (0.00) | (0.00) | (0.22) | (0.00) |
| 4 | 0.03 | 0.00 | 0.00 | 1.43 | 1.00 |
| | (0.00) | (0.00) | (8.77) | (0.73) | (0.00) |
| 5 | 0.02 | 0.00 | 0.00 | 0.67 | 1.00 |
| | (0.00) | (0.00) | (0.00) | (0.11) | (0.00) |
| 6 | 0.00 | 0.00 | 0.00 | 1.06 | 1.00 |
| | (0.01) | (0.00) | (0.00) | (0.31) | (0.00) |
| 7 | 0.01 | 0.00 | 0.00 | 2.43 | 1.00 |
| | (0.01) | (0.00) | (0.00) | (0.83) | (0.00) |
| 8 | 0.02 | 0.00 | 0.00 | 0.71 | 1.00 |
| | (0.01) | (0.00) | (0.00) | (0.25) | (0.00) |
| 9 | 0.03 | 0.00 | 0.00 | 1.25 | 0.92 |
| | (0.01) | (0.00) | (0.00) | (0.28) | (0.04) |
| 10 | 0.01 | 0.00 | 0.00 | 1.16 | 1.00 |
| | (0.01) | (0.00) | (0.00) | (0.38) | (0.00) |
| 11 | 0.03 | 0.00 | 0.00 | 0.48 | 1.00 |
| | (0.00) | (0.00) | (0.00) | (0.08) | (0.00) |
| 12 | 0.01 | 0.00 | 0.00 | 0.91 | 1.00 |
| | (0.01) | (0.00) | (0.00) | (0.39) | (0.00) |

Bootstrap standard errors in parenthesis.

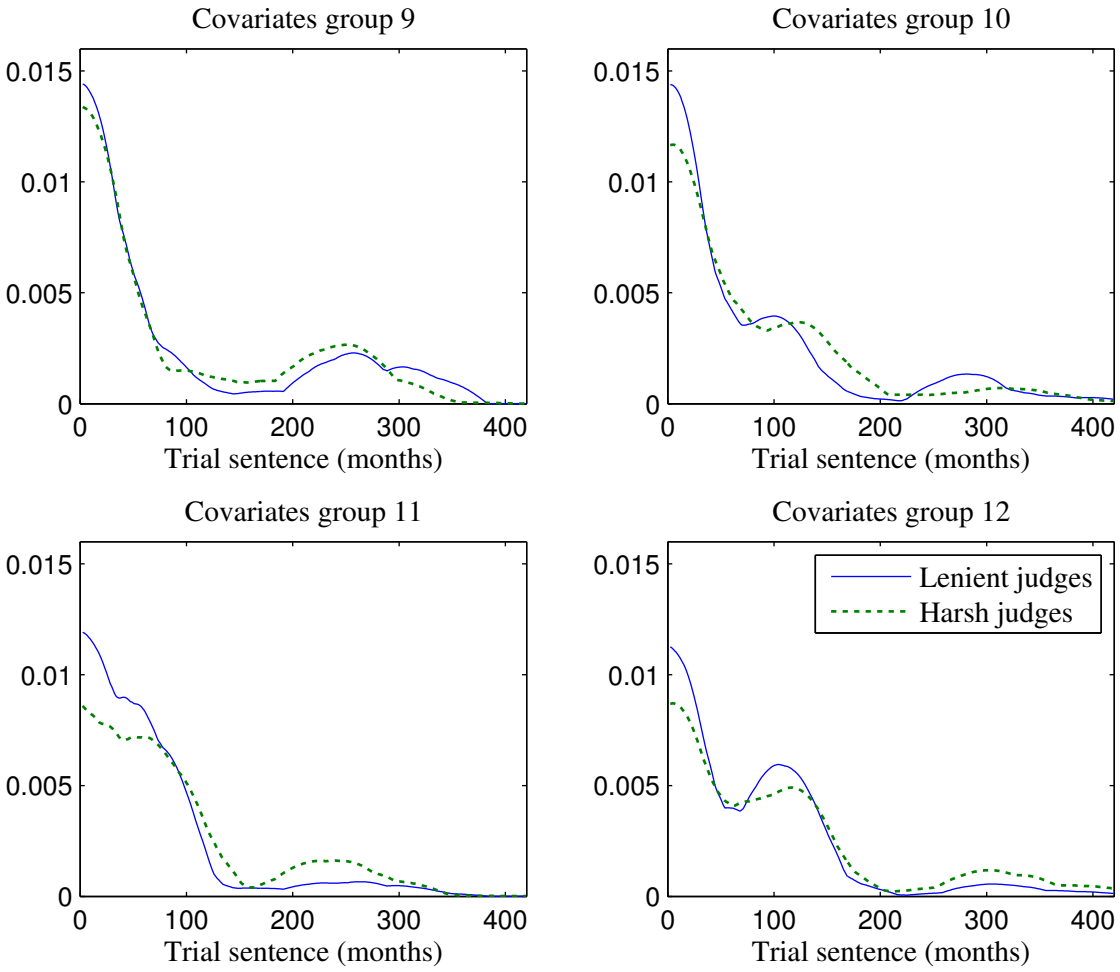
See table 4 for a description of the covariate. groups

FIGURE 4. Conditional trial sentence densities – lenient and harsh judges




See table 4 for a description of the covariate groups.

FIGURE 5. Conditional trial sentence densities – lenient and harsh judges (cont.)




See table 4 for a description of the covariate groups.

FIGURE 6. Settlement offer – covariate groups 3 to 7

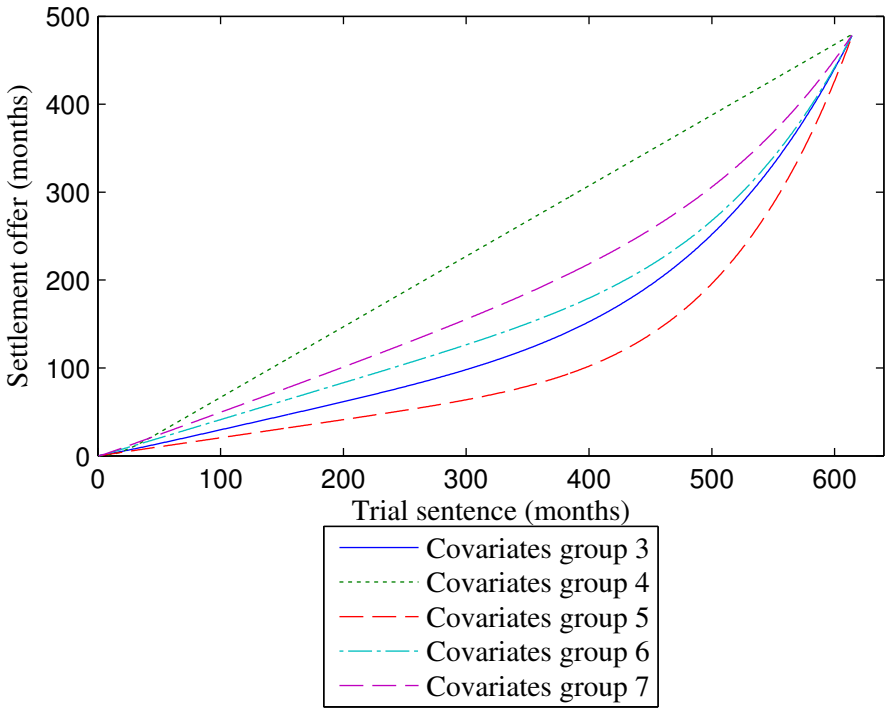



FIGURE 7. Settlement offer – covariate groups 8 to 12

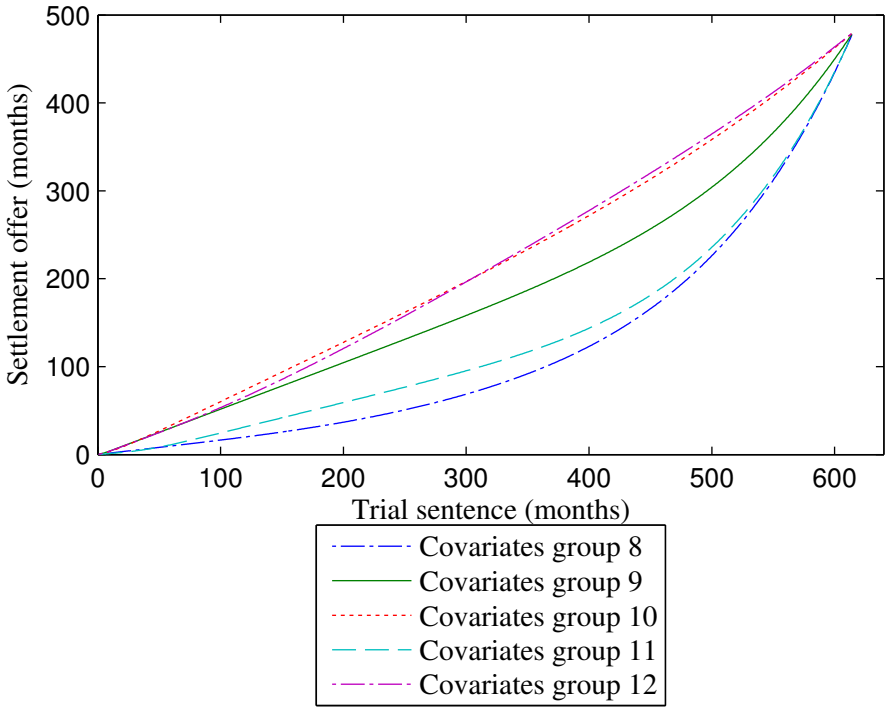
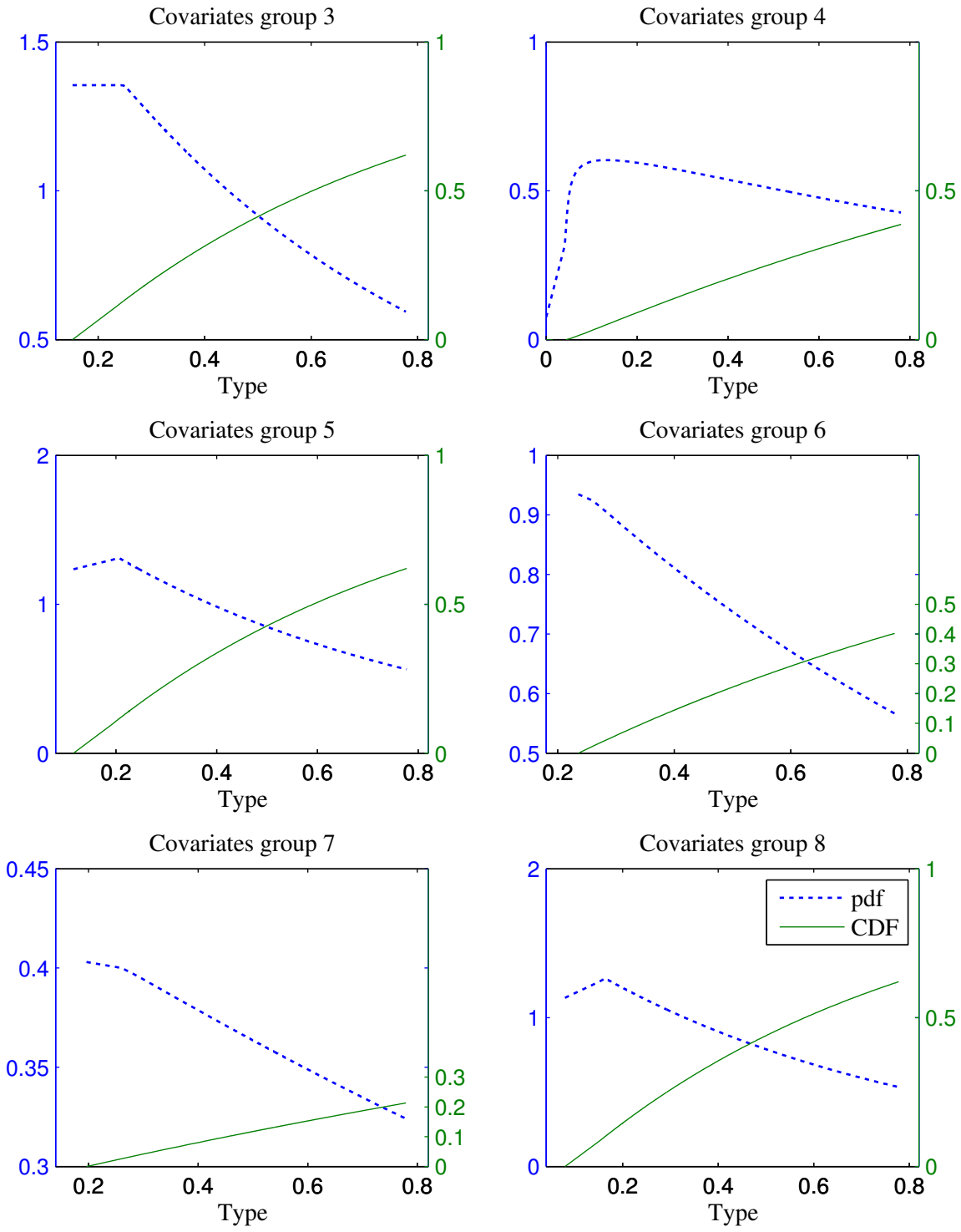
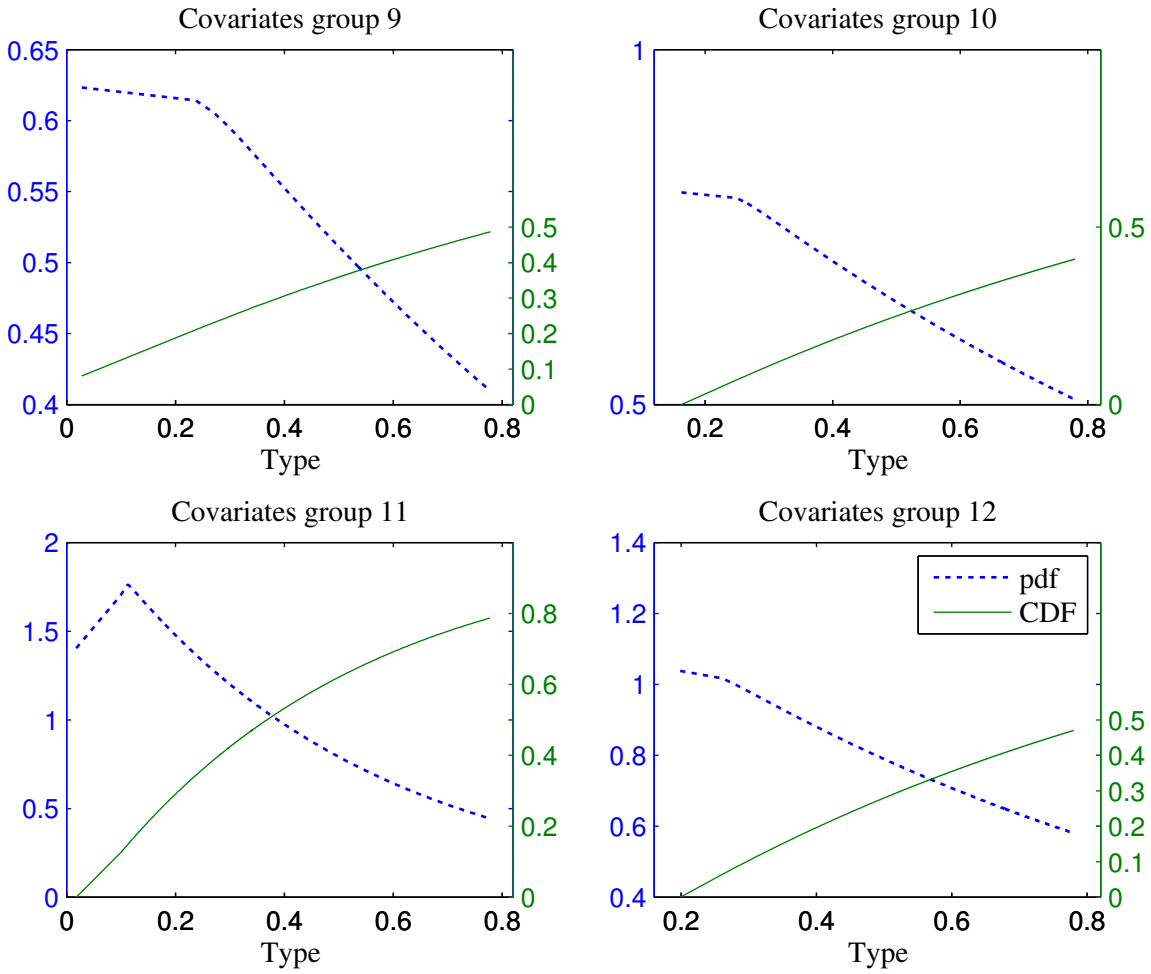


FIGURE 8. Distribution of defendants' types – density and CDF



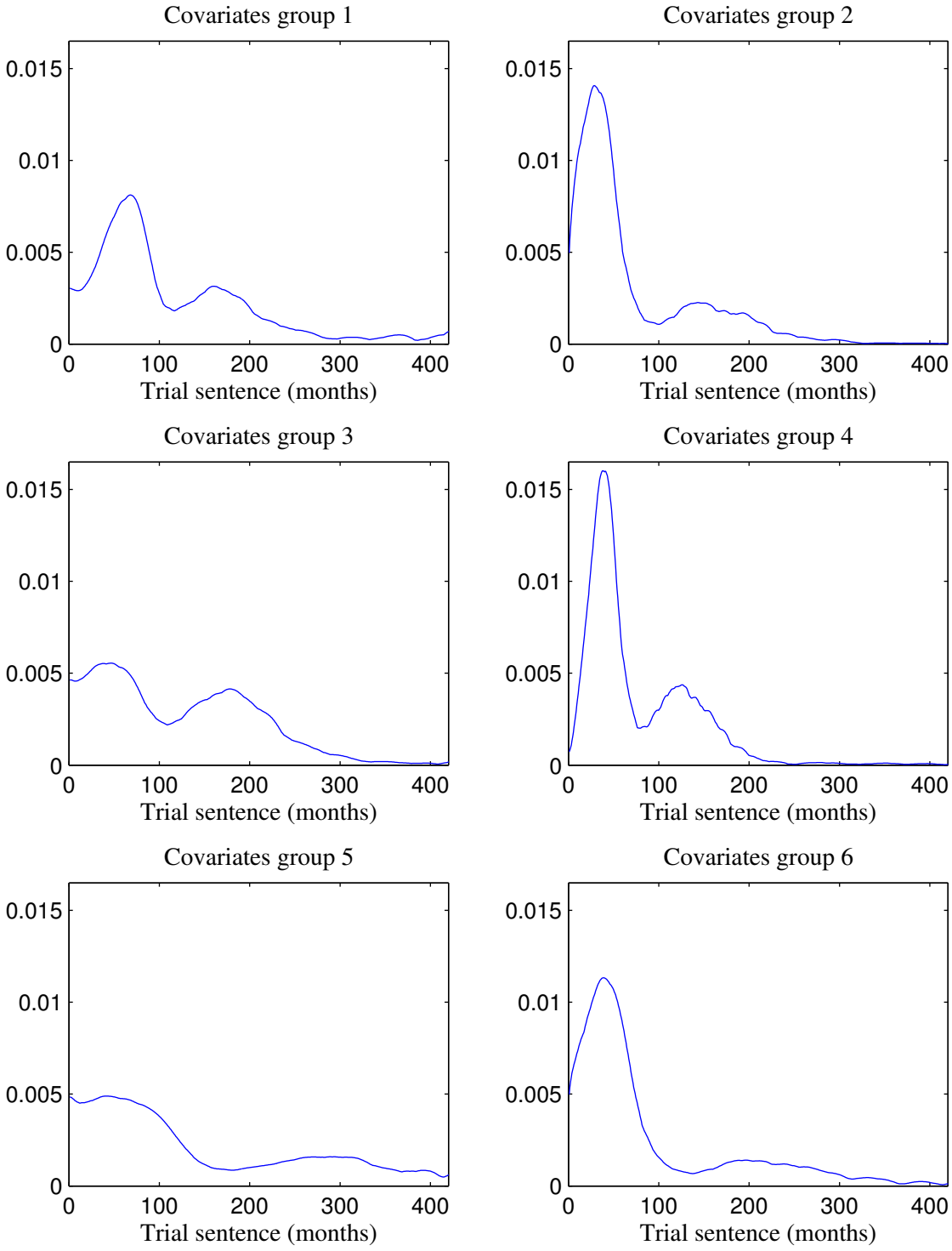

See table 4 for a description of the covariate groups.

FIGURE 9. Distribution of defendants' types – density and CDF (cont.)



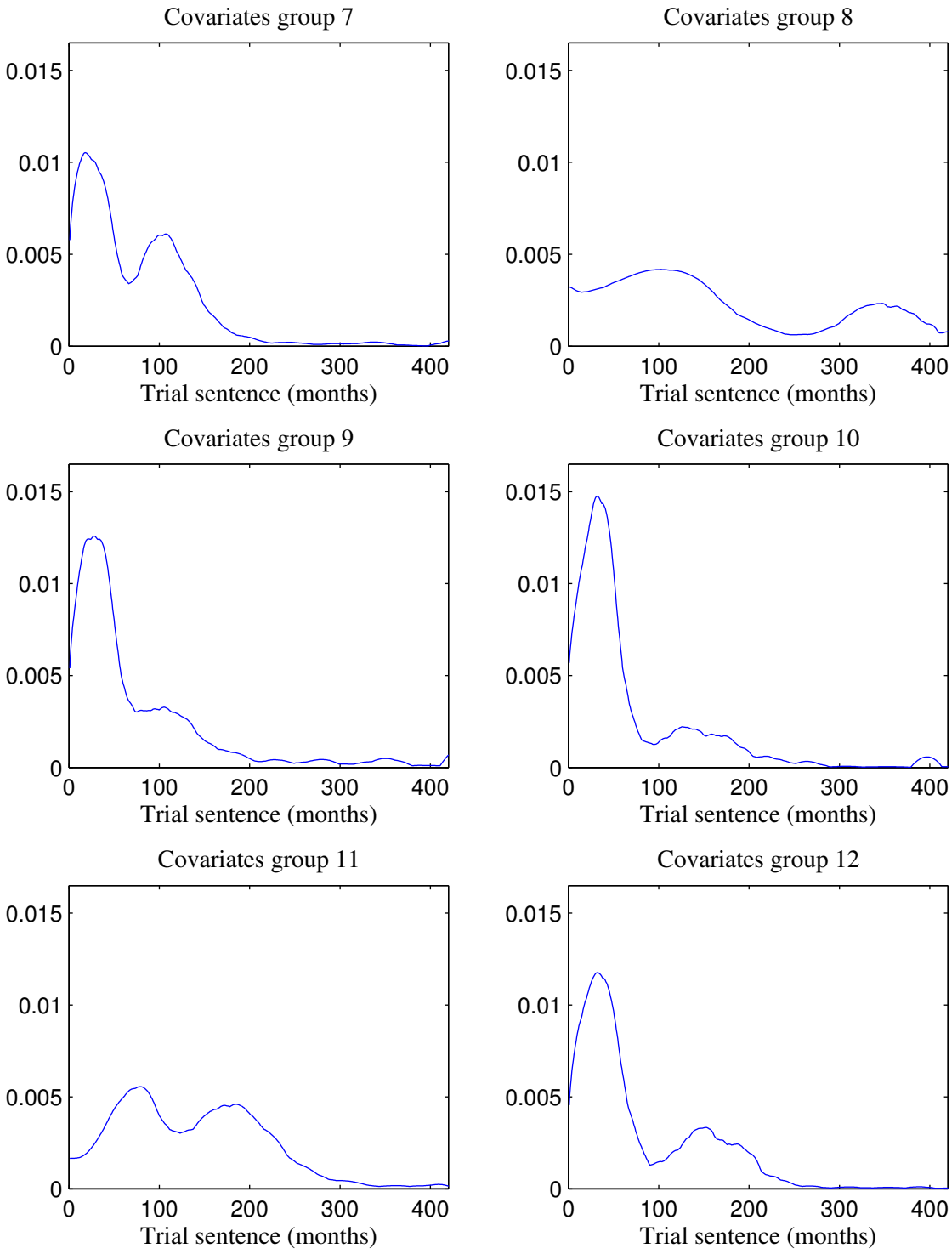

See table 4 for a description of the covariate groups.

FIGURE 10. Full distribution of trial sentences




See table 4 for a description of the covariate groups.

FIGURE 11. Full distribution of trial sentences (cont.)




See table 4 for a description of the covariate groups.

TABLE 15. Fitted values versus data – Distribution of outcomes

| Group | | Conviction | | |
|---|---|---|---|---|
| | | Any ($\Psi \in \{1,2\}$) | Settlement ($\Psi = 1$) | Trial ($\Psi = 2$) |
| 3 | Data | 38.35% | 34.60% | 3.75% |
| | Model | 36.66% | 34.59% | 2.08% |
| 4 | Data | 44.11% | 36.66% | 7.45% |
| | Model | 40.68% | 36.64% | 4.04% |
| 5 | Data | 38.16% | 35.11% | 3.05% |
| | Model | 35.55% | 34.44% | 1.10% |
| 6 | Data | 40.32% | 37.53% | 2.79% |
| | Model | 39.68% | 37.64% | 2.04% |
| 7 | Data | 38.16% | 35.11% | 3.05% |
| | Model | 37.53% | 36.10% | 1.43% |
| 8 | Data | 40.32% | 37.53% | 2.79% |
| | Model | 38.62% | 37.60% | 1.01% |
| 9 | Data | 21.65% | 19.37% | 2.28% |
| | Model | 21.59% | 19.51% | 2.08% |
| 10 | Data | 29.43% | 25.51% | 3.92% |
| | Model | 29.09% | 25.83% | 3.26% |
| 11 | Data | 21.65% | 19.37% | 2.28% |
| | Model | 20.91% | 19.33% | 1.58% |
| 12 | Data | 29.43% | 25.51% | 3.92% |
| | Model | 28.61% | 25.02% | 3.59% |

See table 4 for a description of the covariate groups.

TABLE 16. Fitted values versus data – Sentences

| Group | | Average sentence, conditional on method of resolution† | | |
|---|---|---|---|---|
| | | All ($\Psi \in \{1,2\}$) | Settlement ($\Psi = 1$) | Trial ($\Psi = 2$) |
| 3 | Data | 52.43 | 46.79 | 104.45 |
| | Model | 54.29 | 45.64 | 198.33 |
| 4 | Data | 60.48 | 50.51 | 109.54 |
| | Model | 51.98 | 45.96 | 106.46 |
| 5 | Data | 53.53 | 47.65 | 121.25 |
| | Model | 52.76 | 45.55 | 277.60 |
| 6 | Data | 41.27 | 38.92 | 72.95 |
| | Model | 42.93 | 39.13 | 113.04 |
| 7 | Data | 47.35 | 42.96 | 98.01 |
| | Model | 43.43 | 41.21 | 99.55 |
| 8 | Data | 44.81 | 38.49 | 129.96 |
| | Model | 47.07 | 40.66 | 284.73 |
| 9 | Data | 47.76 | 41.13 | 104.00 |
| | Model | 46.15 | 42.25 | 82.86 |
| 10 | Data | 42.67 | 37.19 | 78.36 |
| | Model | 43.55 | 38.83 | 80.99 |
| 11 | Data | 44.68 | 41.35 | 72.95 |
| | Model | 55.21 | 41.45 | 223.86 |
| 12 | Data | 54.54 | 47.64 | 99.47 |
| | Model | 50.59 | 43.56 | 99.63 |

† : Measured in months
See table 4 for a description of the covariate groups.

TABLE 17. Counterfactual results – Sentencing reform (distribution of outcomes)

| Group | | Conviction | | |
|---|---|---|---|---|
| | | Any | Settlement | Trial |
| 3 | Current | 36.66% | 34.59% | 2.08% |
| | -20% trial sentence length | 37.08% | 35.49% | 1.59% |
| | -10% incarceration cases | 32.86% | 31.02% | 1.84% |
| 4 | Current | 40.68% | 36.64% | 4.04% |
| | -20% trial sentence length | 41.58% | 38.21% | 3.37% |
| | -10% incarceration cases | 36.40% | 32.56% | 3.84% |
| 5 | Current | 35.55% | 34.44% | 1.10% |
| | -20% trial sentence length | 36.08% | 35.43% | 0.65% |
| | -10% incarceration cases | 32.02% | 31.23% | 0.79% |
| 6 | Current | 39.68% | 37.64% | 2.04% |
| | -20% trial sentence length | 40.00% | 37.95% | 2.05% |
| | -10% incarceration cases | 35.76% | 33.70% | 2.06% |
| 7 | Current | 37.53% | 36.10% | 1.43% |
| | -20% trial sentence length | 37.44% | 36.18% | 1.26% |
| | -10% incarceration cases | 33.58% | 32.36% | 1.22% |
| 8 | Current | 38.62% | 37.60% | 1.01% |
| | -20% trial sentence length | 39.46% | 38.81% | 0.65% |
| | -10% incarceration cases | 34.91% | 34.07% | 0.84% |
| 9 | Current | 21.59% | 19.51% | 2.08% |
| | -20% trial sentence length | 21.57% | 19.56% | 2.01% |
| | -10% incarceration cases | 19.24% | 17.36% | 1.88% |
| 10 | Current | 29.09% | 25.83% | 3.26% |
| | -20% trial sentence length | 29.44% | 26.64% | 2.80% |
| | -10% incarceration cases | 26.07% | 23.09% | 2.98% |
| 11 | Current | 20.91% | 19.33% | 1.58% |
| | -20% trial sentence length | 21.52% | 20.55% | 0.97% |
| | -10% incarceration cases | 18.23% | 17.07% | 1.16% |
| 12 | Current | 28.61% | 25.02% | 3.59% |
| | -20% trial sentence length | 28.98% | 25.92% | 3.06% |
| | -10% incarceration cases | 25.69% | 22.53% | 3.16% |

See table 4 for a description of the covariate groups.

TABLE 18. Counterfactual results – Sentencing reform (sentences)

| Group | | Expected sentence† | |
|---|---|---|---|
| | | Given $\Psi \in \{1, 2\}$ | Unconditional |
| 3 | Current | 54.29 | 19.91 |
| | -20% trial sentence length | 38.83 | 14.40 |
| | -10% incarceration cases | 59.38 | 19.51 |
| 4 | Current | 51.98 | 21.14 |
| | -20% trial sentence length | 38.79 | 16.13 |
| | -10% incarceration cases | 57.77 | 21.03 |
| 5 | Current | 52.76 | 18.75 |
| | -20% trial sentence length | 34.47 | 12.44 |
| | -10% incarceration cases | 56.46 | 18.08 |
| 6 | Current | 42.93 | 17.03 |
| | -20% trial sentence length | 33.85 | 13.54 |
| | -10% incarceration cases | 47.69 | 17.05 |
| 7 | Current | 43.43 | 16.30 |
| | -20% trial sentence length | 33.71 | 12.62 |
| | -10% incarceration cases | 47.80 | 16.05 |
| 8 | Current | 47.07 | 18.18 |
| | -20% trial sentence length | 31.42 | 12.40 |
| | -10% incarceration cases | 51.09 | 17.84 |
| 9 | Current | 46.15 | 9.96 |
| | -20% trial sentence length | 36.41 | 7.85 |
| | -10% incarceration cases | 51.18 | 9.85 |
| 10 | Current | 43.55 | 12.67 |
| | -20% trial sentence length | 33.45 | 9.85 |
| | -10% incarceration cases | 48.06 | 12.53 |
| 11 | Current | 55.21 | 11.54 |
| | -20% trial sentence length | 36.73 | 7.90 |
| | -10% incarceration cases | 58.95 | 10.75 |
| 12 | Current | 50.59 | 14.47 |
| | -20% trial sentence length | 38.57 | 11.18 |
| | -10% incarceration cases | 55.52 | 14.26 |

† : Measured in months
See table 4 for a description of the covariate groups.

TABLE 19. Counterfactual results – No asymmetric information

| Group | | Outcome | | |
|---|---|---|---|---|
| | | Probability of conviction | Expected sentence† (given $\Psi \in \{1, 2\}$) | Expected sentence† (unconditional) |
| 3 | Current | 36.66% | 54.29 | 19.91 |
| | No asym, info. | 43.61% | [78.07 , 90.09] | [34.05 , 39.29] |
| 4 | Current | 40.68% | 51.98 | 21.14 |
| | No asym. info. | 50.26% | [49.70 , 60.40] | [24.98 , 30.36] |
| 5 | Current | 35.55% | 52.76 | 18.75 |
| | No asym. info. | 40.50% | [[99.78 , 115.60] | [40.41 , 46.82] |
| 6 | Current | 39.68% | 42.93 | 17.03 |
| | No asym. info. | 44.36% | [62.82 , 75.40] | [27.87 , 33.45] |
| 7 | Current | 37.53% | 43.43 | 16.30 |
| | No asym. info. | 40.50% | [58.37 , 72.62] | [23.64 , 29.41] |
| 8 | Current | 38.62% | 47.07 | 18.18 |
| | No asym. info. | 44.36% | [96.11 , 111.54] | [42.63 , 49.48] |
| 9 | Current | 21.59% | 46.15 | 9.96 |
| | No asym. info. | 30.19% | [45.86 , 55.44] | [13.84 , 16.74] |
| 10 | Current | 29.09% | 43.55 | 12.67 |
| | No asym. info. | 35.48% | [44.26 , 53.28] | [15.70 , 18.90] |
| 11 | Current | 20.91% | 55.21 | 11.54 |
| | No asym. info. | 30.19% | [64.39 , 71.70] | [19.44 , 21.65] |
| 12 | Current | 28.61% | 50.59 | 14.47 |
| | No asym. info. | 35.48% | [51.40 , 61.19] | [18.24 , 21.71] |

† : Measured in months
See table 4 for a description of the covariate groups.

TABLE 20. Counterfactual results – No plea bargaining

| Group | | Outcome |
|---|---|---|
| | | Probability of conviction |
| 3 | Current | 36.66% |
| | No plea bargaining | [24.03% , 27.81%] |
| 4 | Current | 40.68% |
| | No plea bargaining | [31.53% , 38.32%] |
| 5 | Current | 35.55% |
| | No plea bargaining | [21.62% , 25.25%] |
| 6 | Current | 39.68% |
| | No plea bargaining | [29.35% , 35.19%] |
| 7 | Current | 37.53% |
| | No plea bargaining | [28.68% , 35.91%] |
| 8 | Current | 38.62% |
| | No plea bargaining | [23.44% , 27.29%] |
| 9 | Current | 21.59% |
| | No plea bargaining | [16.22% , 19.91%] |
| 10 | Current | 29.09% |
| | No plea bargaining | [22.39% , 27.71%] |
| 11 | Current | 20.91% |
| | No plea bargaining | [12.04% , 13.61%] |
| 12 | Current | 28.61% |
| | No plea bargaining | [21.84% , 26.21%] |

See table 4 for a description of the covariate groups.