CRIMINAL SPECIALIZATION IN THE CRIMINAL JUSTICE CONTEXT

by

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Abstract

The dissertation consists of two studies. Study 1 examines how criminal specialization predicts the sentencing outcomes. Theories of sentencing have pointed out the association between the sentence and the assessment of the defendant's risk and culpability, and one of the most important indicators of an individual's risk is his or her criminal records. Most quantitative studies of sentencing today take criminal records into consideration by controlling for the number of prior criminal justice contacts, and overlook the nature of the prior crimes. The concept criminal specialization refers to the tendency for an individual to repeat the same or a set of related crimes. In the present study, I use four different measures, which model different dimensions of criminal specialization. I model criminal specialization from the records of over 110,000 defendants convicted in New York State between 2010 and 2012, and add the measures of criminal specialization to models explaining incarceration and incarceration length. Study 1 finds that even though the four different measures capture different aspects of specialization, all the measures find that the analytic sample contained a mix of versatile defendants and specialized defendants. However, the four measures perform very differently in predicting the sentence.

Study 2 estimates the magnitude of the plea discount in New York State during three different observation periods. Piehl and Bushway (2007), building on the methodological framework of Smith (1986), introduced an approach to estimate the magnitude of sentence difference due to charge bargaining. However, what is absent in this framework is the estimate of overcharging. Prosecutors may, intentionally or unintentionally, file initial charges that are unlikely to secure a conviction at trial. As a result, the counterfactual sentence estimated from

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the initial charge may not be a credible threat when the defendant decides between going to trial or pleading guilty. The present study takes overcharging into consideration, and compare the estimates of the plea discount when overcharging is taken into account and when it is not. I obtain the benchmark of the estimates from the prediction of the model “bargaining in the shadow of trial.” The study finds that taking overcharging into account brings the estimates of the plea discount closer to the prediction of the “shadow of trial” model.

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"Don't say that you have chosen to study law. Without adequate information, it's hard to tell whether you made this 'choice,' or you listened to other people who made the choice for you, or you simply followed 'the choice of the time.'"

—Zhu Suli, Dean (2001-2010) and Professor, Peking University Law School

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Chapter 1

Introduction

Laws, politicians, and decision makers in the criminal justice system categorize individuals who commit crimes into types, and make legislative and judicial decisions around these "offender types." For example, Section 70.10 of the New York State Penal Law is entitled "Sentence of Imprisonment for Persistent Felony Offender." In 2013, the former U.S. Attorney General Eric Holder announced actions to reduce the sentences for "certain non-violent drug offenders" (Merica & Perez, 2013). These "offender types" are not merely labels, but can also lead to substantial consequences. A typical example is the mandatory registration requirement for individuals convicted of sex crimes (Adams, 2002; see also *United States v. Kebodeaux*). A more frequent consequence associated with these "offender types" is a sentencing enhancement, as most states prescribe an enhanced sentence for a conviction of a repeat, violent, or "dangerous" crime (Ditton & Wilson, 1999; Roberts, 1997; National Research Council, 2014). The association between the "offender types" and the enhanced sentence builds on the concern of criminal specialization—the concern that defendants who commit certain types of crimes will tend to repeat these crimes in the future. For example, Section 57.581 of Oklahoma Statutes explicitly points out that "[t]he Legislature finds that sex offenders who commit other predatory acts against children and persons who prey on others as a result of mental illness pose a high risk of re-offending after release from custody."

The focus of sentencing research has long been the estimation and explanation of the extralegal disparities, particularly the racial disparity, in the sentence (Baumer, 2013; Spohn,

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2000; Ulmer, 2012). In the estimation of the racial disparity, most published studies controlled for the numbers of criminal records of the defendants, but few further modeled more than the numbers. Criminal records are meaningful to sentencing. The dominant theories of sentencing have contended that sentencing is essentially a process that assesses the defendant's risk (Albonetti, 1991) and culpability (Steffensmeier et al., 1998; Wasik & von Hirsch, 1995), and criminological research have established the connection between criminal records and future crimes (e.g., Champion, 1994; Kurlychek et al, 2006; Nagin & Paternoster, 1991). Study 1 of the dissertation models one aspect of criminal records, criminal specialization, and investigates how the inclusion of criminal specialization adds to our understanding of sentencing. I first estimate a series of measures of criminal specialization found in criminal careers research, then add these measures to sentencing models and investigate whether criminal specialization explains the variation in the sentence received by the defendants.

A seemingly natural next step from Study 1 is to investigate how criminal specialization predicts the sentence through the plea bargaining process, especially because recent studies of sentencing have highlighted the importance of pre-conviction decisions (such as charging and plea bargaining; see Kutateladze et al., 2014; Rehavi & Starr, 2014; Shermer & Johnson, 2010). However, the foremost issue, in order to study plea bargaining, is the lack of measures of the plea discount itself. Only a few studies attempted to estimate the plea discount, and these studies assumed that the entirety of the discount could be attributed to the plea. However, one of the neglected sources of the discount is overcharging, an issue that has led to a heated discussion among legal scholars (e.g., Alschuler, 1968; Caldwell, 2001; Graham, 2014) but has never been adequately modeled (see Graham, 2014; R. Wright & Engen, 2006; 2007). Therefore, instead of directly explaining the plea discount with criminal specialization, Study 2 of the dissertation

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proposes a new framework to study the plea discount, and demonstrates the use of this framework at the aggregate level. It builds on the theory of bargaining in the "shadow of trial," and adopts the analytic approach of Smith (1986) and Piehl and Bushway (2007). I investigate whether adding overcharging to the framework of plea bargaining leads to better modeling of the plea discount, by modeling the discount with and without the consideration for overcharging.

I present the two studies of the dissertation in Chapters 2 and 3, both taking the form of a research paper. In Chapter 4, I discuss some more general issues and takeaways on and above the substantive findings of the two studies, and lay out a plan for future works.

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Chapter 2

Does Criminal Specialization Predict the Sentence?

Abstract

Theories of sentencing have pointed out the association between the sentence and the assessment of the defendant's risk and culpability, and one of the most important indicators of the risk and culpability is the defendant's criminal records. Most quantitative studies of sentencing take criminal records into consideration by controlling for the number of prior criminal justice contacts, and overlook the nature of the priors. The nature of the prior crimes may be correlated with the sentence. For example, laws sometimes prescribe an enhanced sentence for certain types of criminal records. Even when no specific sentence enhancement is prescribed, the types of crimes in a defendant's criminal records may help shaping the image of defendant types based on the pattern of criminal specialization.

The concept criminal specialization, which refers to the tendency for an individual to repeat the same or a set of related crimes, emerges from the research of criminal careers. Researchers have applied a variety of statistical tools to model criminal specialization. These different measures translate into different ways to categorize the defendants into types. In the present study, I use four different measures, the identical preceding conviction (IPC), the specialization index, latent class analysis (LCA), and the number of identical records (NIR). These different measures model the defendant types at different levels, from a general, unidimensional scale of criminal specialization to narrow types of defendants specialized in

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specific crimes. I model criminal specialization from the criminal records of over 110,000 defendants convicted in New York State between 2010 and 2012, and then add the measures of criminal specialization to the models explaining incarceration and the incarceration length.

The present study finds that all the measures suggest that the analytic sample contains a mix of versatile defendants and specialized defendants. However, these measures have a low level of correlation with each other. Moreover, when these measures are added to the models explaining incarceration and the incarceration length, they reveal very different correlations with the sentence. The inclusion these measures does not seem to change the correlation between the sentence and the extralegal variables. The implications of the findings are discussed.

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Criminal records pervade Americans' lives today. As of December 31st, 2014, over 105 million criminal records were stored in state repositories (Bureau of Justice Statistics, 2015). Recent studies have estimated that nearly a third of adults in the United States had been arrested by the age of 23 (Brame et al., 2012). The sheer numbers have inspired a variety of research projects on the impact of criminal records on many aspects of life, such as employment (e.g., Bushway, Stoll, & Weiman, 2007; Pager, 2003), political rights (e.g., Uggen & Manza, 2002), and future criminal activities (e.g., Kurlychek et al., 2006). Criminal records are especially prevalent among people involved in the criminal justice system. Among felony defendants in the 75 largest U.S. counties, 60% had at least one prior conviction and 30% had five or more (Reaves, 2013). However, compared with the implication of criminal records in daily life, relatively less attention has been paid to the full implication of criminal records in the criminal justice context. Researchers of sentencing, one of the most well-studied components of the criminal justice process, have long recognized criminal records as one of the most important predictors of the sentence (Baumer, 2013; Roberts, 1997; Spohn, 2000, 2009; Ulmer, 2012). However, most quantitative studies only considered the number of prior criminal justice contacts such as convictions and arrests, and paid little attention to the nature of the priors (Baumer, 2013; Ulmer, 2012).

In the context of sentencing, a defendant's criminal records (often takes the form of and known as the "rap sheet") is the complete list of that defendant's criminal activities known to and processed through the criminal justice system. In addition to the number of prior criminal justice contacts, it also contains a rich set of information about the criminal career of the individual, such as the type, severity, and legal consequence (i.e., the disposition and the sentence) of each arrest. A rap sheet documents the defendant's criminal career known to the criminal justice

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system, or the "criminal justice career" (Bushway & Tahamont, 2016; Tahamont et al., 2015). Generations of researchers have endeavored in describing and making sense of the criminal careers (for two seminal reviews, see Blumstein et al., 1986; Piquero et al., 2003). The present study builds on the premise that sentencing research may be improved by integrating the insights of criminal careers research.

The present study contributes to the literature as, to my knowledge, the first study that directly adopts the insights and methods of criminal careers research to answer research questions on sentencing. Out of the many aspects of the criminal justice careers, I analyze criminal specialization reflected in the defendants' criminal records, and investigate how that adds to our understanding of the relationship between criminal records and sentencing. As to be discussed in detail below, criminal specialization not only speaks directly to the notions of "offender types," but also underlies some state and federal legislation. I use four different measures of criminal specialization, found in or inspired by the existing studies of criminal careers, with each capturing a different dimension of specialization. To model the defendants' criminal justice careers, this study is made possible by a unique dataset obtained from New York State, which contains much richer criminal record information than do most datasets of which I am aware. It allows me to track each defendant's complete criminal records back to 1990. Each of the records contains the arrest date, type, severity, as well as the disposition, which is essentially what the prosecutors and judges see on the rap sheet.

The Use of Criminal Records in Sentencing

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The association between a defendant's criminal records and the sentence is not self-evident, even if it may seem so. A strict retributivist would consider the current crime as the only legitimate determinant of the sentence, and would reject any consideration of the behaviors earlier than the current crime (Fletcher, 1978). Nevertheless, the majority of legal scholars consider criminal records as a legitimate factor in determining the sentence, and have sought justification of the use of criminal records from a variety of grounds (for an excellent review on the use of criminal records in sentencing, see Roberts, 1997). Justifications from the deterrence and the incapacitation perspectives both build on the criminological finding that past crimes highly correlate with future crimes (Champion, 1994; Nagin & Paternoster, 1991). Therefore, only a harsher sentence would deter the individuals who have criminal records, and prevent them from committing more crimes (van den Haag, 1978; see also United States Sentencing Commission, 2015). Theorists of the retribution perspective (also known as the perspective of "just deserts" or "deserts"), on the other hand, tend to view the sentence difference between first-time defendants and recidivists as a discount granted to the former, rather than a premium imposed on the latter (see Roberts, 1997, Figure 1). As Wasik and von Hirsch (1995, p.140; see Roberts, 1997) contended, "[w]hat we do, in granting the discount is to… give the offender a so-called 'second chance.' With repetitions, however, the discount should begin to diminish and eventually disappear" (see also Frase, 1997; Morris, 1982; von Hirsch, 1982; Wasik & von Hirsch, 1995).

These thoughts were reflected in the sentencing reform over the past few decades (Spohn 2000; 2009). The laws not only prescribe enhanced sentences based on the number of prior criminal justice contacts (convictions and incarcerations in most circumstances), but sometimes also consider the nature of the prior crimes, as well as the relationship between the priors and the

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current crime. Many states and the federal system have adopted sentencing guidelines, in which a defendant's criminal records, typically calculated into a criminal history score, directly determines the grid where the recommended sentence is located (for an example, see United States Sentencing Commission, 2015; for a discussion on the factors considered in the sentencing guidelines, see Breyer, 1988; Frase, 1997; Morris, 1977; 1982; Savelsberg, 1992; Tonry, 1996). For example, the federal sentencing guidelines assign special criminal history scores for "crimes of violence" (United States Sentencing Commission, 2015). Another example is the sentencing guidelines of Washington State, which assign additional criminal history points if the defendant is convicted of violent crimes, burglary, or felony traffic crimes, and has convictions of the same type of crime in the past (Revised Code of Washington, 9.94A.525; see also Caseload Forecast Council, 2015). Criminal statutes in non-guidelines states also prescribe enhanced sentence for defendants who have criminal records (Roberts, 1997). For example, the New York State Penal Law prescribes enhanced sentence for "second violent felony offenders" and "persistent violent felony offenders" in Article 70. The statutory severity of driving while intoxicated (DWI) also depends on the number of prior convictions of DWI (New York State Vehicle and Traffic Law, 31.1193). It is also noteworthy that criminal records do not play an equally important role on all the defendants. Rather, criminal records tend to matter more for the defendants convicted of less serious crimes, because a serious crime itself would largely warrant a harsh sentence regardless of the criminal records. For example, the federal sentencing guidelines prescribe a life sentence, regardless of the criminal history score, for the crimes at offense level 43 (such as first-degree murder). However, the recommended sentence for the crimes at offense level 4 (such as trespassing) is largely determined by the criminal history score (see United States Sentencing Commission, 2015).

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Of course, one cannot simply infer from the statutes the way the criminal justice system actually works.[1] In fact, the main goal of quantitative sentencing research is to use empirical data to investigate the operation of the criminal justice system in reality. Many early studies suffered from the lack of adequate control of criminal records. This led to questions to the validity of the findings, as well as calls for improved data collection and research design (Hagan & Bumiller, 1983; see also Blumstein et al., 1983).[2] Electronic databases of criminal records and criminal case disposition are now well-established and available to researchers (see Henry & Hinton, 2008; Jacobs & Crepet, 2008). Perhaps as a result, quantitative sentencing research papers today typically include criminal records as a part of the regression models explaining the sentence (Baumer, 2013; Ulmer, 2012; cf. Spohn, 2000). Most studies focus on the sentencing disparity associated with extralegal variables (such as the race and sex of the defendant) and consider criminal records as a control variable (or a "legitimized influence on criminal sentencing," Hagan & Bumiller, 1983, p. 12; see also Spohn, 2000; Ulmer, 2012), which Baumer (2013) called the "modal approach" of sentencing research. The general consensus of this approach is that the defendant's prior criminal records, alongside with the seriousness of the current crime, is a "primary determinant" of the sentence (Spohn, 2000; p. 481). Empirical studies also found that criminal records had a larger impact on the sentence when the current crime is less serious (e.g., Bushway & Piehl, 2001; Tahamont et al., 2015).

[1] For example, the New York State Penal Law impose a sentence enhancement on "second felony offenders" and "persistent felony offenders." However, in the spring of 2013, I learned from a conversation with a former prosecutor in an upstate county that these articles were rarely applied in his office. Because of this, I do not create specific variables to model these offender statuses (i.e., "second felony offenders" and "persistent felony offenders") in the empirical models presented later in the paper.
[2] According to Spohn (2000), some published studies in the late 1980s or even the 1990s still lacked control of the criminal history because of practical data constraints.

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Researchers have realized the limitations of the "modal" approach of sentencing research (for a review, see Baumer, 2013). Yet alongside with his critique, Baumer (2013, p. 234-235) also contended that "[t]his does not mean that the model [sic] approach should be abandoned; quite to the contrary … it is vital that this approach be supplemented significantly with alternative approaches." The inclusion of criminal records gradually became the standard practice of quantitative sentencing research (now called as the "modal" approach) in the 1980s and the 1990s (Spohn, 2000). A reasonable way to move forward is to include more comprehensive measures of criminal records. A crucial document that prosecutors and judges review in case processing is the defendant's rap sheet, which contains the key information about the defendant's every known criminal justice contact—dates, charges, the disposition, and the sentences (Jacobs & Crepet, 2008). This information depicts the defendant's "criminal justice career"—the set of crimes known to and processed through the criminal justice system (Bushway & Tahamont, 2016; Tahamont et al., 2015). As discussed in detail below, the modeling of criminal justice careers in sentencing research is important for two reasons.

The first reason is the defendant's criminal justice career is relevant to the theories of sentencing. Utilitarian perspectives, such as the perspective of bounded rationality as well as a component of the focal concerns perspective (the protection of the community), have pointed out that a major element in the sentencing consideration is the defendant's risk of recidivism (Albonetti, 1991; D. Gottfredson, 1998; Hogarth, 1971; Spohn, 2009; Steffensmeier et al., 1998). Retributive perspectives, such as the notion of "blameworthiness" from the focal concerns perspective, emphasize the defendant's degree of culpability (Steffensmeier et al., 1998; Wasik & von Hirsch, 1995). The criminal careers perspective focuses on four elements of the trajectory of an individual's criminal behaviors: onset, frequency, severity, and desistance (Blumstein et

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al., 1986; Piquero et al., 2003), all of which directly speak to both the risk and culpability of that individual. It might not be sufficient to assess the risk and culpability of the defendant by solely looking at the number of prior criminal justice contacts. Bushway and Piehl (2007) gave a good example to support the argument. They contended that if a young defendant had the same number of prior criminal records as an older defendant (assuming everything else being equal), it would be justifiable to punish the young defendant harsher, because the young defendant had a higher frequency of crimes and therefore a higher degree of risk and culpability. The similar logic is also applicable to other aspects of the criminal justice careers, such as the severity and type of the prior crimes, because these properties of the criminal justice careers also contain information about the risk and culpability on and above the number of priors.

The second reason is the manner criminal records are coded may affect the relationship between the sentence and the extralegal variables. As stated above, the focus of most sentencing research is to estimate and explain the extralegal disparities in the sentence, especially the racial disparity (Baumer, 2013; Spohn, 2000; Ulmer, 2012). Spohn (2000, p. 481) noted that although the severity of the current crime and criminal records were the "primary determinants" of the sentence, "race/ethnicity and other legally irrelevant offender characteristics also play a role" (see also Baumer, 2013; Mitchell, 2005; Ulmer, 2012). However, in his review of research on the racial disparity in sentencing, Mitchell (2005) found that the observed racial disparity was related to the way criminal records were controlled for. Specifically, "contrasts (i.e., comparisons of the sentence by race, explanation added) that employed less precise measures of criminal history and offense seriousness produced larger estimates of unwarranted racial disparity than contrasts that used more precise measurements" (Mitchell, 2005, p. 457). If the criminal justice careers contain information associated with the risk and culpability, and if such information correlates with the

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extralegal variables, then the observed relationships between these variables and the sentence might change after the criminal justice careers are more precisely modeled.

The issues related to the measurement of criminal records and the criminal careers are especially problematic in the studies using data from non-guidelines jurisdictions. Many recent studies using data from guidelines jurisdictions used the criminal history score as the only control for the criminal records (e.g., Rehavi & Starr, 2014; Shermer & Johnson, 2010; Ulmer & Bradley, 2006). Sentencing guidelines often, although only to a certain extent, take the nature of the prior crimes into account in addition to the numbers. More importantly, sentencing guidelines might limit judicial discretion by setting a narrow range of sentences once the severity and criminal history scores are determined (see Reitz, 1998; Savelsberg, 1992). It is therefore more reasonable to assume that in guidelines jurisdictions, there is less consideration of criminal records on and above the criminal history score. This assumption, however, is much less likely the case in non-guidelines jurisdictions such as New York, given the amount of discretion allowed by the statutes and the less frequent application of the "persistent felony offender" enhancements (see Footnote 1).

What Do We Know about Criminal Specialization?

In his assessment of the use of criminal records in state sentencing guidelines, Roberts (1997, p. 332) argued that the connection between the type of prior crimes and the sentence enhancement—such as the Washington State example—built on the assumption of criminal specialization, as the guidelines assumed that "all things being equal, an offender with two prior burglary convictions is more likely to commit further burglaries than an offender with two prior

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felonies of a different nature." Evidence from qualitative sentencing research also hints at the consideration of the prior crime types in sentencing, as a judge in Miami said,

> I consider the crime itself and whether this person has the potential to be rehabilitated. I look at the types of crimes the offender has been involved in the past (violent crimes, burglaries of occupied dwellings, versus relatively nonserious crimes; contents in parenthesis original), the offender's situation at home, whether there is potential for more violent crimes (Spohn, 2009, p. 89).

So do individuals specialize when they engage in criminal behaviors? Sometimes criminological theories make predictions of criminal specialization. Theories that attempt to explain crimes using a single variable (such as "the lack of self-control") tend to predict that individuals who engage in criminal behaviors are versatile (e.g., M. Gottfredson & Hirschi, 1990), whereas theories emphasizing the difference among different types of offenders (e.g., Cloward & Ohlin, 1960) or the learning process (e.g., Spelman, 1994) are more likely to predict the existence of individuals who commit only certain types of crimes (i.e., the specialists). That being said, whether individuals specialize in criminal activities is largely an empirical question (Sullivan et al., 2009). Findings over the degree of criminal specialization seems to be "mixed" (Roberts, 1997, p. 332), which is at least partly attributable to the reality that "studies confuse conceptualizations of specialization, making it difficult to summarize from past studies" (Nieuwbeerta et al., 2011, p. 4; see also Osgood & Schreck, 2007; Sullivan et al., 2009). While the concept of criminal specialization—the tendency for an individual to commit a type of crime or similar types of crimes (Sullivan, 2009)—seems clear, in the literature there have been multiple interpretations, and therefore multiple measures, of the concept.

One perspective was to define criminal specialization as "the tendency to repeat the same offense type *on successive crimes*" (Piquero et al., 2003, p. 453, emphasis added). This

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perspective started from the use of transition matrices, which investigated the consistency between the "crime k" and the "crime $k + 1$" (Bursik, 1980; Wolfgang et al., 1972). Farrington et al. (1988) took the frequency of crimes in the sample into consideration, and introduced the forward specialization coefficient (FSC), which continued to be a popular method into the next decades (see Armstrong, 2008). Brame et al. (2004) further developed this perspective with the use of the latent class Poisson regression model, which allowed the probability to repeat the last crime to vary among different groups of individuals. Yet overall, these studies found little evidence supporting the tendency to repeat the immediately preceding crime. For example, Farrington et al. found on average, the tendency for the individuals in their sample to repeat the immediate preceding crime was "roughly one-tenth of the distance between complete versatility and perfect specialization" (p. 475). Brame et al. found the probability of repetition stayed at about 0.05, regardless of the individual's frequency of criminal behaviors. These findings led Piquero et al. (2003, p. 455, citations in the original text omitted) to conclude that up to the date of their review, "although there is some evidence of specialization, most criminal careers are marked by versatile offending patterns" (see also Roberts, 1997 for a similar conclusion).

A different perspective focused on the overall pattern of the individual criminal careers, and analyzed the overall variation of crimes without a particular emphasis on the sequence. In doing so, this approach defined criminal specialization as "the lack of variety, such as an offense record with a preponderance of violent crimes and a relative absence of other crimes" (Osgood & Schreck, 2007, p. 277). Studies following this approach adopted a variety of statistical techniques, such as the diversity index (e.g., Bouffard et al., 2008; K. Wright et al., 2008; Nieuwbeerta et al., 2011), latent class analysis (LCA, e.g., Francis et al., 2004; McGloin et al., 2009), and the multi-level item-response theory (IRT) models (e.g., Osgood & Schreck, 2007).

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These methods all emphasized the (lack of) variation in general over the exact sequence of crimes, but also had different assumptions and different underlying definitions of criminal specialization. Nevertheless, compared with the methods that emphasized the sequence, they tended to identify a subset of individuals whose criminal career concentrated on a narrow range of crimes. For example, McGloin et al. found that 38% of the sample were specialized in drug crimes, and another 8% were specialized in burglary and theft. Findings of these studies led to the argument that "it has become clear that this tendency towards offending generality is not a constant" (Sullivan et al., 2009, p. 421).

Sullivan et al. (2009) noticed the different conceptualizations under the different analytic approaches, and directly compared the pattern of criminal specialization found using four measures—the FSC, the diversity index, LCA, and the IRT model—using the same analytic sample. They found these methods produced somewhat different results: the FSC and the diversity index led to results that supported versatility more, whereas LCA and the IRT models found relatively stronger evidence towards specialization. Nevertheless, they contended that each of the methods found "some degree of offending specialization was present in the data, but that it was not very strong" (p. 435). Their findings, as well as the general findings of the literature on criminal specialization, point to two take-away points. First, the finding depends on the measure used, and therefore depends on the definition of criminal specialization. Second, unlike Piquero et al. (2003) and Roberts (1997) had contended based on studies available at that time, the up-to-date literature seems to agree on that the population consists of a mix of versatile and specialized individuals. Studies emphasizing the sequence tend to find more evidence towards versatility, and studies emphasizing concentration tend to find more evidence towards specialization. That, however, is not absolute. Studies using measures such as the FSC still found some types of

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crimes that were likely to be repeated (see Farrington et al., 1988), whereas studies examining the preponderance of certain types of crimes also found the majority of the sample to be non-specialists (see McGloin et al., 2009).

Criminal Specialization and Defendant Types

As summarized above, in support of the jurisprudential considerations such as deterrence and retribution, theories of sentencing consider the defendant's risk and culpability as the major determinants of the sentence (Albonetti, 1991; D. Gottfredson, 1998; Hogarth, 1971; Spohn, 2009; Steffensmeier et al., 1998). While the risk can rarely be readily and accurately assessed from the observed characteristics of the defendant, studies have indicated the use of "perceptual shorthand" (Albonetti, 1991). In the literature, the shorthand traditionally refers to extralegal variables such as race and sex (see Steffensmeier et al., 1998). However, there would be little reason to negate the use of criminal records as a stronger shorthand than the extralegal variables, because criminal records have a clearer connection to recidivism than race and sex do (Champion, 1994; Nagin & Paternoster, 1991). The connecting point between criminal specialization and the perceptual shorthand is that prosecutors and judges classify defendants into types based on their criminal careers, and make assessments of risk based on the types (for two good reviews of classification in criminal justice system, see Brennan, 1987; D. Gottfredson, 1987). From the just deserts perspective, the number of prior crimes may indicate the level of culpability of the defendant, as the sentence discount goes away with the accumulation of criminal records (Wasik & von Hirsch, 1995). On and above the number of prior records, the nature of the priors may also have a relationship with the level of culpability.

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The defendant types defined based on the crimes committed, such as “sex offenders” or “drug offenders,” are widely used in either colloquial terms of actors in the criminal justice system or statutes and case laws. In fact, the effort to identify the specialists has a history almost as long as modern criminology (e.g., Gibbons, 1975; Goring, 1913; Lombroso, 1911). That being said, existing literature has not examined the exact way in which prosecutors and judges construct the defendant types. Specifically, the relationship between criminal specialization and the assessment of the risk and culpability of the defendant is ambiguous. There would be little problem to consider a defendant specialized in serious violent crimes (e.g., murder and rape) as more dangerous and culpable than a defendant who commits all kinds of crimes. However, it is less clear that whether a defendant specialized in less serious, nonviolent crimes (e.g., prostitution or possession of marijuana) is more or less dangerous and culpable than a versatile one. Because of these two reasons, the relationship between criminal specialization and the sentence needs to be examined separately for each type of crime. Also because of the ambiguities around the way prosecutors and judges make use of criminal specialization, I follow Sullivan et al.’s (2009) approach and use four different measures of criminal specialization. The measures and how they model the prosecutors’ and judges’ way of thinking are detailed below.

My first measure of criminal specialization inherits the idea of successive repetition of crimes. The classic measure of successive repetition is the FSC. However, the FSC measures specialization at the crime type level, rather than at the individual level. The assumption that there is no variation in the degree of specialization among all the defendants convicted of the same type of crime seems too strong. The present study focuses on explaining the variation in the sentence among the defendants convicted of the same type of crime, in which case the FSC will be completely collinear with the crime type. However, the idea behind the FSC, the successive

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repetition of crimes, is potentially important (see Piquero et al., 2003). Instead of the FSC, I use a dichotomous, individual level variable, the identical preceding conviction (IPC), to indicate whether the conviction immediately preceding the current crime is of the same type (i.e., whether the defendant had repeated the last crime). On the one hand, the IPC is inspired by the FSC, and can capture the successive repetition of crimes. On the other hand, the IPC also allows for variation at the individual level. It assumes that prosecutors and judges consider specialization as the repetition of the most recent crime.

The three remaining measures focus on modeling the preponderance and variation of crimes within one's criminal records, rather than the exact sequence of crimes. My second measure of criminal specialization is the specialization index (see Bouffard et al., 2008; Nieuwbeerta et al., 2011; K. Wright et al., 2008).[3] It is calculated the exact same way as the diversity index, only with an opposite sign. It measures criminal specialization in a single dimension— "versatile" being one end and "specialized" being the other, and does not provide any information about the type of crimes each defendant specialized in. It assumes that prosecutors and judges evaluate the defendant's degree of specialization/versatility without any attention to the types of crimes the defendant had committed.

My third measure of criminal specialization is LCA. LCA is a maximum likelihood estimation of groups within a mix of observations (see Francis et al., 2004; McGloin et al., 2009). It divides the sample into finite groups that are different from each other, and assumes homogeneity within each group. While LCA models criminal specialization as the overall

[3] In this paper, I change the diversity index to the opposite sign to construct the specialization index for consistency purpose—I would like the measures to have a higher numerical value when the defendant is more specialized. However, the paper keeps using the term diversity index when earlier studies using that method are mentioned.

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preponderance of crimes like the specialization index does, it also contains information about the type of crimes each defendant specializes in. It assumes that prosecutors and judges evaluate the defendant's criminal records holistically, and categorize the defendants into types.

My fourth and last measure of criminal specialization is the number of identical records (NIR), which counts the number of past convictions that is of the same type as the current crime. The NIR also models defendant types based on specialized crimes, but takes a different perspective from LCA. First, the NIR assumes a linear relationship between the prior convictions and degree of specialization, which LCA can only do to a limited extent.[4] Second, the value of NIR does not depend on the presence or absence of other crimes, whereas LCA can only evaluate a defendant holistically based on the overall pattern in his or her criminal records. The NIR assumes that prosecutors and judges would first look for whether the defendant has ever been convicted of the current type of crime, which makes it different from the IPC. If the defendant has convictions, the NIR also assumes that prosecutors and judges would examine the number of prior convictions.

It is noteworthy that the scope of the current study is different from that of Sullivan et al. (2009). In addition to the pattern of specialization, I am also interested in how the degree of specialization reflected on the rap sheets predicts the sentence. Because of this, the selection of measures is also different. Other than the FSC, I am also not including the multilevel IRT model (Osgood & Schreck, 2007) because of data limitation (the dataset I use does not contain sufficient explanatory variables to replicate their models). I have also noticed some of the recent

[4] For instance, LCA can differentiate defendants with one conviction of a given crime from defendants with multiple convictions of that crime, but cannot differentiate defendants with four convictions and defendants with five. NIR, on the other hand, can differentiate defendants with any number of past convictions of the same crime type. See Method section for details.

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developments in the measurement of criminal specialization (e.g., the correlation matrix used by MacDonald et al., 2014), but decide not to use them in the present study because they are less relevant in the sentencing context.

The four measures used in the present study differ considerably in both their substantive meaning and the properties of measurement. Substantively, as stated in each of the preceding paragraphs, the measures make very different assumptions on how prosecutors and judges make use of the criminal records. In terms of measurement, these four measures also vary considerably (see Brennan, 1987). Overall, LCA and the NIR utilize more information on the rap sheet than the IPC and the specialization index do. The IPC discards all the previous crimes except for the most recent one, whereas the specialization index models only the proportion of crimes, but not the type of crimes. LCA and the NIR each captures some information the other approach misses. LCA considers crimes other than the current type, and models the defendant types by estimating the similarity of the pattern among the defendants' criminal records. The NIR, on the other hand, can better capture the number of prior crimes, whereas LCA has only limited capability to model the number of repetition.

Method

Data

The present study uses the Computerized Criminal History (CCH) dataset of New York State, maintained by and obtained from New York State Division of Criminal Justice Services (DCJS). The dataset contains all the fingerprintable arrests (i.e., felonies, misdemeanors, and a limited range of violations) under the state's jurisdiction between 1990 and late 2014. It records

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the top charge (i.e., the most serious charge) at arrest, arraignment, and disposition for each arrest event, as well as the sentence for those who were convicted.

Having only the top charge is not a rare situation for researchers. Many research works of criminal specialization relied on the top charge (e.g., Nieuwbeerta et al., 2011; K. Wright et al., 2008). Moreover, sometimes researchers used only the top charge even when less serious charges were available in the data. For example, Sullivan et al. (2009, p. 429; citations original) described that in order to address multiple arrests on the same date, "[p]revious work that acknowledged this issue typically used the most serious offense in cases where individuals were charged with more than one offense on a particular date (Blumstein et al., 1988; Farrington et al., 1988)."

In New York State, an arrestee is fingerprinted at arrest. The fingerprints are then transmitted to DCJS to look for a match with any existing profile. If no match is found, a new state ID will be assigned to the defendant. If the fingerprints match to an existing state ID, the arrest and the subsequent disposition information will be attached to the records under that state ID. This allows me to track the complete criminal records back to 1990 for each defendant in the dataset, and therefore to model the criminal justice careers.

The analytic sample consists of the complete set of non-sealed criminal records of all the individuals (represented by state IDs) who meet all the three following criteria.[5] First, the defendant had an arrest between the years 2010 and 2012. If only one arrest happened in the time

[5] The laws on the sealing of criminal records in New York State are very complicated, and as to my informal conversations with multiple people with experience working in the criminal justice system or working with the data, a particular criminal event marked as "sealed" may still be seen or unsealed, and there does not seem to be a clear-cut standard that would allow me to identify whether or not the prosecutors and judges can actually see a record marked as "sealed." Therefore, I only consider cases clearly marked as non-sealed in the present study to ensure the uniformity in the selection of the sample. This may result in systematic underestimation of criminal records of the whole sample.

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frame, I consider that arrest as the current crime. If more than one arrests happened in the time period, I consider the last arrest as the current crime. If multiple arrests happened on the date when the last arrest happened (e.g., a defendant who involved in multiple criminal events was apprehended while at large), I consider the one with the most serious charge as the current crime. Second, the current arrest resulted in a conviction, regardless whether the conviction date was before or after the last day of 2012 (i.e., this study uses a conviction sample). In fact, a major reason why I choose 2012 as the ending year of the sample selection is to allow for the maximum number of cases to be disposed. Third, the defendant had two or more convictions prior to the current arrest. If a defendant had no prior conviction or one prior conviction, then he or she would almost be a specialist by definition. Some measures used in the study, such as the IPC, would be undefined for those with no prior. Other measures such as LCA and specialization index would be biased toward detecting more specialists considering the large number of individuals with no or minimum level of prior records. Because of the selection, the analytic sample is not representative of all the defendants convicted in New York State between 2010 and 2012. Instead, it represents the subsample of convicted defendants who had relatively serious criminal records. The selection process results in an analytic sample of 113,545 cases, which is the population of convictions in New York State between 2010 and 2012 in which the defendant met all the criteria above.

Measures of Criminal Specialization

I estimate all the four measures of criminal specialization with all the non-sealed convictions that are available in the data (i.e., convictions for arrests that took place after January 1, 1990) and that happened (defined by the disposition date) prior to the arrest date of the current

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crime. I use prior convictions instead of prior arrests for two reasons. First, according to the principles of criminal law, an arrest only means the defendant has allegedly committed a crime. By contrast, a conviction is a crime confirmed by the criminal justice system and therefore legitimate in the sentencing consideration (see Roberts, 1997). For a defendant to be considered a predicate, most sentencing guidelines as well as the sentence enhancements in New York require a conviction rather than an arrest. Second, as a robustness check, I estimated all these measures using prior arrests instead of prior convictions, and then estimated a series of sentencing models. All the measures estimated from the arrests were not as good predictors as those estimated from the convictions.

Two of the four measures (i.e., the IPC and the NIR) rely on the type of the current crime as the benchmark to examine the degree of repetition. For these two measures, I use the arrest charge of the current crime as opposed to the disposition charge as the benchmark (i.e., I compare *the current arrest crime type* and *prior conviction crime types*). This is because the prosecutors and judges only had the arrest charge of the current crime when they decide the plea offer, which has a close relationship with the sentence (Rehavi & Starr, 2014; Shermer & Johnson, 2010).

The identical preceding conviction (IPC). The IPC is a dichotomous variable indicating whether the defendant had repeated the same crime in a successive manner. Specifically, it is coded as one if the type of the current arrest crime is the same as the conviction immediately preceding (i.e., the conviction that has the disposition date earlier than and closest to the arrest date of the current crime), and zero if the two crime types are different. The value of the IPC can only be one or zero, and cannot be undefined, because all the defendants in the analytic sample had at least two prior convictions before the current crime.

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The specialization index. The specialization index is created as the opposite of the diversity index, which is one of the earliest individual-level measurement of criminal specialization found in published studies (Agresti & Agresti, 1987).[6] As Osgood and Schreck (2007) noted, the specialization index would model specialization as the degree of preponderance of a certain type of crime. It is calculated as

$$Specialization\ Index = \sum p_j^2 \quad (1)$$

in which p_j stands for the proportion of each crime j out of the total number of prior crimes, which varies between zero and one. For example, if a defendant had one conviction of robbery and four convictions of larceny, the value of the diversity index would be 0.68 (0.04 + 0.64). By definition, the value of specialization index falls between zero and one. A specialization index value towards zero indicates versatility. For a total of n crime types, the index's minimum possible value is $\frac{1}{n}$, which happens and only happens when the number of convictions are equal for each crime type the defendant had ever been convicted of. Conversely, a value of one indicates complete specialization, which happens when and only when the individual has committed only one type of crime.

Latent class analysis (LCA). LCA addresses the potential heterogeneity in the parameters of postulated statistical models due to unobserved subgroups (McCutcheon, 1987; Vermunt & Magidson, 2004). LCA assumes the existence of a latent categorical variable, X, and assumes each category of X represents a subgroup. In the present study, X could be considered as

[6] Specialization Index = 1 – Diversity Index

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the variable defendant type. The classes are inferred from the sample's pattern in a group of L observed categorical variables Y_l ($l = 1, 2, \dots, L$), known as the manifest variables.

In the present study, each manifest variable is one type of crime in a defendant's criminal records (murder, sex crimes, etc.). Many studies using LCA coded each manifest variable dichotomously as the presence/absence of the crime in the defendant's criminal records (e.g., Francis et al., 2004; McGloin et al., 2009). I move one step further, and code each variable into three categories: having no prior conviction of that crime, having one prior conviction of that crime, and having two or more convictions of that crime. Compared with having only one conviction of a crime, being convicted multiple times for the same crime type may indicate a higher degree of criminal specialization. This three-category approach has the potential of better capturing the defendants who repeatedly involved in the same type of crimes.

Two groups of class-level parameters, as well as one group of individual-level parameters, are of particular interest in LCA (McCutcheon, 1987; Vermunt & Magidson, 2004). The first group of class parameters, $\Pr(X = x)$, is the set of *latent class probabilities*. These parameters indicate the relative size of each class, and indicate whether the defendants are relatively evenly distributed among the classes, or tend to concentrate in one class. The second group of class-level parameters are the set of *conditional probabilities*, denoted by $\Pr(\boldsymbol{Y} = \boldsymbol{y} | X = x)$. These parameters indicate the probability that an individual, conditional on being in class *x*, has the manifest variables at a given value. For each class x there is a conditional probability for observing each category of each manifest variable. In the present study, for each combination of the crime and the class, there would be three conditional probabilities—the probabilities of defendants identified into that class having no prior conviction of that crime, having one conviction of that crime, and having multiple convictions of that crime. Because of

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that, I refrain from going even further to differentiate among the defendants with multiple convictions, which will lead to results that are essentially uninterpretable. These parameters would illustrate the characteristics of each class. For example, if the defendants in one class have high conditional probabilities of having multiple convictions of larceny, burglary, and stolen property crimes, but low conditional probabilities of having convictions of other crimes, that class is likely to reflect a group of defendants specialized in property crimes. If the defendants in one class have conditional probabilities close to the sample average for most of the crimes, that class is likely to represent the versatile defendants (see Osgood & Schreck, 2007).

To estimate an LCA model, it is necessary to specify the number of classes before the estimation. To select the model that best fits the data, one commonly-used model fitting statistic is the Bayesian Information Criterion (BIC, see Nagin, 2005). Therefore, I start with a 1-class model, and increase the number of classes until the BIC worsens for three consecutive models (which happened at the 24-class model in the present study). Yet in the circumstances when both the sample size and the number of variables are large, BIC is likely to continue to improve as the number of classes increase, which will result in models that are extremely cumbersome to interpret and classes that constitute negligible proportions of the sample (Nagin, 2005). Therefore, I use a set of diagnostic statistics, the average posterior probabilities (avePP, see Nagin, 2005) to help determine the model. After the estimation of each model, one can use Bayesian methods to estimate the probabilities of class assignment for every single defendant and every class. These probabilities are called the posterior probabilities. A defendant is considered as a member of the class for which he or she has the highest probability of assignment. For each class, the avePP is the average posterior probability for all of its members, which indicates whether the members are identified into that class without ambiguity. I use the

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latent class analysis plugin (doLCA) version 1.2 (Lanza et al., 2015) in Stata 14 to estimate the LCA models.[7]

The number of identical records (NIR). The NIR is a discrete measure of how many times the defendant had been convicted of the current arrest crime. When the NIR is included in the models, the numbers of convictions of other crimes are also controlled for. It estimates how did each additional conviction of the same crime correlate to the sentence.

Variables

There are two key dependent variables in the present study. *Incarceration* is a dichotomous indicator of whether the defendant was sentenced to a prison or post-sentencing jail term. *Incarceration length* is coded continuously, in months. The key independent variables of the study are the four measures of *criminal specialization*, as detailed above. I use 17 types of crimes in the estimation: murder, sex crimes, robbery, aggravated assault, simple assault, burglary, larceny, motor vehicle larceny (hereinafter MV larceny), stolen property crimes, forgery, fraud, criminal mischief, drug trafficking, drug possession, weapon crimes, driving crimes, and nuisance crimes. These types of crimes largely follow the coding of Bureau of Justice Statistics' State Court Processing Statistics (see Reaves, 2013), with some modifications

[7] I use two approaches to generate different starting values to prevent local maxima. The first is the option –nstarts– as part of the –doLCA– command, which automatically generate a set of different starting values and repeat the estimation each time I execute the command. The second is the –seed– option, which directly determines the first set of starting value each time I execute the command. For every model (from 1-group to 24-group), I use 20 different starting values by specifying in the nstarts option. For the key models (5- to 8-group models), I use 5 different seeds, and 20 different starting values for each seed (for details of the commands, see Lanza et al., 2015). The converge of the key models was good.

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based on the crimes' theoretical significance and actual prevalence in the data. Details of these crime types are presented in Table 1.

[Table 1 approximately here.]

The use of narrow crime categories, as opposed to broad crime categories (such as violent crimes and property crimes), is the standard practice in criminal specialization research. For example, Sullivan et al. (2009) used 16 crime types in their study (moreover, the categories were very similar to mine), and many studies had over 20 categories (e.g., Farrington et al., 1988; Francis, 2004). In fact, using broad categories (e.g., violent crimes, property crimes, etc.) tends to overestimate the number of specialists in the sample (e.g., if there is only one crime type, then everyone will be a specialist of that crime). Moreover, some of the measures would make little sense if the crimes were coded in broad categories. For example, McGloin et al. (2009, p. 251; citations original) argued that the point of the LCA was to identify broad categories of defendants using narrower types of crimes they had committed,

> [t]hough these offence types can be further reduced into broader categories, one of the basic purposes of a latent variable model is to infer these categories or classes—collapsing them prior to this analysis is arguably counterproductive (Francis et al., 2004; Massoglia, 2006).

In the regression models, I also include a variety of legal and extralegal variables as the control variables. *The crime severity* is the statutory seriousness of the conviction crime, with felonies ranging from Class A (most serious) to Class E (least serious) and misdemeanors coded as Class A (more serious) and Unclassified/Class B (less serious). To represent how most quantitative sentencing studies control for the criminal records, I included *the number of prior*

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felony convictions as an additional control variable in addition to criminal specialization.[8] *Trial* is a dichotomous indicator of whether the conviction was the result of a trial or a plea. To control for extralegal correlations, I include *the race*, *ethnicity*, *sex*, *age*, and *age squared* of the defendant. I also include *the disposition county* and *the arrest year* in the models to control for the specific fixed effects associated with them.

Analytic Procedure

The present study does not seek to investigate is not how criminal specialization predicts the sentence in a general sense. Instead, what I am interested in examining is the relationship between criminal specialization and the sentence, conditional on the conviction crime. For example, if two defendants are both convicted of larceny, would the defendant with three prior convictions of larceny be sentenced differently from the one with three prior convictions of drug possession? Because of that, I am estimating one regression model for each conviction crime type. The modeling of the sentence using narrow categories allows for the maximum amount of flexibility. The measures of criminal specialization, as well as the other legal and extralegal variables, are allowed to have different correlations with the sentence for different types of crimes. Substantively, this approach assumes that specialization, as well as other control variables, matters conditional on the current crime type.

[8] The models in the present study do not have the number of prior misdemeanor convictions. Because the models with the NIR includes the number of convictions of all crime types, including the number of prior misdemeanor convictions will result in multi-collinearity. Yet it is a legitimate concern that the relationship between the sentence and the measures of criminal specialization (except for the NIR) would change if the misdemeanor convictions are included. I conducted a series of robustness check by including the prior misdemeanor convictions alongside with criminal specialization and the prior felony convictions. The results basically stay the same as the ones to be presented in the Results section.

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In the present study, I estimate a set of linear probability models (LPMs, the OLS models to explain a dichotomous outcome), instead of logit or probit models, to explain the incarceration outcome. For researchers, the intuition is to employ a logit or a probit model when the outcome is dichotomous. The LPMs, however, has also been used in econometrics for a variety of reasons (Horrace & Oaxaca, 2006), such as the ease of interpretation of the marginal effects (McGarry, 2000) or to avoid the potential perfect correlation problem in the probit/logit models (Reiley, 2006). There are two major concerns with using the LPMs. First, the predicted probability of the outcome can fall out of the unit interval (i.e., a predicted probability greater than one or smaller than zero). Second, the error terms are heteroscedastic by definition (i.e., the variance varies with the latent probability). For the first issue, the interest of the present study is to estimate the correlations between the measures of specialization and the sentence (i.e., the slopes), not to predict the outcome. Econometricians have shown that the coefficients are unbiased, and the slopes estimated from the LPM are similar to the marginal effects computed in probit models (Angrist & Pischke, 2009). Therefore, the fact that the predicted probabilities may fall outside the unit interval would not be a concern (see also Wooldridge, 2010). The second problem could be overcome by reporting the robust standard errors, which are to be presented in the Results section.[9]

After the estimation of the incarceration models, I simply use the two-part model approach (TPM, see Bushway, Johnson, & Slocum, 2007) to estimate the models explaining the incarceration length. I am unable to use the Heckman (1979) correction in the present study because of the high level of multi-collinearity among the regressors as well as the lack of the

[9] As a robustness check, I also estimated a probit model for all the incarceration models (not presented in the paper). The substantive findings looked very similar. Therefore, in the present paper I go with the LPMs because (1) the findings are not different from the probit models, and (2) the marginal effects are much more straightforward.

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exclusion restriction (see Leung & Yu, 1996). Therefore, the coefficients of specialization in the incarceration length models may be biased because of the selection at the incarceration stage.

To present the findings of the present study, I first estimate the four measures of criminal specialization for the entire sample. I next conduct a correlation analysis to investigate how much the measures overlap. I then estimate a series of baseline models explaining incarceration and the incarceration length without any of the measures of specialization. Last but not least, I present the regression models with the measures of criminal specialization included. Although there are a total of 17 crime types, I can only estimate regression models for 15 of them. The defendants convicted of two types of crimes—murder and robbery—were almost all incarcerated (over 96% of the samples). The lack of variation in the dependent variable prevents the estimation of regression models. However, for the defendants currently convicted of crimes other than murder and robbery, I still include their prior convictions of murder and robbery in estimating specialization. This is because the prosecutors and judges would still see the murder and robbery convictions on the rap sheets of these defendants. All the regression models cluster standard error by the disposition county.

Results

Descriptive Statistics

Table 2 presents the descriptive statistics of the sample. Slightly over a half (54%) of the sample was sentenced to incarceration. The sample was predominantly male (87%), with an average age at 38 years. Blacks and Whites each consisted about a half of the sample, and approximately 38% of the sample was identified as Hispanic. Approximately 30% of the sample

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was convicted of a felony. The most frequent crime types for the current conviction are drug possession (22%), nuisance (16%), and larceny (15%). On average, the sample had 7.1 convictions, with 1.3 felonies and 5.8 misdemeanors. These numbers are high because of the selective nature of the sample—the minimum number of prior convictions is two.

[Table 2 approximately here.]

Table 3 presents more detailed information about the prior convictions of the sample. The most prevalent prior convictions were for drug possession (with 53% of the defendants having at least one), nuisance (49%), and larceny (41%). These are also the crimes that the defendants on average had the most number of prior convictions. Murder (1%), sex crimes (4%), and motor vehicle larceny (6%) were the least frequent types of priors. This is not surprising because these crimes were relatively rare. In general, for a given crime there were more defendants having a single prior conviction than those having multiple convictions, with larceny (19% vs. 22%) and drug possession (20% vs. 33%) being the exceptions.

[Table 3 approximately here.]

Table 4 presents the descriptive statistics of all the subsamples divided by the conviction crime type. The proportion of defendants incarcerated, as well as the severity distribution, varied considerably among the subsamples. Males were predominant in all the subsamples. The racial composition also varied by crime type. White defendants constituted a higher proportion of the defendants convicted of burglary, stolen property, criminal mischief, and driving crimes. Black defendants, on the other hand, constituted a higher proportion of those convicted of drug crimes, fraud, and weapon crimes.

[Table 4 approximately here.]

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Patterns of Criminal Specialization

The identical preceding conviction (IPC). The average value of the IPC for the analytic sample was 0.24, which means that approximately a quarter of the defendants repeated the last crime they were convicted of. Table 5 presents the values of the IPC by conviction crime type. The defendants convicted of driving crimes (41%), drug possession (33%), nuisance (28%), and larceny (26%) were the most likely to repeat their last crime, and defendants of murder (2%), aggravated assault (5%), and stolen property (5%) were the least likely to repeat their last crime. From the numbers we can see that the vast majority of the defendants (76%) did not repeat their last crime, and none of the crimes had over 50% of successive repeaters. However, defendants convicted of some crimes (driving, drug possession, etc.) had a relatively high probability to repeat the same crime successively.

[Table 5 approximately here.]

The specialization index. Table 6 presents the average value of the specialization index for the entire sample, as well as the average value by crime type. The average defendant in the sample had more than 7 prior convictions, which would translate to a specialization index value of 0.14 if the defendant was completely versatile. The mean observed value of the specialization index for the sample was 0.46. Regardless of the conviction crime type, the average value of the specialization index was always above 0.40. Compared with IPC, the average values of the specialization index among the subsamples were much more similar. The only subsample that stands out is defendants convicted of driving crimes, who had an average specialization index value over 0.5. Of course, the specialization index does not increase in a linear manner (i.e., 0.5

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does not mean the "halfway" between versatility and specialization). The pattern still suggests the existence of some specialized defendants in the sample as well as in all the subsamples divided by crime type.

[Table 6 approximately here.]

Latent class analysis. Based on the fitting statistics (BIC), the diagnostic statistics (avePP), and the substantive meaning of the classes, I choose a seven-class model as the best fit for the data (see the Appendix for details). Table 7 presents the class parameters of the seven-class model. For each crime and each class, I only present the conditional probabilities of having one prior conviction and having multiple convictions, because the conditional probability of having zero prior would always be one minus the sum of the two probabilities presented.

[Table 7 approximately here.]

One problem with presenting only the conditional probabilities is that one cannot tell whether the probabilities are high or low relative to the sample average. To facilitate the interpretation of the results, in Table 8 I present the class-average ratios (CARs), calculated by dividing the class conditional probabilities by the sample average. The value of the CAR could be interpreted as "compared with an average defendant in the whole sample, how many times were defendants in a given class as likely to have one conviction (multiple convictions) for a given crime?" Compared with the raw conditional probabilities, the CARs take into account the fact that the conditional probabilities may be affected by the overall prevalence of the crimes, especially for rare crimes such as murder and sex crimes (see Osgood & Schreck, 2007; see also Sullivan et al., 2009). A specialist class would have high CAR values for some crimes and low CAR values for other crimes, whereas a generalist class would have CAR values close to one for

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most of the crimes. Using this criterion, the seven classes can be roughly divided into two broad types. For the defendants assigned to Classes 1 to 3, most conditional probabilities were slightly higher than one. This indicates the defendants' high and balanced level of participation in a broad range of crimes, which means that the defendants were the generalists. To the contrary, the defendants assigned to Classes 4 to 7 had high conditional probabilities for some crimes and low for other crime types. These defendants were the specialists.

[Table 8 approximately here.]

Even though one common feature of Classes 1 to 2 is the diversity of crime in the defendants' criminal records, a closer look can still differentiate them. The defendants assigned to Class 1 (21% of the sample) had high CAR values for sex crimes. However, the CAR values of having one single conviction of most of the crimes were *close to one* (*in both directions*). Moreover, the defendants were less likely than the average to have multiple convictions of most of the crimes. I name Class 1 as the "Low Involvement Generalists." By contrast, the defendants assigned to Class 2 (11%) had most CAR values *higher than one*, and had a CAR value of two or higher for having multiple convictions of some types of crimes (simple assault, forgery, fraud, drug crimes, weapons crimes, and nuisance crimes). Compared with the defendants assigned to Class 1, these defendants were more likely to have multiple convictions of many types of crimes. Moreover, the defendants assigned to Class 2 had higher CAR values for drug crimes compared with those assigned to Classes 1 and 3. Therefore, Class 2 can be considered as an approximation of the defendants who were at the same time involved in drug crimes and other types of crimes, and I name Class 2 as the "Drug Generalists." The defendants assigned to Class 3 (6%) had CAR values greater than two for most of the property crimes (with some as high as eight), as well as CAR values of above one for all the violent crimes except for murder. These defendants

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committed both a large number and a large variety of crimes. I name Class 3 as the "High Involvement Generalists."

The defendants assigned to Classes 4 to 7 had a combination of high CAR values (2 or greater) and low CAR values (0.5 or lesser). The defendants assigned to Class 4 (8% of the sample) had very low CAR values (0.33 or lesser) for almost all the crimes, but high CAR values for driving crimes. This class represents the individuals who essentially had no criminal records other than for driving-related crimes, and I name them as the "Driving Specialists." The defendants assigned to Classes 5 to 7 had high CAR values for multiple convictions of property crimes (17%), drug crimes (25%), and violent crimes (12%) respectively, and low CAR values for other types of crimes. I name them as the "Property Specialists," the "Drug Specialists," and the "Violent Specialists" respectively, based on the type of crimes these defendants specialized in.

Table 9 presents the assignment of the class by conviction crime type. All the subsamples had a non-negligible proportion of generalists. However, a considerable amount of those convicted of property crimes were specialists of these crimes, which was also true for drug and driving crimes. The patterns for violent crimes were slightly different. Over 30% of the defendants convicted of murder and robbery were the Violent Specialists, which was higher than any other class. However, most defendants convicted of assault (both aggravated and simple) were more likely to be generalists and the Drug Specialists. Defendants convicted of sex crimes concentrated in the Low Involvement Generalist class, because LCA considered that the defendants with prior sex crime convictions were more similar to other low involvement defendants. Overall, the patterns revealed by LCA also provide some support for the existence of

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criminal specialization, especially since over a half of the defendants were eventually assigned to one of the specialist classes.

[Table 9 approximately here.]

The number of identical records (NIR). The NIR records the number of convictions of the same crime as the current conviction, regardless of the timing and the sequence of these convictions. The results are presented in Table 10. The defendants in the analytic sample had an average of 1.9 prior convictions of the same type as the current crime, which constituted over a quarter of their total convictions (7.1). When I examine NIR by subsamples, it turns out that the defendants convicted of larceny had the most prior convictions of the same type, as they accumulated an average of 3.5 prior convictions of larceny. The defendants convicted of drug possession were also likely to have prior convictions of the same crime (3.2 convictions of drug possession). The defendants convicted of murder (0.05), aggravated assault (0.2), and weapons crimes (0.3) on average had the fewest number of prior convictions of the same crime.

[Table 10 approximately here.]

Correlation analysis. As presented above, all the four measures have found some support for the existence of specialized defendants. The IPC has found that a quarter of the defendants repeated their last crime. The average value of the specialization index is higher than the value that would have been observed if the defendants were completely versatile. LCA has identified four specialist classes out of a total of seven, which include over a half of the defendants. The NIR has found that an average defendant had nearly two convictions of the same type of crime as the current one. However, as summarized earlier in the paper, these measures point to different definitions of criminal specialization. Therefore, it is necessary to examine how

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much do the measures correlate with each other before I move on to present the regression models.

The pairwise correlation coefficients among the measures are presented in Table 11. Although the correlations between the specialization index, the IPC, and the NIR are all positive, they are all below 0.2. The correlations between these three measures and the classes identified by LCA are not strong either. Clearly, these four measures are capturing something different. In other words, a specialist identified using one measure may be considered as a versatile defendant using another.

[Table 11 approximately here.]

Table 12 further presents of the average values of the IPC, the specialization index, and the NIR, divided by the class. In general, the defendants assigned to the specialist classes had a higher IPC and specialization index, except for the Violent Specialists. However, two of the generalist classes, the Drug Generalists and the High Involvement Generalists, had the highest NIR on average, while the Violent Specialists had the lowest NIR. This pattern suggests that repetition and concentration of crimes do not necessarily overlap. The defendants in the two generalist classes had a variety of crimes in their criminal records (i.e., low concentration), but also had the highest number of repetitions of the current crime.

[Table 12 approximately here.]

Consider a specific example. A defendant has three convictions of larceny, two convictions of forgery, one conviction of fraud, one conviction of drug possession, two convictions of driving crimes, and one conviction of nuisance crimes. LCA has assigned this defendant to the Property Specialist class with a posterior probability of 0.87. This does not seem

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to be surprising given the concentration of property crimes in the defendant's criminal records. However, the value of the specialization index is 0.2, which is relatively small and identifies the defendant closer to a generalist. This is not surprising either, given the variety of crimes the defendant has committed. The value of the NIR and the IPC both depend on the current crime. When the NIR is used, the defendant would be a specialist if the current conviction is for larceny (NIR = 3), but would not be a specialist if the current crime is burglary (NIR = 0). The value of the IPC not only depends on the type of the current crime, but also depends on the timing of the prior conviction.

Of course, there are many circumstances in which the four measures agree with each other. Yet the example above demonstrates one possible scenario where the four measures might lead to different answers. The disagreement among the measures is a result of the different definitions behind them, and does not necessarily mean that any of the measures is wrong. However, given the low level of correlation among the four measures, the ways the measures correlate with the sentence may also be different. The rest of the Results section presents the regression models explaining the incarceration outcome as well as the incarceration length.

Regression Models

The baseline models. Table 13 presents the baseline regression models explaining the incarceration outcome.[10] For all types of crimes, the most important predictors of incarceration were the class (severity) of the conviction crime and the total number of prior felony convictions.

[10] In the regression tables presented in this chapter, I use the Class E Felony, rather than the most (the Class A Felony) or the least serious crime class (the Class B/Unclassified Misdemeanor), as the reference group for the variable crime severity. This is because all the subsamples had observations convicted of a Class E Felony.

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Compared with the defendants convicted of a Class E Felony, those convicted of more a serious crime (a Class A to Class D Felony) were more likely to be incarcerated, whereas those convicted of a less serious crime (a Classes A or B or an Unclassified Misdemeanor) were less likely to be incarcerated. The defendant's criminal records, measured as the total number of prior felony convictions, was significantly correlated with incarceration for all the crimes. The pattern of the extralegal disparity varied among the crimes. Yet the main pattern is less favorable outcomes for male defendants, as well as for Black defendants, even after controlling for the legal variables including the conviction crime severity and the number of prior felony convictions. Male defendants were around 5-10 percentage points more likely to be incarcerated for most crimes, and were more than 20 percentage points more likely to be incarcerated for sex crimes. The coefficients for Black defendants were smaller, but still statistically significant for most crimes. In general, Black defendants were three to five percentage points more likely to be incarcerated. The disparities associated with Hispanic ethnicity and the age of the defendant were less likely to be statistically significant.

[Table 13 approximately here.]

Table 14 presents the baseline models explaining the incarceration length, conditional on the defendant being sentenced to an incarceration term. Similar to the incarceration models, the major correlates of the incarceration length were current the crime severity and the number of prior felony convictions. Male defendants still received longer sentences. However, in contrast with the incarceration models, Black defendants did not receive longer sentences, except when convicted of drug crimes, weapon crimes, and simple assault. Even when the coefficients were significant, they were much smaller than the coefficients of the legal variables and male. Similar to the baseline models, age and Hispanic ethnicity were largely non-significant.

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[Table 14 approximately here.]

Models with the IPC. Table 15 presents the results of regression models with the IPC included. For most types of crimes, repeating the last crime would predict a higher probability of incarceration. However, the coefficient was significant and positive for only 4 out of the 15 crimes (sex crimes, burglary, larceny, and fraud), and was significant and negative for drug possession. Even when the correlations were significant, the coefficients were small (with sex crimes as the only exception—those whose last conviction was also for a sex crime were eight percentage points more likely to be incarcerated). In general, adding in the IPC did not seem to improve the model fit very much, as the difference in the R^2 values tended to be in the third decimal (around .001, again except for the model for sex crimes). Moreover, adding in the IPC did not seem to change the existing relationship between incarceration and the extralegal variables. In other words, the repetition of the last crime did not seem to be correlated with the extralegal predictor variables, and did not mediate the existing relationships. Table 16 presents the results for the incarceration length. The overall pattern is very similar to the incarceration models. The IPC only significantly predicted the sentence length for burglary, weapon crimes, and nuisance crimes. The coefficient for nuisance crimes was negative, but very small. Also similar to incarceration models, adding in the IPC did not seem to change the correlations between the sentence and the extralegal variables.

[Tables 15 and 16 approximately here.]

Models with the specialization index. Table 17 presents the regression models explaining incarceration with the specialization index included. According to the models, a more specialized defendant would be *less likely* to be incarcerated compared with a similarly situated versatile defendant. Compared with the average defendant in the sample (i.e., specialization

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index = 0.47), a completely specialized defendant (i.e., a defendant with all the priors being the same type of crime; specialization index = 1) would be between two and nine percentage points less likely to be incarcerated. Similar to the IPC, the specialization index also does not seem to mediate the existing correlations, even though the IPC and the specialization index were correlated with incarceration in the opposite directions. The change in the model fit after including the specialization index was larger than the change after including the IPC, as in most models the R^2 value increased by 0.005 or more.

[Table 17 approximately here.]

Table 18 presents the sentence length models with the specialization index. Conditional on incarceration, the specialization index significantly predicted a *shorter* sentence for five crimes (sex crimes, stolen property, drug trafficking, drug possession, and nuisance), and a *longer* sentence for burglary. Still, most of the coefficients were very small (fewer than three months' difference between an average defendant and a completely specialized one, except for sex crimes and burglary). Overall, the specialization index was less likely to be significant when predicting the incarceration length than when predicting incarceration.

[Table 18 approximately here.]

Models with the classes identified by LCA. Table 19 presents the regression models explaining incarceration with the results of the latent class analysis, the classes. Most of the coefficients of the classes were not significantly different from the reference group, the Low Involvement Generalists. When convicted of most crimes, those identified as the Drug Generalists and the High Involvement Generalists were *more* likely to be incarcerated, whereas those identified as the Driving Specialists, the Property Specialists, and the Drug Specialists

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were *less* likely to be incarcerated (regardless of significance). The Violent Specialists had a mix of positive and negative correlations with incarceration, depending on the conviction crime. For most of the conviction crimes, there was a "corresponding specialist group" (i.e., the Violent Specialists for sex crimes, aggravated assault, and simple assault; the Property Specialists for burglary, larceny, MV larceny, stolen property, forgery, fraud, and criminal mischief; the Drug Specialists for drug trafficking and drug possession; and the Driving Specialists for driving crimes). Compared with the Low Involvement Generalists, the probability for the defendants in the corresponding specialist group to receive an incarceration sentence was either not significantly different or significantly *lower*, and this was particularly the case for the defendants convicted of violent crimes.[11] Adding in the classes did improve the model fit by 0.005 to 0.01 for most of the models. Similar to the results of the models with the IPC and the specialization index, adding in the class variables did not seem to change the correlation between the sentence and the extralegal variables.

[Table 19 approximately here.]

Table 20 presents the incarceration length models with the classes. The Violent Specialists and the Property Specialists received a longer sentence for violent and property crimes respectively, although most of the coefficients were small (two months or shorter) and non-significant. The Drug Specialists and the Driving Specialists did not receive a longer sentence than the Low Involvement Generalists, for drug crimes and driving crimes respectively.

[Table 20 approximately here.]

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[11] A series of robustness check models using the posterior probabilities of assignment instead of categorical class variables found basically the same pattern.

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Models with the NIR. Table 21 presents the results of the regression models explaining incarceration with the NIR. For most of the crimes (except for aggravated assault, burglary, criminal mischief, and weapons), each prior conviction of the same type of crime predicted 0.6 to 4.7 additional percentage points in the probability of incarceration. After adding in the NIR, the coefficients of the number of felony convictions dropped considerably, which can be explained by the degree of correlation between the NIR and the number of felony convictions. Nevertheless, in most of the models, the number of felony convictions still significantly predicted incarceration (except for aggravated assault), which means that the *nature* of the prior convictions has its own predictive ability on and above the *total number* of felony convictions. Another noteworthy pattern is that compared with the defendants convicted of serious and violent current crimes (e.g., sex crimes and burglary), the sentence of the defendants convicted of less serious current crimes (e.g., larceny, fraud, drug possession, and nuisance) was more likely to be correlated with the numbers of prior convictions of other crimes. Compared with the addition of the IPC, the specialization index, and the classes, the model fit improved the most with the inclusion the NIR. Most of the models' R^2 value increased by about 0.02 or larger. in general, the models with the NIR had a better model fit than the models with the other measures. However, the inclusion of the NIR may not be the only reason why the model fit increased. Alongside with the NIR, a number of regressors (i.e., the number of convictions of the other crimes) were also included. These regressors were not included in the models with the other measures. Therefore, even though the NIR models did have a better model fit, it cannot be simply concluded that the increase in model fit was only because of the NIRs. Similar to the models with the IPC, the specialization index, and the classes, the correlations between incarceration and the extralegal variables were largely unchanged.

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[Table 21 approximately here.]

Last but not least, Table 22 presents the incarceration length models with the NIR. While NIR significantly predicted incarceration in all the models, it only predicted a longer sentence in five models (aggravated assault, burglary, weapons, driving, and nuisance), and two of the coefficients were small (driving and nuisance). It performed much weaker in predicting the sentence length than in predicting incarceration.

[Table 22 approximately here.]

Models with all the specialization measures. As a robustness check, I also estimate a series of models explaining the incarceration outcome, and put in all the four measures of criminal specialization at the same time. The results are presented in Table 23. For all the measures, the coefficient did not appear to be dramatically different from the models with only that measure. When compared with the baseline models, the correlations between incarceration and the extralegal variables (i.e., the extralegal disparity) also did not change much. The finding suggests that all the measures mattered, even after controlling for other measures. Each of the measures has a unique contribution in explaining the variation in the incarceration outcome, which is not surprising given the relatively low level of correlation among the measures (see Tables 11 and 12). Moreover, there does not seem to be strong joint correlations between the measures and the extralegal variables either. The similar pattern is also found in the models explaining the incarceration length with all the measures included, as presented in Table 24.

[Tables 23 and 24 approximately here.]

Discussion

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The present study seeks to answer one question: can the defendant's degree of criminal specialization predict the sentence, on and above the number of criminal records? In order to answer this question, the study also investigates the degree of criminal specialization among the sample of defendants, using four measures that capture different aspects of criminal specialization (both separately and at the same time). To my knowledge, this is the first study that explicitly incorporates the ideas and approaches of the criminal careers research in order to address a research question on sentencing. The results reveal that criminal specialization does matter in sentencing—although the way each measure predicts the sentence is quite different.

As the research of criminal careers has pointed out, whether individuals specialize in criminal behaviors is not only a theoretical question (Cloward & Ohlin, 1960; M. Gottfredson & Hirschi, 1990; Spelman, 1994), but also an empirical question (Blumstein et al., 1986; Piquero et al., 2003; Sullivan et al., 2009). The first part of the empirical investigation estimates the degree of criminal specialization on the same analytic sample—all the defendants in New York State, who were convicted for an arrest that took place between 2010 and 2012, and who had at least two prior convictions. As presented in the Results section, *all of these measures have found that the sample consists of a mix of versatile and specialized defendants*. This finding largely echoes with the finding of Sullivan et al. (2009), who also concluded that while most of the individuals were versatile, there was some evidence supporting the notion of criminal specialization. What is probably more interesting, however, is the low level of correlation among the four measures. The findings presented in Tables 11 and 12, as well as the example discussed in the correlation analysis, clearly demonstrate that *the assessment of criminal specialization depends on the perspective behind the measure*, which is a crucial take-away from the research of criminal careers over the past decades (Blumstein et al., 1986; Piquero et al., 2003; Sullivan et al., 2009).

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It is beyond the scope of the present study to determine which measure is the best at capturing criminal specialization. These questions, as well as the development of additional measures of criminal specialization, have to be left for future research.

Before I estimate the regression models explaining the sentence with the measures of criminal specialization, I start with a set of baseline regression models. After I control for the type of the conviction crime by estimating a separate model for each crime type, the strongest predictors of the sentence were the current crime severity and the number of prior felony convictions. Incarceration was also significantly correlated with the sex and the race of the defendant, but the coefficients were smaller than those of the crime severity and the number of priors. In the incarceration length models, there was still some observed sexual disparity, but the observed racial disparity was minimal. These patterns are also largely consistent with the existing sentencing research (see Baumer, 2013; Mitchell, 2005; Spohn, 2000; Ulmer, 2012).

There are some common patterns found in the models after the addition of the four measures of criminal specialization. First, these measures all provide some additional explanatory power of the sentencing models. All of the measures were significantly correlated with the sentence in some of the models. Moreover, the addition of the specialization measures does improve the model fit, albeit only slightly. The inclusion of the NIR adds most to the model fit, but as discussed in the Results section, it could also be due to the inclusion of the additional regressors—the number of convictions of other crime types. Therefore, it cannot be simply interpreted as that the NIR improves the model fit most. Second, criminal specialization does not seem to alter the existing relationship between incarceration and the extralegal variables, which is contrary to one of the hypothesis of the study. In other words, there does not seem to be a

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strong correlation between criminal specialization and the extralegal variables in this particular analytic sample. The inclusion of criminal specialization does affect the relationship between the sentence and the criminal record variable (i.e., the number of felony convictions), which is not surprising because the specialization measures (especially the NIR and the number of convictions of other crimes) tend to correlate with the number of prior felony convictions. The sentence length models reveal that criminal specialization, in general, is not a good predictor of the sentence length as demonstrated by the coefficients that were either small or non-significant. Therefore, either all of these measures fail to model the way the prosecutors and judges make use of criminal specialization in the decision of the sentence length, or perhaps criminal specialization does not matter to the sentence length.

What is different, however, is how each of the measures correlated with the sentence. In general, the four measures demonstrate two different patterns in explaining incarceration. The IPC and the NIR are both direct measures of repetition. Repetition means a higher level of individual risk (e.g., Champion, 1994; Kurlychek et al., 2006; Nagin & Paternoster, 1991), as well as a higher level of culpability (e.g., Wasik & von Hirsch, 1995). Therefore, sometimes there is a specific sentence enhancement for the defendants who repeat certain types of crimes (e.g., Caseload Forecast Council, 2015; United States Sentencing Commission, 2015). From the standpoint of either the focal concerns (Steffensmeier et al., 1998) or the bounded rationality (Albonetti, 1991) perspectives, it would not be surprising if the prosecutors and judges impose a more serious sentence on the defendants who repeat the same type of crimes even in the absence of the specific sentence enhancement. In the empirical models, the NIR significantly predicted the sentence for most of the crimes, while the IPC significantly predicted the sentence for fewer types of crimes. However, one pattern in common is that the correlation was *always positive*

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when significant. The difference between the IPC and the NIR is that the IPC only focuses on *the last crime,* whereas the NIR focuses on *all the criminal records*. It is also not surprising for the prosecutors and the judges to evaluate the defendants' criminal records holistically. In other words, compared with the NIR, the focus of the IPC might be too narrow.

To the contrary, criminal specialization predicted a *lower* probability of incarceration when measured as the specialization index and the classes. Unlike the IPC and the NIR, both the specialization index and the classes model the overall preponderance of crime types in the criminal records, and do not directly model the degree of repetition. The coefficients for the specialization index were negative in 14 of the 15 models, and were negative and significant in 12 of the 15 models. The defendants assigned to the specialist classes had a statistically-non-differentiable probability of incarceration when compared with the Low Involvement Generalists, and had a lower probability of incarceration than the Drug Generalists and the High Involvement Generalists. There are at least two possible explanations to this seemingly counterintuitive pattern. The first possibility is that the two measures are flawed in capturing the meaningful information in the sentencing decisions. For example, the "specialists" found by specialization index could be those who specialized in less serious crimes (such as driving crimes) or crimes that were different from the current one (see Tables 9 and 12). In LCA, some of the classes may still contained a mix of defendants the use of the classes precludes further differentiation among them. LCA assumes the homogeneity conditional on the class (McCutcheon, 1987), which is almost certainly a strong one when it is performed on over 100,000 cases and 17 manifest variables. In both scenarios, the true properties that determine the risk could be masked. The second and potentially more interesting possibility is that the prosecutors and judges did consider the generalists as more dangerous and culpable than the

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specialists. As mentioned in the beginning of the paper, the theoretical link between criminal specialization and risk/culpability is ambiguous. It is totally possible for the prosecutors and judges to consider the defendants who specialize (especially for those who specialize in non-serious crimes) as more predictable (and therefore less risky) than those who commit all kinds of crimes, and therefore for them to punish the specialized defendants *less* harshly than the generalists.

Because the dataset used in the current study has no direct information on the prosecutors' and judges' decision process, it is probably more appropriate to acknowledge the possibility that both sets of measures have captured a portion of the decision making process, rather than to simply conclude that some of the measures are right, and some of the measures are wrong. After all, repetition and concentration are both important indicators of criminal specialization. If a defendant has a high value in one indicator, it does not necessarily mean the defendant will have a high value in the other. Therefore, the present study joins the research of criminal specialization (e.g., Sullivan et al., 2009) and contends that it is probably too early to claim that there is a single best measure of criminal specialization and none of the other measures are necessary, regardless for the purpose of understanding the criminal careers themselves or the use of criminal careers by the actors in the criminal justice system. That being said, there is no guarantee that the explanations to the findings (particularly to the negative coefficients for the specialization index and the classes) are valid. It would be important for future research works to explore the way criminal specialization works in the sentencing context, and preferably with other kinds of research design (such as interviews or experiments) which can have the potential to address the questions that cannot be answered by the use of large-scale administrative datasets.

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The design of the present study has some limitations. First, I use a selective sample—a conviction sample—for the analyses. That means the pre-conviction decision points are not considered. The literature has recognized that the pre-conviction decision points shape the final observed sentence (e.g., Kutateladze et al., 2014; Rehavi & Starr, 2014), which cannot not be tested in the present study. The selection process into conviction may have correlated error terms with the selection into incarceration, therefore, the coefficients found in the current model, even those in the incarceration model (the first stage) may be biased (see Bushway, Johnson, & Slocum, 2007). Second, the present study uses a separate model for each conviction crime type. Some of the models have a small sample size and might suffer from the lack of statistical power, and this is particularly problematic for the incarceration length models. For example, almost none of the variables was able to predict incarceration significantly in the MV larceny model ($n < 600$). Nevertheless, the models are still able to detect some significant correlations between the sentence and criminal specialization, even in some of the models with a small sample size.

The unique characteristics of the dataset used may also have affected the findings. First, the present dataset has only the top charge in the criminal records. If a defendant was convicted of two different types of crimes for the same event (e.g., one count of robbery and one count of drug possession), only the most serious crime (robbery in the current example) would be recorded, and the defendant's record would appear as if there was no conviction for the drug crime. However, the prosecutors and judges may see the complete list of charges, rather than only the top charges, on the defendants' rap sheet. This could further result in a systematic underestimation of the defendants' degree of specialization in the less serious crimes. Second, the dataset has no reliable records of the defendants' "exposure time" (i.e., the time at which these defendants were not incarcerated in jail or prison). The classic criminal careers perspective

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considers the frequency of criminal activities as a crucial indicator of the defendant's risk (see Blumstein et al., 1986; Bushway & Piehl, 2007; Bushway & Tahamont, 2016). For example, one defendant had two convictions of robbery in a five-year period, and spent one year in prison. Another defendant also had two convictions of robbery in the five years, but spent four years in prison during the period. It would be totally possible for the prosecutors and judges to have different assessments of the risk and culpability of the two defendants. While it is unambiguous that failing to control for the exposure time will lead to the underestimation of the crime frequency, how the issue would impact the estimates of specialization is ambiguous. If the defendant is specialized, then the degree of specialization will be underestimated. If the defendant is versatile, then the degree of specialization may be overestimated because the crimes that defendant would have committed may be of different types. Third, the dataset does not have information on the out-of-state criminal records, which may also be visible to the prosecutors and judges and might make a crucial impact for some defendants. For example, some of the defendants processed in New York City, owing to its geographic proximity to Connecticut, New Jersey, and Pennsylvania, may also have criminal records in other states. While I have acknowledged the possible impacts on the findings due to the dataset itself, there does not seem to be a realistic way to correct for these issues. I can only advise the readers of the paper to be aware of these potential limitations.

As summarized, the present study has demonstrated the potential use of criminal specialization from the criminal careers literature in the efforts to understand the sentencing process. Many other aspects of the criminal justice careers, such as escalation, the onset age, the frequency, and the duration of the career, can also relate to the assessment of the defendant's risk and culpability, and therefore affect the sentencing decisions. I hope the present study can serve

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as the beginning, rather than the end, of a conversation that has the potential to be very productive.

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Chapter 3

What Hides in the Shadow? The Magnitude of the Plea Discount in New York State

Abstract

Many research works have pointed out that defendants who plead guilty receive a less harsh sentence than those convicted at trial. Most quantitative studies of the plea discount used solely conviction samples, and were unable to capture the sentence discount due to the movement of the charges (i.e., the magnitude of charge bargaining or the charge discount). Building on Smith's (1986) methodological framework, Piehl and Bushway (2007) introduced an approach to estimate the magnitude of the charge discount. For every defendant who pled guilty, they estimated a counterfactual—the sentence the defendant would have received if he or she pled guilty to the arraignment charge. The difference between the counterfactual and the observed plea sentence was considered the charge discount.

However, this framework neglected the issue of overcharging. Prosecutors may, intentionally or unintentionally, file initial charges that are unlikely to result in a conviction at trial. As a result, the counterfactual estimated from the arraignment charge may not be a credible threat in the defendant's contemplation between going to trial and pleading guilty. In other words, the counterfactual, as well as the plea discount calculated from the counterfactual, may be overestimated if the researcher fails to take overcharging into account.

The present study is the first one, to my knowledge, to estimate the magnitude of the plea discount using statewide samples. Moreover, it improves the quality of the estimates by

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proposing a new analytic framework of the plea discount, which takes overcharging into consideration. I estimate a "charge bargaining" model using the subsamples of defendants who were convicted at trial. However, this estimated discount cannot be due to charge bargaining, and may instead indicate the magnitude of overcharging.

To demonstrate the use of the new framework, I compare the estimates of the plea discount when overcharging is taken into account and the estimates when it is not. I obtain the benchmarks of the estimates from the prediction of the model "bargaining in the shadow of trial," one that is dominant in explaining the plea discount and is supported by existing studies at the aggregate level. The study finds that taking overcharging into account brings the estimates of the plea discount closer to the prediction of the "shadow of trial" model.

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Many research works have found that, on average, defendants who pled guilty receive less harsh sentence than comparable defendants who were convicted at trial (e.g., Brereton & Casper, 1982; Johnson, 2003; King et al., 2005; Ulmer, 1997). This difference in the sentence is known as the "trial penalty" among sociologists and criminologists (e.g., Ulmer & Bradley, 2006; Ulmer et al., 2010), and the "plea discount" among legal scholars, economists, and psychologists (e.g., Abrams, 2011; Bushway & Redlich, 2012; Bushway et al., 2014). Plea bargaining has become the norm, rather than the exception, for the disposition of criminal cases, Statistics have shown that over 95% of convictions are the results of a guilty plea (e.g., Reaves, 2013, Table 21). Yet compared with the numerous works explaining the disparity at the sentencing stage, researchers have made relatively less progress in estimating and explaining the plea discount (Piehl & Bushway, 2007; Ulmer & Bradley, 2006).

The main difficulty in the estimation of the plea discount is that a defendant either pleads guilty or goes to trial. Unlike studies of the treatment effect in experimental settings, the researcher cannot directly observe the pre- and post-treatment measures on the same individual. For a given defendant who pleads guilty, the counterfactual (i.e., the sentence he or she would have received if convicted at trial) has to be obtained from a reasonable estimation. To address this problem, Smith (1986) introduced an approach to estimate the counterfactual for the defendants who pled guilty, which was further applied in a more recent study by Piehl and Bushway (2007) to estimate the magnitude of the charge discount in two large urban counties.

Although Piehl and Bushway's (2007) study clearly demonstrated the use of the counterfactual approach, there were three major limitations. First, they used only a total of 500 cases collected from two counties, and the estimates might be different from studies using a representative sample. Second, they estimated the counterfactual *plea sentence*, rather than the

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counterfactual *trial sentence*. Therefore, they were not able to capture the total plea discount, and were not able to differentiate the charge discount and the sentence discount. Third and most importantly, they attributed the entire sentence discount associated with the charge movement (which takes the form of charge reduction in most circumstances) to charge bargaining, and did not take the possibility of overcharging into consideration. Overcharging refers to the circumstances in which a defendant is charged with a crime that is more serious than one that would secure a conviction (Caldwell, 2011; Carp et al., 2014; Graham, 2014). In the case of overcharging, the estimated counterfactual trial sentence is likely to be higher than what the defendant would actually have received if he or she opted for trial.

The present study attempts to make three contributions to the existing literature. First, it is, to my knowledge, the first attempt to estimate the magnitude of the plea discount using statewide populations of defendants who pled guilty, with a total *n* of over two million. Second, it is also the first study to differentiate between the charge discount and the sentence discount. Third, I address the overcharging problem by proposing a revised framework for the original counterfactual approach. I first estimate a counterfactual for the plea defendants following exactly Smith's (1986) method. I then discount that counterfactual by an adjustment factor to rule out the impact of overcharging. In order to evaluate the validity of the estimation, I examine the estimates of the plea discount with and without overcharging against the prediction of the theory "bargaining in the shadow of trial," which contends that the ratio between the plea sentence and the trial sentence would be equal to the probability of conviction at trial (Bibas, 2004; Landes, 1971; Mnookin & Kornhauser, 1979; Nagel & Neef, 1979). The results demonstrate that taking overcharging into consideration does bring the estimates of the plea discount much closer to the prediction of the shadow model.

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The Estimation of the Plea Discount

A major motivation for the defendants to plead guilty is to receive a less harsh sentence. A convention among researchers of plea bargaining is to divide the whole process into two components, sentence bargaining and charge bargaining (e.g., Figueira-McDonough, 1985; Maynard, 1984; Miethe, 1987; Nagel & Schulhofer, 1992; Spohn, 2009). In return for a guilty plea, the prosecutor may opt to offer a sentence towards the lenient end within the statutory range. The prosecutor may also offer to reduce the severity of the charges, or to drop some of the initial charges. Both options can lead to a less harsh sentence, compared with what would have been meted out if the defendant were convicted at trial. These options may be, and often are, applied simultaneously in a given case.

While many researchers have attempted to investigate and explain plea bargaining using qualitative methods (e.g., Eisenstein & Jacob, 1977; Heumann, 1978; Nardulli et al., 1988; Ulmer, 1997), there has also been considerable effort to investigate both components of the plea discount quantitatively. The typical way to estimate the sentence discount is to estimate a regression model explaining sentence length, on a sample of convicted defendants, using a dichotomous trial variable as the key independent variable and a set of observed legal and extralegal variables as the control variables (e.g., Brereton & Casper, 1982; Ulmer & Bradley, 2006; Ulmer et al., 2010). This approach estimates the sentence discount (often described as the "trial penalty") as the sentence difference between the defendants who were convicted at trial and the defendants who pled guilty, controlling for the observed legal and extralegal variables. A major concern over this approach is that it does not capture the impact of the charging decision and charge bargaining, which is considered a major source of sentence disparity in contemporary

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sentencing research (e.g., Kutateladze et al., 2014; Rehavi & Starr, 2014; Shermer & Johnson, 2010). Moreover, this approach also does not consider the probability of acquittal at trial, and has only a limited capability to address the difference between the defendants who pled guilty and the defendants who were convicted at trial (Bushway & Redlich, 2012). Simply estimating a regression model using a conviction sample cannot provide a credible estimate of the counterfactual for those who pled guilty.

The estimation of the charge discount is even more complicated. The simplest dependent variable used to study the charge reduction is whether or not the initial charge was reduced (e.g., Albonetti, 1992; Figueira-McDonough, 1985; Kutateladze et al., 2015; 2016; Spohn & Horney, 1993).[12] More sophisticated methods to measure the charge reduction include the number of statutory levels reduced (e.g., counting the movement from a Class A Felony to a Class B Felony as one and the movement from a Class A Felony to a Class C Felony as two; see Vance & Oleson, 2014; R. Wright & Engen, 2006; 2007), or the reduction of the statutory maximum sentence in percentage (e.g., Bernstein et al., 1977; Bishop & Frazier, 1984). These studies typically sought explanation of the charge reduction using legal and extralegal variables, and did shed lights on our understanding of the disparities in this process. Yet one critical shortcoming of these studies is that in most cases, they cannot establish the link between the charge reduction and the reduction of the sentence. In other words, the study of *the charge reduction* is not necessarily capturing *the charge discount*.[13]

[12] Of course, sometimes the defendant is convicted of a charge that is more serious than the initial one. However, it is relatively rare in practice. I use the term "charge reduction" to describe the most likely result of plea bargaining, and I have no intention to deny the possibility that the charge may go up in individual cases.
[13] The connection between charge reduction and the sentence is stronger in some circumstances where the sentence and the charge are closely connected by the law. Examples include the federal sentencing guidelines as well as the mandatory minimums (see Rehavi & Starr, 2014; Shermer & Johnson, 2010). However, in the majority of jurisdictions, a given charge is associated with a broad range of sentencing options, which would lead to problems making direct inference from the charge reduction to the charge discount.

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Piehl and Bushway (2007) moved one step forward and attempted to estimate the charge discount by adopting an approach introduced by Smith (1986). They first estimated a regression model to explain the sentences defendants pled guilty to, using *the disposition charge* and other observed variables, assuming the regression equation modeled the sentence generating process in guilty pleas. They then used the coefficients obtained from the model and the information of *the initial charge* to predict the sentence the defendants *would have received had they pled guilty to the initial charge*. The difference between the counterfactual sentence and the plea sentence was the charge discount—*the amount of sentence reduction explained by the charge reduction*.

Smith's (1986) approach, which has been referred to as "the best previous empirical work comparing sentences after trial and after plea bargain" (Abrams, 2011, p. 203), can also be used to estimate the entirety of the plea discount (i.e., the charge discount plus the sentence discount), by estimating *a counterfactual trial sentence* (as opposed to *a counterfactual plea sentence* like Piehl and Bushway did) for the defendants who pled guilty. As Piehl and Bushway (2007, p. 108) summarized,

> In [Smith's] case, he needed to know the sentencing outcome at trial for someone who pled guilty. To create an estimate of this unobservable value, he first estimated regression models for conviction and incarceration for those who went to trial. He then used the coefficient estimates from these models to predict both the probability of conviction at trial and the probability of incarceration for those who plead guilty.

In his original work, Smith (1986) was interested in estimating the probability of incarceration, rather than the sentence length. Presumably because of the lack of trial cases in the data used (State Court Processing Statistics, SCPS, see Reaves, 2013 for more details about the dataset), Piehl and Bushway (2007) only estimated the charge discount rather than the entire plea discount. Following the approach of Smith and Piehl and Bushway, a researcher can estimate the plea discount in a straightforward manner, if the dataset he or she uses has a sufficient number of

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trial cases. However, as I discuss in detail below, and demonstrate using a series of empirical examples later in this paper, one major limitation of Smith's original approach is that it fails to account for the possibility of overcharging. Mathematically, failing to consider overcharging may lead to the overestimation of the counterfactual, and may therefore also lead to the overestimation of the plea discount. Substantively, a researcher would attribute all the discount to plea bargaining if overcharging is not taken into account, which may lead to incorrect interpretation of the quantitative findings.

Overcharging and the Components of the Plea Discount

The legitimacy of the American plea bargaining process has been hotly debated among legal scholars for nearly half a century (e.g., Alschuler, 1968; 1976; Easterbrook, 1992; Langbein, 1978; Schulhofer, 1984; 1992; Scott & Stuntz, 1992). Among the issues raised by the legal scholars, one is that prosecutors may sometimes intentionally charge the defendant more seriously than they should have (e.g., Alschuler, 1968; 1976; Davis, 2007; Caldwell, 2011; Meares, 1995; Rakoff, 2014; Schulhofer & Nagel, 1997).[14] According to these arguments, the main purpose of overcharging is for the prosecutor to gain a leverage at plea bargaining, because the defendant would face a more serious "threat" for insisting in going to trial instead of pleading

[14] Some scholars contended that overcharging exists in both "horizontal" and "vertical" forms (e.g., Alschuler, 1968; but see Graham, 2014). Horizontal overcharging refers to filing more counts of charges than appropriate, while vertical overcharging is the filing of more serious charges than appropriate. This paper mainly addresses vertical overcharging, and only addresses horizontal overcharging to a limited extent. This is for two reasons. First, scholars holding this view believed that vertical overcharging was more problematic than horizontal (e.g., Alschulerl, 1968, 1976). Second, the dataset used in the study has only the information on the top (most serious) charge (including the count of the top charge) and does not record whether additional charges of other types are being filed.

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guilty. Nearly four decades ago, U.S. Supreme Court Justice Blackmun has stated in his dissenting opinion in *Bordenkircher v. Hayes* (1978, p. 368),

> That prosecutors, without saying so, may sometimes bring charges more serious than they think appropriate for the ultimate disposition of a case, in order to gain bargaining leverage with a defendant, does not add support to today's decision, for this Court, in its approval of the advantages to be gained from plea negotiations, has never openly sanctioned such deliberate overcharging or taken such a cynical view of the bargaining process.

Despite of the debate, there does not seem to be a universal agreement on the definition of overcharging. This is because "overcharging" would depend on the perception of the "appropriate" charge, which is not well-defined. Recently, Graham (2014) argued that the practice of overcharging would not necessarily indicate prosecutorial misbehavior, and might not even be intended by the prosecutors. The standard of proof for filing a charge is probable cause, and the standard of proof for a conviction is beyond reasonable doubt. At arraignment, the prosecutor may largely follow the charges suggested by the police officer (Clair & Winter, 2016). As the case moves further down the pipeline, and especially when evidence is being exchanged with the defense, the prosecutor may gain more information about the case, and may realize that the initial charge is too serious to be readily proven by the evidence. This type of overcharging is less problematic, and may result in the reduction or the dismissal of the original charge, even without the bargaining. What is more problematic, as Graham contended, are the circumstances involving "prosecutorial insincerity," which occurs when "a prosecutor files an 'excessive' charge or charges *without any subjective desire to pursue these offenses to conviction*" (p. 712, emphasis added, notes in the original text omitted). Carp et al., (2014, p. 233) reported an example of this type,

> Grand Juror: In this case where one fellow killed another in the barroom fight, why do you want us to indict on a first-degree murder charge? There doesn't seem to be any premeditation here. *You'll never get a conviction on that*.

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[The District Attorney]: Oh, I know. But it will strengthen our hand at the time when we talk with his attorney.

The intention of the prosecutor differs considerably in these two scenarios. However, what is common is that in both circumstances, the prosecutor *files a charge that is unlikely to result in a conviction if the defendant opts for trial*. In other words, the counterfactual—the initial charge and the sentence associated with it—is not as realistic a threat for the defendant as it is in cases without overcharging.[15]

I present this problem graphically. Figure 1 presents Smith's (1986) original framework, without the consideration of overcharging. A defendant faces two options when he or she is charged. The defendant can either opt for a trial for the initial charge, or plead guilty and waive the trial. For each defendant who pleads guilty, we observe the sentence associated with the charge he or she pleads guilty to (hereinafter denoted by S_3, in which S stands for sentence). To estimate the size of the plea discount, one necessary counterfactual is what would have happened if the defendant had opted to trial for the initial charge and ended up convicted (hereinafter denoted by S_1). This counterfactual S_1, which is unobservable and has to be estimated, is typically the harshest sentence a defendant could receive (Piehl & Bushway, 2007). To further disaggregate the plea discount into the charge discount and the sentence discount, another necessary counterfactual is what would have happened if the defendant were convicted of the

[15] Because of this criterion, and in order to be parsimonious in the use of terms, I consider both types of practices described in the paragraph above as "overcharging," as opposed to using a lengthier term such as "intentional and unintentional overcharging." Whenever overcharging is mentioned in this paper, there is no normative argument associated with the term, and I do not indicate that the prosecutor has done so intentionally. There are also circumstances in which the prosecutor files a charge that is more serious than he or she would file normally in similar cases, but can still prove the charge beyond a reasonable doubt. I do not consider those cases to be overcharging based on my criterion, even if the appropriateness of such practice might be questionable (Graham, 2014).

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disposition charge at trial (hereinafter denoted by S_2).[16] Compared with S_3, S_2 is estimated holding the charge constant, and the only difference between S_2 and S_3 is a conviction at trial and a guilty plea. Therefore, the total plea discount is $S_1 - S_3$, the charge discount is $S_1 - S_2$, and the sentence discount is $S_2 - S_3$.

[Figure 1 approximately here.]

Figure 2 depicts the revised framework, after taking overcharging into account. There are four components, instead of three, in this framework. The plea sentence S_3, as well as the counterfactuals S_1 and S_2, are the same as in Figure 1. The only difference is that I add in an adjustment to the counterfactual S_1, hereinafter denoted by S_1^*, to represent the "true" trial sentence, after excluding the portion associated with overcharging from the counterfactual S_1. Under this new framework, the plea discount is $S_1^* - S_3$, as opposed to $S_1 - S_3$. The charge discount is $S_1^* - S_2$, and the sentence discount is still $S_2 - S_3$. The distance between S_1 and S_1^*, on the other hand, is the overcharging discount, a discount to reflect the argument that not all the initial charges would result in a conviction. The overcharging discount is unrelated to the fact that the defendant pleads guilty, and therefore should not be considered as a component of the plea discount.

[Figure 2 approximately here.]

While the framework is straightforward, the question is how to estimate the overcharging discount. As Justice Blackmun (1978, p. 368) argued, "[n]ormally, … it is impossible to show" that a prosecutor is overcharging, particularly because there is "a paucity of reliable data"

[16] Both S_1 and S_2 (as well as S_1^*, p, and d, which are defined later in the paper) are predicted values from regression models. For simplicity, the paper does not denote these estimated counterfactuals by the hat symbol (such as $\widehat{S_1}$). However, it is necessary to recognize that only S_3 is an observable variable, and the counterfactuals are not.

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(Caldwell, 2011, p. 82). It is true that the estimation of the overcharging discount, in the sense of prosecutorial insincerity noted by Graham (2014), is not possible when using administrative case processing data. However, it is necessary to recognize that the defendants convicted at trial sometimes also receive a charge reduction from arraignment to conviction. Unlike the defendants who plead guilty, this charge reduction cannot be associated with plea bargaining. Instead, I argue that this discount serves as a correction for overcharging, regardless of whether the overcharging is intentional. This argument builds on the assumptions under a rational choice framework. Specifically, it assumes that both parties possess the complete set of information related to the sentence, and are therefore aware of the overcharging and the exaggerated threat. While the assumption seems strong, it is supported by two reasons. First, as contended earlier in the subsection, the prosecutor may adjust the charge after the exchange of information with the defense, under which circumstances the defense would be aware of the overcharging. Second, the assumptions under the rational choice framework are parsimonious and have been widely used as the basis to model the plea bargaining process (see the discussion of the "shadow of trial" model in the next subsection). Under the assumption that the charge reduction received by the defendants convicted at trial is the result of overcharging, the magnitude of the overcharging discount can be estimated using Piehl and Bushway's (2007) approach to model charge bargaining.

The Shadow Model: The Benchmark of the Plea Discount

Figures 1 and 2 clearly demonstrate that for the defendants who plead guilty, both the counterfactual trial sentence and the plea discount may be overestimated if overcharging is not taken into account (i.e., if S_1 rather than S_1^* is used). An immediate question is how can one tell

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whether the estimated discount looks accurate or too big. In fact, sometimes researchers have indicated that the plea discount they estimated seems large. For example, Ulmer and Bradley (2006, p. 658, emphasis added) acknowledged that while they were unable to discount the trial sentence by the probability of conviction because of the dataset they used (a conviction sample), "the size of the trial penalties we have found here are *so substantial* that it is unlikely that they would be completely offset by the chances of acquittal." The present study contends that the benchmark of the estimates comes from the dominant theory of plea bargaining—the model "bargaining in the shadow of trial" (hereinafter referred to as "the shadow model;" see Bibas, 2004; Bushway & Redlich, 2012; Bushway et al., 2014; Landes, 1971; Mnookin & Kornhauser, 1979; Nagel & Neef, 1979). The shadow model seeks to explain the variation in the plea discount at the individual case level, and argues that the plea sentence should be equal to the expected sentence at trial, that is, the sentence if convicted at trial discounted by the probability of conviction at trial. Mathematically,

$$S_P = p * S_T \tag{2}$$

in which S_P stands for the plea sentence and S_T stands for the trial sentence. The variable p stands for the probability of conviction, which is typically associated with the strength of evidence. For example, if a defendant faces a prison sentence of 10 years if convicted at trial, and the probability of conviction at trial is 0.7 (or 70%), then the defendant would accept a plea offer with a prison sentence of 7 years.

The shadow model builds on a set of assumptions. For instance, both the prosecutor and the defendant are rational and risk-neutral, and both parties possess the complete set of information relevant to the outcome of the case (Bushway & Redlich, 2012; see also the subsection above). Because of these assumptions, researchers have raised serious questions on

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the validity of the model (e.g., Bibas, 2004; Stuntz, 2004). Nevertheless, a series of studies using empirical case processing data largely supported the model at the aggregate level (i.e., there was no significant difference between the sentence received by the defendants who pled guilty and the sentence received by the defendants convicted at trial, after discounting the latter by the probability of conviction; see Elder, 1989; LaFree, 1985; Rhoades, 1979; Smith, 1986). Bushway and Redlich (2012) directly tested the shadow model, and found support of the model at the aggregate level but not the individual case level. In a more recent experimental study, Bushway et al. (2014) found that the prosecutors and defense attorneys largely behaved in accordance with the shadow model, but the judges tended to offer a fixed discount regardless of the probability of conviction.

While quantitative studies seem to provide support of the shadow model at the aggregate level, one notable exception comes from Abrams (2011), who also followed Smith's (1986) original approach and found that the defendants, on average, pled to a harsher sentence than the expectation at trial. He contended that the finding could imply a variety of possibilities, including the defendants being irrational or risk-averse, or the shadow model simply failed to consider the considerable non-sentence costs associated with trials (such as the time costs of the court involvement and the monetary costs of legal representation; see also Kohler-Hausmann, 2013). In the last circumstance, a revision to the original shadow model could be written as

$$S_P = p * S_T + C \qquad (3)$$

in which C stands for the non-sentence costs.

If the original shadow model is true, from Equation 2 we have

$$p = \frac{S_P}{S_T} \qquad (4)$$

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Given existing studies' support of the shadow model at the aggregate level, I consider it reasonable to use p as the benchmark in the estimation of the plea discount. In Smith's (1986) original framework presented in Figure 1, S_P is S_3, and S_T is S_1. In the revised framework presented in Figure 2, S_P is still S_3, but S_T would be S_1^* instead of S_1. In both cases, p would be estimated separately from the counterfactual sentences.

The present study assumes that, on average, the realistic counterfactual trial sentence for the defendants who pleads guilty (i.e., the sentence would have been meted out if he or she *were convicted at trial*) is only a portion of the sentence estimated using Smith's (1986) approach (i.e., the sentence would have been meted out if he or she *were convicted of the arraignment charge at trial*),

$$S_1^* = d * S_1, 0 < d < 1 \quad (5)$$

in which d is the adjustment factor, which is unrelated to plea bargaining but represents the correction to overcharging.

The present study has two key hypotheses. First, failing to consider overcharging would lead to the overestimation of both the counterfactual trial sentence and the plea discount. Second, taking overcharging into consideration fixes, or at least considerably alleviates, the problem. If the hypotheses are true, it would turn out that

$$p > \frac{S_3}{S_1} \quad (6)$$

and

$$p = \frac{S_3}{S_1^*} \quad (7)$$

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The following hypothetical example demonstrates the point. Assume that for a hypothetical defendant, the probability of conviction at trial is 0.5 (p, 50%), and the defendant pleads guilty to a sentence of 3.5 years (S_3), If the original framework predicts that the defendant would receive a sentence of 10 years if convicted of the arraignment charge at trial (S_1), then the ratio of the plea sentence and the counterfactual trial sentence would be 0.35 ($\frac{3.5}{10}$), which is smaller than 0.5 and indicates that the plea discount is overestimated. If the adjustment factor (d) is 0.7 (i.e., on average, 30% of the original counterfactual trial sentence is associated with overcharging and would not be imposed even if the defendant is convicted at trial), then the sentence that defendant would have received if convicted at trial is 7 years (S_1^*, 0.7 * 10), and the ratio of the plea sentence and the adjusted counterfactual trial sentence would be 0.5 ($\frac{3.5}{7}$), which is in accordance with the shadow model.

The reason why differentiating S_1^* from S_1 is crucial is that these numbers have a substantive meaning. If a researcher believes in the shadow model, and does not consider overcharging in the example above, it would appear as if the defendant pleads guilty when he or she has only a 35% probability of conviction at trial. This implies that the plea bargaining process is highly coercive. Bjerk (2007) contended that the plea bargaining process cannot simultaneously punish the guilty defendants to the maximum extent and identify and exonerate the innocent defendants. He argued that an innocent defendant would plead guilty if the threat was too harsh, or if the deal was "too good" relative to the threatened sentence and the probability of conviction. Indeed, if a rational defendant is facing a 10-year sentence with a 50% probability of conviction, a plea offer of 3 years is a good deal, and he or she should accept that deal even when innocent. While this seems to fit the definition of coercion, it is noteworthy that the statement is only valid when the estimate of 10 years is a valid and reasonable expectation of

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the trial sentence. The situation might look different if the expected trial sentence is lower, which is what would happen once overcharging is taken into account. In the example above, once the overcharging discount is applied to the original counterfactual, the plea deal conforms with the prediction of the shadow model.

To demonstrate empirically how overcharging affects the estimation of the plea discount, I will next present my analyses using actual, large-scale case processing data. It is necessary to explicitly state that this study itself does not, and cannot, test the validity of the shadow model. Instead I simply assume the validity of the shadow model at the aggregate level (Bushway & Redlich, 2012; Elder, 1989; LaFree, 1985; Rhoades, 1979; Smith, 1986). Building on the assumption, I use the prediction of the shadow model (Equations 6 and 7) as the benchmark to evaluate the quality of the estimates of the plea discount.

Method

The Empirical Models

The original counterfactual approach. In Smith's (1986; see also Bushway & Redlich, 2012; Piehl & Bushway, 2007) approach, for each defendant who pleads guilty, there is a counterfactual trial sentence (S_1 in Figure 1), that is, the sentence the defendant would have received if convicted at trial of the arraignment charge. To estimate S_1, I start with a regression model explaining the sentence of the defendants who were convicted at trial, using observed legal and extralegal variables as predictors,

$$(S|conviction\ at\ trial) = \beta_0 + \beta_1 * Arraignment\ Charge\ + \beta_2 * Criminal\ Record + \beta_3 * Extralegal\ Variables + \varepsilon \quad (8)$$

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This model does not establish any causal relationship. Rather, it simply estimates how these legal and extralegal variables correlated with the trial sentence. I then use the coefficients obtained from this model to predict the sentence that would have been meted out at trial (i.e., S_1) for the defendants who pled guilty, assuming Equation 8 reflects the generation process of the trial sentence.

To further disaggregate the charge discount and the plea discount, I estimate a second counterfactual trial sentence (S_2 in Figure 1), which is the sentence the defendant would have received if convicted of the disposition charge at trial. The only purpose of estimating S_2 is to disaggregate the charge discount and the sentence discount. Most defendants who pled guilty would never be convicted of (or tried for) *the disposition charge* (i.e., the charge they pled guilty to) at trial, because they would only face *the arraignment charge* had they opted for trial. Following a similar logic as in Equation 8, I first estimate a regression model explaining the trial sentence from the sample of defendants who were convicted at trial,

$$(S|conviction\ at\ trial) = \gamma_0 + \gamma_1 * Disposition\ Charge\ + \gamma_2 * Criminal\ Record + \gamma_3 * Extralegal\ Variables + \varepsilon \qquad (9)$$

and then use these coefficients to predict S_2 for the defendants who pled guilty.

The plea sentence, S_3, is an observed value. The ratio of the plea sentence and the trial sentence is simple $\frac{S_3}{S_1}$. The total plea discount is $S_1 - S_3$, which could be further disaggregated into two components: the charge discount ($S_1 - S_2$) and the sentence discount ($S_2 - S_3$).

The probability of conviction, p, can be estimated using a probit model explaining conviction using all the defendants who opted for trial,

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$$(Conviction|trial) = \delta_0 + \delta_1 * Arraignment\ Charge + \delta_2 * Criminal\ Record + \delta_3 * Extralegal\ Variables + \varepsilon \quad (10)$$

Similarly, I use the coefficients in Equation 10 to predict the probability of conviction at trial (p) for the defendants who pled guilty.

The adjustment factor and the revised counterfactual approach. The key difference between Smith's (1986) approach and mine is that I assume the counterfactual trial sentence to be only a portion of S_1 (i.e., S_1^* in Figure 2, see also Equation 5), rather than the entirety of S_1, because of overcharging. To estimate the adjustment factor (i.e., d in Equation 5), I follow the approach of Piehl and Bushway (2007) in estimating a "charge bargaining" model for the defendants who were convicted at trial. Even for these defendants, sometimes the conviction charge is one lesser than the arraignment charge. Here I place the term "charge bargaining" in quotation marks, because this charge reduction is unlikely to be actually due to charge bargaining—these defendants did not plead guilty. Rather, one reasonable assumption is that the initial charges filed against the defendants were too serious to be proven by the evidence. This "charge discount" found among the defendants who were convicted at trial can be seen as the overcharging discount (i.e., $S_1 - S_1^*$ in Figure 2).

Just like Piehl and Bushway's (2007) original approach to estimate the charge discount, the estimation of the adjustment factor starts with Equation 9. However, instead of estimating the trial sentence for *the defendants who pled guilty*, I stay with *the defendants who were convicted at trial*, and use the coefficients in Equation 9 and the *arraignment charge* of those defendants to predict the sentence that would have been meted out should they have been convicted of the arraignment charge (i.e., the "overcharge"). I then calculate the adjustment factor, d, as the ratio

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between the average sentence predicted using the conviction charge and the average sentence predicted using the arraignment charge, both using the sample of defendants who were convicted at trial.

Lastly, I discount the estimated trial sentence (S_1) for the defendants who pled guilty by d to estimate the adjusted counterfactual trial sentence (S_1^*), which is the more realistic estimate of the sentence they would have received at trial after overcharging is taken into account. With all of S_1, S_1^*, and p obtained, I can test the key hypotheses of the present study, presented as Equations 6 and 7.

Two methodological clarifications are necessary before I move on to present the results. First, even though the shadow model is supposed to work at the individual case level (Bushway & Redlich, 2012; Bushway et al., 2014), all the estimates in the present study are at the aggregate level. This is mainly because I only have limited ability to predict the probability of conviction (p) at the individual case level. One major predictor of conviction is the strength of evidence, which is not available in the current dataset (cf. Bushway & Redlich, 2012). Even though Equation 10 would not provide an ideal estimate of p at the individual case level, it is the best estimate I have. In fact, Smith (1986) himself estimated the conviction probability using a logistic regression in his paper.[17] Second, I estimate all the regression models explaining the sentence length using the ordinary least squares (OLS) approach. This modeling choice may lead to a truncation problem when a using the incarceration length as the dependent variable in sentencing studies (e.g., Albonetti, 1997; Piehl & Bushway, 2007). Defendants who are not

[17] An alternative approach to estimate p is not to use any regression model, and simply assume that the plea sample had the same probability of conviction at trial as defendants who went to trial (see Bushway & Redlich, 2012, p. 446). This approach relies on even stronger assumptions and completely neglects the potential difference between the plea sample and the trial sample. Because of that, I still go with a probit model, while acknowledging it is informative only to a limited extent.

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incarcerated may receive alternative sanctions, which would be coded as zero. To convert the dependent variable into a "sentence severity score," one possible approach is the Tobit regression model (Tobin, 1958; see Albonetti, 1997; Piehl & Bushway, 2007). However, the Tobit model builds on a set of strong assumptions that are sometimes seen as arbitrary. Econometricians have found that the Tobit model may severely bias the estimates, and have argued for alternative, semiparametric approaches such as the censored least absolute deviations (CLAD) model (see Chay & Powell, 2001; Sullivan et al., 2008). However, I was not able to estimate the CLAD models because of a series of practical constraints.[18] Among the two remaining options, I decided to use the OLS estimates because both Chay and Powell and Sullivan et al. have pointed out that the OLS estimated would be less biased than the Tobit estimates. However, it is necessary to realize that because of the number of defendants not incarcerated in the samples, all the estimates of the sentence severity are likely to decrease if I estimated the CLAD models instead of the OLS ones. Based on the information available to me, the exact amount of change in each of the estimates, or how that may affect the key ratios (S_3 over S_1 and S_1^* respectively). Therefore, the relationship between the ratios and the estimates of p might not endure if the CLAD approach was used to estimate the models.

Data

[18] First, the CLAD models relied on bootstrapping, which was extremely computation-intensive and time-demanding. This per se was not a huge issue, because I was interested in predicting the sentence severity, which did not necessarily rely on the bootstrap estimates of the standard errors. Second, and more problematically, many of the regressors used in the study (e.g., the crime severity, the interaction terms, the numbers of prior convictions) would lead to the failure for the models to converge. Up to this moment, I am still working on figuring out the reason and the solution.

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The present study uses the Computerized Criminal History (CCH) data in New York State, maintained by and obtained from New York State Division of Criminal Justice Services (DCJS). The CCH dataset includes the population of arrests made under the jurisdiction of New York State between 1990 and late 2014. It has the top charge (i.e., the most serious charge) at arrest, arraignment, and disposition for each case, the case outcome (i.e., conviction or not), and the sentence for those who were convicted. These characteristics of the dataset allow for a comprehensive investigation of the plea discount. Specifically, unlike the Pennsylvania Commission of Sentencing data and the federal sentencing data (Ulmer & Bradley, 2006; Ulmer et al., 2010), the CCH has pre-conviction information (i.e., the top arraignment charge), and therefore allows for the estimation of the charge discount. Compared with other frequently-used plea bargaining datasets that have pre-conviction information (such as SCPS and the *Plea Bargaining in the United States* data collected by Miller et al., 1978, whose *n* are normally in hundreds or a couple of thousands; see Bushway & Redlich, 2012; Piehl & Bushway, 2007; Smith, 1986), the CCH contains a much larger sample (hundreds of thousands in all the samples used in the present study). The CCH's quality of the coding of some key variables such as crime type and crime severity is also better than the other plea bargaining datasets.[19]

The observation period of the dataset is from January 1990 to September 2014. I select three analytic samples for the present study, each consisting a segment of four years to guarantee the number of trial cases: between 1990 and 1993 (hereinafter the 90-93 sample), between 1999 and 2002 (hereinafter the 99-02 sample), and between 2009 and 2012 (hereinafter the 09-12

[19] For example, studies using the data collected by Miller et al. (1978; see Bushway & Redlich, 2012; Smith, 1986) typically limited the analysis to burglary and robbery defendants because of sample size concerns. SCPS (see Piehl & Bushway, 2007) did not have the statutory crime severity, and only recorded crime severity as felonies and misdemeanors. However, the CCH has a sufficiently large number of cases for most crime types (see also Chapter 2), and has the statutory charge class, both of which would allow for a better explanation of the sentence.

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sample).[20] There are two purposes for selecting three analytic samples. The first is to test the robustness of the method. The second is to examine whether the pattern of the plea discount is stable over time. In each time segment, the key sample of interest is the defendants who pled guilty (the plea samples). Yet in order to estimate the counterfactuals for the plea samples, I also conduct analyses on two other sets of samples. The first is the defendants who were convicted at trial (the trial conviction samples), which I use to estimate S_1, S_2, d, and S_1^* (Equations 8 and 9). The second is the defendants who opted for trial (regardless of convicted or not), which I use to estimate p (Equation 10). There have been some changes in the state criminal statutes over the three observation segments (for details, see New York State Commission on Sentencing Reform, 2009), with the most notable being the introduction of determinate sentencing in 1995 (which affects the 99-02 and 09-12 samples) and the expansion of determinate sentencing up to 2008 (which affects the 09-12 sample). Yet there was still ample room for discretion even after the introduction of determinate sentencing laws. For example, a defendant convicted of a Class B Violent Felony may be sentenced to a determinate prison sentence of anywhere between 5 and 25 years. Because of that, it is impossible to establish the direct relationship between *the charge reduction* and *the charge discount* as the studies using the federal sentencing data did (see Footnote 11), and I have to estimate the plea discount from the counterfactuals estimated for those who pled guilty.

Variables

[20] Each segment is defined as the arrests that took place between January 1st of the starting year and December 31st of the ending year, regardless of the actual crime date and the disposition date.

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The dependent variable of this study is the sentence length, which is directly obtained from the data. The term for defendants received indeterminate prison sentence has a lower bound and an upper bound. I consider the lower bound as the sentence length because most defendants serve only the lower bound (New York State Commission on Sentencing Reform, 2009). I code the sentence length in months, and top code both sentences longer than 480 months and life sentences as 480 months.

I use a set of legal and extralegal variables as the independent variables to predict the sentence in the regression models. I use both the top arraignment charge and the top disposition charge in the present study. Each charge is coded into four variables. I code *crime severity* into seven categories, Class A to Class E Felony (Class A being the most serious and Class E being the least serious), as well as Class A Misdemeanor and Class B/Unclassified Misdemeanor. I code *crime type* into 17 categories, largely based on the categories used in the State Court Processing Statistics, with some modification in consideration of the prevalence and importance of the crime types (see also Table 1 and the Method section of Chapter 2). I also *interact crime type and felony* to allow for the different interaction effects between the crime type and the crime severity,[21] and include *the count of the top charge*. To control for criminal records, I include *the numbers of prior convictions of felonies* and *the number of prior convictions of misdemeanors* in the models. To control for the correlation between the sentence and the extralegal variables, I also include the *race*, *sex*, *ethnicity* (i.e., Hispanic or non-Hispanic), *age*, and *age-squared* of the

[21] Murder, robbery, and burglary had only felony charges, and were not included in the interaction terms. I also tried to interact crime type with crime severity coded in classes (such as robbery * Class D Felony). The substantive results stayed the same, yet the regression models were much more complicated and much more difficult to present. The present paper only presents models with interaction terms in the form of crime type * felony.

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defendant. Lastly, I control for *the county fixed effects* as well as the *year fixed effects*. I cluster standard errors by county in all the regression models.[22]

Results

Explaining the Trial Sentence

Although the present study's samples of interest are the defendants who pled guilty, the analysis begins with the trial conviction samples because the estimation of the counterfactuals relies on regression models using these cases. Table 25 presents the descriptive statistics of the three trial conviction samples. The average incarceration length for the three samples was nearly the same, at around 80 months (6 and 2/3 years). Between 1990 and 1993, 75% of the defendants who were convicted at trial were incarcerated, and the proportion dropped to 67% in the two later time segments. In all the three samples, over two thirds of the defendants were arraigned for a felony, and nearly a half were arraigned for a violent crime. Around 60% of the defendants were convicted of a felony, and around 40% of the defendants were convicted of a violent crime, in all the three time segments. There were also some differences in the distribution of charge severity and type among the samples. Compared with the 09-12 trial conviction sample, the defendants in the 90-93 and 99-02 samples were more likely to be charged with a Class A or a Class B Felony, and less likely to be charged with and convicted of a misdemeanor. The

[22] As a robustness check, I estimated a series of models clustering the standard errors at the county-year level. The results stayed the same. The suggestion of econometrics research is to cluster the standard errors at the higher level because doing so would lead to more conservative estimates (Cameron & Miller, 2015). This is because one potential problem with the use of lower-level clusters (i.e., county-year) is that it might lead to the failure to account for the within-county, cross-county-year correlations between the regressors and the errors. In my case, this did not seem to be a huge problem, since clustering at the lower level did not change the results much. Meanwhile, this also suggested that I would not gain much by clustering the SEs at the county-year level as opposed to the county level. Therefore, I follow the suggestion of econometrics research and only present the models with the standard errors clustered at the county level.

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proportion of defendants charged with and convicted of murder, robbery, and drug trafficking declined over the years, whereas the proportion of defendants charged with assault and driving crimes increased. The average number of prior convictions increased slightly over the time. The defendants in the 90-93 sample on average had 2.7 convictions, while the defendants in the 09-12 sample had over 3.3 convictions. The extralegal characteristics of the defendants in the three time segments were relatively similar, with the vast majority (around 90%) being male, about a half being Black, and about 30% being Hispanic. The more recent defendants were older and were more likely to be White.

[Table 25 approximately here.]

Table 26 presents the regression models explaining the sentence length for the trial conviction samples, using the arraignment charge (Equation 8). For all the three samples, the most important predictors of the sentence length are the severity and the type of the disposition charge. Compared with the defendants convicted of a Class A Felony, those convicted of other severity classes received significantly shorter sentences, although the coefficients of a misdemeanor conviction were similar to those of a Class E Felony conviction. In both the 99-02 and 09-12 samples, compared with the defendants arraigned for murder, the defendants arraigned for other crimes received a shorter sentence. One seemingly counterintuitive finding is that between 1990 and 1993, the defendants arraigned for some non-murder crimes (robbery, assault, stolen property, and public order crimes) received longer sentence than the defendants arraigned for murder. The coefficients of the interaction terms reveal that being arraigned for the same type of crime, a felony arraignment charge predicts a longer sentence, with one notable exception being the defendants arraigned for drug crimes. The relationship between the count of the arraignment charge and the sentence length was significant and positive, but small in magnitude.

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Prior felony records had a positive and significant relationship with the sentence length, whereas prior misdemeanor records had a small negative but significant relationship with the sentence length. There seems to be some extralegal disparity. The Black defendants did not receive a significantly different sentence from the White defendants did except between 1999 and 2002. The Hispanic defendants, to the contrary, received a shorter sentence than the non-Hispanic defendants did. The male defendants received a longer sentence than the female defendants did. The relationship between age and the sentence length was curvilinear. The models perform reasonably well in explaining the variation in the sentence length. The R^2 value of the 90-93 sample model is 0.55, and the R^2 value of the 09-12 sample model is 0.68. Most of the findings in these models are consistent with the overall findings of sentencing research (see Mitchell, 2005; Spohn, 2000; Ulmer, 2012). Although there are some seemingly counterintuitive relationships, they need to be compared and contrasted against the models estimated using the disposition charge to fully understand whether these seemingly abnormalities can be explained by the difference in charge reduction.

[Table 26 approximately here.]

Table 27 presents the regression models estimated with the disposition charge instead of the arraignment charge. The basic pattern is very similar to the models using the arraignment charge, with two major differences. First, for the 90-93 sample, the sentence difference between the defendants of other crimes and the murder defendants largely diminishes or becomes negative (with burglary as an exception). Second, the racial and gender disparities observed in the models using the arraignment charge diminishes. By comparing these models with those presented in Table 26, it seems that the male defendants and the defendants of non-murder crimes received a more favorable charge discount. Not surprisingly, the models with the

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disposition charge do an even better job explaining the sentence length, as all the three models have an R^2 value higher than 0.78.

[Table 27 approximately here.]

Predicting the Counterfactuals

The key task of the present study is to estimate the counterfactuals for the plea samples. Before I present the results, it is necessary to examine the descriptive statistics of the plea samples, presented in Table 28. In all the three segments, approximately 45% of the defendants received incarceration. The average sentence lengths were all between five and seven months, considerably shorter than those of the trial conviction samples. Both sets of numbers indicate that the defendants who pled, on average, received a much less harsh sentence than those who were convicted at trial. This, of course, does not per se imply any evidence supporting the plea discount (or the trial penalty), particularly given that the defendants who pled guilty were convicted of much less serious crimes. In all the three time segments, over a half of the defendants were arraigned for a misdemeanor, and the vast majority of the defendants (70% in 90-93, nearly 80% in both 99-02 and 09-12) pled guilty to a misdemeanor. For both the arraignment charge and the conviction charge, the most frequent types were larceny, drug possession, nuisance, and driving crimes, which stands in stark contrast to the concentration of violent crimes in the trial conviction samples. The average counts of both the arraignment charge and the disposition charge were just above one. The average number of prior convictions was 4.7 in 90-93, 5.2 in 99-02, and 6.5 in 09-12, which were all higher than those of the corresponding trial conviction samples. However, it is notable that compared with the defendants convicted at

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trial, the defendants who pled had fewer felony convictions in 90-93 and in 99-02, and had only slightly more felony convictions in 09-12. The demographic composition of the plea samples was similar to that of the trial conviction samples. In all the three samples, the vast majority of defendants (all approximately 82%) were male, and White and Black defendants each consisted about a half of the sample. The average age was 29 in 90-93, 32 in 99-02, and 34 in 09-12. This age trend is mirrored in national data (Porter et al., 2016).

[Table 28 approximately here.]

I now present the predicted trial sentences for the plea samples in the upper rows of Table 29. I estimate S_1 using the regression models presented in Table 26. The average value of S_1, the estimated sentence if the defendants were convicted of the arraignment charge at trial, is 16.5 months for the 90-93 sample, 14.8 months for the 99-02 sample, and 13.7 months for the 09-12 sample. All the three values are considerably lower than the average sentence received by the defendants convicted at trial, which is not surprising given that the defendants in the plea samples faced much less serious charges. Meanwhile, the predicted values of S_1 are much higher than the mean values of the plea sentence, S_3, which means that the defendants would have received a longer sentence if they were tried for the arraignment charge and were convicted. In other words, there does appear to be a plea discount. To disaggregate the total plea discount into the charge discount and the sentence discount, I also estimate the values of S_2 using the regression models presented in Table 27. Between 1990 and 1993, the average value of S_2 would be lower than the average value of S_3. Yet it is necessary to emphasize that this finding does not indicate that there was no plea discount in those years, because the counterfactual trial sentence—the "threat" faced by the defendants—would be S_1, not S_2. A more appropriate interpretation of the results is that between 1990 and 1993, as well as between 1999 and 2002,

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the plea discount can almost be completely explained by the charge discount, and there was little sentence discount. For the 09-12 sample, the charge discount and the sentence discount each explained about a half of the total plea discount.

The sentence discounts estimated using the counterfactual approach—the difference between S_2 and S_3—is smaller than those estimated using a single regression (e.g., Ulmer & Bradley, 2006). This can be partly explained by the fact that the single regression approach is essentially comparing the mean sentence of *two different groups*—those convicted at trial and those who pled guilty—conditional on the observed characteristics. The approach used in this study, on the other hand, is comparing the observed sentences and the estimated counterfactuals on *the same defendants*. Table 29 also presents the ratios of S_3 and S_1. In all the three samples, the average plea sentence would be approximately 40% of the estimated trial sentence. This means that if the shadow model is true, on average the plea sample had only a 40% average probability of conviction.

[Table 29 approximately here.]

In order to determine whether or not these ratios look accurate or too large, it would be necessary to estimate the values of p for the samples. Table 30 presents the probit regression models explaining the conviction outcome for all the defendants who went to trial. As one might have expected, these models have only a limited capability to explain conviction. Because of the absence of evidence information in the dataset, I refrain from making too much interpretation of the findings. It cannot be readily inferred that whether these coefficients just reflect the degree of the variables' correlation with the evidence strength, or whether they mean something

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substantive.[23] Nevertheless, they are the best available models to predict the probability of conviction for the plea samples. I present the average predicted probabilities of conviction in Table 29, which were 0.56, 0.55, and 0.53 respectively for the three samples.[24] In all the three samples, the average estimated probability of conviction is higher than the ratio of S_3 and S_1, which, as predicted by Equation 6, is what would happen if the value of S_1 is overestimated.

[Table 30 approximately here.]

Does the Adjustment Factor Help?

I now present the adjustment factor, d, and investigate how its inclusion affects the estimates. I go back to the trial conviction samples, and follow the approach of Piehl and Bushway (2007) to estimate the magnitude of "charge bargaining," which would be interpreted as the magnitude of overcharging in the current situation. In order to estimate these counterfactuals, I use the arraignment charge of the defendants in the trial conviction samples, and the coefficients estimated from the models in Table 27, to predict the sentence those defendants would have received if they were convicted of the arraignment charge (i.e., the

[23] The situation is different in models explaining the sentence length, like the ones presented earlier in the paper. A general consensus among sentencing research is that evidence affects conviction, but not the sentence (see Bushway, Johnson, & Slocum, 2007). Therefore, with the absence of evidence information, it is more acceptable to interpret a model explaining the sentence than one explaining conviction.

[24] These predicted values of the probability of conviction may seem lower than the predicted values in other studies using the counterfactual approach. For example, both Smith (1986) and Bushway and Redlich (2012) found that the probability of conviction at trial in their samples to be around 70%. The main reason of this difference relates to the definition of a conviction in New York State. Defendants, especially those initially charged with a misdemeanor, may eventually be convicted of a violation or an infraction. However, violations and infractions are not considered crimes in New York State, and these "convictions" do not lead to the consequences of a criminal conviction. Therefore, I only consider convictions of felonies and misdemeanors as convictions, and that explains the low probability of conviction (both observed in the trial samples and predicted for the plea samples) in the present study. The probability of conviction of the trial sample would be over 70% if I counted violation and infraction convictions.

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“overcharge”) at trial. The results are presented in Table 31. If the defendants in the trial conviction samples were all convicted of the arraignment charge, the average sentence they would have received would be around 105 months, as opposed to 80 months. The value of d is around 0.75 in all the three samples. This means that, realistically, an average defendant would only receive 74-78% of the maximum possible sentence estimated from the arraignment charge, and an average discount of 22-26% of the original estimated trial sentence (S_1) can be explained by overcharging.

[Table 31 approximately here.]

Table 32 presents the results once I take overcharging into account (i.e., the results using the framework presented in Figure 2). Under this new framework, S_1^*, as opposed to S_1, is the sentence the defendants would face if they were convicted at trial, and the distance between S_3 and S_1^*, as opposed to the distance between S_3 and S_1, is the adjusted plea discount. For both the 90-93 and 99-02 samples, the ratio of S_3 and S_1^* are impressively close to p, which is what Equation 7 has predicted. For the 09-12 sample, including d brings the estimate much closer to the prediction of the shadow model, even though there still appears to be some distance between p and $\frac{S_3}{S_1^*}$.

[Table 32 approximately here.]

In sum, if the shadow model’s prediction is considered as the benchmark, then in all the three plea samples, the magnitude of the plea discount estimated directly using Smith’s (1986) counterfactual approach appear to be too large. After I adjust for overcharging, the magnitude of the plea discount in two of the three samples (the 90-93 sample and the 99-02 sample) becomes essentially the same as predicted by the shadow model. The estimated magnitude of the plea

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discount in the 09-12 sample is still larger than the shadow model has predicted, although the estimate after adjusting for overcharging is much closer to the shadow model's prediction than the estimate before the adjustment. This trend itself is interesting. First, compared with the two earlier observation periods, fewer defendants (in absolute numbers, not in proportion among the defendants who pled) pled to an incarceration sentence between 2009 and 2012, and defendants on average pled guilty to a much shorter incarceration term. Second, compared with the earlier years, defendants between 2009 and 2012 received much better plea offers, if the assumptions of the estimates are valid. Both are in accordance with the decline of the incarcerated population in New York State (Mauer & Ghandnoosh, 2015; New York State Commission on Sentencing Reform, 2009). Nevertheless, it seems that the defendants in the most recent observation period were not pleading guilty "under the shadow of trial," and additional analysis would be necessary to explain the discrepancy between the estimated plea discount and the prediction of the shadow model.

Discussion

Legal scholars hold that plea bargaining has become the actual norm for criminal case processing (Bibas, 2004; Schulhofer, 1992; Scott & Stuntz, 1992 Stuntz, 2004). Meanwhile, social scientists view plea bargaining as a major pre-conviction decision that directly impacts the sentence received by the defendants (Baumer, 2013; Spohn, 2000; Ulmer, 2012). Both viewpoints highlight the importance of investigating and explaining the plea bargaining process. Yet before one can explain plea bargaining, it is absolutely necessary to generate reasonable estimates of the plea discount, the dependent variable of interest. Researchers have made some attempts to estimate the plea discount using small case processing datasets (Bushway & Redlich,

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2012; Piehl & Bushway, 2007; Smith, 1986). To my knowledge, the present study is the first to estimate the magnitude of the plea discount using data obtained from an entire state, and the first to estimate both the charge discount and the sentence discount. The estimation serves as the groundwork for future studies seeking to further explain the plea discount.

The shadow model, which is the dominant theory of plea bargaining, argues that pleas occur under the shadow of the trial sentence (Landes, 1971; Mnookin & Kornhauser, 1979; Nagel & Neef, 1979). Yet if researchers move on to model the counterfactuals for the defendants who pleads guilty without further theoretical clarification and empirical disaggregation, the "shadow" that lies between the plea sentence and the estimated trial sentence can be a smog—a mixture of multiple components that masks the true plea discount. The present study contributes to the literature by proposing a framework to differentiate three processes: overcharging (and the correction for it), charge bargaining, and sentence bargaining. Building on the approach of Piehl and Bushway (2007), I provide an empirical estimate of overcharging. Legal scholars have noted the existence of overcharging for decades (Alschuler, 1968; Caldwell, 2001; Meares, 1995), but have only tested it using basic quantitative techniques (Graham, 2014; R. Wright & Engen, 2006; 2007). It turns out that the sizes of the plea discount look much more reasonable when the overcharging discount is excluded from the total discount estimated using Smith's (1986) original approach.

With these findings, the present study provides one additional possibility to explain why the estimated plea discount may look "so substantial" (Ulmer & Bradley, 2006, p. 658). It is simply possible that the total observed discount has an additional component that has been neglected. The present study estimates that approximately 22-26% of the counterfactual predicted using Smith's (1986) approach can be attributed to overcharging. Substantively, it

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means that this portion of the sentence *is unlikely to be imposed even if the defendant opted for trial at the beginning and ended up convicted*. Here, it is necessary to reemphasize that overcharging, in the present study, is defined as whether the defendant would receive a conviction of the initial charge at trial, and does not necessarily come from the prosecutors' intention to press for a plea. Factors such as the misunderstanding of the case strength at the beginning, the exchange of information with the defense, and even the strategic allocation of prosecutorial resource, may all result in the arraignment charge being an overcharge (see Graham, 2014). These factors might be particularly relevant to the present study because I use the arraignment charge as the initial charge. Prosecutors may have only limited involvement in the investigation process prior to arraignment, and it would not be surprising if they reduce the charge in some of the cases even if the defendant does not plead guilty (Clair & Winter, 2016). Because of the nature of the current data, this study cannot identify the presence and the degree of coercion in the plea bargaining process (see Bjerk, 2007; Rakoff, 2014). Moreover, the results of the 09-12 plea sample, that the plea discount still looks large even after considering overcharging, imply that there might be additional components that the new proposed framework have also neglected. Future theoretical and empirical efforts would be necessary to identify additional explanations of the remaining difference.

The present study also has some limitations. The first is that the method builds on a set of strong assumptions. This problem is inherent in Smith's (1986) approach, and the present study has not provided a solution to address it. The estimation of counterfactuals assumes that the trial conviction samples and the plea samples share the same sentence generating process, which, as Klepper et al. (1983) pointed out, may not actually be the case (see also Ulmer & Bradley, 2006). This concern needs at least to be treated seriously since the defendants who opted for trial and

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the defendants who pled may differ in a variety of aspects, such as risk preference and quality of legal representation. If that is the case, then for the defendants who pled, the counterfactuals estimated using regression coefficients obtained from the trial defendants can be inaccurate. This study also assumes that the dependent variable, the sentence length, is not truncated. The results might change if the CLAD models are estimated, and future studies should estimate both the OLS and the CLAD models as a robustness check. Moreover, the sentence generating process might also differ by extralegal characteristics of defendants, such as race, gender, and age, as well as by region. It would be helpful if future studies can propose empirical models that allow for additional flexibility across the different defendant groups.

The second limitation is the insufficiency of information on the charges. The CCH dataset used in the present study has only the top charge (type and count), and does not include less serious charges filed in the same case. In reality it is not rare for a defendant to be charged not only for multiple counts of the same charge, but multiple types of charges as well. For example, a defendant of armed robbery may at the same time face a charge of robbery and a charge of unlawful possession of firearms. The bargaining around the less serious charges is also of potential importance. Moreover, the dataset only has the arraignment charge and the disposition charge, and does not capture the potential movement of charge between these two points (i.e., the "bargain"). It would potentially be helpful if more information on the charges were available.

The third, and perhaps the most crucial limitation, is that the entire story assumes that the shadow model is true on the aggregate level. While this assumption has support in the existing literature (Bushway & Redlich, 2012; Bushway et al., 2014; LaFree, 1985; Rhoades, 1979; Smith, 1986), the legal scholars' concerns over the shadow model (Bibas, 2004; Stuntz, 2004)

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should also to be treated seriously. This need of further testing of the shadow model is particularly salient, since some researchers have started to report findings contrary to the prediction of the model. For example, Abrams (2011) found that the shadow model seemed to neglect key components at the aggregate level, and Bushway and Redlich (2012) failed to find support of the model at the individual case level. If the shadow model is fundamentally flawed, then the validity of the benchmarks, as well as the framework proposed in this study, are called into serious question. As stated earlier in the paper, the present study itself cannot test the validity of the shadow model because of the limitation of the data. Therefore, I join the calls for additional empirical tests of the shadow model and the call for competing mathematical frameworks to explain the plea discount.

Even if the shadow model is valid, it does not necessarily mean that all the other theoretical attempts to explain plea bargaining and the plea discount should be abandoned. The present study has found considerable variation in the composition of the plea discount among the three samples. The plea discount mostly came from the charge discount in the two earlier samples, and came from the both charge discount and the sentence discount in the most recent sample. The shadow model does not seem to be capable of disaggregating the plea discount, and theories from the courtroom workgroup perspective (e.g., Nardulli et al., 1988; Steffensmeier et al., 1998; Ulmer, 1997) may be necessary to further explain the division between the charge discount and the sentence discount. I hope the present study can motivate future methodological and theoretical endeavors in plea bargaining research.

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Chapter 4

General Discussion

The two studies presented above comes from one idea, that is, would it be possible to improve our understanding of the sentencing process by the adoption of the criminal careers perspective? Researchers have been seeking alternatives to the “modal” approach of sentencing research. Examples include the use of case processing data (as opposed to conviction data) to examine the “cumulative advantage” that results from the pre-conviction stages (Kutateladze et al., 2014), and the use of experimental approaches to study the plea process (Bushway et al., 2014). The two studies attempt to point out one additional possible future direction, that is, to better model and make sense of the defendants’ criminal records. Study 1 directly investigates how criminal specialization—one aspect of the criminal justice careers—predicts the sentence. It finds that all the measures could predict the sentence in some way, but the patterns found by the measures are different. Study 2 estimates the magnitude of the plea discount in New York State in three different periods, and finds that taking overcharging into consideration improves the estimates of the plea discount. It does not directly make use of criminal specialization, or any aspect of the criminal justice careers. However, it lays the groundwork for future related works. It would be impossible to study, say, the relationship between criminal specialization and the plea discount, without first figuring out what the plea discount is. I have presented the substantive findings of the two studies in the chapters above. Two themes emerge from the findings The first is the integration of theories and methods, and the second is the search of data.

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Both themes are of considerable significance to future works. This concluding chapter discusses the two themes, and ends with a discussion on potential future works.

The Integration of Theories and Methods

Criminology has its roots in many disciplines. It comes from sociologists, psychologists, political scientists, legal scholars, statisticians, as well as researchers from many other disciplines who are interested in investigating the cause of, and the solution to, crimes (Bernard et al., 2010; Laub, 2004; Newman, 1993). The study of the criminal justice system, including the study of sentencing and plea bargaining, is also multi-disciplinary in both theories and methods. The perspectives of courtroom workgroup (Nardulli et al., 1988) and focal concerns (Steffensmeier et al., 1998) both originate from sociological studies of the courts; the bounded rationality perspective (Albonetti, 1991) comes from social psychological studies; and the "shadow of trial" model comes from economics. Following the sociological tradition of the study of crimes, many prominent works on sentencing and plea bargaining relied heavily on field observation and interviews (e.g., Eisenstein & Jacob, 1977; Flemming et al., 1992; Heumann, 1978; Hogarth, 1971; Nardulli et al., 1988; Ulmer et al., 1997). As large, quantitative datasets have become available, researchers have also adopted more complicated econometrical methods to analyze the correlates of the sentence (for reviews, see Baumer, 2013; Ulmer, 2012).

Given that the existing sentencing research has highlighted the significance of integration, there is little reason to negate the integration of criminological knowledge into criminal justice research. Study 1 demonstrates the use of criminological studies to answer a

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research question on sentencing.[25] Theories of sentencing emphasize the assessment of the defendants' risk (Albonetti, 1991) and culpability (Steffensmeier et al., 1998; Wasik & von Hirsch, 2005), which is what criminologists have sought to measure and to explain over a century ago (Goring, 1913; Lombroso, 1911). More recently, the criminal careers perspective employed a series of more rigorous statistical methods to promote the understanding of individual trajectories of criminal behaviors (Blumstein et al., 1986; Piquero et al., 2003). When applied to criminal defendants, the criminal careers, or "criminal justice careers," directly speak to the risk of committing future crimes as well as the personal culpability. Study 1 starts from this connecting point to examine the use of one aspect of the criminal careers, criminal specialization, in predicting the sentence. The study has benefited both methodologically and substantively from the criminal specialization research. It adopted a set of measures used in the studies of criminal specialization (Sullivan et al., 2009). The findings echoed the general findings of criminal specialization research: the mix of specialists and versatile defendants, and the dependence of finding on the measure.

Study 2, on the other hand, speaks to the integration of perspectives and methods of other disciplines, especially the empirical legal studies and underlying econometrics. The model "bargaining in the shadow of trial" has been present for over three decades in legal studies (Bibas, 2004; Landes, 1971; Mnookin & Kornhauser, 1979; Nagel & Neef, 1979), but was not formally introduced to criminology until very recently (Bushway & Redlich, 2012; Bushway et al., 2014). Similarly, legal scholars have debated for decades over the issue of overcharging (Alschuler, 1968; 1976; Davis, 2007; Caldwell, 2011; Meares, 1995; Rakoff, 2014; Schulhofer &

[25] It is also possible and necessary for criminological studies to learn from the knowledge accumulated in criminal justice studies. However, that is beyond the scope of the dissertation and here I will not articulate on that.

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Nagel, 1997), but overcharging has not been formally modeled in quantitative sentencing studies. Study 2 integrates the shadow model (Mnookin & Kornhauser, 1979; Nagel & Neef, 1979) with empirical estimates of plea discount (Bushway & Redlich, 2012; Piehl & Bushway, 2007; Smith, 1986), and provides the first estimates of the plea discount using data from an entire state. In addition to that, it also proposes an analytic approach to take overcharging into account, and the results from empirical data have shown that the new framework does seem to help improving the estimates.

The Search of Data

The two studies presented in the dissertation are the products of intellectual integration. However, these studies, as well as future studies that would further develop the lines of research, can never come to reality without the data that are suitable for the analyses. There have been some large administrative datasets on sentencing available to researchers, which has led to the publication of some influential studies (for a review, see Ulmer, 2012). Yet the two studies in this dissertation have been made possible by two unique features of the CCH dataset that are absent in the other datasets. First, the CCH contains the complete criminal records of the defendants, rather than only the number of prior criminal justice contacts. This allows for the modeling of the criminal justice careers, which includes, but is not limited to, criminal specialization. Second, it also contains both the top initial (arraignment) charge and the top disposition charge, which allows for the modeling of the plea discount. Of course, both features are not exclusive to the CCH dataset. Small datasets collected by researchers (as opposed to administrative agencies) sometimes contain richer information than the administrative datasets

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(see Bushway & Redlich, 2012; Smith, 1986). However, these datasets typically have much fewer cases and would not allow for the estimation of all the models presented in the two studies.

The dissertation demonstrates the kinds of inquiries that can be made once the data permit. The increasing availability of criminal records data (Henry & Hinton, 2008; Jacobs & Crepet, 2008) would be an opportunity for research projects to replicate the studies, and to further develop the ideas presented herein. Meanwhile, it is necessary to recognize that large administrative datasets are not the only type of data that would help further understanding of sentencing and plea bargaining. Small quantitative datasets with richer case-level information (Miller et al., 1978); experimental data (Bushway et al., 2014), and qualitative data (e.g., Heumann, 19; Nardulli et al., 1988; Ulmer, 1997) have all been, and will still be, useful to future studies of sentencing. What would benefit future research is the collection, discovery, and sharing of data, as well as the replication of published studies using different data.

Future Directions

The two studies each points to a variety of future research projects. Study 1 has found that the measures made very different predictions of the sentence. This is because all the estimates have only captured a portion of criminal specialization, and it would be necessary to develop additional measures of criminal specialization. Moreover, there is also the need to turn to other aspects of criminal justice careers, such as the escalation, the frequency, the onset age, and so on. Like summarized at the end of Study 1, much work needs to be done to fully reveal how the criminal careers perspective may help understanding the sentence.

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Study 2 builds on the shadow model, and has found that plea bargaining did not seem to work as the shadow model predicted in recent years. Competing theories and mathematical models would be necessary to explain the finding. The analyses in Study 2 use the simplest specification of plea bargaining, and has not taken factors such as risk preference and information asymmetry into consideration. Moreover, it estimates only one model for each analytic sample, and has not allowed for much modeling flexibility to reflect the potentially different sentence generating process among different groups of defendants. It would be necessary to address these issues with more sophisticated econometric techniques as well as a broader range of research design.

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Table 1. Description of the 17 Crime Types

Main Crime Type	Includes
Murder	Murder, Non-negligent manslaughter
Sex Crimes	Rape, Sex offenses, Other sex offenses
Robbery	Robbery
Aggravated Assault	Aggravated Assault, Negligent manslaughter, Kidnapping
Simple Assault	Simple Assault, Coercion
Burglary	Burglary
Larceny	Extortion
MV Larceny	MV larceny, Unauthorized use of vehicle
Stolen Property	Stolen property
Forgery	Forgery
Fraud	Fraud, Embezzlement
Criminal Mischief	Criminal mischief, Arson
Drug Trafficking	Sale of opium & cocaine, Sale of marijuana, Sale of synthetics, Sale of other controlled substances
Drug Possession	Possession of opium & cocaine, Possession of marijuana, Possession of synthetics, Possession of other controlled substances
Weapons	Weapons-related crimes
Driving	DWI-alcohol, DWI-drug
Nuisance	Bribery, Prostitution, Gambling, Offense against public order, Offense against family, Possession of burglary tools, other offenses, liquor law violations, disorderly conduct, Public narcotics intoxication, Loitering

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Table 2. Descriptive Statistics of the Full Sample, Except for the Prior Convictions

	Mean	SD
Incarceration	0.540	0.498
Male	0.867	0.340
White	0.486	0.500
Black	0.503	0.500
Other race	0.008	0.090
Race unknown	0.003	0.054
Hispanic	0.377	0.485
Age	37.862	11.397
Age squared	1563.454	905.038
Trial	0.015	0.121
A Felony	0.003	0.056
B Felony	0.040	0.197
C Felony	0.038	0.192
D Felony	0.094	0.292
E Felony	0.096	0.294
A Misdem	0.549	0.498
B/U Misdem	0.179	0.384
Total felony conv	1.274	1.278
n	113,553	

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Table 3. Descriptive Statistics of the Prior Convictions

	Average Number	% Having One Conviction	% Having Multiple Convictions
Murder	0.005	0.50%	0.01%
Sex Crimes	0.054	3.80%	0.63%
Robbery	0.158	10.50%	2.40%
Agg Assault	0.093	7.66%	0.77%
Sim Assault	0.446	20.58%	9.26%
Burglary	0.157	8.86%	2.80%
Larceny	1.300	19.25%	21.73%
MV Larceny	0.078	5.09%	1.11%
Stolen Prop	0.184	10.61%	3.10%
Forgery	0.104	5.58%	1.57%
Fraud	0.570	13.34%	10.34%
Crim Misch	0.210	11.50%	3.20%
Drug Traff	0.449	16.38%	10.46%
Drug Poss	1.745	19.73%	32.91%
Weapons	0.134	9.90%	1.63%
Driving	0.241	9.08%	6.35%
Nuisance	1.123	25.51%	23.14%
n	113,553		

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Table 4. Descriptive Statistics by the Conviction Crime

	(1) Sex Crimes	(2) Agg Assault	(3) Sim Assault	(4) Burglary	(5) Larceny	(6) MV Larceny	(7) Stolen Prop
Incarceration	0.824	0.807	0.597	0.925	0.536	0.618	0.611
	(0.381)	(0.395)	(0.491)	(0.263)	(0.498)	(0.486)	(0.487)
Male	0.986	0.924	0.914	0.954	0.726	0.913	0.866
	(0.118)	(0.265)	(0.280)	(0.209)	(0.446)	(0.281)	(0.341)
White	0.547	0.433	0.472	0.593	0.545	0.547	0.569
	(0.498)	(0.496)	(0.499)	(0.491)	(0.498)	(0.498)	(0.495)
Black	0.438	0.556	0.515	0.396	0.446	0.441	0.419
	(0.496)	(0.497)	(0.499)	(0.489)	(0.497)	(0.497)	(0.494)
Other race	0.012	0.007	0.009	0.009	0.006	0.007	0.009
	(0.107)	(0.080)	(0.097)	(0.092)	(0.079)	(0.082)	(0.096)
Race unknown	0.003	0.004	0.003	0.002	0.002	0.005	0.003
	(0.057)	(0.067)	(0.059)	(0.048)	(0.044)	(0.071)	(0.052)
Hispanic	0.329	0.370	0.348	0.367	0.348	0.363	0.369
	(0.470)	(0.483)	(0.476)	(0.482)	(0.476)	(0.481)	(0.483)
Age	36.321	34.377	35.351	33.853	39.197	33.800	35.563
	(11.361)	(11.322)	(10.630)	(11.185)	(11.383)	(10.234)	(11.271)
Age squared	1448.176	1309.917	1362.694	1271.098	166.012	1246.964	1391.692
	(894.966)	(856.677)	(807.599)	(811.066)	(909.304)	(732.369)	(846.793)
Trial	0.098	0.052	0.018	0.037	0.005	0.007	0.008
	(0.298)	(0.022)	(0.131)	(0.188)	(0.073)	(0.082)	(0.091)

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Table 4. Descriptive Statistics by the Conviction Crime (cont'd)

	(1) Sex Crimes	(2) Agg Assault	(3) Sim Assault	(4) Burglary	(5) Larceny	(6) MV Larceny	(7) Stolen Prop
A Felony	0.017	0.001					
	(0.131)	(0.029)					
B Felony	0.120	0.071		0.029	<0.001		
	(0.326)	(0.257)		(0.168)	(0.015)		
C Felony	0.045	0.068		0.184	0.004		0.002
	(0.208)	(0.252)		(0.388)	(0.060)		(0.042)
D Felony	0.195	0.295	0.040	0.625	0.024	0.002	0.038
	(0.396)	(0.456)	(0.196)	(0.484)	(0.153)	(0.041)	(0.192)
E Felony	0.212	0.231	0.082	0.162	0.076	0.171	0.181
	(0.410)	(0.421)	(0.275)	(0.368)	(0.265)	(0.377)	(0.385)
A Misdem	0.228	0.317	0.726		0.812	0.759	0.706
	(0.420)	(0.465)	(0.446)		(0.391)	(0.428)	(0.456)
B/U Misdem	0.181	0.017	0.152		0.084	0.068	0.072
	(0.385)	(0.130)	(0.359)		(0.278)	(0.252)	(0.259)
Total felony conv	1.127	1.335	1.221	1.739	1.156	1.423	1.434
	(1.142)	(1.225)	(1.209)	(1.510)	(1.284)	(1.355)	(1.405)
n	1,212	2,455	8,995	3,968	16,869	589	2,254

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Table 4. Descriptive Statistics by the Conviction Crime (cont'd)

	(8) Forgery	(9) Fraud	(10) Crim Misch	(11) Drug Traff	(12) Drug Poss	(13) Weapons	(14) Driving	(15) Nuisance
Incarceration	0.547	0.291	0.485	0.809	0.410	0.692	0.481	0.499
	(0.498)	(0.454)	(0.500)	(0.393)	(0.492)	(0.462)	(0.500)	(0.500)
Male	0.816	0.875	0.921	0.907	0.871	0.973	0.885	0.867
	(0.388)	(0.331)	(0.270)	(0.290)	(0.335)	(0.161)	(0.319)	(0.340)
White	0.460	0.359	0.620	0.362	0.399	0.358	0.754	0.500
	(0.499)	(0.480)	(0.485)	(0.481)	(0.490)	(0.479)	(0.431)	(0.500)
Black	0.522	0.632	0.366	0.632	0.594	0.632	0.222	0.487
	(0.500)	(0.482)	(0.482)	(0.482)	(0.491)	(0.482)	(0.416)	(0.500)
Other race	0.016	0.007	0.011	0.004	0.005	0.007	0.018	0.009
	(0.124)	(0.082)	(0.104)	(0.060)	(0.071)	(0.083)	(0.132)	(0.095)
Race unknown	0.003	0.002	0.003	0.003	0.002	0.003	0.006	0.003
	(0.052)	(0.040)	(0.054)	(0.051)	(0.044)	(0.053)	(0.076)	(0.058)
Hispanic	0.336	0.419	0.320	0.450	0.439	0.388	0.259	0.373
	(0.472)	(0.493)	(0.466)	(0.498)	(0.496)	(0.487)	(0.438)	(0.484)
Age	38.042	39.898	34.432	36.889	40.380	34.000	39.298	37.505
	(11.284)	(11.473)	(10.758)	(11.227)	(11.288)	(11.214)	(10.659)	(11.081)
Age squared	1574.444	1723.449	1301.227	1486.792	1757.992	1281.696	1657.929	1529.389
	(909.237)	(931.313)	(811.475)	(891.762)	(934.662)	(860.712)	(883.977)	(882.327)
Trial	0.005	0.002	0.009	0.016	0.005	0.035		0.009
	(0.073)	(0.042)	(0.096)	(0.127)	(0.071)	(0.185)		(0.092)

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Table 4. Descriptive Statistics by the Conviction Crime (cont'd)

	(8) Forgery	(9) Fraud	(10) Crim Misch	(11) Drug Traff	(12) Drug Poss	(13) Weapons	(14) Driving	(15) Nuisance
A Felony			<0.001	0.019	0.004			<0.001
			(0.018)	(0.135)	(0.061)			(0.015)
B Felony			0.004	0.396	0.049	0.002		0.005
			(0.062)	(0.489)	(0.217)	(0.047)		(0.068)
C Felony	0.012		0.017	0.205	0.037	0.160		0.003
	(0.111)		(0.130)	(0.404)	(0.189)	(0.367)		(0.052)
D Felony	0.214	0.017	0.023	0.154	0.039	0.288	0.121	0.027
	(0.410)	(0.130)	(0.149)	(0.361)	(0.194)	(0.453)	(0.327)	(0.163)
E Felony	0.118	0.023	0.063	0.031	0.014	0.063	0.358	0.097
	(0.323)	(0.150)	(0.243)	(0.173)	(0.116)	(0.243)	(0.479)	(0.295)
A Misdem	0.627	0.828	0.795	0.180	0.633	0.449		0.604
	(0.484)	(0.378)	(0.404)	(0.385)	(0.482)	(0.497)		(0.489)
B/U Misdem	0.029	0.132	0.098	0.015	0.224	0.038	0.521	0.265
	(0.168)	(0.338)	(0.297)	(0.121)	(0.417)	(0.192)	(0.500)	(0.441)
Total felony conv	1.280	1.157	1.088	1.683	1.353	1.400	0.960	1.204
	(1.295)	(1.215)	(1.175)	(1.379)	(1.282)	(1.207)	(1.083)	(1.258)
n	1,861	6,927	3,038	5,304	25,363	3,565	9,690	18,474

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Table 5. Average Values of the Identical Preceding Conviction (IPC), by the Conviction Crime

	IPC
Sample Average	0.235
Murder	0.021
Sex Crimes	0.111
Robbery	0.140
Agg Assault	0.049
Sim Assault	0.122
Burglary	0.163
Larceny	0.259
MV Larceny	0.061
Stolen Prop	0.053
Forgery	0.111
Fraud	0.139
Crim Misch	0.069
Drug Traff	0.135
Drug Poss	0.330
Weapons	0.063
Driving	0.409
Nuisance	0.279

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Table 6. Average Values of the Specialization Index, by the Conviction Crime

	Spec. Index
Sample Average	0.458
Murder	0.440
Sex Crimes	0.463
Robbery	0.436
Agg Assault	0.433
Sim Assault	0.431
Burglary	0.418
Larceny	0.467
MV Larceny	0.410
Stolen Prop	0.420
Forgery	0.463
Fraud	0.428
Crim Misch	0.437
Drug Traff	0.437
Drug Poss	0.455
Weapons	0.440
Driving	0.567
Nuisance	0.451

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Table 7. Conditional Probabilities of the Classes

	(1) Low Invol. Gen.	(2) Drug Gen.	(3) High Invol. Gen.	(4) Driving Spec.	(5) Property Spec.	(6) Drug Spec.	(7) Violent Spec.
Single Conv. of							
Murder	0.002	0.001	0.001	0.001	0.001	0.004	0.027
Sex Crimes	0.091	0.042	0.040	0.017	0.022	0.015	0.028
Robbery	0.043	0.156	0.147	0.010	0.078	0.066	0.326
Agg Assault	0.129	0.095	0.112	0.028	0.024	0.039	0.137
Sim Assault	0.301	0.263	0.285	0.138	0.116	0.143	0.252
Burglary	0.117	0.062	0.230	0.025	0.145	0.024	0.086
Larceny	0.222	0.229	0.150	0.091	0.329	0.114	0.167
MV Larceny	0.050	0.046	0.176	0.015	0.049	0.032	0.055
Stolen Prop	0.080	0.149	0.339	0.027	0.171	0.042	0.082
Forgery	0.042	0.069	0.101	0.019	0.117	0.034	0.026
Fraud	0.092	0.241	0.211	0.034	0.142	0.134	0.116
Crim Misch	0.214	0.136	0.240	0.076	0.091	0.033	0.092
Drug Traff	0.057	0.297	0.187	0.028	0.055	0.295	0.178
Drug Poss	0.144	0.083	0.201	0.126	0.199	0.271	0.278
Weapons	0.077	0.134	0.129	0.032	0.025	0.113	0.208
Driving	0.132	0.019	0.065	0.401	0.070	0.040	0.038
Nuisance	0.342	0.223	0.256	0.210	0.226	0.251	0.216

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Table 7. Conditional Probabilities of the Classes (cont'd)

	(1) Low Invol. Gen.	(2) Drug Gen.	(3) High Invol. Gen.	(4) Driving Spec.	(5) Property Spec.	(6) Drug Spec.	(7) Violent Spec.
Muiltipe Convs. of							
Murder	0.000	0.000	0.000	0.000	0.000	0.000	0.001
Sex Crimes	0.019	0.008	0.011	0.001	0.002	0.001	0.001
Robbery	0.002	0.030	0.027	0.000	0.020	0.006	0.114
Agg Assault	0.017	0.009	0.020	0.000	0.000	0.002	0.011
Sim Assault	0.185	0.196	0.209	0.017	0.011	0.035	0.065
Burglary	0.033	0.009	0.099	0.002	0.058	0.005	0.019
Larceny	0.099	0.427	0.766	0.011	0.484	0.052	0.041
MV Larceny	0.005	0.004	0.094	0.000	0.010	0.003	0.009
Stolen Prop	0.011	0.029	0.267	0.000	0.041	0.003	0.006
Forgery	0.006	0.042	0.030	0.003	0.038	0.003	0.005
Fraud	0.038	0.438	0.253	0.002	0.072	0.059	0.036
Crim Misch	0.059	0.043	0.170	0.005	0.014	0.002	0.007
Drug Traff	0.009	0.272	0.056	0.002	0.010	0.244	0.047
Drug Poss	0.066	0.881	0.557	0.029	0.097	0.607	0.094
Weapons	0.008	0.033	0.020	0.003	0.001	0.018	0.041
Driving	0.049	0.003	0.031	0.599	0.019	0.006	0.001
Nuisance	0.303	0.631	0.551	0.035	0.063	0.179	0.052
Pr(Class)	0.206	0.108	0.064	0.077	0.170	0.254	0.120

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Table 8. Class-average Ratios (CARs) of the Classes

	(1) Low Invol. Gen.	(2) Drug Gen.	(3) High Invol. Gen.	(4) Driving Spec.	(5) Property Spec.	(6) Drug Spec.	(7) Violent Spec.
Single Conv. of Murder	0.435	0.118	0.280	0.236	0.122	0.721	5.492
Sex Crimes	2.383	1.101	1.052	0.444	0.572	0.396	0.746
Robbery	0.407	1.483	1.402	0.091	0.741	0.630	3.108
Agg Assault	1.679	1.239	1.463	0.361	0.316	0.507	1.793
Sim Assault	1.461	1.277	1.384	0.669	0.566	0.696	1.225
Burglary	1.317	0.699	2.597	0.282	1.633	0.275	0.973
Larceny	1.154	1.191	0.781	0.473	1.712	0.595	0.870
MV Larceny	0.979	0.907	3.463	0.303	0.959	0.634	1.082
Stolen Prop	0.755	1.403	3.198	0.250	1.613	0.395	0.775
Forgery	0.756	1.237	1.816	0.347	2.100	0.605	0.468
Fraud	0.689	1.806	1.581	0.257	1.061	1.007	0.871
Crim Misch	1.861	1.181	2.088	0.657	0.794	0.283	0.803
Drug Traff	0.347	1.814	1.144	0.173	0.337	1.801	1.084
Drug Poss	0.731	0.423	1.021	0.639	1.008	1.372	1.407
Weapons	0.777	1.355	1.304	0.326	0.250	1.138	2.107
Driving	1.449	0.206	0.716	4.412	0.767	0.440	0.419
Nuisance	1.339	0.874	1.004	0.822	0.884	0.982	0.845

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Table 8. Class-average Ratios (CARs) of the Classes (cont'd)

	(1) Low Invol. Gen.	(2) Drug Gen.	(3) High Invol. Gen.	(4) Driving Spec.	(5) Property Spec.	(6) Drug Spec.	(7) Violent Spec.
Muiltipe Convs. of							
Murder	0.000	0.000	0.000	0.000	0.000	0.000	8.362
Sex Crimes	3.038	1.233	1.731	0.217	0.345	0.126	0.175
Robbery	0.084	1.236	1.131	0.016	0.816	0.266	4.749
Agg Assault	2.259	1.226	2.652	0.007	0.005	0.227	1.432
Sim Assault	1.996	2.117	2.256	0.182	0.121	0.375	0.700
Burglary	1.193	0.336	3.527	0.059	2.089	0.189	0.695
Larceny	0.454	1.964	3.526	0.053	2.229	0.241	0.187
MV Larceny	0.461	0.404	8.497	0.017	0.877	0.257	0.828
Stolen Prop	0.352	0.922	8.611	0.013	1.318	0.096	0.200
Forgery	0.383	2.659	1.916	0.193	2.393	0.195	0.320
Fraud	0.370	4.237	2.446	0.018	0.698	0.570	0.351
Crim Misch	1.836	1.352	5.335	0.160	0.439	0.075	0.211
Drug Traff	0.086	2.603	0.536	0.017	0.099	2.337	0.445
Drug Poss	0.199	2.676	1.692	0.089	0.295	1.844	0.284
Weapons	0.505	2.030	1.211	0.175	0.031	1.092	2.519
Driving	0.766	0.048	0.494	9.434	0.298	0.098	0.010
Nuisance	1.308	2.727	2.383	0.152	0.272	0.773	0.224
Pr(Class)	0.206	0.108	0.064	0.077	0.170	0.254	0.120

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Table 9. Class Assignment, by the Conviction Crime

	(1) Low Invol. Gen.	(2) Drug Gen.	(3) High Invol. Gen.	(4) Driving Spec.	(5) Property Spec.	(6) Drug Spec.	(7) Violent Spec.	Total
Sample Average	20.63%	10.57%	5.53%	8.77%	17.99%	27.22%	9.28%	100%
Murder	20.31%	4.11%	3.34%	3.86%	11.57%	26.22%	30.59%	100%
Sex Crimes	44.39%	6.85%	3.80%	6.68%	15.43%	13.94%	8.91%	100%
Robbery	15.54%	9.58%	5.81%	1.65%	18.31%	17.46%	31.65%	100%
Agg Assault	32.34%	6.56%	4.64%	6.88%	11.20%	20.24%	18.13%	100%
Sim Assault	35.45%	8.17%	4.44%	7.60%	12.67%	19.47%	12.20%	100%
Burglary	24.47%	5.49%	11.32%	3.28%	33.01%	11.42%	11.01%	100%
Larceny	15.54%	11.36%	10.43%	4.36%	39.86%	12.97%	5.47%	100%
MV Larceny	20.88%	5.43%	15.79%	6.11%	27.16%	13.24%	11.38%	100%
Stolen Prop	19.34%	7.63%	12.60%	4.44%	33.36%	14.20%	8.43%	100%
Forgery	17.14%	9.51%	4.78%	5.96%	32.62%	21.60%	8.38%	100%
Fraud	15.61%	20.85%	4.91%	2.96%	18.91%	28.04%	8.73%	100%
Crim Misch	38.81%	5.53%	6.65%	9.38%	18.04%	13%	8.59%	100%
Drug Traff	10.69%	13.37%	2.94%	2.39%	8.84%	51.43%	10.33%	100%
Drug Poss	9.55%	14.78%	4.23%	3.43%	10.29%	50.09%	7.62%	100%
Weapons	21.37%	7.63%	3.14%	5.41%	10.24%	31.28%	20.93%	100%
Driving	21.53%	0.77%	1.37%	49.82%	10.85%	11.07%	4.58%	100%
Nuisance	31.66%	9.92%	4.68%	7.31%	13.01%	24.59%	8.84%	100%

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Table 10. Average Values of the Number of Identical Records (NIR), by the Conviction Crime

	Average NIR
Sample Average	1.917
Murder	0.046
Sex Crimes	0.522
Robbery	0.678
Agg Assault	0.215
Sim Assault	0.786
Burglary	0.782
Larceny	3.488
MV Larceny	0.455
Stolen Prop	0.458
Forgery	0.707
Fraud	1.816
Crim Misch	0.510
Drug Traff	1.109
Drug Poss	3.158
Weapons	0.311
Driving	1.139
Nuisance	1.672

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Table 11. Pairwise Correlation Coefficients among the Measures of Criminal Specialization

	Spec. Index	IPC	NIR
IPC	0.155		
NIR	0.023	0.185	
Drug Gen.	-0.257	-0.023	0.259
High Invol. Gen.	-0.211	-0.031	0.175
Driving Spec.	0.228	0.098	-0.071
Property Spec.	0.114	-0.001	-0.038
Drug Spec.	0.094	0.054	-0.007
Violent Spec.	-0.045	-0.061	-0.119

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Table 12. Averages Values of the Measures of Criminal Specialization, by the Class

	IPC	Spec. Index	NIR
Low Invol. Gen.	0.195	0.447	1.043
Drug Gen.	0.207	0.293	4.755
High Invol. Gen.	0.180	0.266	4.642
Driving Spec.	0.370	0.620	1.060
Property Spec.	0.234	0.511	1.614
Drug Spec.	0.272	0.491	1.877
Violent Spec.	0.155	0.427	0.518

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Table 13. Baseline Regression Models Explaining Incarceration

	(1) Sex Crimes	(2) Agg Assault	(3) Sim Assault	(4) Burglary	(5) Larceny	(6) MV Larceny	(7) Stolen Prop
Male	0.221**	0.066***	0.087***	0.058**	0.159***	0.032	0.129***
	(0.103)	(0.024)	(0.018)	(0.026)	(0.013)	(0.080)	(0.023)
Black	0.012	0.024	0.046***	0.022**	0.048***	-0.026	0.010
	(0.022)	(0.016)	(0.011)	(0.010)	(0.008)	(0.046)	(0.024)
Other Race	0.004	-0.097	0.019	0.034	-0.131***	0.304*	-0.006
	(0.094)	(0.078)	(0.074)	(0.038)	(0.034)	(0.176)	(0.136)
Race Unknown	0.030	0.005	0.009	0.011	-0.064	0.215***	0.123
	(0.080)	(0.087)	(0.045)	(0.011)	(0.070)	(0.047)	(0.101)
Hispanic	0.045**	0.004	0.008	0.006	0.026**	0.040	-0.005
	(0.018)	(0.015)	(0.011)	(0.010)	(0.010)	(0.036)	(0.019)
Age	-0.001	-0.006	-0.012***	-0.002	0.002	-0.013	-0.008
	(0.006)	(0.003)	(0.003)	(0.003)	(0.002)	(0.012)	(0.007)
Age Squared	0.000	0.000	0.000***	0.000	-0.000*	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trial	0.068***	0.011	0.071	0.025*	0.106***	0.083*	0.069
	(0.018)	(0.015)	(0.057)	(0.013)	(0.039)	(0.043)	(0.083)
A Felony	-0.007	0.024					
	(0.029)	(0.016)					

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 13. Baseline Regression Models Explaining Incarceration (cont'd)

	(1) Sex Crimes	(2) Agg Assault	(3) Sim Assault	(4) Burglary	(5) Larceny	(6) MV Larceny	(7) Stolen Prop
B Felony	0.039*	0.074***		0.080***	0.130***		
	(0.021)	(0.014)		(0.025)	(0.017)		
C Felony	0.048**	0.055***		0.086***	-0.013		-0.178
	(0.020)	(0.013)		(0.022)	(0.057)		(0.234)
D Felony	0.015	0.051***	-0.002	0.011	-0.057**	0.046	0.019
	(0.022)	(0.014)	(0.017)	(0.018)	(0.026)	(0.083)	(0.031)
A Misdem	-0.221***	-0.362***	-0.339***		-0.265***	-0.241***	-0.291***
	(0.037)	(0.033)	(0.020)		(0.021)	(0.062)	(0.031)
B Misdem	-0.437***	-0.543***	-0.501***		-0.416***	-0.378***	-0.533***
	(0.046)	(0.118)	(0.035)		(0.036)	(0.088)	(0.050)
Total Fel Conv	0.019***	0.020***	0.043***	0.027***	0.047***	0.050***	0.043***
	(0.006)	(0.007)	(0.005)	(0.005)	(0.003)	(0.011)	(0.008)
Constant	0.702***	0.935***	0.984***	0.831***	0.530***	1.056***	0.839***
	(0.167)	(0.064)	(0.060)	(0.060)	(0.058)	(0.219)	(0.118)
n	1,212	2,455	8,995	3,968	16,869	589	2,254
R-squared	0.318	0.331	0.142	0.114	0.150	0.234	0.186

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 13. Baseline Regression Models Explaining Incarceration (cont'd)

	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Forgery	Fraud	Crim Misch	Drug Traff	Drug Poss	Weapons	Driving	Nuisance
Male	0.083***	0.066***	0.102***	0.075***	0.009	-0.030	0.069***	0.032
	(0.029)	(0.017)	(0.029)	(0.014)	(0.012)	(0.033)	(0.017)	(0.020)
Black	0.070**	0.033***	0.029	0.009	0.044***	0.026**	0.012	0.033***
	(0.027)	(0.012)	(0.032)	(0.011)	(0.009)	(0.011)	(0.016)	(0.008)
Other Race	-0.114	-0.053	-0.072	-0.054	-0.022	0.027	-0.064*	0.008
	(0.101)	(0.058)	(0.064)	(0.072)	(0.035)	(0.082)	(0.034)	(0.042)
Race Unknown	-0.313***	0.037	-0.282***	-0.006	-0.012	-0.049	-0.064	-0.030
	(0.092)	(0.088)	(0.104)	(0.039)	(0.094)	(0.124)	(0.059)	(0.073)
Hispanic	0.043**	0.004	0.003	0.009	0.024**	0.003	0.025**	0.023***
	(0.021)	(0.007)	(0.020)	(0.011)	(0.011)	(0.017)	(0.011)	(0.006)
Age	-0.012**	-0.008***	-0.006	-0.002	-0.004**	-0.010***	-0.003	-0.001
	(0.006)	(0.002)	(0.005)	(0.004)	(0.002)	(0.004)	(0.003)	(0.003)
Age Squared	0.000	0.000**	0.000	-0.000	0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trial	0.130***	0.041	0.063	0.060***	0.049	0.034	0.115***	0.080**
	(0.028)	(0.144)	(0.049)	(0.016)	(0.045)	(0.023)	(0.043)	(0.037)
A Felony			0.199***	0.091***	0.173***			0.087**
			(0.042)	(0.031)	(0.029)			(0.040)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 13. Baseline Regression Models Explaining Incarceration (cont'd)

	(8) Forgery	(9) Fraud	(10) Crim Misch	(11) Drug Traff	(12) Drug Poss	(13) Weapons	(14) Driving	(15) Nuisance
B Felony			0.147***	0.040	0.091***	0.101***		0.200***
			(0.039)	(0.030)	(0.029)	(0.018)		(0.040)
C Felony	0.120		0.139***	0.030	0.069**	0.047*		0.128**
	(0.078)		(0.036)	(0.023)	(0.029)	(0.024)		(0.062)
D Felony	0.043	0.080	0.012	-0.017	0.015	0.028	0.097***	0.102***
	(0.050)	(0.057)	(0.056)	(0.024)	(0.027)	(0.018)	(0.016)	(0.019)
A Misdem	-0.297***	-0.406***	-0.367***	-0.362***	-0.331***	-0.464***		-0.261***
	(0.040)	(0.088)	(0.038)	(0.055)	(0.040)	(0.032)		(0.029)
B Misdem	-0.552***	-0.388***	-0.474***	-0.487***	-0.562***	-0.593***	-0.399***	-0.403***
	(0.080)	(0.065)	(0.051)	(0.063)	(0.054)	(0.055)	(0.038)	(0.041)
Total Fel Conv	0.069***	0.025***	0.053***	0.044***	0.033***	0.038***	0.054***	0.037***
	(0.008)	(0.005)	(0.007)	(0.003)	(0.003)	(0.007)	(0.007)	(0.002)
Constant	0.855***	0.729***	0.755***	0.802***	0.787***	1.104***	0.614***	0.697***
	(0.107)	(0.080)	(0.088)	(0.061)	(0.065)	(0.084)	(0.064)	(0.078)
n	1,861	6,927	3,038	5,304	25,363	3,565	9,690	18,474
R-squared	0.233	0.128	0.167	0.290	0.227	0.415	0.294	0.135

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Table 14. Baseline Regression Models Explaining the Incarceration Length

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Sex Crimes	Agg Assault	Sim Assault	Burglary	Larceny	MV Larceny	Stolen Prop
Male	13.462	10.122***	-0.214	6.879**	0.873***	0.179	0.836*
	(11.586)	(1.715)	(0.317)	(3.305)	(0.154)	(1.335)	(0.440)
Black	-0.261	2.620	0.867**	-2.485	0.010	-0.253	0.265
	(3.356)	(2.326)	(0.414)	(1.903)	(0.232)	(0.319)	(0.224)
Other Race	-9.550	-7.226	1.409	-5.467*	-0.758	-1.173	0.639
	(8.091)	-6.421	(0.945)	(3.140)	(0.760)	(0.708)	(0.760)
Race Unknown	3.503	2.898	-1.163*	0.523	-3.541*	-1.467	-0.979
	(9.894)	(7.690)	(0.630)	(2.355)	(1.967)	(2.011)	(0.843)
Hispanic	-4.056	1.533	0.278	-3.341**	-0.115	-0.170	0.014
	(3.396)	(1.734)	(0.482)	(1.617)	(0.247)	(0.378)	(0.231)
Age	1.104*	1.537***	-0.017	0.873	-0.133**	0.047	0.039
	(0.590)	(0.355)	(0.063)	(0.534)	(0.055)	(0.177)	(0.061)
Age Squared	-0.012	-0.019***	-0.000	-0.005	0.001**	-0.000	-0.001
	(0.008)	(0.004)	(0.001)	(0.008)	(0.001)	(0.002)	(0.001)
Trial	46.255***	60.256***	19.513***	80.017***	26.024***	7.556***	6.775**
	(13.258)	(10.290)	(6.747)	(13.725)	(7.527)	(1.091)	(2.579)
A Felony	408.170***	401.781***					
	(18.910)	(9.458)					

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 14. Baseline Regression Models Explaining the Incarceration Length (cont'd)

	(1) Sex Crimes	(2) Agg Assault	(3) Sim Assault	(4) Burglary	(5) Larceny	(6) MV Larceny	(7) Stolen Prop
B Felony	142.501***	112.557***		122.282***	26.210***		
	(5.201)	(6.326)		(5.031)	(2.943)		
C Felony	71.049***	63.857***		63.830***	22.850***		7.763*
	(9.247)	(5.926)		(2.794)	(8.471)		(4.339)
D Felony	26.612***	22.205***	13.759***	17.339***	3.305***	21.704***	6.840***
	(3.982)	(1.526)	(1.786)	(1.438)	(0.985)	(1.038)	(1.252)
A Misdem	-19.942***	-9.907***	-9.267***		-11.339***	-10.160***	-10.352***
	(2.021)	(1.037)	(0.418)		(1.037)	(0.913)	(0.446)
B Misdem	-24.715***	-10.827***	-12.799***		-14.161***	-14.383***	-14.284***
	(2.666)	(3.898)	(0.490)		(1.080)	(1.313)	(0.559)
Total Fel Conv	5.149***	5.355***	1.185***	5.886***	1.067***	0.733***	1.075***
	(1.046)	(0.785)	(0.270)	(0.694)	(0.122)	(0.141)	(0.102)
Constant	-14.932	-31.295***	12.613***	-20.151**	15.975***	13.299***	12.847***
	(16.295)	(8.199)	(1.744)	(8.382)	(0.657)	(3.456)	(1.198)
n	999	1,981	5,370	3,672	9,042	364	1,379
R-squared	0.795	0.631	0.283	0.327	0.320	0.634	0.674

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 14. Baseline Regression Models Explaining the Incarceration Length (cont'd)

	(8) Forgery	(9) Fraud	(10) Crim Misch	(11) Drug Traff	(12) Drug Poss	(13) Weapons	(14) Driving	(15) Nuisance
Male	1.666**	0.175	2.442**	7.454***	0.855***	9.103**	1.139**	0.435**
	(0.638)	(0.441)	(1.057)	(0.694)	(0.262)	(3.566)	(0.453)	(0.215)
Black	0.460	-0.108	-0.240	3.042***	1.314***	2.916**	-0.557	0.155
	(0.627)	(0.223)	(0.785)	(0.859)	(0.471)	(1.250)	(0.576)	(0.214)
Other Race	-6.026*	0.802	1.163	-2.007	-0.308	0.697	0.251	0.271
	(3.220)	(0.605)	(2.083)	(3.803)	(1.266)	(5.313)	(0.681)	(0.861)
Race Unknown	-1.665	-3.377*	2.942	-6.156	-2.983*	13.463***	2.017*	0.743
	(1.123)	(1.789)	(3.299)	(7.784)	(1.611)	(4.566)	(1.121)	(0.566)
Hispanic	-0.190	-0.071	0.834	0.818*	0.022	-0.725	-0.134	0.306**
	(0.577)	(0.156)	(1.120)	(0.471)	(0.374)	(1.473)	(0.376)	(0.135)
Age	0.313**	-0.097**	-0.147	0.437*	0.057	0.696	-0.038	0.034
	(0.146)	(0.039)	(0.233)	(0.228)	(0.072)	(0.480)	(0.067)	(0.038)
Age Squared	-0.004**	0.001**	0.001	-0.007***	-0.001	-0.008	0.001	-0.001*
	(0.002)	(0.001)	(0.003)	(0.003)	(0.001)	(0.007)	(0.001)	(0.000)
Trial	8.453***	8.336***	11.507	59.002***	28.918***	62.627***	19.536	13.847***
	(2.008)	(2.444)	(7.256)	(6.690)	(3.842)	(10.810)	(12.810)	(3.216)
A Felony			469.493***	69.806***	67.141***			263.084***
			(2.145)	(7.148)	(3.648)			(2.269)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 14. Baseline Regression Models Explaining the Incarceration Length (cont'd)

	(8) Forgery	(9) Fraud	(10) Crim Misch	(11) Drug Traff	(12) Drug Poss	(13) Weapons	(14) Driving	(15) Nuisance
B Felony			117.903***	13.573***	20.007***	140.284***		46.842***
			(13.091)	(2.659)	(2.013)	(25.209)		(6.659)
C Felony	16.076***		42.473***	8.250***	12.420***	53.736***		24.415***
	(4.776)		(12.273)	(1.846)	(1.900)	(5.541)		(2.849)
D Felony	4.165***	6.872***	5.571***	2.745*	3.957***	13.121***	4.564***	6.013***
	(0.898)	(0.624)	(1.357)	(1.572)	(1.270)	(2.734)	(0.728)	(0.949)
A Misdem	-9.664***	-12.590***	-9.523***	-12.110***	-10.566***	-12.483***		-6.024***
	(1.133)	(1.311)	(0.832)	(2.009)	(1.155)	(2.775)		(0.891)
B Misdem	-13.790***	-13.914***	-11.581***	-17.898***	-12.982***	-13.617***	-4.339***	-8.645***
	(1.079)	(0.984)	(0.754)	(3.869)	(1.126)	(3.369)	(0.392)	(0.829)
Total Fel Conv	1.867***	0.575***	1.079***	4.038***	1.287***	4.686***	2.013***	0.590***
	(0.241)	(0.080)	(0.164)	(0.576)	(0.159)	(1.123)	(0.548)	(0.064)
Constant	5.989**	15.589***	12.714***	-1.446	11.297***	-9.676	5.472***	9.342***
	(2.914)	(1.679)	(3.793)	(6.724)	(2.726)	(9.595)	(1.478)	(1.099)
n	1,018	2,017	1,474	4,292	10,408	2,468	4,663	9,220
R-squared	0.612	0.747	0.559	0.502	0.588	0.444	0.184	0.567

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Table 15. Regression Models Explaining Incarceration, with the Identical Preceding Conviction (IPC)

	(1) Sex Crimes	(2) Agg Assault	(3) Sim Assault	(4) Burglary	(5) Larceny	(6) MV Larceny	(7) Stolen Prop
IPC	0.083***	0.028	0.024	0.018*	0.041***	0.075	0.013
	(0.021)	(0.029)	(0.015)	(0.010)	(0.006)	(0.080)	(0.033)
Male	0.223**	0.066***	0.086***	0.058**	0.164***	0.036	0.129***
	(0.103)	(0.024)	(0.018)	(0.026)	(0.012)	(0.081)	(0.023)
Black	0.015	0.023	0.045***	0.022**	0.048***	-0.024	0.010
	(0.022)	(0.016)	(0.011)	(0.010)	(0.008)	(0.047)	(0.024)
Other Race	0.001	-0.096	0.018	0.033	-0.134***	0.306*	-0.005
	(0.100)	(0.078)	(0.074)	(0.038)	(0.033)	(0.177)	(0.137)
Race Unknown	0.035	0.003	0.010	0.009	-0.064	0.219***	0.123
	(0.083)	(0.087)	(0.045)	(0.012)	(0.068)	(0.047)	(0.102)
Hispanic	0.047**	0.003	0.008	0.007	0.027**	0.040	-0.005
	(0.018)	(0.015)	(0.011)	(0.010)	(0.010)	(0.036)	(0.019)
Age	-0.000	-0.006	-0.012***	-0.002	0.003	-0.013	-0.008
	(0.006)	(0.003)	(0.003)	(0.003)	(0.002)	(0.012)	(0.007)
Age Squared	-0.000	0.000	0.000***	0.000	-0.000**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trial	0.072***	0.010	0.072	0.026*	0.108***	0.089**	0.068
	(0.019)	(0.015)	(0.057)	(0.013)	(0.039)	(0.042)	(0.083)
A Felony	-0.017	0.026*					
	(0.026)	(0.015)					

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 15. Regression Models Explaining Incarceration, with the Identical Preceding Conviction (IPC, cont'd)

	(1) Sex Crimes	(2) Agg Assault	(3) Sim Assault	(4) Burglary	(5) Larceny	(6) MV Larceny	(7) Stolen Prop
B Felony	0.039*	0.074***		0.081***	0.130***		
	(0.020)	(0.014)		(0.025)	(0.022)		
C Felony	0.054***	0.055***		0.084***	-0.015		-0.177
	(0.019)	(0.014)		(0.022)	(0.058)		(0.236)
D Felony	0.016	0.051***	-0.001	0.010	-0.057**	0.055	0.019
	(0.021)	(0.013)	(0.017)	(0.018)	(0.026)	(0.085)	(0.031)
A Misdem	-0.218***	-0.361***	-0.336***		-0.265***	-0.238***	-0.291***
	(0.037)	(0.033)	(0.019)		(0.021)	(0.063)	(0.031)
B Misdem	-0.439***	-0.541***	-0.498***		-0.413***	-0.379***	-0.532***
	(0.046)	(0.118)	(0.035)		(0.036)	(0.087)	(0.050)
Total Fel Conv	0.019***	0.020***	0.043***	0.026***	0.048***	0.049***	0.043***
	(0.005)	(0.007)	(0.005)	(0.004)	(0.003)	(0.012)	(0.008)
Constant	0.673***	0.933***	0.978***	0.825***	0.514***	1.046***	0.838***
	(0.165)	(0.064)	(0.060)	(0.061)	(0.056)	(0.223)	(0.116)
n	1,212	2,455	8,995	3,968	16,869	589	2,254
R-squared	0.323	0.331	0.143	0.115	0.151	0.236	0.186

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

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Table 15. Regression Models Explaining Incarceration, with the Identical Preceding Conviction (IPC, cont'd)

	(8) Forgery	(9) Fraud	(10) Crim Misch	(11) Drug Traff	(12) Drug Poss	(13) Weapons	(14) Driving	(15) Nuisance
IPC	-0.002	0.037***	0.036	0.011	-0.011**	-0.006	-0.018	0.002
	(0.034)	(0.009)	(0.033)	(0.009)	(0.005)	(0.027)	(0.013)	(0.016)
Male	0.083***	0.065***	0.102***	0.075***	0.009	-0.030	0.070***	0.032
	(0.029)	(0.016)	(0.029)	(0.014)	(0.012)	(0.033)	(0.017)	(0.019)
Black	0.070**	0.032**	0.030	0.009	0.045***	0.026**	0.010	0.033***
	(0.026)	(0.012)	(0.032)	(0.011)	(0.009)	(0.011)	(0.016)	(0.008)
Other Race	-0.114	-0.052	-0.074	-0.057	-0.022	0.027	-0.063*	0.008
	(0.102)	(0.058)	(0.063)	(0.071)	(0.035)	(0.083)	(0.034)	(0.042)
Race Unknown	-0.313***	0.037	-0.279***	-0.007	-0.011	-0.048	-0.063	-0.030
	(0.092)	(0.090)	(0.103)	(0.040)	(0.094)	(0.126)	(0.060)	(0.073)
Hispanic	0.043*	0.004	0.002	0.009	0.024**	0.003	0.025**	0.023***
	(0.022)	(0.007)	(0.020)	(0.011)	(0.011)	(0.017)	(0.011)	(0.006)
Age	-0.012**	-0.008***	-0.006	-0.002	-0.005**	-0.011***	-0.003	-0.001
	(0.006)	(0.002)	(0.005)	(0.004)	(0.002)	(0.004)	(0.003)	(0.003)
Age Squared	0.000	0.000**	0.000	-0.000	0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trial	0.130***	0.042	0.063	0.061***	0.049	0.034	0.117***	0.080**
	(0.028)	(0.145)	(0.049)	(0.017)	(0.045)	(0.024)	(0.043)	(0.037)
A Felony			0.199***	0.090***	0.175***			0.086**
			(0.042)	(0.031)	(0.029)			(0.039)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 15. Regression Models Explaining Incarceration, with the Identical Preceding Conviction (IPC, cont'd)

	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Forgery	Fraud	Crim Misch	Drug Traff	Drug Poss	Weapons	Driving	Nuisance
B Felony			0.146***	0.040	0.092***	0.100***		0.200***
			(0.040)	(0.030)	(0.029)	(0.018)		(0.040)
C Felony	0.120		0.138***	0.030	0.070**	0.047*		0.128**
	(0.077)		(0.036)	(0.023)	(0.029)	(0.024)		(0.062)
D Felony	0.043	0.078	0.013	-0.017	0.015	0.028	0.099***	0.102***
	(0.050)	(0.057)	(0.056)	(0.024)	(0.027)	(0.018)	(0.016)	(0.019)
A Misdem	-0.297***	-0.408***	-0.366***	-0.362***	-0.331***	-0.464***		-0.261***
	(0.040)	(0.088)	(0.038)	(0.055)	(0.040)	(0.032)		(0.029)
B Misdem	-0.553***	-0.389***	-0.473***	-0.488***	-0.562***	-0.593***	-0.402***	-0.403***
	(0.081)	(0.066)	(0.051)	(0.063)	(0.054)	(0.055)	(0.037)	(0.041)
Total Fel Conv	0.069***	0.026***	0.053***	0.043***	0.033***	0.038***	0.053***	0.037***
	(0.008)	(0.005)	(0.007)	(0.003)	(0.003)	(0.007)	(0.006)	(0.002)
Constant	0.855***	0.731***	0.750***	0.799***	0.791***	1.104***	0.620***	0.696***
	(0.106)	(0.081)	(0.088)	(0.062)	(0.066)	(0.084)	(0.063)	(0.080)
n	1,861	6,927	3,038	5,304	25,363	3,565	9,690	18,474
R-squared	0.233	0.129	0.167	0.290	0.227	0.415	0.294	0.135

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 16. Regression Models Explaining the Incarceration Length, with the Identical Preceding Conviction (IPC)

	(1) Sex Crimes	(2) Agg Assault	(3) Sim Assault	(4) Burglary	(5) Larceny	(6) MV Larceny	(7) Stolen Prop
IPC	-0.707	7.997	0.103	14.107***	0.126	0.871	-0.599
	(3.112)	(5.573)	(0.208)	(5.044)	(0.178)	(0.603)	(0.550)
Male	13.356	10.215***	-0.212	7.042**	0.885***	0.230	0.840*
	(11.561)	(1.711)	(0.318)	(3.392)	(0.154)	(1.347)	(0.437)
Black	-0.288	2.429	0.866**	-1.998	0.011	-0.206	0.260
	(3.288)	(2.402)	(0.414)	(1.797)	(0.231)	(0.319)	(0.223)
Other Race	-9.563	-6.877	1.406	-6.415**	-0.773	-1.138	0.592
	(8.079)	(6.385)	(0.946)	(2.766)	(0.760)	(0.732)	(0.772)
Race Unknown	3.456	2.285	-1.164*	-0.903	-3.541*	-1.407	-0.992
	(9.817)	(8.035)	(0.630)	(2.474)	(1.971)	(2.002)	(0.846)
Hispanic	-4.086	1.422	0.279	-2.969*	-0.113	-0.152	0.022
	(3.388)	(1.751)	(0.482)	(1.657)	(0.248)	(0.386)	(0.233)
Age	1.095*	1.559***	-0.017	1.076**	-0.133**	0.048	0.040
	(0.601)	(0.354)	(0.063)	(0.536)	(0.055)	(0.181)	(0.061)
Age Squared	-0.012	-0.019***	-0.000	-0.008	0.001**	-0.000	-0.001
	(0.008)	(0.004)	(0.001)	(0.008)	(0.001)	(0.003)	(0.001)
Trial	46.213***	60.266***	19.516***	80.452***	26.032***	7.622***	6.842***
	(13.316)	(10.301)	(6.747)	(13.486)	(7.522)	(1.115)	(2.550)
A Felony	408.263***	402.153***					
	(19.123)	(9.446)					

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Table 16. Regression Models Explaining the Incarceration Length, with the Identical Preceding Conviction (IPC, cont'd)

	(1) Sex Crimes	(2) Agg Assault	(3) Sim Assault	(4) Burglary	(5) Larceny	(6) MV Larceny	(7) Stolen Prop
B Felony	142.491***	112.744***		122.949***	26.211***		
	(5.199)	(6.368)		(5.136)	(2.910)		
C Felony	70.990***	63.645***		62.352***	22.846***		7.717*
	(9.173)	(5.970)		(2.691)	(8.476)		(4.366)
D Felony	26.603***	22.260***	13.766***	16.630***	3.306***	21.854***	6.848***
	(3.973)	(1.558)	(1.788)	(1.353)	(0.984)	(1.080)	(1.244)
A Misdem	-19.966***	-9.768***	-9.257***		-11.338***	-10.165***	-10.371***
	(2.022)	(1.015)	(0.417)		(1.037)	(0.912)	(0.440)
B Misdem	-24.672***	-10.235**	-12.786***		-14.149***	-14.499***	-14.325***
	(2.720)	(3.846)	(0.490)		(1.082)	(1.345)	(0.554)
Total Fel Conv	5.154***	5.254***	1.186***	5.277***	1.069***	0.713***	1.077***
	(1.041)	(0.756)	(0.270)	(0.743)	(0.121)	(0.147)	(0.102)
Constant	-14.565	-32.037***	12.591***	-24.863***	15.931***	13.225***	12.865***
	(16.558)	(8.298)	(1.745)	(8.455)	(0.666)	(3.522)	(1.202)
n	999	1,981	5,370	3,672	9,042	364	1,379
R-squared	0.795	0.632	0.283	0.333	0.320	0.635	0.675

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 16. Regression Models Explaining the Incarceration Length, with the Identical Preceding Conviction (IPC, cont'd)

	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Forgery	Fraud	Crim Misch	Drug Traff	Drug Poss	Weapons	Driving	Nuisance
IPC	0.727	0.207	0.461	1.873	-0.175	7.281*	-0.352	-0.275*
	(0.697)	(0.180)	(1.355)	(1.326)	(0.275)	(4.003)	(0.249)	(0.149)
Male	1.667**	0.174	2.449**	7.401***	0.852***	9.061**	1.133**	0.418*
	(0.640)	(0.438)	(1.063)	(0.703)	(0.263)	(3.583)	(0.453)	(0.217)
Black	0.460	-0.117	-0.227	3.080***	1.320***	2.771**	-0.587	0.154
	(0.627)	(0.223)	(0.792)	(0.848)	(0.474)	(1.262)	(0.568)	(0.215)
Other Race	-6.132*	0.817	1.084	-2.446	-0.311	0.071	0.274	0.277
	(3.128)	(0.604)	(2.087)	(3.723)	(1.265)	(5.435)	(0.680)	(0.861)
Race Unknown	-1.613	-3.362*	2.960	-6.365	-2.949*	9.915**	2.067*	0.769
	(1.145)	(1.786)	(3.329)	(7.430)	(1.621)	(4.828)	(1.110)	(0.563)
Hispanic	-0.160	-0.072	0.829	0.852*	0.021	-0.713	-0.136	0.309**
	(0.575)	(0.155)	(1.132)	(0.483)	(0.373)	(1.519)	(0.374)	(0.134)
Age	0.319**	-0.099**	-0.148	0.464*	0.055	0.728	-0.038	0.035
	(0.146)	(0.040)	(0.232)	(0.244)	(0.071)	(0.487)	(0.066)	(0.038)
Age Squared	-0.004**	0.001**	0.001	-0.008***	-0.001	-0.009	0.001	-0.001*
	(0.002)	(0.001)	(0.003)	(0.003)	(0.001)	(0.007)	(0.001)	(0.000)
Trial	8.466***	8.356***	11.497	59.131***	28.906***	62.296***	19.582	13.837***
	(2.013)	(2.439)	(7.269)	(6.725)	(3.833)	(10.865)	(12.802)	(3.217)
A Felony			469.482***	69.705***	67.162***			263.175***
			(2.161)	(7.089)	(3.655)			(2.251)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 16. Regression Models Explaining the Incarceration Length, with the Identical Preceding Conviction (IPC, cont'd)

	(8) Forgery	(9) Fraud	(10) Crim Misch	(11) Drug Traff	(12) Drug Poss	(13) Weapons	(14) Driving	(15) Nuisance
B Felony			117.897***	13.525***	20.021***	140.825***		46.835***
			(13.082)	(2.641)	(2.020)	(25.437)		(6.665)
C Felony	16.061***		42.456***	8.202***	12.427***	53.499***		24.368***
	(4.777)		(12.304)	(1.844)	(1.895)	(5.496)		(2.844)
D Felony	4.161***	6.859***	5.583***	2.709*	3.964***	13.096***	4.610***	6.021***
	(0.891)	(0.624)	(1.361)	(1.572)	(1.267)	(2.688)	(0.735)	(0.939)
A Misdem	-9.638***	-12.597***	-9.513***	-12.142***	-10.562***	-12.351***		-6.022***
	(1.146)	(1.318)	(0.832)	(2.006)	(1.156)	(2.690)		(0.892)
B Misdem	-13.691***	-13.916***	-11.572***	-18.277***	-12.974***	-13.419***	-4.398***	-8.635***
	(1.109)	(0.987)	(0.745)	(3.672)	(1.125)	(3.338)	(0.407)	(0.828)
Total Fel Conv	1.862***	0.580***	1.085***	3.967***	1.286***	4.650***	1.993***	0.584***
	(0.239)	(0.080)	(0.164)	(0.545)	(0.159)	(1.122)	(0.553)	(0.065)
Constant	5.766*	15.617***	12.680***	-1.994	11.371***	-10.430	5.628***	9.424***
	(2.935)	(1.710)	(3.854)	(7.006)	(2.704)	(9.736)	(1.476)	(1.121)
n	1,018	2,017	1,474	4,292	10,408	2,468	4,663	9,220
R-squared	0.613	0.748	0.559	0.502	0.588	0.445	0.184	0.567

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 17. Regression Models Explaining Incarceration, with the Specialization Index

	(1) Sex Crimes	(2) Agg Assault	(3) Sim Assault	(4) Burglary	(5) Larceny	(6) MV Larceny	(7) Stolen Prop
Specialization index	-0.075	-0.098***	-0.206***	-0.021	-0.163***	-0.021	-0.169***
	(0.054)	(0.029)	(0.026)	(0.017)	(0.025)	(0.110)	(0.050)
Male	0.216**	0.062**	0.075***	0.056**	0.141***	0.032	0.114***
	(0.103)	(0.025)	(0.017)	(0.026)	(0.012)	(0.081)	(0.023)
Black	0.008	0.022	0.041***	0.021**	0.046***	-0.025	0.007
	(0.021)	(0.016)	(0.011)	(0.010)	(0.008)	(0.046)	(0.024)
Other Race	0.018	-0.094	0.027	0.035	-0.120***	0.302*	-0.007
	(0.090)	(0.074)	(0.071)	(0.038)	(0.032)	(0.175)	(0.133)
Race Unknown	0.033	0.011	0.018	0.013	-0.053	0.218***	0.131
	(0.092)	(0.088)	(0.048)	(0.010)	(0.063)	(0.049)	(0.124)
Hispanic	0.042**	0.002	0.005	0.006	0.024**	0.040	-0.007
	(0.018)	(0.015)	(0.011)	(0.010)	(0.010)	(0.035)	(0.019)
Age	-0.002	-0.007**	-0.015***	-0.003	0.000	-0.013	-0.011
	(0.006)	(0.004)	(0.003)	(0.003)	(0.003)	(0.013)	(0.007)
Age Squared	0.000	0.000	0.000***	0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trial	0.068***	0.007	0.081	0.025*	0.101**	0.082*	0.064
	(0.018)	(0.015)	(0.056)	(0.013)	(0.041)	(0.043)	(0.081)
A Felony	-0.008	0.026					
	(0.029)	(0.018)					

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 17. Regression Models Explaining Incarceration, with the Specialization Index (cont'd)

	(1) Sex Crimes	(2) Agg Assault	(3) Sim Assault	(4) Burglary	(5) Larceny	(6) MV Larceny	(7) Stolen Prop
B Felony	0.038*	0.076***		0.080***	0.174***		
	(0.020)	(0.014)		(0.024)	(0.023)		
C Felony	0.045**	0.057***		0.086***	0.003		-0.159
	(0.020)	(0.014)		(0.022)	(0.058)		(0.219)
D Felony	0.017	0.051***	0.003	0.012	-0.051*	0.051	0.021
	(0.022)	(0.014)	(0.017)	(0.018)	(0.026)	(0.093)	(0.031)
A Misdem	-0.220***	-0.362***	-0.331***		-0.268***	-0.240***	-0.290***
	(0.037)	(0.034)	(0.020)		(0.021)	(0.063)	(0.031)
B Misdem	-0.437***	-0.540***	-0.490***		-0.420***	-0.376***	-0.527***
	(0.045)	(0.118)	(0.035)		(0.036)	(0.089)	(0.050)
Total Fel Conv	0.016**	0.017**	0.034***	0.027***	0.040***	0.049***	0.037***
	(0.007)	(0.007)	(0.006)	(0.005)	(0.003)	(0.010)	(0.008)
Constant	0.760***	1.019***	1.153***	0.852***	0.671***	1.073***	0.981***
	(0.159)	(0.073)	(0.063)	(0.058)	(0.060)	(0.268)	(0.129)
n	1,212	2,455	8,995	3,968	16,869	589	2,254
R-squared	0.320	0.333	0.149	0.115	0.154	0.234	0.191

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 17. Regression Models Explaining Incarceration, with the Specialization Index (cont'd)

	(8) Forgery	(9) Fraud	(10) Crim Misch	(11) Drug Traff	(12) Drug Poss	(13) Weapons	(14) Driving	(15) Nuisance
Specialization index	-0.185***	-0.133***	-0.198***	-0.140***	-0.132***	-0.122**	-0.095***	-0.167***
	(0.046)	(0.024)	(0.057)	(0.036)	(0.020)	(0.046)	(0.017)	(0.018)
Male	0.072**	0.057***	0.091***	0.068***	0.003	-0.038	0.067***	0.021
	(0.029)	(0.016)	(0.029)	(0.014)	(0.012)	(0.033)	(0.017)	(0.020)
Black	0.064**	0.031**	0.024	0.008	0.044***	0.023**	0.005	0.028***
	(0.027)	(0.013)	(0.032)	(0.011)	(0.010)	(0.010)	(0.016)	(0.008)
Other Race	-0.092	-0.050	-0.060	-0.038	-0.018	0.040	-0.060*	0.017
	(0.103)	(0.057)	(0.065)	(0.070)	(0.035)	(0.082)	(0.033)	(0.041)
Race Unknown	-0.312***	0.048	-0.273***	0.008	-0.001	-0.043	-0.056	-0.017
	(0.108)	(0.084)	(0.094)	(0.033)	(0.097)	(0.125)	(0.063)	(0.072)
Hispanic	0.042**	0.003	0.001	0.009	0.024**	0.002	0.026**	0.022***
	(0.021)	(0.007)	(0.019)	(0.011)	(0.011)	(0.016)	(0.011)	(0.006)
Age	-0.014**	-0.009***	-0.009*	-0.003	-0.006***	-0.012***	-0.004	-0.003
	(0.006)	(0.002)	(0.005)	(0.004)	(0.002)	(0.004)	(0.003)	(0.003)
Age Squared	0.000	0.000***	0.000	0.000	0.000	0.000*	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trial	0.113***	0.037	0.056	0.060***	0.046	0.035	0.120***	0.086**
	(0.033)	(0.143)	(0.047)	(0.017)	(0.045)	(0.024)	(0.042)	(0.037)
A Felony			0.165***	0.103***	0.182***			0.125***
			(0.039)	(0.029)	(0.030)			(0.040)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 17. Regression Models Explaining Incarceration, with the Specialization Index (cont'd)

	(8) Forgery	(9) Fraud	(10) Crim Misch	(11) Drug Traff	(12) Drug Poss	(13) Weapons	(14) Driving	(15) Nuisance
B Felony			0.138***	0.047	0.096***	0.116***		0.201***
			(0.040)	(0.029)	(0.028)	(0.018)		(0.038)
C Felony	0.115		0.141***	0.035	0.072**	0.048**		0.129**
	(0.080)		(0.033)	(0.024)	(0.029)	(0.024)		(0.061)
D Felony	0.047	0.081	0.013	-0.013	0.015	0.028	0.109***	0.100***
	(0.050)	(0.057)	(0.056)	(0.024)	(0.027)	(0.017)	(0.015)	(0.018)
A Misdem	-0.297***	-0.410***	-0.364***	-0.361***	-0.333***	-0.463***		-0.270***
	(0.041)	(0.090)	(0.038)	(0.056)	(0.040)	(0.032)		(0.029)
B Misdem	-0.535***	-0.391***	-0.469***	-0.485***	-0.564***	-0.590***	-0.401***	-0.407***
	(0.081)	(0.068)	(0.051)	(0.064)	(0.054)	(0.053)	(0.038)	(0.041)
Total Fel Conv	0.060***	0.019***	0.044***	0.039***	0.028***	0.034***	0.050***	0.030***
	(0.007)	(0.005)	(0.007)	(0.003)	(0.002)	(0.006)	(0.006)	(0.003)
Constant	1.001***	0.832***	0.928***	0.904***	0.892***	1.203***	0.676***	0.843***
	(0.094)	(0.077)	(0.099)	(0.072)	(0.060)	(0.095)	(0.065)	(0.075)
n	1,861	6,927	3,038	5,304	25,363	3,565	9,690	18,474
	0.239	0.131	0.173	0.295	0.230	0.417	0.296	0.140

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Table 18. Regression Models Explaining the Incarceration Length, with the Specialization Index

	(1) Sex Crimes	(2) Agg Assault	(3) Sim Assault	(4) Burglary	(5) Larceny	(6) MV Larceny	(7) Stolen Prop
Specialization index	-16.784**	-1.381	0.505	11.683**	-0.350	-1.380	-2.441**
	(6.350)	(5.383)	(1.306)	(5.323)	(0.327)	(1.286)	(0.944)
Male	13.737	10.048***	-0.193	7.775**	0.837***	0.227	0.665
	(11.770)	(1.876)	(0.304)	(3.435)	(0.157)	(1.301)	(0.438)
Black	-1.101	2.590	0.871**	-2.212	0.006	-0.216	0.229
	(3.418)	(2.264)	(0.422)	(1.849)	(0.232)	(0.314)	(0.228)
Other Race	-6.776	-7.260	1.369	-6.239**	-0.755	-1.330*	0.546
	(8.007)	(6.331)	(0.950)	(3.048)	(0.754)	(0.689)	(0.729)
Race Unknown	3.982	2.960	-1.215**	-0.446	-3.535*	-1.247	-0.837*
	(7.836)	(7.729)	(0.584)	(2.359)	(1.978)	(1.949)	(0.454)
Hispanic	-4.580	1.507	0.285	-3.134**	-0.120	-0.191	-0.021
	(3.475)	(1.701)	(0.494)	(1.555)	(0.250)	(0.375)	(0.236)
Age	1.007*	1.511***	-0.008	1.169**	-0.138**	0.023	0.002
	(0.566)	(0.368)	(0.067)	(0.564)	(0.057)	(0.170)	(0.065)
Age Squared	-0.011	-0.019***	-0.000	-0.009	0.001**	0.000	-0.000
	(0.007)	(0.005)	(0.001)	(0.008)	(0.001)	(0.002)	(0.001)
Trial	46.330***	60.220***	19.484***	80.074***	26.015***	7.530***	6.667**
	(13.242)	(10.327)	(6.703)	(13.657)	(7.524)	(1.140)	(2.520)
A Felony	407.957***	401.798***					
	(19.019)	(9.464)					

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 18. Regression Models Explaining the Incarceration Length, with the Specialization Index (cont'd)

	(1) Sex Crimes	(2) Agg Assault	(3) Sim Assault	(4) Burglary	(5) Larceny	(6) MV Larceny	(7) Stolen Prop
B Felony	142.432***	112.593***		122.141***	26.306***		
	(5.245)	(6.250)		(4.949)	(2.978)		
C Felony	70.479***	63.881***		63.591***	22.893***		7.662*
	(9.274)	(5.904)		(2.751)	(8.494)		(4.270)
D Felony	27.202***	22.200***	13.747***	17.081***	3.317***	22.123***	6.863***
	(3.957)	(1.525)	(1.764)	(1.341)	(0.984)	(1.175)	(1.278)
A Misdem	-19.356***	-9.918***	-9.277***		-11.346***	-10.093***	-10.347***
	(2.123)	(1.035)	(0.410)		(1.036)	(0.934)	(0.445)
B Misdem	-25.385***	-10.870***	-12.815***		-14.174***	-14.304***	-14.149***
	(2.682)	(3.922)	(0.479)		(1.077)	(1.336)	(0.565)
Total Fel Conv	4.297***	5.310***	1.202***	6.070***	1.053***	0.673***	1.011***
	(1.114)	(0.884)	(0.310)	(0.743)	(0.116)	(0.152)	(0.093)
Constant	-4.640	-30.042***	12.199***	-31.547***	16.273***	14.316***	14.902***
	(15.824)	(10.449)	(2.523)	(10.981)	(0.691)	(3.282)	(1.478)
n	999	1,981	5,370	3,672	9,042	364	1,379
R-squared	0.796	0.631	0.283	0.328	0.320	0.636	0.677

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Table 18. Regression Models Explaining the Incarceration Length, with the Specialization Index (cont'd)

	(8) Forgery	(9) Fraud	(10) Crim Misch	(11) Drug Traff	(12) Drug Poss	(13) Weapons	(14) Driving	(15) Nuisance
Specialization index	-0.498	0.468	0.652	-4.733***	-1.265**	0.866	-0.255	-0.919*
	(1.106)	(0.306)	(1.121)	(1.320)	(0.602)	(4.432)	(0.726)	(0.547)
Male	1.635**	0.203	2.492**	7.199***	0.792***	9.173**	1.127**	0.374
	(0.638)	(0.448)	(1.097)	(0.710)	(0.257)	(3.587)	(0.447)	(0.241)
Black	0.453	-0.102	-0.220	2.984***	1.306***	2.928**	-0.579	0.136
	(0.630)	(0.220)	(0.780)	(0.839)	(0.470)	(1.264)	(0.536)	(0.213)
Other Race	-5.958*	0.819	1.094	-1.322	-0.294	0.588	0.265	0.327
	(3.147)	(0.606)	(2.075)	(3.764)	(1.280)	(5.384)	(0.680)	(0.872)
Race Unknown	-1.721	-3.406*	2.902	-5.663	-2.853*	13.462***	2.039*	0.847
	(1.121)	(1.793)	(3.333)	(7.926)	(1.639)	(4.606)	(1.102)	(0.593)
Hispanic	-0.187	-0.063	0.847	0.813*	0.018	-0.724	-0.130	0.301**
	(0.570)	(0.156)	(1.125)	(0.474)	(0.373)	(1.479)	(0.382)	(0.136)
Age	0.307**	-0.094**	-0.138	0.376	0.038	0.709	-0.039	0.023
	(0.143)	(0.039)	(0.233)	(0.230)	(0.071)	(0.510)	(0.065)	(0.040)
Age Squared	-0.004**	0.001**	0.001	-0.007**	-0.001	-0.008	0.001	-0.001
	(0.002)	(0.001)	(0.003)	(0.003)	(0.001)	(0.007)	(0.001)	(0.000)
Trial	8.416***	8.379***	11.530	59.006***	28.869***	62.616***	19.550	13.883***
	(2.022)	(2.442)	(7.254)	(6.671)	(3.843)	(10.828)	(12.782)	(3.224)
A Felony			469.606***	70.257***	67.244***			263.292***
			(2.188)	(7.179)	(3.650)			(2.175)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 18. Regression Models Explaining the Incarceration Length, with the Specialization Index (cont'd)

	(8) Forgery	(9) Fraud	(10) Crim Misch	(11) Drug Traff	(12) Drug Poss	(13) Weapons	(14) Driving	(15) Nuisance
B Felony			117.921***	13.817***	20.069***	140.174***		46.852***
			(13.086)	(2.640)	(2.014)	(25.122)		(6.663)
C Felony	16.085***		42.460***	8.419***	12.452***	53.730***		24.425***
	(4.770)		(12.250)	(1.874)	(1.898)	(5.538)		(2.863)
D Felony	4.182***	6.862***	5.554***	2.859*	3.969***	13.123***	4.597***	6.011***
	(0.914)	(0.623)	(1.367)	(1.582)	(1.267)	(2.726)	(0.746)	(0.937)
A Misdem	-9.664***	-12.566***	-9.529***	-12.121***	-10.584***	-12.477***		-6.074***
	(1.144)	(1.295)	(0.833)	(1.993)	(1.155)	(2.753)		(0.906)
B Misdem	-13.729***	-13.903***	-11.591***	-17.877***	-13.025***	-13.641***	-4.348***	-8.680***
	(1.173)	(0.977)	(0.756)	(3.810)	(1.124)	(3.406)	(0.392)	(0.839)
Total Fel Conv	1.848***	0.594***	1.100***	3.929***	1.247***	4.714***	2.002***	0.553***
	(0.233)	(0.080)	(0.174)	(0.565)	(0.153)	(1.127)	(0.569)	(0.068)
Constant	6.372**	15.246***	12.168***	2.093	12.344***	-10.406	5.642***	10.122***
	(2.648)	(1.634)	(3.917)	(6.809)	(2.606)	(10.808)	(1.507)	(1.387)
n	1,018	2,017	1,474	4,292	10,408	2,468	4,663	9,220
R-squared	0.612	0.748	0.559	0.503	0.588	0.444	0.184	0.567

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Table 19. Regression Models Explaining Incarceration, with the LCA Classes

	(1) Sex Crimes	(2) Agg Assault	(3) Sim Assault	(4) Burglary	(5) Larceny	(6) MV Larceny	(7) Stolen Prop
Drug Gen.	0.093***	0.032	0.070***	0.025**	0.130***	0.016	0.067*
	(0.028)	(0.030)	(0.015)	(0.012)	(0.015)	(0.077)	(0.039)
High Inv. Gen.	0.096**	0.034	0.103***	-0.006	0.157***	0.109*	0.031
	(0.041)	(0.028)	(0.029)	(0.014)	(0.015)	(0.063)	(0.043)
Driving Spec.	-0.039	-0.132***	-0.112***	-0.036	-0.125***	-0.087	-0.119**
	(0.049)	(0.044)	(0.021)	(0.032)	(0.015)	(0.082)	(0.055)
Property Spec.	-0.022	-0.021	-0.045***	-0.008	0.004	0.035	-0.024
	(0.029)	(0.028)	(0.016)	(0.010)	(0.013)	(0.052)	(0.026)
Drug Spec.	-0.038	-0.045*	-0.052***	-0.028*	-0.032**	-0.007	-0.054
	(0.037)	(0.027)	(0.018)	(0.016)	(0.012)	(0.070)	(0.033)
Violent Spec.	0.012	-0.058***	-0.039**	-0.001	-0.026	-0.024	-0.095***
	(0.036)	(0.022)	(0.016)	(0.010)	(0.016)	(0.084)	(0.031)
Male	0.211**	0.072***	0.085***	0.057**	0.150***	0.032	0.127***
	(0.104)	(0.024)	(0.018)	(0.027)	(0.012)	(0.078)	(0.024)
Black	0.005	0.018	0.039***	0.021**	0.035***	-0.021	0.009
	(0.022)	(0.015)	(0.011)	(0.010)	(0.007)	(0.051)	(0.024)
Other Race	0.021	-0.086	0.018	0.033	-0.123***	0.266*	-0.005
	(0.090)	(0.082)	(0.074)	(0.038)	(0.033)	(0.152)	(0.132)
Race Unknown	0.009	0.010	0.022	0.005	-0.035	0.231***	0.147
	(0.105)	(0.083)	(0.043)	(0.011)	(0.060)	(0.053)	(0.099)
Hispanic	0.042**	0.003	0.002	0.006	0.019*	0.041	-0.007
	(0.019)	(0.015)	(0.011)	(0.010)	(0.010)	(0.036)	(0.020)
Age	-0.002	-0.006*	-0.014***	-0.002	-0.001	-0.015	-0.010
	(0.006)	(0.003)	(0.003)	(0.003)	(0.002)	(0.013)	(0.007)
Age Squared	0.000	0.000	0.000***	0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

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Table 19. Regression Models Explaining Incarceration, with the LCA Classes (cont'd)

	(1) Sex Crimes	(2) Agg Assault	(3) Sim Assault	(4) Burglary	(5) Larceny	(6) MV Larceny	(7) Stolen Prop
Trial	0.074***	0.014	0.084	0.025*	0.101***	0.097*	0.060
	(0.019)	(0.015)	(0.057)	(0.013)	(0.037)	(0.055)	(0.080)
A Felony	-0.013	0.048**					
	(0.033)	(0.019)					
B Felony	0.043**	0.077***		0.081***	0.179***		
	(0.021)	(0.014)		(0.024)	(0.016)		
C Felony	0.055***	0.063***		0.087***	0.019		-0.174
	(0.020)	(0.012)		(0.022)	(0.057)		(0.220)
D Felony	0.019	0.052***	0.008	0.012	-0.043	0.194*	0.019
	(0.022)	(0.014)	(0.016)	(0.018)	(0.026)	(0.116)	(0.031)
A Misdem	-0.222***	-0.361***	-0.324***		-0.265***	-0.225***	-0.292***
	(0.037)	(0.033)	(0.020)		(0.021)	(0.059)	(0.031)
B Misdem	-0.436***	-0.550***	-0.483***		-0.409***	-0.351***	-0.523***
	(0.044)	(0.113)	(0.036)		(0.035)	(0.090)	(0.049)
Total Fel Conv	0.016***	0.020***	0.041***	0.027***	0.040***	0.043***	0.040***
	(0.006)	(0.007)	(0.005)	(0.005)	(0.003)	(0.010)	(0.008)
Constant	0.731***	0.977***	1.040***	0.836***	0.614***	1.083***	0.911***
	(0.166)	(0.070)	(0.065)	(0.063)	(0.051)	(0.241)	(0.126)
n	1,212	2,455	8,995	3,968	16,869	589	2,254
R-squared	0.327	0.341	0.152	0.117	0.166	0.243	0.194

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Table 19. Regression Models Explaining Incarceration, with the LCA Classes (cont'd)

	(8) Forgery	(9) Fraud	(10) Crim Misch	(11) Drug Traff	(12) Drug Poss	(13) Weapons	(14) Driving	(15) Nuisance
Drug Gen.	0.201***	0.109***	0.087**	0.098***	0.125***	0.043	0.068	0.089***
	(0.037)	(0.029)	(0.033)	(0.024)	(0.028)	(0.038)	(0.045)	(0.031)
High Inv. Gen.	0.055	0.078**	0.144***	0.032	0.154***	0.086**	0.134***	0.107***
	(0.055)	(0.030)	(0.032)	(0.036)	(0.019)	(0.034)	(0.041)	(0.024)
Driving Spec.	-0.047	-0.060**	-0.029	0.009	-0.085***	-0.021	-0.005	-0.052***
	(0.060)	(0.029)	(0.029)	(0.033)	(0.019)	(0.030)	(0.015)	(0.014)
Property Spec.	0.008	0.017	0.004	-0.033	-0.004	-0.065***	-0.039***	-0.028**
	(0.037)	(0.015)	(0.022)	(0.027)	(0.015)	(0.024)	(0.014)	(0.011)
Drug Spec.	-0.025	-0.005	-0.054*	0.020	0.001	-0.046**	-0.045***	-0.046***
	(0.038)	(0.012)	(0.028)	(0.016)	(0.013)	(0.021)	(0.016)	(0.013)
Violent Spec.	0.051	-0.039	0.010	0.024	-0.003	-0.029	-0.047*	0.001
	(0.047)	(0.027)	(0.027)	(0.018)	(0.011)	(0.022)	(0.026)	(0.016)
Male	0.081***	0.067***	0.094***	0.071***	0.004	-0.037	0.066***	0.030
	(0.027)	(0.017)	(0.027)	(0.015)	(0.012)	(0.033)	(0.017)	(0.019)
Black	0.060**	0.027**	0.028	0.001	0.034***	0.026**	0.017	0.029***
	(0.026)	(0.013)	(0.031)	(0.010)	(0.008)	(0.011)	(0.016)	(0.008)
Other Race	-0.104	-0.047	-0.069	-0.043	-0.018	0.010	-0.065*	0.013
	(0.111)	(0.061)	(0.065)	(0.071)	(0.035)	(0.082)	(0.034)	(0.040)
Race Unknown	-0.300***	0.044	-0.266***	-0.011	0.002	-0.046	-0.067	-0.026
	(0.086)	(0.086)	(0.098)	(0.039)	(0.091)	(0.122)	(0.060)	(0.069)
Hispanic	0.041*	0.001	-0.001	0.006	0.020*	0.002	0.026**	0.021***
	(0.021)	(0.007)	(0.019)	(0.011)	(0.011)	(0.016)	(0.011)	(0.006)
Age	-0.014***	-0.011***	-0.007	-0.004	-0.008***	-0.012***	-0.004	-0.002
	(0.005)	(0.002)	(0.005)	(0.004)	(0.002)	(0.004)	(0.003)	(0.003)
Age Squared	0.000	0.000***	0.000	0.000	0.000**	0.000*	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

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Table 19. Regression Models Explaining Incarceration, with the LCA Classes (cont'd)

	(8) Forgery	(9) Fraud	(10) Crim Misch	(11) Drug Traff	(12) Drug Poss	(13) Weapons	(14) Driving	(15) Nuisance
Trial	0.131***	0.037	0.062	0.063***	0.052	0.035	0.116**	0.084**
	(0.030)	(0.142)	(0.050)	(0.016)	(0.047)	(0.024)	(0.045)	(0.037)
A Felony			0.186***	0.094***	0.183***			0.129***
			(0.043)	(0.029)	(0.032)			(0.041)
B Felony			0.141***	0.043	0.092***	0.108***		0.212***
			(0.042)	(0.028)	(0.029)	(0.019)		(0.038)
C Felony	0.120		0.131***	0.030	0.069**	0.052**		0.128*
	(0.084)		(0.034)	(0.024)	(0.030)	(0.024)		(0.068)
D Felony	0.051	0.083	0.017	-0.017	0.014	0.031*	0.093***	0.101***
	(0.048)	(0.058)	(0.056)	(0.024)	(0.027)	(0.017)	(0.016)	(0.019)
A Misdem	-0.294***	-0.409***	-0.362***	-0.362***	-0.342***	-0.459***		-0.265***
	(0.042)	(0.089)	(0.037)	(0.057)	(0.040)	(0.033)		(0.029)
B Misdem	-0.536***	-0.391***	-0.467***	-0.491***	-0.566***	-0.588***	-0.392***	-0.402***
	(0.078)	(0.067)	(0.051)	(0.064)	(0.055)	(0.053)	(0.037)	(0.042)
Total Fel Conv	0.063***	0.022***	0.047***	0.041***	0.029***	0.039***	0.055***	0.033***
	(0.007)	(0.005)	(0.008)	(0.003)	(0.002)	(0.006)	(0.006)	(0.003)
Constant	0.894***	0.803***	0.792***	0.831***	0.868***	1.165***	0.646***	0.753***
	(0.098)	(0.097)	(0.088)	(0.059)	(0.066)	(0.086)	(0.064)	(0.073)
n	1,861	6,927	3,038	5,304	25,363	3,565	9,690	18,474
R-squared	0.248	0.139	0.175	0.296	0.238	0.420	0.296	0.143

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Table 20. Regression Models Explaining the Incarceration Length, with the LCA Classes

	(1) Sex Crimes	(2) Agg Assault	(3) Sim Assault	(4) Burglary	(5) Larceny	(6) MV Larceny	(7) Stolen Prop
Drug Gen.	1.469	-0.895	-0.086	-17.366***	0.298	-3.298**	-0.765
	(3.434)	(4.417)	(0.297)	(4.610)	(0.536)	(1.328)	(0.490)
High Inv. Gen.	-0.531	-0.963	-0.273	-8.682	1.180***	0.007	0.035
	(3.864)	(4.440)	(0.427)	(6.079)	(0.323)	(0.683)	(0.415)
Driving Spec.	-5.776	-4.519	-1.736***	-8.998***	-1.083**	-2.422	-0.276
	(6.608)	(2.724)	(0.540)	(2.809)	(0.502)	(2.395)	(1.519)
Property Spec.	2.161	-5.407**	-0.272	1.424	0.522***	-1.064	-0.502
	(5.243)	(2.065)	(0.314)	(2.107)	(0.156)	(0.884)	(0.390)
Drug Spec.	-0.130	-4.514**	-1.044***	-7.419**	-0.098	-1.339	-0.702
	(3.070)	(2.180)	(0.221)	(3.512)	(0.245)	(0.936)	(0.562)
Violent Spec.	2.563	1.901	2.241**	8.958***	0.298	0.607	1.081**
	(8.182)	(2.315)	(1.063)	(3.290)	(0.318)	(0.898)	(0.453)
Male	13.608	9.666***	-0.353	6.343*	0.898***	-0.050	0.689
	(12.244)	(1.747)	(0.333)	(3.261)	(0.152)	(1.261)	(0.447)
Black	-0.655	2.147	0.693*	-2.591	-0.010	-0.111	0.240
	(3.560)	(2.298)	(0.351)	(1.954)	(0.201)	(0.348)	(0.211)
Other Race	-7.586	-8.731	1.388	-6.493*	-0.748	-1.307	0.501
	(9.218)	(6.462)	(0.973)	(3.885)	(0.717)	(0.892)	(0.688)
Race Unknown	2.596	2.249	-0.732	0.709	-3.581*	-1.858	-0.885
	(9.243)	(8.333)	(0.680)	(1.214)	(1.986)	(2.336)	(0.833)
Hispanic	-3.939	1.488	0.285	-2.371	-0.126	-0.075	0.056
	(3.487)	(1.705)	(0.490)	(1.715)	(0.253)	(0.414)	(0.234)
Age	1.165*	1.628***	0.047	1.474***	-0.142**	0.140	0.048
	(0.628)	(0.402)	(0.073)	(0.439)	(0.060)	(0.189)	(0.063)

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Table 20. Regression Models Explaining the Incarceration Length, with the LCA Classes (cont'd)

	(1) Sex Crimes	(2) Agg Assault	(3) Sim Assault	(4) Burglary	(5) Larceny	(6) MV Larceny	(7) Stolen Prop
Age Squared	-0.013	-0.020***	-0.001	-0.012*	0.001**	-0.001	-0.001
	(0.008)	(0.005)	(0.001)	(0.007)	(0.001)	(0.003)	(0.001)
Trial	46.713***	59.971***	19.457***	79.999***	26.049***	7.977***	6.570**
	(13.352)	(10.204)	(6.683)	(13.683)	(7.517)	(1.167)	(2.526)
A Felony	407.105***	401.708***					
	(19.491)	(10.072)					
B Felony	142.018***	112.793***		120.051***	26.429***		
	(5.410)	(6.339)		(4.593)	(2.882)		
C Felony	71.078***	64.520***		63.350***	22.977***		7.469*
	(9.343)	(5.884)		(2.464)	(8.520)		(4.150)
D Felony	26.360***	22.280***	13.907***	16.893***	3.408***	24.108***	6.773***
	(4.188)	(1.552)	(1.801)	(1.415)	(0.970)	(2.487)	(1.269)
A Misdem	-20.084***	-9.470***	-9.152***		-11.307***	-9.965***	-10.334***
	(2.061)	(1.124)	(0.431)		(1.007)	(0.916)	(0.449)
B Misdem	-24.797***	-10.530**	-12.623***		-14.065***	-14.168***	-14.298***
	(2.473)	(4.460)	(0.521)		(1.042)	(1.327)	(0.551)
Total Fel Conv	4.943***	5.250***	1.104***	5.711***	1.033***	0.657***	1.060***
	(1.173)	(0.819)	(0.255)	(0.716)	(0.115)	(0.148)	(0.103)
Constant	-16.447	-31.060***	11.504***	-30.193***	15.906***	12.346***	12.982***
	(17.981)	(9.170)	(2.120)	(7.859)	(0.681)	(3.427)	(1.180)
n	999	1,981	5,370	3,672	9,042	364	1,379
R-squared	0.795	0.633	0.288	0.336	0.321	0.652	0.678

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Table 20. Regression Models Explaining the Incarceration Length, with the LCA Classes (cont'd)

	(8) Forgery	(9) Fraud	(10) Crim Misch	(11) Drug Traff	(12) Drug Poss	(13) Weapons	(14) Driving	(15) Nuisance
Drug Gen.	-0.559	-0.261	-0.117	-0.083	-0.308	-3.906	0.031	0.311
	(0.961)	(0.219)	(1.187)	(2.302)	(0.718)	(4.171)	(1.060)	(0.314)
High Inv. Gen.	0.921	0.008	-0.754	-0.091	-0.520	-3.746	0.159	0.311
	(1.002)	(0.255)	(1.092)	(1.865)	(0.779)	(4.949)	(1.173)	(0.248)
Driving Spec.	-0.792	0.474	-2.153*	-7.867***	-1.773	-6.602**	0.585	-0.261
	(1.207)	(0.616)	(1.199)	(2.226)	(1.616)	(2.785)	(0.501)	(0.421)
Property Spec.	1.596***	0.874**	-1.554	-2.707**	-0.091	-3.256	0.589	-0.201
	(0.575)	(0.346)	(0.984)	(1.157)	(0.807)	(2.316)	(0.519)	(0.237)
Drug Spec.	1.457**	-0.118	-1.917	0.281	-0.244	-1.005	-0.979*	-0.025
	(0.609)	(0.258)	(1.225)	(1.627)	(0.633)	(3.009)	(0.527)	(0.302)
Violent Spec.	3.011***	0.122	-2.002	8.565***	3.713***	5.133**	-1.618**	1.642***
	(1.122)	(0.356)	(1.464)	(1.795)	(1.130)	(1.956)	(0.643)	(0.349)
Male	1.844***	0.322	2.288**	6.841***	0.689***	8.455**	1.183**	0.328
	(0.627)	(0.428)	(1.079)	(0.667)	(0.252)	(3.341)	(0.447)	(0.227)
Black	0.197	0.003	-0.191	2.432**	1.167***	2.269*	-0.254	-0.000
	(0.553)	(0.215)	(0.766)	(1.016)	(0.400)	(1.196)	(0.519)	(0.198)
Other Race	-6.589**	0.925	1.531	-1.116	-0.311	1.694	0.264	0.282
	(2.817)	(0.654)	(2.144)	(3.670)	(1.267)	(4.888)	(0.694)	(0.862)
Race Unknown	-1.124	-3.357*	2.804	-7.366	-2.691*	11.789**	1.873*	0.541
	(1.388)	(1.915)	(2.910)	(7.982)	(1.610)	(5.257)	(1.066)	(0.604)
Hispanic	-0.159	-0.014	0.800	0.652	0.006	-0.541	-0.123	0.284**
	(0.529)	(0.157)	(1.151)	(0.468)	(0.368)	(1.713)	(0.371)	(0.134)
Age	0.352**	-0.079*	-0.137	0.622***	0.121*	0.885*	-0.038	0.056
	(0.142)	(0.045)	(0.217)	(0.173)	(0.069)	(0.506)	(0.067)	(0.041)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 20. Regression Models Explaining the Incarceration Length, with the LCA Classes (cont'd)

	(8) Forgery	(9) Fraud	(10) Crim Misch	(11) Drug Traff	(12) Drug Poss	(13) Weapons	(14) Driving	(15) Nuisance
Age Squared	-0.004**	0.001	0.001	-0.009***	-0.002**	-0.010	0.001	-0.001**
	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)	(0.007)	(0.001)	(0.001)
Trial	8.502***	8.376***	11.708	58.017***	28.458***	62.582***	19.530	13.744***
	(1.967)	(2.561)	(7.288)	(6.661)	(3.711)	(10.738)	(12.772)	(3.141)
A Felony			470.419***	70.259***	67.523***			263.145***
			(2.446)	(6.712)	(3.632)			(2.197)
B Felony			118.147***	14.340***	20.322***	140.176***		46.923***
			(13.082)	(2.207)	(1.996)	(24.991)		(6.627)
C Felony	16.243***		42.348***	8.560***	12.547***	52.977***		24.398***
	(4.750)		(12.250)	(1.604)	(1.847)	(5.245)		(2.824)
D Felony	4.196***	6.888***	5.595***	3.209**	3.994***	12.587***	4.385***	5.993***
	(0.912)	(0.603)	(1.371)	(1.343)	(1.282)	(2.779)	(0.706)	(0.909)
A Misdem	-9.387***	-12.297***	-9.433***	-11.285***	-10.302***	-12.507***		-6.022***
	(1.037)	(1.322)	(0.839)	(1.573)	(1.170)	(2.762)		(0.881)
B Misdem	-13.420***	-13.639***	-11.522***	-17.156***	-12.654***	-14.242***	-4.052***	-8.625***
	(1.307)	(1.014)	(0.762)	(3.201)	(1.160)	(3.454)	(0.412)	(0.821)
Total Fel Conv	1.802***	0.611***	1.147***	3.786***	1.227***	4.304***	2.108***	0.523***
	(0.249)	(0.081)	(0.180)	(0.528)	(0.143)	(0.984)	(0.607)	(0.063)
Constant	3.702	14.525***	13.547***	-5.590	9.655***	-11.925	5.121***	8.928***
	(2.851)	(1.892)	(3.897)	(5.714)	(2.862)	(9.203)	(1.498)	(1.103)
n	1,018	2,017	1,474	4,292	10,408	2,468	4,663	9,220
R-squared	0.621	0.751	0.560	0.513	0.591	0.447	0.185	0.569

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Table 21. Regression Models Explaining Incarceration, with the Number of Identical Records (NIR)

	(1) Sex Crimes	(2) Agg Assault	(3) Sim Assault	(4) Burglary	(5) Larceny	(6) MV Larceny	(7) Stolen Prop
NIR	0.038***	0.010	0.028***	-0.001	0.011***	0.036*	0.022*
	(0.006)	(0.015)	(0.003)	(0.005)	(0.001)	(0.020)	(0.013)
Number of Convictions of							
Murder	0.095	0.039**	0.038	-0.064	0.217***	-0.674***	0.019
	(0.086)	(0.018)	(0.057)	(0.093)	(0.074)	(0.048)	(0.125)
Sex Crimes		0.014	0.039***	0.043***	0.001	0.061	0.030
		(0.032)	(0.012)	(0.012)	(0.013)	(0.093)	(0.027)
Robbery	0.015	0.015	0.028***	0.003	0.022	0.066	0.011
	(0.022)	(0.014)	(0.007)	(0.006)	(0.014)	(0.043)	(0.027)
Agg Assault	0.002		0.042***	0.000	-0.005	0.083	-0.001
	(0.026)		(0.010)	(0.013)	(0.012)	(0.052)	(0.026)
Sim Assault	0.001	0.021***		-0.003	0.018***	0.019	0.021*
	(0.012)	(0.006)		(0.004)	(0.006)	(0.026)	(0.012)
Burglary	0.014	0.036**	0.021**		0.021**	-0.007	0.053***
	(0.017)	(0.017)	(0.010)		(0.010)	(0.041)	(0.020)
Larceny	0.012***	0.005	0.006***	0.002**		0.029***	0.009***
	(0.004)	(0.003)	(0.002)	(0.001)		(0.007)	(0.003)
MV Larceny	0.006	-0.002	0.009	-0.003	0.025***		0.003
	(0.020)	(0.023)	(0.015)	(0.007)	(0.009)		(0.018)
Stolen Prop	-0.037	-0.002	0.024*	-0.006	0.003	0.008	
	(0.023)	(0.016)	(0.013)	(0.004)	(0.005)	(0.019)	
Forgery	-0.011	-0.015	-0.004	0.012	0.009	0.021	0.002
	(0.033)	(0.014)	(0.009)	(0.009)	(0.007)	(0.048)	(0.015)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 21. Regression Models Explaining Incarceration, with the Number of Identical Records (NIR, cont'd)

	(1) Sex Crimes	(2) Agg Assault	(3) Sim Assault	(4) Burglary	(5) Larceny	(6) MV Larceny	(7) Stolen Prop
Fraud	0.006	-0.004	0.002	0.000	-0.001	-0.035	0.001
	(0.004)	(0.006)	(0.003)	(0.002)	(0.001)	(0.029)	(0.007)
Crim Misch	-0.016	0.006	0.004	0.003	0.006*	-0.005	0.015
	(0.011)	(0.008)	(0.007)	(0.004)	(0.003)	(0.037)	(0.017)
Drug Traff	0.006	-0.001	-0.000	-0.010*	0.002	-0.004	-0.015
	(0.011)	(0.006)	(0.003)	(0.006)	(0.004)	(0.030)	(0.013)
Drug Poss	0.014***	0.006*	0.006**	-0.001	0.010***	0.004	0.010**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.008)	(0.004)
Weapons	0.006	0.009	0.010	0.017**	0.015	0.009	-0.021
	(0.019)	(0.013)	(0.013)	(0.008)	(0.011)	(0.048)	(0.023)
Driving	-0.009	-0.022*	-0.015	-0.012	-0.027***	-0.021	-0.024
	(0.023)	(0.013)	(0.012)	(0.008)	(0.005)	(0.029)	(0.021)
Nuisance	0.003	0.009***	0.017***	0.003*	0.015***	-0.005	-0.000
	(0.008)	(0.003)	(0.002)	(0.002)	(0.002)	(0.015)	(0.007)
Male	0.191*	0.069***	0.084***	0.059**	0.154***	0.023	0.122***
	(0.098)	(0.024)	(0.019)	(0.027)	(0.013)	(0.081)	(0.023)
Black	0.003	0.018	0.033***	0.019*	0.023***	-0.031	0.006
	(0.023)	(0.015)	(0.012)	(0.010)	(0.008)	(0.042)	(0.024)
Other Race	0.038	-0.088	0.015	0.035	-0.116***	0.209	-0.003
	(0.094)	(0.069)	(0.070)	(0.039)	(0.031)	(0.165)	(0.119)
Race Unknown	0.045	0.005	0.021	0.011	-0.031	0.241***	0.148
	(0.094)	(0.086)	(0.043)	(0.011)	(0.065)	(0.053)	(0.104)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 21. Regression Models Explaining Incarceration, with the Number of Identical Records (NIR, cont'd)

	(1) Sex Crimes	(2) Agg Assault	(3) Sim Assault	(4) Burglary	(5) Larceny	(6) MV Larceny	(7) Stolen Prop
Hispanic	0.037**	0.004	0.002	0.006	0.012	0.030	-0.011
	(0.018)	(0.015)	(0.011)	(0.010)	(0.010)	(0.037)	(0.019)
Age	-0.001	-0.008**	-0.016***	-0.002	-0.002	-0.018	-0.009
	(0.006)	(0.004)	(0.003)	(0.003)	(0.002)	(0.013)	(0.006)
Age Squared	-0.000	0.000	0.000***	0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trial	0.080***	0.016	0.085	0.023*	0.106***	0.085	0.054
	(0.017)	(0.015)	(0.057)	(0.013)	(0.038)	(0.053)	(0.074)
A Felony	-0.006	0.021					
	(0.029)	(0.033)					
B Felony	0.041*	0.080***		0.084***	0.218***		
	(0.022)	(0.013)		(0.023)	(0.025)		
C Felony	0.061***	0.061***		0.088***	0.036		-0.176
	(0.019)	(0.013)		(0.021)	(0.055)		(0.236)
D Felony	0.022	0.053***	0.014	0.013	-0.041	0.237*	0.019
	(0.021)	(0.013)	(0.017)	(0.017)	(0.025)	(0.134)	(0.035)
A Misdem	-0.228***	-0.358***	-0.314***		-0.274***	-0.217***	-0.288***
	(0.037)	(0.033)	(0.020)		(0.020)	(0.057)	(0.032)
B Misdem	-0.447***	-0.534***	-0.469***		-0.409***	-0.328***	-0.512***
	(0.045)	(0.117)	(0.035)		(0.035)	(0.085)	(0.050)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 21. Regression Models Explaining Incarceration, with the Number of Identical Records (NIR, cont'd)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Sex Crimes	Agg Assault	Sim Assault	Burglary	Larceny	MV Larceny	Stolen Prop
Total Fel Conv	0.012*	0.013	0.033***	0.029***	0.036***	0.028**	0.027***
	(0.007)	(0.009)	(0.006)	(0.006)	(0.003)	(0.013)	(0.009)
Constant	0.737***	0.942***	0.996***	0.824***	0.621***	1.111***	0.847***
	(0.163)	(0.069)	(0.067)	(0.063)	(0.046)	(0.230)	(0.115)
n	1,212	2,455	8,995	3,968	16,869	589	2,254
R-squared	0.346	0.343	0.161	0.120	0.180	0.270	0.207

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Table 21. Regression Models Explaining Incarceration, with the Number of Identical Records (NIR, cont'd)

	(8) Forgery	(9) Fraud	(10) Crim Misch	(11) Drug Traff	(12) Drug Poss	(13) Weapons	(14) Driving	(15) Nuisance
NIR	0.009**	0.008***	0.007	0.013***	0.012***	0.001	0.047***	0.006***
	(0.004)	(0.002)	(0.007)	(0.001)	(0.001)	(0.021)	(0.008)	(0.002)
Number of Convictions of								
Murder	0.170*	0.033	-0.037	0.180***	0.070*	0.077**	0.169*	0.171***
	(0.094)	(0.052)	(0.155)	(0.042)	(0.040)	(0.033)	(0.087)	(0.052)
Sex Crimes	0.004	0.026**	0.017	0.021	0.051***	0.030	0.002	0.029***
	(0.037)	(0.010)	(0.024)	(0.023)	(0.017)	(0.039)	(0.023)	(0.008)
Robbery	0.037**	-0.008	0.059***	0.025***	0.013**	0.027	0.022	0.039***
	(0.016)	(0.011)	(0.017)	(0.007)	(0.006)	(0.018)	(0.019)	(0.006)
Agg Assault	-0.041	0.016	0.047**	0.017	0.034***	0.034***	0.009	0.022**
	(0.032)	(0.024)	(0.020)	(0.013)	(0.008)	(0.012)	(0.015)	(0.009)
Sim Assault	-0.003	0.012***	0.015	0.016***	0.018***	0.025***	0.035***	0.032***
	(0.027)	(0.004)	(0.009)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Burglary	0.025	0.008	0.062***	0.022**	0.027***	0.017	0.021	0.037***
	(0.025)	(0.015)	(0.017)	(0.010)	(0.008)	(0.018)	(0.018)	(0.008)
Larceny	0.012**	0.007***	0.008	0.005**	0.008***	0.008	0.014***	0.009***
	(0.006)	(0.001)	(0.005)	(0.002)	(0.001)	(0.005)	(0.003)	(0.002)
MV Larceny	0.015	0.022**	0.055***	0.011	0.026**	0.021	0.009	0.012
	(0.025)	(0.010)	(0.015)	(0.021)	(0.012)	(0.020)	(0.015)	(0.008)
Stolen Prop	0.018	0.006	0.003	-0.008	0.008*	0.021*	0.017	0.010
	(0.027)	(0.011)	(0.015)	(0.012)	(0.004)	(0.011)	(0.012)	(0.012)
Forgery		0.013***	0.008	-0.002	-0.003	0.000	-0.019	0.000
		(0.004)	(0.010)	(0.014)	(0.003)	(0.013)	(0.015)	(0.009)

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Table 21. Regression Models Explaining Incarceration, with the Number of Identical Records (NIR, cont'd)

	(8) Forgery	(9) Fraud	(10) Crim Misch	(11) Drug Traff	(12) Drug Poss	(13) Weapons	(14) Driving	(15) Nuisance
Fraud	0.015*		-0.001	0.004**	0.002	-0.004	0.017*	0.003
	(0.009)		(0.006)	(0.002)	(0.002)	(0.008)	(0.010)	(0.002)
Crim Misch	0.003	0.000		-0.003	0.005	-0.032***	0.014	0.008**
	(0.013)	(0.004)		(0.003)	(0.006)	(0.007)	(0.010)	(0.004)
Drug Traff	0.005	0.005*	0.026		0.008**	0.005	0.010	0.001
	(0.025)	(0.003)	(0.017)		(0.003)	(0.015)	(0.015)	(0.006)
Drug Poss	0.003	0.006***	0.005	0.009***		0.006	0.020***	0.008**
	(0.006)	(0.000)	(0.007)	(0.001)		(0.007)	(0.006)	(0.003)
Weapons	0.042**	0.011	0.025	0.022**	0.008		0.006	0.026**
	(0.021)	(0.012)	(0.035)	(0.009)	(0.006)		(0.017)	(0.011)
Driving	-0.042	-0.005	0.011	0.009	-0.011	0.037**		0.008
	(0.027)	(0.012)	(0.014)	(0.014)	(0.007)	(0.015)		(0.006)
Nuisance	0.021***	0.006*	0.026***	0.000	0.007***	0.017**	0.020***	
	(0.006)	(0.003)	(0.007)	(0.001)	(0.002)	(0.008)	(0.006)	
Male	0.086***	0.066***	0.097***	0.069***	0.022**	-0.019	0.062***	0.032*
	(0.026)	(0.016)	(0.028)	(0.014)	(0.009)	(0.034)	(0.017)	(0.017)
Black	0.055*	0.016	0.017	-0.001	0.027***	0.025**	0.016	0.024***
	(0.027)	(0.017)	(0.031)	(0.011)	(0.007)	(0.011)	(0.016)	(0.008)
Other Race	-0.110	-0.045	-0.076	-0.038	-0.011	0.031	-0.064*	0.017
	(0.108)	(0.062)	(0.070)	(0.071)	(0.033)	(0.078)	(0.034)	(0.039)
Race Unknown	-0.318***	0.040	-0.254**	0.003	0.006	-0.035	-0.053	-0.023
	(0.089)	(0.090)	(0.096)	(0.042)	(0.098)	(0.121)	(0.061)	(0.069)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 21. Regression Models Explaining Incarceration, with the Number of Identical Records (NIR, cont'd)

	(8) Forgery	(9) Fraud	(10) Crim Misch	(11) Drug Traff	(12) Drug Poss	(13) Weapons	(14) Driving	(15) Nuisance
Hispanic	0.038*	-0.005	-0.001	0.008	0.016	0.001	0.027**	0.019***
	(0.022)	(0.008)	(0.020)	(0.011)	(0.010)	(0.015)	(0.011)	(0.006)
Age	-0.017***	-0.011***	-0.009**	-0.005	-0.009***	-0.013***	-0.007**	-0.004
	(0.005)	(0.002)	(0.004)	(0.004)	(0.002)	(0.004)	(0.003)	(0.003)
Age Squared	0.000**	0.000***	0.000	0.000	0.000***	0.000*	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trial	0.157***	0.034	0.053	0.051***	0.050	0.033	0.112***	0.078**
	(0.035)	(0.143)	(0.051)	(0.016)	(0.044)	(0.025)	(0.042)	(0.036)
A Felony			0.206***	0.117***	0.191***			0.166***
			(0.042)	(0.029)	(0.032)			(0.041)
B Felony			0.173***	0.051*	0.097***	0.118***		0.212***
			(0.050)	(0.028)	(0.030)	(0.027)		(0.039)
C Felony	0.136*		0.140***	0.039*	0.070**	0.055**		0.136**
	(0.070)		(0.030)	(0.023)	(0.030)	(0.026)		(0.063)
D Felony	0.044	0.081	-0.002	-0.012	0.013	0.032*	0.078***	0.099***
	(0.048)	(0.058)	(0.057)	(0.023)	(0.027)	(0.018)	(0.015)	(0.018)
A Misdem	-0.292***	-0.414***	-0.361***	-0.369***	-0.346***	-0.460***		-0.272***
	(0.044)	(0.092)	(0.037)	(0.053)	(0.041)	(0.035)		(0.030)
B Misdem	-0.511***	-0.397***	-0.459***	-0.495***	-0.560***	-0.587***	-0.374***	-0.409***
	(0.076)	(0.069)	(0.052)	(0.064)	(0.055)	(0.053)	(0.039)	(0.042)

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Table 21. Regression Models Explaining Incarceration, with the Number of Identical Records (NIR, cont'd)

	(8) Forgery	(9) Fraud	(10) Crim Misch	(11) Drug Traff	(12) Drug Poss	(13) Weapons	(14) Driving	(15) Nuisance
Total Fel Conv	0.056***	0.022***	0.022**	0.033***	0.024***	0.029***	0.034***	0.023***
	(0.008)	(0.005)	(0.009)	(0.002)	(0.002)	(0.010)	(0.008)	(0.004)
Constant	0.920***	0.811***	0.783***	0.840***	0.843***	1.107***	0.628***	0.738***
	(0.090)	(0.091)	(0.081)	(0.072)	(0.065)	(0.083)	(0.063)	(0.074)
n	1,861	6,927	3,038	5,304	25,363	3,565	9,690	18,474
R-squared	0.256	0.148	0.187	0.305	0.249	0.426	0.304	0.151

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Table 22. Regression Models Explaining the Incarceration Length, with the Number of Identical Records (NIR)

	(1) Sex Crimes	(2) Agg Assault	(3) Sim Assault	(4) Burglary	(5) Larceny	(6) MV Larceny	(7) Stolen Prop
NIR	0.455	6.685*	0.150	3.037*	0.017	0.400	0.058
	(1.348)	(3.809)	(0.109)	(1.550)	(0.016)	(0.283)	(0.164)
Number of Convictions							
Murder	72.771	10.919	7.952	32.264	0.031		0.522
	(73.223)	(9.188)	(7.696)	(28.466)	(0.647)		(0.820)
Sex Crimes		1.071	0.023	-1.890	-1.084***	0.717	0.496
		(1.545)	(0.205)	(2.042)	(0.286)	(0.991)	(0.382)
Robbery	4.443	2.191	2.084	7.170***	-0.273	1.058*	0.485
	(3.005)	(1.521)	(1.685)	(2.370)	(0.249)	(0.602)	(0.327)
Agg Assault	0.541		0.393	-3.195	0.411	0.151	0.357
	(3.938)		(0.254)	(1.915)	(0.410)	(0.453)	(0.419)
Sim Assault	2.339**	-0.478		-1.063	0.243	0.364*	0.247
	(1.032)	(0.783)		(1.047)	(0.155)	(0.195)	(0.209)
Burglary	4.626	0.488	0.085		-0.340	0.930*	0.167
	(4.561)	(1.117)	(0.269)		(0.212)	(0.512)	(0.167)
Larceny	0.184	-0.001	0.022	-0.355		-0.061	0.041
	(0.405)	(0.223)	(0.034)	(0.238)		(0.099)	(0.027)
MV Larceny	-1.627	1.802	-0.270	0.613	0.026		-0.011
	(2.802)	(1.655)	(0.226)	(1.697)	(0.142)		(0.205)
Stolen Prop	-0.663	-2.854*	0.109	-1.309	0.234	0.747***	
	(3.505)	(1.530)	(0.150)	(0.908)	(0.220)	(0.264)	
Forgery	-0.606	-1.594	0.335	-2.621***	-0.200	-0.232	0.322
	(2.268)	(1.026)	(0.825)	(0.906)	(0.147)	(0.760)	(0.300)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 22. Regression Models Explaining the Incarceration Length, with the Number of Identical Records (NIR)

	(1) Sex Crimes	(2) Agg Assault	(3) Sim Assault	(4) Burglary	(5) Larceny	(6) MV Larceny	(7) Stolen Prop
Fraud	0.974	-1.094***	-0.040	-0.911**	-0.048	0.460*	-0.249***
	(0.651)	(0.278)	(0.049)	(0.354)	(0.032)	(0.267)	(0.071)
Crim Misch	-0.375	0.298	-0.085	0.180	-0.083	0.373	0.254
	(0.849)	(0.751)	(0.215)	(0.951)	(0.082)	(0.384)	(0.152)
Drug Traff	0.077	-2.245***	-0.194**	-3.591***	-0.804***	0.116	-0.060
	(1.819)	(0.799)	(0.087)	(1.245)	(0.133)	(0.340)	(0.164)
Drug Poss	-0.936***	-0.117	-0.070**	-1.565***	0.058*	-0.116	-0.137**
	(0.219)	(0.531)	(0.029)	(0.230)	(0.032)	(0.074)	(0.062)
Weapons	3.291	3.214	0.513	5.208***	-0.165	1.693**	0.558*
	(5.862)	(2.200)	(0.334)	(1.788)	(0.178)	(0.643)	(0.287)
Driving	-3.872**	-1.506	-0.646**	-3.231**	-0.687***	-0.235	0.037
	(1.841)	(1.222)	(0.246)	(1.374)	(0.173)	(0.539)	(0.402)
Nuisance	-1.299	1.088**	0.083	-1.002***	-0.040	-0.019	0.100*
	(0.802)	(0.494)	(0.061)	(0.263)	(0.037)	(0.147)	(0.052)
Male	12.868	10.520***	-0.371	5.703*	0.979***	-0.327	0.763*
	(11.909)	(1.909)	(0.383)	(3.264)	(0.146)	(1.281)	(0.455)
Black	-1.652	2.112	0.525**	-1.570	-0.062	-0.106	0.354
	(3.428)	(2.338)	(0.238)	(1.699)	(0.225)	(0.365)	(0.227)
Other Race	-7.330	-9.559*	1.024	-8.534**	-0.660	-2.013	0.347
	(8.596)	(5.620)	(1.080)	(3.422)	(0.788)	(1.260)	(0.611)
Race Unknown	3.102	2.527	-0.795	-0.284	-3.602*	-0.900	-0.914
	(10.251)	(7.980)	(0.675)	(1.107)	(1.979)	(2.118)	(0.817)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 22. Regression Models Explaining the Incarceration Length, with the Number of Identical Records (NIR, cont'd)

	(1) Sex Crimes	(2) Agg Assault	(3) Sim Assault	(4) Burglary	(5) Larceny	(6) MV Larceny	(7) Stolen Prop
Hispanic	-4.022	1.514	0.298	-2.262	-0.113	-0.243	0.076
	(3.875)	(1.628)	(0.503)	(1.611)	(0.241)	(0.447)	(0.228)
Age	1.099*	1.648***	0.027	1.768***	-0.125**	0.125	0.008
	(0.561)	(0.378)	(0.062)	(0.503)	(0.058)	(0.175)	(0.065)
Age Squared	-0.012	-0.020***	-0.000	-0.015**	0.001*	-0.001	-0.000
	(0.008)	(0.004)	(0.001)	(0.007)	(0.001)	(0.002)	(0.001)
Trial	48.647***	59.877***	19.281***	79.721***	26.121***	6.930***	6.529**
	(13.578)	(9.998)	(6.582)	(13.198)	(7.503)	(1.867)	(2.537)
A Felony	405.740***	393.283***					
	(19.121)	(16.156)					
B Felony	141.428***	113.311***		119.329***	26.380***		
	(5.141)	(6.294)		(4.801)	(2.806)		
C Felony	68.855***	64.547***		62.132***	22.760***		7.283*
	(7.688)	(5.801)		(2.315)	(8.474)		(4.323)
D Felony	26.451***	22.322***	13.799***	15.803***	3.360***	25.583***	6.695***
	(3.976)	(1.572)	(1.735)	(1.306)	(0.969)	(1.578)	(1.343)
A Misdem	-21.262***	-9.294***	-9.161***		-11.188***	-9.814***	-10.410***
	(2.051)	(0.968)	(0.406)		(0.997)	(0.914)	(0.441)
B Misdem	-24.947***	-9.722***	-12.682***		-13.912***	-14.067***	-14.327***
	(2.278)	(3.521)	(0.476)		(1.039)	(1.485)	(0.563)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 22. Regression Models Explaining the Incarceration Length, with the Number of Identical Records (NIR, cont'd)

	(1) Sex Crimes	(2) Agg Assault	(3) Sim Assault	(4) Burglary	(5) Larceny	(6) MV Larceny	(7) Stolen Prop
Total Fel Conv	4.124***	4.745***	0.937***	4.078***	1.312***	0.124	0.960***
	(1.159)	(0.661)	(0.140)	(1.222)	(0.181)	(0.166)	(0.113)
Constant	-14.180	-35.407***	11.520***	-32.144***	15.693***	11.669***	13.126***
	(15.931)	(8.635)	(1.921)	(8.527)	(0.633)	(3.481)	(1.222)
n	999	1,981	5,370	3,672	9,042	364	1,379
R-squared	0.801	0.639	0.292	0.343	0.324	0.663	0.681

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 22. Regression Models Explaining the Incarceration Length, with the Number of Identical Records (NIR, cont'd)

	(8) Forgery	(9) Fraud	(10) Crim Misch	(11) Drug Traff	(12) Drug Poss	(13) Weapons	(14) Driving	(15) Nuisance
NIR	-0.148	-0.029	-0.120	-0.307	-0.003	3.619**	0.500***	-0.043**
	(0.131)	(0.024)	(0.148)	(0.199)	(0.016)	(1.521)	(0.145)	(0.019)
Number of Convictions								
Murder	0.504	-0.107	2.264	16.126***	9.855***	-4.344	-0.375	5.155***
	(1.502)	(0.784)	(1.874)	(5.933)	(2.545)	(5.171)	(2.350)	(1.311)
Sex Crimes	1.125	0.105	-0.052	-0.985	-0.069	-0.506	-0.232	-0.205
	(0.837)	(0.193)	(0.784)	(1.498)	(0.395)	(4.892)	(0.658)	(0.206)
Robbery	0.280	-0.376**	-0.082	4.861***	1.087***	2.267	-1.660*	0.676***
	(0.473)	(0.162)	(0.666)	(1.101)	(0.385)	(2.077)	(0.879)	(0.221)
Agg Assault	0.904	-0.133	0.489	4.022***	2.034***	2.435	-0.547	0.494***
	(0.544)	(0.143)	(0.759)	(0.943)	(0.548)	(2.161)	(0.354)	(0.126)
Sim Assault	-0.567	-0.083**	0.565**	0.465	0.160	-1.474	0.001	0.233**
	(0.400)	(0.039)	(0.277)	(0.413)	(0.206)	(0.979)	(0.207)	(0.098)
Burglary	0.072	-0.431**	1.567	0.266	0.066	-3.613**	-2.398**	0.417**
	(0.565)	(0.167)	(1.044)	(1.167)	(0.273)	(1.583)	(0.982)	(0.159)
Larceny	0.030	0.014	0.179***	-0.146	0.035*	-0.138	0.345***	0.008
	(0.078)	(0.012)	(0.060)	(0.098)	(0.021)	(0.401)	(0.090)	(0.025)
MV Larceny	-0.561	-0.344	-0.108	-0.642	-0.149	-0.431	1.755	-0.009
	(0.605)	(0.221)	(0.309)	(1.027)	(0.253)	(2.212)	(1.299)	(0.156)
Stolen Prop	0.371	0.349*	-0.413	-0.525	-0.633***	-3.266**	-0.199	-0.056
	(0.437)	(0.203)	(0.305)	(0.450)	(0.180)	(1.366)	(0.353)	(0.116)
Forgery		0.182**	0.338**	0.117	-0.618***	-2.119**	-1.132	-0.209**
		(0.089)	(0.164)	(0.382)	(0.173)	(0.980)	(0.689)	(0.089)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 22. Regression Models Explaining the Incarceration Length, with the Number of Identical Records (NIR, cont'd)

	(8) Forgery	(9) Fraud	(10) Crim Misch	(11) Drug Traff	(12) Drug Poss	(13) Weapons	(14) Driving	(15) Nuisance
Fraud	0.286*		-0.117*	-0.341***	-0.011	-1.383**	-0.216	-0.022
	(0.159)		(0.066)	(0.118)	(0.024)	(0.675)	(0.254)	(0.023)
Crim Misch	-0.130	-0.045*		-0.204	-0.082	0.383	-0.215	0.014
	(0.371)	(0.027)		(0.238)	(0.082)	(2.245)	(0.283)	(0.054)
Drug Traff	-0.441	-0.178***	0.056		-0.543***	-3.838***	-1.504**	-0.193**
	(0.353)	(0.030)	(0.287)		(0.128)	(1.231)	(0.643)	(0.085)
Drug Poss	-0.205**	-0.010	-0.007	-0.034		-0.240	-0.076	0.031
	(0.084)	(0.008)	(0.159)	(0.112)		(0.321)	(0.202)	(0.028)
Weapons	1.140*	-0.140	0.464	5.603***	1.567***		0.080	0.321**
	(0.664)	(0.153)	(0.553)	(0.751)	(0.409)		(0.593)	(0.129)
Driving	-0.456	-0.261	-0.290	-2.272***	-0.376	-2.539		-0.136
	(0.526)	(0.203)	(0.283)	(0.760)	(0.552)	(2.116)		(0.114)
Nuisance	-0.158	-0.015	0.075	0.010	0.003	-0.008	0.185	
	(0.190)	(0.015)	(0.109)	(0.154)	(0.013)	(0.458)	(0.111)	
Male	1.641***	0.285	2.460**	6.541***	0.569**	8.447**	1.216**	0.229
	(0.611)	(0.452)	(1.019)	(0.678)	(0.244)	(3.392)	(0.464)	(0.216)
Black	0.533	-0.067	-0.252	2.529**	1.192***	2.525***	-0.068	0.031
	(0.608)	(0.216)	(0.699)	(0.967)	(0.432)	(0.892)	(0.450)	(0.202)
Other Race	-6.282**	0.770	1.597	-0.270	-0.497	0.365	0.107	0.260
	(3.080)	(0.616)	(2.152)	(4.004)	(1.343)	(5.323)	(0.708)	(0.878)
Race Unknown	-2.462	-3.422*	2.396	-5.599	-3.046*	9.111*	1.907*	0.407
	(1.604)	(1.862)	(3.587)	(8.149)	(1.589)	(4.985)	(1.110)	(0.594)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 22. Regression Models Explaining the Incarceration Length, with the Number of Identical Records (NIR, cont'd)

	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Forgery	Fraud	Crim Misch	Drug Traff	Drug Poss	Weapons	Driving	Nuisance
Hispanic	-0.123	-0.053	0.786	0.924*	0.029	0.081	-0.085	0.297**
	(0.605)	(0.162)	(1.170)	(0.499)	(0.351)	(1.471)	(0.366)	(0.136)
Age	0.365**	-0.094**	-0.163	0.455**	0.070	1.013*	-0.097	0.044
	(0.144)	(0.038)	(0.229)	(0.185)	(0.067)	(0.510)	(0.067)	(0.041)
Age Squared	-0.005**	0.001**	0.001	-0.007***	-0.001*	-0.011	0.001	-0.001*
	(0.002)	(0.000)	(0.003)	(0.002)	(0.001)	(0.007)	(0.001)	(0.001)
Trial	8.151***	8.392***	12.011	57.147***	28.686***	61.548***	19.386	13.496***
	(1.972)	(2.554)	(7.291)	(6.663)	(3.726)	(10.488)	(12.720)	(3.104)
A Felony			470.301***	72.613***	67.894***			263.721***
			(2.408)	(6.914)	(3.705)			(2.220)
B Felony			117.816***	16.332***	20.772***	139.566***		46.834***
			(13.047)	(2.237)	(2.043)	(25.122)		(6.691)
C Felony	16.165***		42.540***	10.175***	12.761***	52.813***		24.539***
	(4.743)		(12.357)	(1.729)	(1.887)	(5.359)		(2.815)
D Felony	4.128***	6.786***	5.128***	4.381***	4.297***	12.447***	3.865***	5.990***
	(0.887)	(0.607)	(1.588)	(1.523)	(1.263)	(2.745)	(0.744)	(0.884)
A Misdem	-9.603***	-12.328***	-9.524***	-9.939***	-9.972***	-12.334***		-6.120***
	(0.963)	(1.346)	(0.827)	(1.730)	(1.170)	(2.656)		(0.896)
B Misdem	-12.796***	-13.723***	-11.453***	-15.566***	-12.252***	-13.429***	-3.666***	-8.618***
	(1.108)	(1.041)	(0.744)	(3.793)	(1.157)	(3.120)	(0.422)	(0.822)

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Table 22. Regression Models Explaining the Incarceration Length, with the Number of Identical Records (NIR, cont'd)

	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Forgery	Fraud	Crim Misch	Drug Traff	Drug Poss	Weapons	Driving	Nuisance
Total Fel Conv	1.845***	0.701***	0.761***	3.551***	1.372***	5.534***	2.316***	0.476***
	(0.242)	(0.094)	(0.277)	(0.690)	(0.178)	(1.405)	(0.785)	(0.093)
Constant	5.006*	15.277***	12.505***	-4.955	10.202***	-14.501	6.275***	9.150***
	(2.753)	(1.660)	(3.795)	(5.451)	(2.654)	(10.647)	(1.394)	(1.141)
n	1,018	2,017	1,474	4,292	10,408	2,468	4,663	9,220
R-squared	0.624	0.752	0.562	0.520	0.594	0.454	0.195	0.571

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 23. Regression Models Explaining Incarceration, with all the Measures

	(1) Sex Crimes	(2) Agg Assault	(3) Sim Assault	(4) Burglary	(5) Larceny	(6) MV Larceny	(7) Stolen Prop
IPC	0.064***	0.027	0.000	0.019*	0.026***	0.047	-0.018
	(0.023)	(0.028)	(0.016)	(0.010)	(0.007)	(0.085)	(0.032)
Spec. Index	-0.043	-0.048	-0.123***	-0.015	-0.159***	0.059	-0.115**
	(0.054)	(0.031)	(0.027)	(0.023)	(0.022)	(0.119)	(0.056)
Drug Gen.	0.110***	0.026	0.051***	0.025**	0.072***	0.026	0.057
	(0.033)	(0.031)	(0.016)	(0.012)	(0.016)	(0.078)	(0.043)
High Inv. Gen.	0.107**	0.027	0.081***	-0.007	0.059***	0.094	-0.025
	(0.041)	(0.030)	(0.029)	(0.014)	(0.018)	(0.073)	(0.049)
Driving Spec.	-0.000	-0.125***	-0.071***	-0.034	-0.098***	-0.085	-0.105*
	(0.047)	(0.043)	(0.023)	(0.033)	(0.014)	(0.083)	(0.055)
Property Spec.	0.013	-0.018	-0.014	-0.007	-0.005	0.030	-0.026
	(0.028)	(0.028)	(0.016)	(0.011)	(0.014)	(0.052)	(0.029)
Drug Spec.	0.004	-0.042	-0.024	-0.026	-0.010	-0.004	-0.042
	(0.029)	(0.027)	(0.018)	(0.017)	(0.013)	(0.070)	(0.034)
Violent Spec.	0.037	-0.057***	-0.019	-0.000	-0.013	-0.029	-0.086***
	(0.033)	(0.021)	(0.017)	(0.011)	(0.016)	(0.083)	(0.031)
NIR	0.032***	-0.006	0.025***	-0.001	0.011***	0.026	0.037**
	(0.005)	(0.014)	(0.004)	(0.004)	(0.002)	(0.021)	(0.014)
Male	0.194*	0.069***	0.077***	0.056**	0.145***	0.035	0.120***
	(0.102)	(0.025)	(0.018)	(0.026)	(0.012)	(0.079)	(0.024)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 23. Regression Models Explaining Incarceration, with all the Measures (cont'd)

	(1) Sex Crimes	(2) Agg Assault	(3) Sim Assault	(4) Burglary	(5) Larceny	(6) MV Larceny	(7) Stolen Prop
Black	0.005	0.018	0.035***	0.021**	0.025***	-0.019	0.008
	(0.023)	(0.015)	(0.011)	(0.010)	(0.007)	(0.050)	(0.023)
Other Race	0.029	-0.083	0.019	0.032	-0.113***	0.278*	-0.009
	(0.098)	(0.080)	(0.073)	(0.039)	(0.031)	(0.149)	(0.130)
Race Unknown	0.026	0.011	0.022	0.005	-0.021	0.230***	0.148
	(0.112)	(0.083)	(0.045)	(0.011)	(0.055)	(0.058)	(0.118)
Hispanic	0.041**	0.002	0.002	0.006	0.014	0.039	-0.009
	(0.019)	(0.015)	(0.011)	(0.011)	(0.011)	(0.036)	(0.020)
Age	-0.000	-0.007**	-0.017***	-0.002	-0.003	-0.014	-0.010
	(0.005)	(0.003)	(0.003)	(0.003)	(0.002)	(0.013)	(0.006)
Age Squared	-0.000	0.000	0.000***	0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trial	0.079***	0.012	0.091	0.025*	0.108***	0.111**	0.063
	(0.019)	(0.015)	(0.056)	(0.013)	(0.038)	(0.053)	(0.080)
A Felony	-0.018	0.050**					
	(0.026)	(0.024)					
B Felony	0.041*	0.078***		0.082***	0.239***		
	(0.021)	(0.014)		(0.024)	(0.021)		
C Felony	0.062***	0.063***		0.085***	0.037		-0.161
	(0.021)	(0.012)		(0.021)	(0.060)		(0.206)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 23. Regression Models Explaining Incarceration, with all the Measures (cont'd)

	(1) Sex Crimes	(2) Agg Assault	(3) Sim Assault	(4) Burglary	(5) Larceny	(6) MV Larceny	(7) Stolen Prop
D Felony	0.022	0.052***	0.010	0.011	-0.037	0.184	0.016
	(0.021)	(0.014)	(0.017)	(0.017)	(0.025)	(0.118)	(0.031)
A Misdem	-0.219***	-0.360***	-0.319***		-0.273***	-0.220***	-0.287***
	(0.038)	(0.034)	(0.020)		(0.020)	(0.062)	(0.030)
B Misdem	-0.445***	-0.547***	-0.474***		-0.408***	-0.349***	-0.517***
	(0.045)	(0.114)	(0.035)		(0.035)	(0.089)	(0.049)
Total Fel Conv	0.011*	0.019***	0.037***	0.026***	0.036***	0.041***	0.032***
	(0.006)	(0.007)	(0.006)	(0.006)	(0.003)	(0.009)	(0.007)
Constant	0.722***	1.015***	1.125***	0.844***	0.745***	1.033***	0.979***
	(0.155)	(0.077)	(0.066)	(0.059)	(0.051)	(0.286)	(0.129)
n	1,212	2,455	8,995	3,968	16,869	589	2,254
R-squared	0.343	0.341	0.158	0.117	0.180	0.246	0.200

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 23. Regression Models Explaining Incarceration, with all the Measures (cont'd)

	(8) Forgery	(9) Fraud	(10) Crim Misch	(11) Drug Traff	(12) Drug Poss	(13) Weapons	(14) Driving	(15) Nuisance
IPC	-0.024	0.020***	0.014	0.007	-0.012	0.007	-0.019	-0.005
	(0.040)	(0.007)	(0.031)	(0.009)	(0.007)	(0.023)	(0.012)	(0.015)
Spec. Index	-0.120***	-0.067**	-0.150**	-0.118***	-0.086***	-0.087*	-0.122***	-0.124***
	(0.041)	(0.026)	(0.064)	(0.028)	(0.017)	(0.045)	(0.017)	(0.019)
Drug Gen.	0.163***	0.074***	0.069**	0.069***	0.050**	0.034	0.076	0.056
	(0.037)	(0.023)	(0.032)	(0.018)	(0.021)	(0.035)	(0.046)	(0.035)
High Inv. Gen.	0.028	0.050**	0.116***	0.016	0.095***	0.074**	0.117***	0.076***
	(0.056)	(0.024)	(0.033)	(0.033)	(0.015)	(0.034)	(0.043)	(0.025)
Driving Spec.	-0.033	-0.043	-0.003	0.014	-0.078***	-0.007	-0.025	-0.030**
	(0.061)	(0.030)	(0.032)	(0.032)	(0.018)	(0.033)	(0.016)	(0.014)
Property Spec.	0.008	0.017	0.015	-0.033	-0.002	-0.063**	-0.027*	-0.017
	(0.038)	(0.015)	(0.022)	(0.027)	(0.015)	(0.026)	(0.014)	(0.011)
Drug Spec.	-0.018	-0.000	-0.037	0.019	-0.012	-0.040*	-0.019	-0.039**
	(0.037)	(0.012)	(0.027)	(0.016)	(0.011)	(0.021)	(0.017)	(0.015)
Violent Spec.	0.055	-0.038	0.015	0.027	0.000	-0.023	-0.020	0.007
	(0.046)	(0.028)	(0.027)	(0.019)	(0.010)	(0.020)	(0.026)	(0.016)
NIR	0.013***	0.009***	0.009*	0.013***	0.013***	-0.013	0.050***	0.007***
	(0.004)	(0.002)	(0.004)	(0.001)	(0.001)	(0.017)	(0.008)	(0.002)
Male	0.073**	0.058***	0.087***	0.065***	0.014	-0.041	0.059***	0.034*
	(0.028)	(0.016)	(0.028)	(0.015)	(0.009)	(0.033)	(0.017)	(0.017)

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Table 23. Regression Models Explaining Incarceration, with all the Measures (cont'd)

	(8) Forgery	(9) Fraud	(10) Crim Misch	(11) Drug Traff	(12) Drug Poss	(13) Weapons	(14) Driving	(15) Nuisance
Black	0.056**	0.019	0.027	-0.001	0.027***	0.025**	0.019	0.027***
	(0.026)	(0.015)	(0.031)	(0.010)	(0.007)	(0.011)	(0.017)	(0.008)
Other Race	-0.101	-0.045	-0.061	-0.035	-0.010	0.019	-0.060*	0.016
	(0.107)	(0.060)	(0.066)	(0.071)	(0.034)	(0.082)	(0.033)	(0.039)
Race Unknown	-0.294***	0.038	-0.263***	-0.004	0.011	-0.042	-0.055	-0.015
	(0.101)	(0.089)	(0.092)	(0.036)	(0.096)	(0.124)	(0.063)	(0.069)
Hispanic	0.041*	0.001	-0.002	0.006	0.017*	0.001	0.028***	0.020***
	(0.021)	(0.008)	(0.019)	(0.010)	(0.010)	(0.015)	(0.010)	(0.006)
Age	-0.015***	-0.011***	-0.009*	-0.004	-0.009***	-0.013***	-0.006**	-0.004
	(0.005)	(0.002)	(0.005)	(0.004)	(0.001)	(0.004)	(0.003)	(0.003)
Age Squared	0.000*	0.000***	0.000	0.000	0.000***	0.000*	0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Trial	0.122***	0.037	0.055	0.061***	0.049	0.036	0.113***	0.088**
	(0.033)	(0.145)	(0.049)	(0.017)	(0.047)	(0.025)	(0.041)	(0.037)
A Felony			0.162***	0.101***	0.189***			0.157***
			(0.039)	(0.028)	(0.034)			(0.040)
B Felony			0.133***	0.044	0.095***	0.111***		0.212***
			(0.042)	(0.028)	(0.029)	(0.021)		(0.038)
C Felony	0.118		0.134***	0.031	0.070**	0.052**		0.128*
	(0.084)		(0.033)	(0.024)	(0.029)	(0.024)		(0.065)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 23. Regression Models Explaining Incarceration, with all the Measures (cont'd)

	(8) Forgery	(9) Fraud	(10) Crim Misch	(11) Drug Traff	(12) Drug Poss	(13) Weapons	(14) Driving	(15) Nuisance
D Felony	0.054	0.080	0.017	-0.017	0.011	0.030*	0.083***	0.099***
	(0.048)	(0.058)	(0.056)	(0.024)	(0.027)	(0.017)	(0.015)	(0.018)
A Misdem	-0.297***	-0.412***	-0.361***	-0.377***	-0.349***	-0.460***		-0.270***
	(0.043)	(0.091)	(0.038)	(0.055)	(0.040)	(0.033)		(0.029)
B Misdem	-0.526***	-0.394***	-0.465***	-0.509***	-0.561***	-0.589***	-0.370***	-0.408***
	(0.080)	(0.068)	(0.052)	(0.064)	(0.055)	(0.051)	(0.038)	(0.041)
Total Fel Conv	0.057***	0.024***	0.041***	0.031***	0.026***	0.036***	0.035***	0.029***
	(0.007)	(0.004)	(0.008)	(0.003)	(0.002)	(0.006)	(0.006)	(0.003)
Constant	0.983***	0.853***	0.903***	0.914***	0.936***	1.226***	0.729***	0.837***
	(0.099)	(0.093)	(0.103)	(0.065)	(0.062)	(0.097)	(0.066)	(0.075)
n	1,861	6,927	3,038	5,304	25,363	3,565	9,690	18,474
R-squared	0.252	0.144	0.178	0.303	0.248	0.421	0.302	0.147

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

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Table 24. Regression Models Explaining the Incarceration Length, with all the Measures

	(1) Sex Crimes	(2) Agg Assault	(3) Sim Assault	(4) Burglary	(5) Larceny	(6) MV Larceny	(7) Stolen Prop
IPC	-0.244	3.408	-0.121	12.250***	-0.041	0.237	-0.721
	(3.254)	(4.855)	(0.206)	(4.159)	(0.187)	(0.449)	(0.538)
Spec. Index	-18.296**	1.755	1.128	3.194	-0.392	-1.068	-2.663***
	(7.648)	(6.482)	(1.354)	(5.472)	(0.358)	(1.156)	(0.982)
Drug Gen.	-0.806	0.435	0.019	-14.169***	0.204	-3.275**	-1.098**
	(3.781)	(4.456)	(0.305)	(3.720)	(0.532)	(1.451)	(0.461)
High Inv. Gen.	-3.347	0.414	-0.146	-6.778	1.022***	-0.527	-0.395
	(4.472)	(4.383)	(0.334)	(5.751)	(0.376)	(0.862)	(0.427)
Driving Spec.	-1.882	-3.024	-1.768**	-8.851***	-1.031**	-2.260	-0.177
	(6.197)	(2.737)	(0.668)	(2.891)	(0.494)	(2.362)	(1.521)
Property Spec.	3.925	-3.368	-0.200	0.583	0.544***	-1.072	-0.403
	(5.604)	(2.334)	(0.290)	(2.282)	(0.178)	(0.877)	(0.409)
Drug Spec.	2.167	-2.524	-1.001***	-5.157**	-0.057	-1.230	-0.613
	(2.758)	(2.228)	(0.246)	(2.571)	(0.245)	(0.922)	(0.575)
Violent Spec.	3.284	3.002	2.296**	10.815**	0.326	0.600	1.152**
	(8.398)	(2.292)	(1.004)	(4.320)	(0.314)	(0.864)	(0.466)
NIR	1.319	5.428	0.126	1.545	0.018	0.373	0.096
	(1.236)	(3.995)	(0.119)	(1.427)	(0.014)	(0.299)	(0.154)
Male	13.996	10.026***	-0.315	6.556*	0.884***	-0.075	0.546
	(12.199)	(1.973)	(0.322)	(3.280)	(0.150)	(1.279)	(0.443)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 24. Regression Models Explaining the Incarceration Length, with all the Measures (cont'd)

	(1) Sex Crimes	(2) Agg Assault	(3) Sim Assault	(4) Burglary	(5) Larceny	(6) MV Larceny	(7) Stolen Prop
Black	-1.137	1.740	0.679*	-2.109	-0.026	-0.031	0.217
	(3.460)	(2.299)	(0.355)	(1.802)	(0.206)	(0.359)	(0.209)
Other Race	-5.273	-9.373	1.288	-7.442**	-0.741	-1.280	0.377
	(9.152)	(6.074)	(0.984)	(3.683)	(0.719)	(0.864)	(0.709)
Race Unknown	4.050	1.902	-0.843	-0.877	-3.561*	-1.563	-0.794*
	(7.023)	(8.611)	(0.630)	(1.779)	(2.001)	(2.274)	(0.434)
Hispanic	-4.400	1.353	0.292	-1.978	-0.136	-0.117	0.039
	(3.574)	(1.658)	(0.494)	(1.801)	(0.259)	(0.422)	(0.242)
Age	1.128*	1.648***	0.057	1.736***	-0.147**	0.122	0.025
	(0.634)	(0.421)	(0.082)	(0.526)	(0.060)	(0.188)	(0.069)
Age Squared	-0.012	-0.020***	-0.001	-0.015**	0.001**	-0.001	-0.001
	(0.008)	(0.005)	(0.001)	(0.008)	(0.001)	(0.003)	(0.001)
Trial	46.645***	60.213***	19.431***	80.479***	26.059***	8.096***	6.649***
	(13.369)	(10.258)	(6.650)	(13.483)	(7.505)	(1.163)	(2.464)
A Felony	407.253***	400.259***					
	(19.528)	(10.818)					
B Felony	141.858***	113.321***		121.073***	26.566***		
	(5.540)	(6.387)		(4.794)	(2.914)		
C Felony	70.474***	64.276***		61.911***	23.026***		7.215*
	(9.238)	(5.815)		(2.420)	(8.527)		(4.073)

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Table 24. Regression Models Explaining the Incarceration Length, with all the Measures (cont'd)

	(1) Sex Crimes	(2) Agg Assault	(3) Sim Assault	(4) Burglary	(5) Larceny	(6) MV Larceny	(7) Stolen Prop
D Felony	27.025***	22.276***	13.890***	16.073***	3.415***	24.171***	6.784***
	(4.160)	(1.567)	(1.786)	(1.337)	(0.970)	(2.537)	(1.309)
A Misdem	-19.390***	-9.130***	-9.162***		-11.328***	-9.906***	-10.331***
	(2.205)	(1.137)	(0.425)		(1.009)	(0.937)	(0.440)
B Misdem	-26.171***	-10.854**	-12.636***		-14.068***	-14.166***	-14.197***
	(2.496)	(4.240)	(0.512)		(1.048)	(1.387)	(0.551)
Total Fel Conv	4.062***	4.756***	1.140***	4.364***	1.024***	0.582***	0.998***
	(1.259)	(0.655)	(0.290)	(1.158)	(0.115)	(0.166)	(0.094)
Constant	-7.518	-34.184***	10.681***	-37.293***	16.203***	13.107***	14.825***
	(17.721)	(12.179)	(2.844)	(10.672)	(0.706)	(3.278)	(1.466)
n	999	1,981	5,370	3,672	9,042	364	1,379
R-squared	0.797	0.636	0.288	0.341	0.321	0.655	0.681

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 24. Regression Models Explaining the Incarceration Length, with all the Measures (cont'd)

	(8) Forgery	(9) Fraud	(10) Crim Misch	(11) Drug Traff	(12) Drug Poss	(13) Weapons	(14) Driving	(15) Nuisance
IPC	0.706	0.157	0.336	2.507**	0.014	3.573	-0.679**	-0.214
	(0.719)	(0.151)	(1.443)	(1.242)	(0.301)	(3.198)	(0.312)	(0.135)
Spec. Index	-1.572	0.017	2.049	-5.551***	-1.263*	1.874	-1.205**	-0.749
	(1.302)	(0.407)	(1.292)	(1.547)	(0.637)	(4.592)	(0.560)	(0.525)
Drug Gen.	-0.724	-0.208	0.106	0.011	-0.492	-3.938	0.558	0.228
	(1.098)	(0.221)	(1.171)	(2.509)	(0.736)	(4.308)	(1.000)	(0.302)
High Inv. Gen.	0.658	0.056	-0.364	-1.158	-0.706	-3.787	0.199	0.186
	(1.107)	(0.271)	(0.980)	(1.889)	(0.798)	(4.898)	(1.111)	(0.270)
Driving Spec.	-0.687	0.461	-2.547*	-7.527***	-1.639	-7.065**	0.156	-0.266
	(1.213)	(0.631)	(1.400)	(2.238)	(1.590)	(2.975)	(0.529)	(0.410)
Property Spec.	1.587***	0.865**	-1.738	-2.705**	-0.018	-2.794	0.810	-0.284
	(0.556)	(0.360)	(1.090)	(1.176)	(0.796)	(2.342)	(0.500)	(0.240)
Drug Spec.	1.449**	-0.128	-2.152	0.838	-0.123	-1.413	-0.394	-0.073
	(0.580)	(0.259)	(1.396)	(1.674)	(0.650)	(3.034)	(0.522)	(0.301)
Violent Spec.	3.004***	0.117	-2.072	8.522***	3.761***	3.752*	-0.915	1.551***
	(1.094)	(0.356)	(1.535)	(1.883)	(1.127)	(1.913)	(0.659)	(0.332)
NIR	-0.078	-0.020	-0.164	-0.585**	0.018	3.191**	1.037***	-0.030***
	(0.110)	(0.018)	(0.162)	(0.281)	(0.015)	(1.457)	(0.186)	(0.011)
Male	1.762***	0.329	2.433**	6.541***	0.664***	8.246**	1.015**	0.206
	(0.625)	(0.430)	(1.144)	(0.688)	(0.249)	(3.328)	(0.453)	(0.267)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 24. Regression Models Explaining the Incarceration Length, with all the Measures (cont'd)

	(8) Forgery	(9) Fraud	(10) Crim Misch	(11) Drug Traff	(12) Drug Poss	(13) Weapons	(14) Driving	(15) Nuisance
Black	0.186	0.010	-0.178	2.470**	1.145***	2.167*	-0.116	0.000
	(0.565)	(0.221)	(0.780)	(0.975)	(0.399)	(1.185)	(0.490)	(0.199)
Other Race	-6.459**	0.935	1.287	-0.867	-0.296	1.407	0.265	0.313
	(2.629)	(0.654)	(2.137)	(3.494)	(1.285)	(4.940)	(0.727)	(0.865)
Race Unknown	-1.066	-3.324*	2.619	-7.040	-2.580	8.978*	2.064*	0.626
	(1.372)	(1.910)	(2.984)	(7.837)	(1.634)	(5.348)	(1.057)	(0.631)
Hispanic	-0.127	-0.012	0.827	0.695	-0.002	-0.471	-0.037	0.291**
	(0.511)	(0.156)	(1.163)	(0.476)	(0.366)	(1.729)	(0.374)	(0.132)
Age	0.345**	-0.081*	-0.112	0.599***	0.107	0.866	-0.077	0.049
	(0.139)	(0.044)	(0.215)	(0.184)	(0.068)	(0.522)	(0.066)	(0.043)
Age Squared	-0.004**	0.001*	0.001	-0.009***	-0.002**	-0.010	0.001	-0.001*
	(0.002)	(0.001)	(0.003)	(0.002)	(0.001)	(0.007)	(0.001)	(0.001)
Trial	8.335***	8.379***	11.725	58.212***	28.413***	62.296***	19.357	13.751***
	(2.003)	(2.542)	(7.294)	(6.649)	(3.713)	(10.788)	(12.750)	(3.143)
A Felony			470.767***	70.484***	67.593***			263.331***
			(2.583)	(6.714)	(3.627)			(2.113)
B Felony			118.238***	14.554***	20.361***	141.427***		46.905***
			(13.056)	(2.210)	(1.996)	(25.103)		(6.640)
C Felony	16.285***		42.258***	8.676***	12.569***	52.870***		24.366***
	(4.721)		(12.203)	(1.617)	(1.844)	(5.222)		(2.829)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 24. Regression Models Explaining the Incarceration Length, with all the Measures (cont'd)

	(8) Forgery	(9) Fraud	(10) Crim Misch	(11) Drug Traff	(12) Drug Poss	(13) Weapons	(14) Driving	(15) Nuisance
D Felony	4.240***	6.877***	5.548***	3.359**	3.998***	12.636***	4.096***	5.995***
	(0.916)	(0.605)	(1.407)	(1.338)	(1.280)	(2.692)	(0.739)	(0.892)
A Misdem	-9.332***	-12.298***	-9.444***	-10.475***	-10.312***	-12.191***		-6.051***
	(1.085)	(1.328)	(0.827)	(1.654)	(1.173)	(2.590)		(0.890)
B Misdem	-13.204***	-13.645***	-11.503***	-16.576***	-12.679***	-13.402***	-3.677***	-8.617***
	(1.404)	(1.019)	(0.761)	(2.917)	(1.167)	(3.136)	(0.425)	(0.822)
Total Fel Conv	1.755***	0.608***	1.206***	3.816***	1.190***	4.269***	1.674***	0.495***
	(0.234)	(0.079)	(0.189)	(0.562)	(0.138)	(0.966)	(0.590)	(0.066)
Constant	4.580*	14.540***	12.076***	-2.974	10.497***	-12.833	6.254***	9.659***
	(2.730)	(1.824)	(4.031)	(5.983)	(2.829)	(10.354)	(1.453)	(1.375)
n	1,018	2,017	1,474	4,292	10,408	2,468	4,663	9,220
R-squared	0.623	0.751	0.561	0.516	0.592	0.449	0.189	0.569

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Table 25. Descriptive Statistics of the Trial Conviction Samples

	(1) 90-93	(2) 99-02	(3) 09-12
Sentence			
Incarceration	.75	.67	.67
	(.44)	(.47)	(.47)
Incarceration length	81.66	82.58	79.10
	(145.72)	(145.14)	(138.24)
Arraignment Class			
A felony	.13	.10	.09
	(.34)	(.30)	(.28)
B felony	.31	.29	.20
	(.46)	(.45)	(.40)
C felony	.11	.10	.15
	(.31)	(.30)	(.35)
D felony	.15	.13	.14
	(.35)	(.34)	(.35)
E felony	.06	.08	.09
	(.24)	(.27)	(.29)
A misd.	.13	.16	.18
	(.34)	(.36)	(.38)
B/U misd.	.11	.14	.15
	(.31)	(.35)	(.36)
Arraignment Type			
Murder	.14	.09	.08
	(.35)	(.29)	(.27)
Sex crimes	.05	.06	.08
	(.22)	(.24)	(.27)
Robbery	.14	.10	.09
	(.35)	(.30)	(.28)
Agg. assault	.06	.12	.11
	(.25)	(.33)	(.31)
Sim. assault	.05	.07	.11
	(.23)	(.26)	(.31)
Burglary	.06	.06	.07
	(.24)	(.23)	(.25)

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Table 25. Descriptive Statistics of the Trial Conviction Samples (cont'd)

	(1) 90-93	(2) 99-02	(3) 09-12
Larceny	.05	.04	.05
	(.22)	(.21)	(.21)
MV Larceny	<.01	<.01	<.01
	(.05)	(.05)	(.03)
Stolen prop.	.02	.01	.01
	(.14)	(.11)	(.09)
Forgery	.01	.01	.01
	(.08)	(.10)	(.09)
Fraud	.01	.01	.01
	(.07)	(.08)	(.10)
Crim. misch.	.03	.02	.02
	(.16)	(.14)	(.15)
Drug traff.	.12	.10	.03
	(.32)	(.29)	.17)
Drug poss.	.06	.05	.05
	(.23)	(.22)	(.21)
Weapons	.05	.04	.06
	(.21)	(.19)	(.23)
Driving	.11	.15	.17
	(.31)	(.36)	(.38)
Nuisance	.04	.06	.07
	(.19)	(.24)	(.26)
Arraignment Counts	1.12	1.17	1.24
	(.99)	(1.33)	(1.93)
Disposition Class			
A felony	.09	.07	.07
	(.29)	(.26)	(.25)
B felony	.25	.20	.15
	(.43)	(.40)	(.36)
C felony	.10	.08	.12
	(.30)	(.27)	(.32)
D felony	.13	.13	.13
	(.34)	(.34)	(.33)
E felony	.06	.06	.08
	(.24)	(.24)	(.27)
A misd.	.22	.24	.22
	(.41)	(.43)	(.42)
B/U misd.	.14	.21	.24
	(.35)	(.41)	(.43)

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Table 25. Descriptive Statistics of the Trial Conviction Samples (cont'd)

	(1) 90-93	(2) 99-02	(3) 09-12
Disposition Type			
Murder	.11	.08	.07
	(.31)	(.27)	(.26)
Sex crimes	.05	.05	.07
	(.22)	(.23)	(.26)
Robbery	.12	.08	.07
	(.32)	(.27)	(.27)
Agg. assault	.06	.09	.08
	(.23)	(.28)	(.27)
Sim. assault	.08	.11	.12
	(.27)	(.31)	(.33)
Burglary	.04	.04	.05
	(.21)	(.19)	(.22)
Larceny	.06	.06	.05
	(.25)	(.23)	(.22)
MV Larceny	.01	<.01	<.01
	(.08)	(.07)	(.05)
Stolen prop.	.02	.02	.01
	(.16)	(.12)	(.10)
Forgery	.01	.01	.01
	(.08)	(.09)	(.09)
Fraud	.01	.01	.01
	(.08)	(.09)	(.09)
Crim. misch.	.03	.02	.02
	(.16)	(.14)	(.15)
Drug traff.	.10	.08	.03
	(.31)	(.27)	(.17)
Drug poss.	.07	.06	.05
	(.26)	(.24)	(.22)
Weapons	.06	.05	.06
	(.25)	(.22)	(.24)
Driving	.11	.15	.17
	(.31)	(.36)	(.38)
Nuisance	.06	.10	.11
	(.23)	(.29)	(.32)
Disposition Counts	1.12	1.12	1.10
	(.74)	(1.23)	(.95)

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Table 25. Descriptive Statistics of the Trial Conviction Samples (cont'd)

	(1) 90-93	(2) 99-02	(3) 09-12
Criminal Record			
Prior felony conv.	.76	.81	.84
	(1.10)	(1.26)	(1.41)
Prior misd. conv.	1.93	2.27	2.48
	(4.74)	(6.13)	(6.39)
Race			
White	.40	.43	.47
	(.49)	(.49)	(.50)
Black	.51	.49	.50
	(.50)	(.50)	(.50)
Other	.04	.04	.02
	(.19)	(.20)	(.15)
Unknown	.05	.04	.01
	(.21)	(.19)	(.11)
Hispanic	.27	.26	.30
	(.44)	(.44)	(.46)
Male	.92	.90	.87
	(.27)	(.30)	(.34)
Age	30.23	32.70	34.59
	(9.89)	(10.90)	(12.01)
Age Squared	1011.47	1188.36	1340.91
	(716.82)	(807.14)	(924.77)
n	14,509	11,418	8,189

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Table 26. Regression Models Explaining Sentence Length Using Arraignment Charge

	(1) 90-93	(2) 99-02	(3) 09-12
Arraignment Class			
B felony	-274.016***	-264.241***	-218.784***
	(11.803)	(17.964)	(8.942)
C felony	-305.335***	-318.997***	-276.717***
	(9.561)	(19.435)	(9.803)
D felony	-332.727***	-357.598***	-328.475***
	(10.440)	(22.097)	(9.079)
E felony	-345.993***	-354.511***	-326.352***
	(10.532)	(20.768)	(8.656)
A misd.	-349.449***	-339.852***	-317.658***
	(14.463)	(24.115)	(10.131)
B/U misd.	-350.261***	-340.208***	-319.600***
	(16.440)	(24.364)	(10.844)
Arraignment Type			
Sex crimes	15.879	-29.559*	-72.016***
	(11.322)	(16.973)	(8.597)
Robbery	29.062***	27.733	-25.505**
	(6.382)	(17.744)	(9.935)
Agg. assault	19.013*	-31.382*	-69.735***
	(9.790)	(17.245)	(9.204)
Sim. assault	17.330*	-33.846**	-72.485***
	(10.252)	(16.040)	(8.704)
Burglary	11.982	23.990	-36.680***
	(7.494)	(21.339)	(11.754)
Larceny	9.846	-33.718**	-71.792***
	(10.609)	(16.724)	(9.314)
MV Larceny	14.663	-36.206**	-76.629***
	(11.737)	(15.699)	(10.755)
Stolen prop.	18.248*	-18.495	-76.057***
	(10.645)	(22.415)	(9.672)
Forgery	13.350	-41.098**	-70.901***
	(13.806)	(16.622)	(9.409)
Fraud	15.862	-49.642***	-78.167***
	(10.812)	(15.252)	(8.295)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 26. Regression Models Explaining Sentence Length Using Arraignment Charge (cont'd)

	(1) 90-93	(2) 99-02	(3) 09-12
Crim. misch.	12.752	-30.203*	-71.423***
	(9.892)	(17.051)	(9.968)
Drug traff.	4.717	-37.791**	-47.162***
	(10.917)	(17.242)	(9.352)
Drug poss.	5.722	-39.844**	-85.691***
	(9.336)	(18.638)	(9.513)
Weapons	18.616*	-30.991	-67.232***
	(10.883)	(18.660)	(8.998)
Driving	19.734*	-25.525	-64.755***
	(11.311)	(17.799)	(8.420)
Nuisance	21.945**	-30.392*	-72.006***
	(10.227)	(17.611)	(8.400)
Interaction Terms			
Sex crimes * Felony	-4.115	49.134***	64.952***
	(9.188)	(7.770)	(5.200)
Agg. assault * Felony	-7.727	36.984***	30.582***
	(8.834)	(7.075)	(6.446)
Sim. Assault * Felony	-10.439	21.367**	15.449***
	(7.591)	(10.540)	(5.327)
Larceny * Felony	-2.478	8.945	3.988
	(6.968)	(7.605)	(8.075)
MV Larceny * Felony	-16.090*	18.212*	7.220
	(9.076)	(9.611)	(11.266)
Stolen prop. * Felony	-9.171	-4.508	5.884
	(10.040)	(9.532)	(8.668)
Forgery * Felony	-9.321	20.957***	9.200**
	(13.461)	(7.250)	(4.393)
Fraud * Felony	-20.796*	34.045***	24.791**
	(10.618)	(8.684)	(9.872)
Crim. misch. * Felony	-9.858	14.728*	11.237
	(10.308)	(8.175)	(10.206)
Drug traff. * Felony	-26.601***	-50.938***	-92.656***
	(8.407)	(8.650)	(11.204)
Drug poss. * Felony	-30.981**	-42.009***	-60.136***
	(11.949)	(11.413)	(8.485)
Weapons * Felony	11.412	31.294***	26.993***
	(10.014)	(7.670)	(5.895)
Driving * Felony	-7.779	6.996	2.917
	(8.056)	(7.593)	(5.371)

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Table 26. Regression Models Explaining Sentence Length Using Arraignment Charge (cont'd)

	(1) 90-93	(2) 99-02	(3) 09-12
Arraignment Crime Counts	2.312*	1.680**	0.898***
	(1.234)	(0.786)	(0.334)
Criminal Record			
Prior felony conv.	24.656***	25.203***	19.528***
	(1.918)	(1.325)	(2.955)
Prior misd. conv.	-0.552***	-0.705***	-1.116***
	(0.157)	(0.121)	(0.225)
Race			
Black	2.828	4.825**	1.982
	(2.357)	(2.237)	(1.270)
Other	10.300**	-1.425	7.323
	(4.738)	(4.267)	(5.884)
Unknown	21.350***	27.230***	8.130
	(4.254)	(4.326)	(6.877)
Male	10.464***	11.346***	7.000**
	(2.981)	(1.943)	(2.926)
Hispanic	-6.087**	-6.747***	-0.767
	(2.823)	(1.761)	(2.140)
Age	1.291**	1.376***	1.830***
	(0.551)	(0.499)	(0.680)
Age Squared	-0.017**	-0.018***	-0.022***
	(0.007)	(0.006)	(0.008)
Constant	288.759***	329.377***	342.887***
	(14.903)	(12.529)	(12.927)
n	14,509	11,418	8,189
R-squared	0.550	0.631	0.678

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 27. Regression Models Explaining Sentence Length Using Disposition Charge

	(1) 90-93	(2) 99-02	(3) 09-12
Disposition Class			
B felony	-368.844***	-303.903***	-231.274***
	(6.441)	(15.885)	(7.489)
C felony	-401.422***	-365.103***	-294.116***
	(7.109)	(14.200)	(9.853)
D felony	-441.204***	-437.624***	-374.353***
	(6.517)	(13.595)	(8.904)
E felony	-453.779***	-444.283***	-381.548***
	(7.002)	(12.327)	(11.113)
A misd.	-457.983***	-441.158***	-377.767***
	(7.376)	(13.498)	(10.856)
B/U misd.	-461.543***	-441.627***	-378.282***
	(7.678)	(13.658)	(11.365)
Disposition Type			
Sex crimes	-1.204	-25.818**	-83.841***
	(5.128)	(12.725)	(10.625)
Robbery	19.743***	17.934	-49.028***
	(4.852)	(16.892)	(11.226)
Agg. assault	-3.263	-27.877**	-89.435***
	(5.129)	(11.841)	(10.567)
Sim. assault	-3.861	-29.309***	-88.028***
	(4.480)	(10.881)	(10.785)
Burglary	11.164**	45.391***	-39.119***
	(4.957)	(16.880)	(10.605)
Larceny	-10.541**	-34.459***	-87.790***
	(4.389)	(10.391)	(10.394)
MV Larceny	-10.123	-38.878***	-83.360***
	(6.203)	(10.447)	(10.190)
Stolen prop.	-9.714*	-40.792***	-88.455***
	(4.893)	(10.135)	(10.541)
Forgery	-6.995	-39.839***	-84.250***
	(5.574)	(12.872)	(11.026)
Fraud	-7.003	-38.260***	-93.518***
	(5.003)	(10.211)	(11.739)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 27. Regression Models Explaining Sentence Length Using Disposition Charge (cont'd)

	(1) 90-93	(2) 99-02	(3) 09-12
Crim. misch.	-8.039*	-33.262***	-90.199***
	(4.495)	(11.532)	(9.952)
Drug traff.	-9.934*	-35.212***	-74.166***
	(5.426)	(11.862)	(11.772)
Drug poss.	-19.425***	-44.275***	-96.878***
	(4.935)	(10.393)	(12.167)
Weapons	-5.083	-27.030**	-80.951***
	(4.545)	(10.659)	(10.417)
Driving	-0.013	-25.246**	-82.623***
	(5.466)	(12.170)	(11.865)
Nuisance	-6.837	-30.197***	-87.702***
	(4.786)	(11.137)	(10.851)
Interaction Terms			
Sex crimes * Felony	-0.147	54.280***	58.239***
	(5.226)	(6.046)	(5.583)
Agg. assault * Felony	5.169	44.050***	41.628***
	(5.220)	(7.173)	(4.828)
Sim. Assault * Felony	9.856	14.815***	30.591***
	(10.704)	(5.382)	(6.264)
Larceny * Felony	-0.310	7.816	-0.095
	(3.494)	(5.061)	(3.559)
MV Larceny * Felony	18.664	76.848**	-0.957
	(23.672)	(30.953)	(6.090)
Stolen prop. * Felony	-0.412	18.427*	14.036
	(5.601)	(9.799)	(11.349)
Forgery * Felony	-7.916	7.313	8.412
	(8.977)	(9.359)	(10.211)
Fraud * Felony	-5.232	13.119*	3.808
	(6.985)	(7.779)	(4.345)
Crim. misch. * Felony	-11.148**	9.745	22.000**
	(4.572)	(12.258)	(8.671)
Drug traff. * Felony	-38.758***	-88.652***	-117.434***
	(5.699)	(5.935)	(9.864)
Drug poss. * Felony	-19.429***	-53.010***	-76.132***
	(5.552)	(5.868)	(7.840)
Weapons * Felony	18.423***	37.640***	18.428***
	(4.725)	(6.327)	(6.485)
Driving * Felony	-8.621	-5.198	2.246
	(6.168)	(4.734)	(4.440)

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Table 27. Regression Models Explaining Sentence Length Using Disposition Charge (cont'd)

	(1) 90-93	(2) 99-02	(3) 09-12
Disposition Crime Counts	1.482	0.929***	1.395*
	(1.109)	(0.320)	(0.767)
Criminal Record			
Prior felony conv.	22.157***	21.911***	17.537***
	(1.524)	(1.225)	(2.529)
Prior misd. conv.	-0.425***	-0.623***	-0.842***
	(0.099)	(0.161)	(0.200)
Race			
Black	0.432	2.301	0.406
	(1.302)	(2.005)	(1.228)
Other	1.114	-0.397	3.346
	(1.490)	(5.369)	(2.224)
Unknown	1.427	11.740***	9.237
	(3.365)	(3.418)	(5.545)
Male	1.210	1.561	2.440
	(1.504)	(1.186)	(1.839)
Hispanic	-4.612*	-2.642*	-2.130*
	(2.596)	(1.458)	(1.214)
Age	1.814***	1.525***	1.531***
	(0.443)	(0.504)	(0.416)
Age Squared	-0.022***	-0.019***	-0.018***
	(0.006)	(0.006)	(0.005)
Constant	419.476***	434.219***	427.889***
	(9.069)	(8.960)	(9.579)
n	14,509	11,418	8,189
R-squared	0.789	0.802	0.821

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

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Table 28. Descriptive Statistics of the Plea Samples

	(1) 90-93	(2) 99-02	(3) 09-12
Sentence			
Incarceration	.47	.43	.44
	(.50)	(.49)	(.50)
Incarceration length	7.28	6.24	4.87
	(35.01)	(32.33)	(18.91)
Arraignment Class			
A felony	.01	.01	.01
	(.11)	(.10)	(.07)
B felony	.17	.11	.08
	(.37)	(.31)	(.27)
C felony	.06	.05	.06
	(.24)	(.21)	(.23)
D felony	.15	.13	.13
	(.35)	(.34)	(.34)
E felony	.08	.11	.12
	(.27)	(.31)	(.33)
A misd.	.37	.43	.44
	(.48)	(.50)	(.50)
B/U misd.	.16	.16	.16
	(.37)	(.37)	(.36)
Arraignment Type			
Murder	.01	<.01	<.01
	(.09)	(.06)	(.05)
Sex crimes	.02	.02	.02
	(.12)	(.13)	(.13)
Robbery	.06	.03	.04
	(.23)	(.18)	(.18)
Agg. assault	.03	.04	.04
	(.17)	(.21)	(.19)
Sim. assault	.05	.06	.08
	(.21)	(.25)	(.26)
Burglary	.05	.03	.04
	(.21)	(.18)	(.20)

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Table 28. Descriptive Statistics of the Plea Samples (cont'd)

	(1) 90-93	(2) 99-02	(3) 09-12
Larceny	.14	.12	.14
	(.34)	(.33)	(.35)
MV Larceny	.01	.01	<.01
	(.09)	(.08)	(.07)
Stolen prop.	.04	.02	.02
	(.18)	(.15)	(.13)
Forgery	.02	.03	.02
	(.13)	(.16)	(.14)
Fraud	.06	.06	.05
	(.23)	(.23)	(.22)
Crim. misch.	.05	.03	.03
	(.23)	(.18)	(.18)
Drug traff.	.11	.09	.05
	(.32)	(.28)	(.22)
Drug poss.	.13	.21	.19
	(.34)	(.40)	(.40)
Weapons	.04	.02	.03
	(.19)	(.15)	(.17)
Driving	.10	.10	.12
	(.31)	(.30)	(.33)
Nuisance	.11	.13	.12
	(.31)	(.33)	(.33)
Arraignment Counts	1.05	1.06	1.12
	(.67)	(.80)	(2.13)
Disposition Class			
A felony	<.01	<.01	<.01
	(.07)	(.06)	(.04)
B felony	.03	.03	.03
	(.18)	(.16)	(.16)
C felony	.08	.05	.03
	(.28)	(.21)	(.17)
D felony	.11	.08	.07
	(.31)	(.27)	(.26)
E felony	.07	.07	.06
	(.25)	(.25)	(.25)
A misd.	.46	.53	.55
	(.50)	(.50)	(.50)
B/U misd.	.25	.26	.25
	(.43)	(.44)	(.43)

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Table 28. Descriptive Statistics of the Plea Samples (cont'd)

	(1) 90-93	(2) 99-02	(3) 09-12
Disposition Type			
Murder	<.01	<.01	<.01
	(.06)	(.05)	(.04)
Sex crimes	.01	.02	.01
	(.12)	(.12)	(.11)
Robbery	.04	.02	.02
	(.20)	(.15)	(.15)
Agg. assault	.01	.02	.02
	(.11)	(.14)	(.13)
Sim. assault	.06	.07	.08
	(.23)	(.26)	(.27)
Burglary	.03	.02	.02
	(.16)	(.13)	(.15)
Larceny	.16	.14	.16
	(.37)	(.34)	(.37)
MV Larceny	.02	.01	.01
	(.14)	(.11)	(.08)
Stolen prop.	.04	.02	.02
	(.19)	(.15)	(.14)
Forgery	.01	.02	.02
	(.11)	(.15)	(.13)
Fraud	.06	.06	.06
	(.23)	(.23)	(.23)
Crim. misch.	.04	.03	.03
	(.20)	(.17)	(.17)
Drug traff.	.10	.07	.03
	(.30)	(.25)	(.17)
Drug poss.	.14	.21	.20
	(.35)	(.41)	(.40)
Weapons	.04	.02	.03
	(.19)	(.15)	(.16)
Driving	.11	.10	.13
	(.32)	(.30)	(.34)
Nuisance	.13	.17	.16
	(.33)	(.37)	(.37)
Disposition Counts	1.02	1.02	1.02
	(.42)	(.53)	(.57)

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Table 28. Descriptive Statistics of the Plea Samples (cont'd)

	(1) 90-93	(2) 99-02	(3) 09-12
Criminal Record			
Prior felony conv.	.44	.69	.88
	(.84)	(1.14)	(1.44)
Prior misd. conv.	4.23	4.46	5.61
	(13.34)	(9.69)	(10.97)
Race			
White	.48	.48	.52
	(.50)	(.50)	(.50)
Black	.46	.47	.45
	(.50)	(.50)	(.50)
Other	.03	.03	.02
	(.16)	(.16)	(.13)
Unknown	.04	.03	.01
	(.19)	(.16)	(.09)
Hispanic	.31	.33	.38
	(.46)	(.47)	(.49)
Male	.82	.82	.83
	(.38)	(.38)	(.38)
Age	29.09	32.16	34.28
	(9.32)	(10.85)	(12.25)
Age Squared	933.41	1152.15	1325.50
	(643.10)	(770.96)	(919.08)
n	734,346	737,427	682,555

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Table 29. Estimates of the Plea Discount Without Adjusting for Overcharging

	(1) 90-93	(2) 99-02	(3) 09-12
S1: Average Unadjusted Sentence if Convicted of Arraignment Charge at Trial	16.47	14.76	13.69
S2: Average Sentence if Convicted of Disposition Charge at Trial	6.48	6.95	9.05
S3: Average Sentence Defendants Pled Guilty to	7.28	6.24	4.87
S3/S1	**0.44**	**0.42**	**0.36**
p: Average Estimated Probability of Conviction at Trial	**0.56**	**0.55**	**0.53**

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Table 30. Probit Models Explaining Conviction

	(1) 90-93	(2) 99-02	(3) 09-12
Arraignment Class			
B felony	-0.167***	-0.354***	-0.479***
	(0.042)	(0.106)	(0.089)
C felony	-0.225***	-0.421***	-0.568***
	(0.031)	(0.134)	(0.090)
D felony	-0.353***	-0.681***	-0.771***
	(0.044)	(0.115)	(0.092)
E felony	-0.487***	-0.805***	-0.904***
	(0.106)	(0.160)	(0.110)
A misd.	-0.829***	-1.385***	-1.429***
	(0.129)	(0.150)	(0.135)
B/U misd.	-0.712***	-1.421***	-1.466***
	(0.111)	(0.178)	(0.174)
Arraignment Type			
Sex crimes	-0.314**	0.254	0.312*
	(0.148)	(0.170)	(0.169)
Robbery	-0.209***	-0.052	-0.055
	(0.029)	(0.085)	(0.099)
Agg. assault	-0.147	0.284*	-0.031
	(0.169)	(0.160)	(0.184)
Sim. assault	-0.442***	0.065	0.031
	(0.091)	(0.146)	(0.147)
Burglary	-0.032	0.250**	0.063
	(0.058)	(0.106)	(0.124)
Larceny	0.200	0.613***	0.305*
	(0.145)	(0.152)	(0.163)
MV Larceny	-0.231	0.274	0.439
	(0.171)	(0.248)	(0.315)
Stolen prop.	0.210	0.321	0.438
	(0.149)	(0.211)	(0.434)
Forgery	-0.357	-0.150	0.030
	(0.516)	(0.248)	(0.181)
Fraud	-0.118	0.339*	0.480**
	(0.160)	(0.192)	(0.187)

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 30. Probit Models Explaining Conviction (cont'd)

	(1) 90-93	(2) 99-02	(3) 09-12
Crim. misch.	-0.012	0.188	-0.130
	(0.147)	(0.171)	(0.177)
Drug traff.	0.332	0.952***	-0.035
	(0.407)	(0.285)	(0.170)
Drug poss.	-0.120	0.570***	0.174
	(0.108)	(0.171)	(0.193)
Weapons	-0.293**	0.384*	0.195
	(0.142)	(0.201)	(0.199)
Driving	-0.608***	0.024	-0.199
	(0.121)	(0.167)	(0.221)
Nuisance	-0.330***	0.177	0.037
	(0.074)	(0.127)	(0.126)
Interaction Terms			
Sex crimes * Felony	-0.105	-0.370***	-0.465***
	(0.133)	(0.133)	(0.170)
Agg. assault * Felony	-0.220	-0.430***	-0.268*
	(0.198)	(0.115)	(0.161)
Sim. Assault * Felony	-0.060	-0.066	-0.172
	(0.104)	(0.129)	(0.140)
Larceny * Felony	-0.174	-0.325**	-0.077
	(0.189)	(0.150)	(0.119)
MV Larceny * Felony	0.323	0.044	-0.868
	(0.262)	(0.318)	(0.568)
Stolen prop. * Felony	-0.124	-0.165	-0.287
	(0.187)	(0.256)	(0.453)
Forgery * Felony	0.325	0.198	-0.347
	(0.545)	(0.255)	(0.267)
Fraud * Felony	-0.507**	-0.008	-0.390
	(0.207)	(0.270)	(0.256)
Crim. misch. * Felony	-0.369**	-0.302**	-0.199
	(0.161)	(0.141)	(0.173)
Drug traff. * Felony	-0.552	-1.206***	-0.516***
	(0.431)	(0.258)	(0.194)
Drug poss. * Felony	-0.225*	-0.696***	-0.463*
	(0.117)	(0.155)	(0.250)
Weapons * Felony	-0.120	-0.477***	-0.410*
	(0.160)	(0.129)	(0.228)
Driving * Felony	0.738***	0.479	0.018
	(0.233)	(0.325)	(0.181)

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Table 30. Probit Models Explaining Conviction (cont'd)

	(1) 90-93	(2) 99-02	(3) 09-12
Arraignment Crime Counts	0.031	0.021**	0.028**
	(0.020)	(0.011)	(0.011)
Criminal Record			
Prior felony conv.	0.121***	0.092***	0.092***
	(0.010)	(0.012)	(0.012)
Prior misd. conv.	0.010	0.016***	0.011***
	(0.007)	(0.002)	(0.003)
Race			
Black	0.037	0.068***	0.074***
	(0.043)	(0.020)	(0.024)
Other	0.168**	0.234***	0.104**
	(0.066)	(0.070)	(0.050)
Unknown	-0.405***	-0.329***	0.180
	(0.057)	(0.047)	(0.115)
Male	0.082***	0.033	0.002
	(0.030)	(0.020)	(0.025)
Hispanic	0.228***	0.204***	0.159***
	(0.025)	(0.025)	(0.024)
Age	0.008	0.007*	0.005
	(0.006)	(0.004)	(0.005)
Age Squared	-0.000	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)
Constant	0.784***	0.783***	0.958***
	(0.122)	(0.095)	(0.151)
Pseudo R-squared	0.15	0.17	0.18
n	27,778	22,644	17,397

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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Table 31. Estimates of the Adjustment Factor

	(1) 90-93	(2) 99-02	(3) 09-12
For the Trial Conviction Sample			
Average Sentence if Convicted of the Arraignment Charge	105.44	112.18	100.97
Average Sentence if Convicted of the Disposition Charge	81.67	82.58	79.10
d	0.77	0.74	0.78

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Table 32. Estimates of the Plea Discount after Adjusting for Overcharging

	(1) 90-93	(2) 99-02	(3) 09-12
S1: Average Unadjusted Sentence if Convicted of Arraignment Charge at Trial	16.47	14.76	13.69
d: Discount Factor to Remove Overcharging	0.77	0.74	0.78
S1*: Average Adjusted Sentence if Convicted at Trial	12.76	10.87	10.72
S2: Average Sentence if Convicted of Disposition Charge at Trial	6.48	6.95	9.05
S3: Average Sentence Defendants Pled Guilty to	7.28	6.24	4.87
S3/S1:	**0.44**	**0.42**	**0.36**
S3/S1*:	**0.57**	**0.57**	**0.45**
p: Average Estimated Probability of Conviction at Trial	**0.56**	**0.55**	**0.53**

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Figure 1. The Conventional Framework of Plea Discount without Adjusting for Overcharging

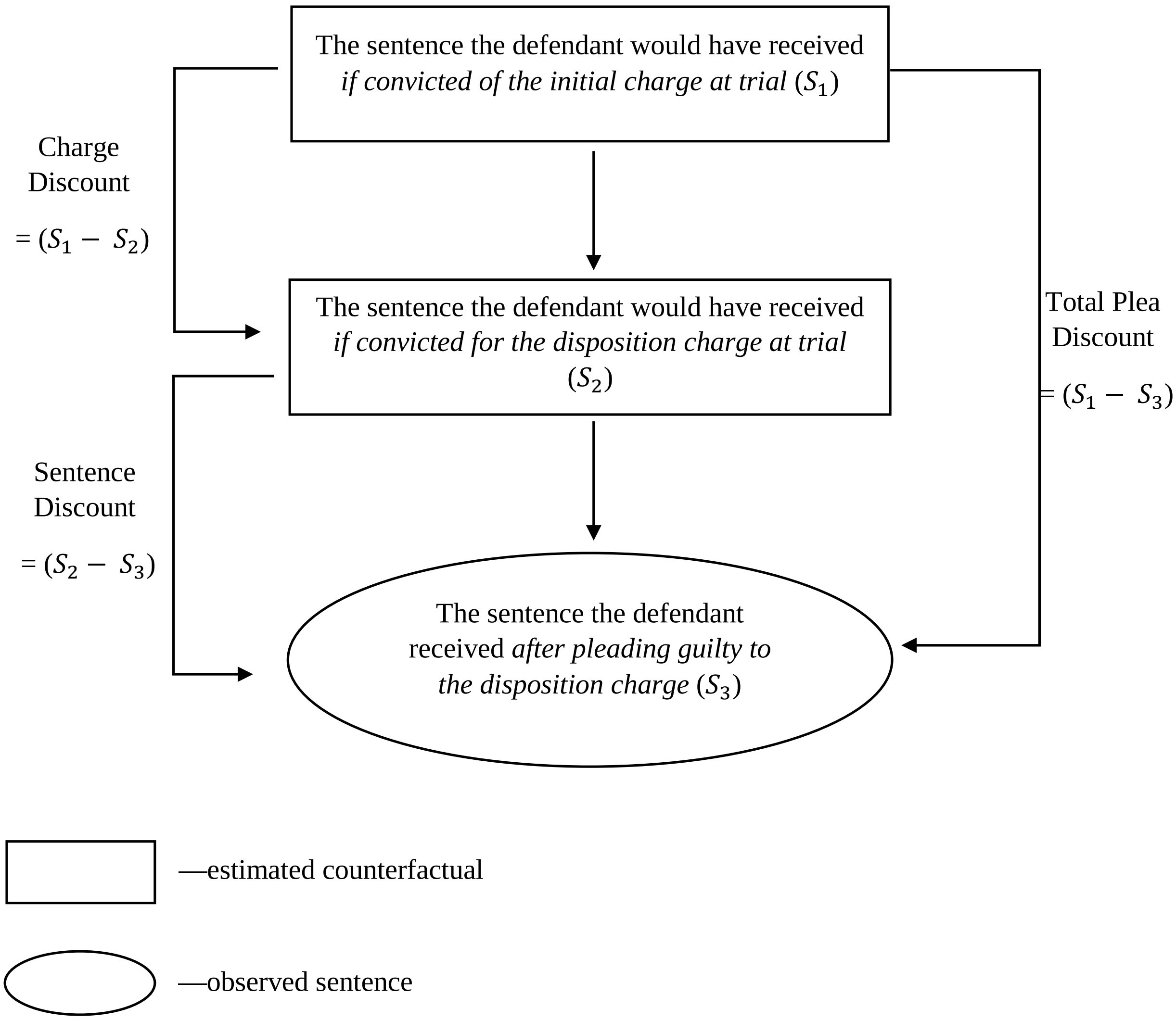

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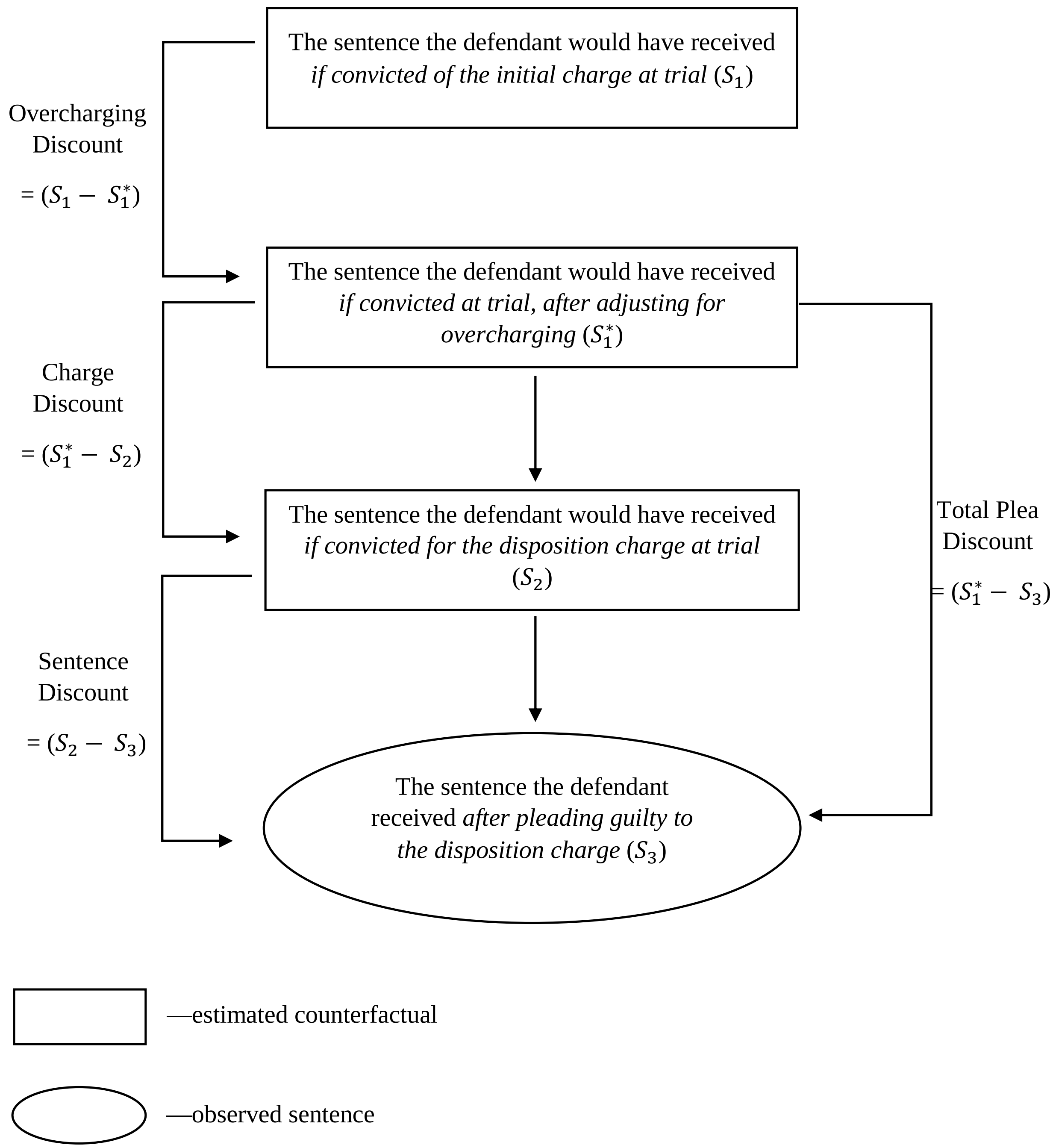
Figure 2. The Revised Framework of Plea Discount after Adjusting for Overcharging



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Appendix

The Selection of the Latent Class Model in Chapter 2

Chapter 2 used latent class analysis (LCA) as one of the measures of criminal specialization. As stated in Chapter 2, I started from a 1-class model and tested all the way up to a 24-group model. Because there were no theoretical priors on the number of classes, I used a set of fitting and diagnostic statistics to select the model.

The first consideration is the Bayesian Information Criterion (BIC). A lower value of BIC indicates better model fit. Figure A1 presents the BIC values of all the models. The BIC declined fast from the one-class to approximately the six-class model, and declined much slower when the number of classes was larger than seven. Apparently, adding each additional class after seven groups improved the model fit slightly.

A second series of statistics used to determine the model was the average posterior probabilities (avePP, Nagin, 2005). AvePP indicates whether individual cases were assigned to the classes without ambiguity. A rule of thumb is that in a desirable model, the avePP of every single class should be higher than 0.70. It turned out that models with seven classes or more all had classes with unsatisfactory avePPs.[26]

However, what is also important in determining the model is judgment on the substantive meaning of the classes. I did a class-by-class comparison between the six-class model and the seven-class model. In order to be straightforward, I only present the class-to-average ratios

[26] The avePP of one class in the six-class model was 0.698. I consider it to be satisfactory given its negligible difference from 0.70.

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(CARs, see the Results section of Chapter 2) instead of the conditional probabilities of the two models in Tables A1 and A2 respectively.[27] Classes 6a to 6d were basically identical as Classes 7a to 7d (which corresponded to "Driving Specialists," "Property Specialists," "Drug Generalists," and "High Involvement Generalists" respectively in Chapter 2). Classes 6e and 7e were very similar (the "Low Involvement Generalists" in Chapter 2), although the sizes within the samples were different by seven percentage points. The main difference came from the remaining classes. The six-class model had one class representing defendants who engaged in violent and drug crimes, and the seven-class model had one class representing non-violent drug specialists and one representing violent specialists. This division is meaningful in a study of criminal specialization, because there is reason to believe these two types of defendants are likely to be treated differently by prosecutors and judges. Even though three out of the seven classes had an avePP below 0.70, the values were not too much off (all higher than 0.65), and I considered the substantive distinction could overweigh the slight ambiguity in determining individual class membership.

[27] The sequence of classes in the tables is designed to maximize the conveniences of comparison, and is not the same as presented in the Results section of Chapter 2. Also to facilitate the comparison, I name each class using a number and a letter, and the number refers to the total number of classes. For example, Class 6c refers to the third class in the six-group model, and Class 7a refers to the first class in the seven-group model.

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Table A1. Class-average Ratios (CARs) of the Six-Class Model

	(1) 6a	(2) 6b	(3) 6c	(4) 6d	(5) 6e	(6) 6f
One Conviction						
Murder	0.093	0.149	0.071	0.185	2.015	1.385
Sex Crimes	0.501	0.561	1.013	1.253	1.998	0.389
Robbery	0.043	0.862	1.315	1.298	1.162	1.004
Agg. Assault	0.345	0.307	1.123	1.557	1.851	0.623
Sim. Assault	0.683	0.559	1.229	1.416	1.463	0.734
Burglary	0.286	1.627	0.685	2.554	1.262	0.294
Larceny	0.496	1.645	1.171	0.817	1.117	0.587
MV Larceny	0.311	0.981	0.893	3.368	0.997	0.683
Stolent Prop.	0.248	1.609	1.379	3.065	0.748	0.416
Forgery	0.366	2.059	1.209	1.822	0.634	0.568
Fraud	0.260	1.061	1.797	1.557	0.725	0.984
Crim. Misch.	0.707	0.773	1.113	2.184	1.632	0.287
Drug Traff	0.152	0.358	1.818	1.093	0.461	1.829
Drug Poss	0.612	1.022	0.387	1.004	0.865	1.469
Weapons	0.286	0.297	1.268	1.293	1.157	1.326
Driving	4.372	0.739	0.202	0.793	1.164	0.431
Nuisance	0.867	0.896	0.882	1.003	1.201	0.955
Multiple Convictions						
Murder	0.000	0.000	0.000	0.000	0.000	3.538
Sex Crimes	0.276	0.333	1.128	2.056	2.275	0.093
Robbery	0.000	1.287	1.004	0.939	1.377	0.742
Agg. Assault	0.002	0.000	1.013	2.938	2.163	0.328
Sim. Assault	0.259	0.108	1.968	2.513	1.698	0.359
Burglary	0.066	2.087	0.352	3.410	1.055	0.186
Larceny	0.081	2.130	1.910	3.470	0.348	0.206
MV Larceny	0.019	0.949	0.411	8.048	0.522	0.317
Stolent Prop.	0.020	1.324	0.977	8.069	0.267	0.093
Forgery	0.193	2.325	2.469	2.020	0.338	0.183
Fraud	0.022	0.699	4.104	2.449	0.366	0.502
Crim. Misch.	0.221	0.423	1.225	5.534	1.369	0.057
Drug Traff	0.013	0.102	2.712	0.494	0.113	2.158
Drug Poss	0.096	0.313	2.734	1.613	0.194	1.644
Weapons	0.118	0.056	1.846	1.191	1.090	1.388

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Table A1. Class-average Ratios (CARs) of the Six-Class Model (cont'd)

	(1) 6a	(2) 6b	(3) 6c	(4) 6d	(5) 6e	(6) 6f
Driving	9.492	0.278	0.049	0.627	0.450	0.086
Nuisance	0.224	0.306	2.705	2.433	0.983	0.661
Pr(Class)	0.079	0.183	0.113	0.068	0.275	0.283
AvePP	0.792	0.698	0.725	0.721	0.730	0.770

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Table A2. Class-average Ratios (CARs) of the Seven-Class Model

	(1) 7a	(2) 7b	(3) 7c	(4) 7d	(5) 7e	(6) 7f	(7) 7g
One Conviction							
Murder	0.236	0.122	0.118	0.280	0.435	0.721	5.492
Sex Crimes	0.444	0.572	1.101	1.052	2.383	0.396	0.746
Robbery	0.091	0.741	1.483	1.402	0.407	0.630	3.108
Agg. Assault	0.361	0.316	1.239	1.463	1.679	0.507	1.793
Sim. Assault	0.669	0.566	1.277	1.384	1.461	0.696	1.225
Burglary	0.282	1.633	0.699	2.597	1.317	0.275	0.973
Larceny	0.473	1.712	1.191	0.781	1.154	0.595	0.870
MV Larceny	0.303	0.959	0.907	3.463	0.979	0.634	1.082
Stolent Prop.	0.250	1.613	1.403	3.198	0.755	0.395	0.775
Forgery	0.347	2.100	1.237	1.816	0.756	0.605	0.468
Fraud	0.257	1.061	1.806	1.581	0.689	1.007	0.871
Crim. Misch.	0.657	0.794	1.181	2.088	1.861	0.283	0.803
Drug Traff	0.173	0.337	1.814	1.144	0.347	1.801	1.084
Drug Poss	0.639	1.008	0.423	1.021	0.731	1.372	1.407
Weapons	0.326	0.250	1.355	1.304	0.777	1.138	2.107
Driving	4.412	0.767	0.206	0.716	1.449	0.440	0.419
Nuisance	0.822	0.884	0.874	1.004	1.339	0.982	0.845
Multiple Convictions							
Murder	0.000	0.000	0.000	0.000	0.000	0.000	8.362
Sex Crimes	0.217	0.345	1.233	1.731	3.038	0.126	0.175
Robbery	0.016	0.816	1.236	1.131	0.084	0.266	4.749
Agg. Assault	0.007	0.005	1.226	2.652	2.259	0.227	1.432
Sim. Assault	0.182	0.121	2.117	2.256	1.996	0.375	0.700
Burglary	0.059	2.089	0.336	3.527	1.193	0.189	0.695
Larceny	0.053	2.229	1.964	3.526	0.454	0.241	0.187
MV Larceny	0.017	0.877	0.404	8.497	0.461	0.257	0.828
Stolent Prop.	0.013	1.318	0.922	8.611	0.352	0.096	0.200
Forgery	0.193	2.393	2.659	1.916	0.383	0.195	0.320
Fraud	0.018	0.698	4.237	2.446	0.370	0.570	0.351
Crim. Misch.	0.160	0.439	1.352	5.335	1.836	0.075	0.211
Drug Traff	0.017	0.099	2.603	0.536	0.086	2.337	0.445
Drug Poss	0.089	0.295	2.676	1.692	0.199	1.844	0.284
Weapons	0.175	0.031	2.030	1.211	0.505	1.092	2.519

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Table A2. Class-average Ratios (CARs) of the Seven-Class Model (cont'd)

	(1) 7a	(2) 7b	(3) 7c	(4) 7d	(5) 7e	(6) 7f	(7) 7g
Driving	9.434	0.298	0.048	0.494	0.766	0.098	0.010
Nuisance	0.152	0.272	2.727	2.383	1.308	0.773	0.224
Pr(Class)	0.077	0.170	0.108	0.064	0.206	0.254	0.120
AvePP	0.795	0.681	0.714	0.715	0.679	0.746	0.658

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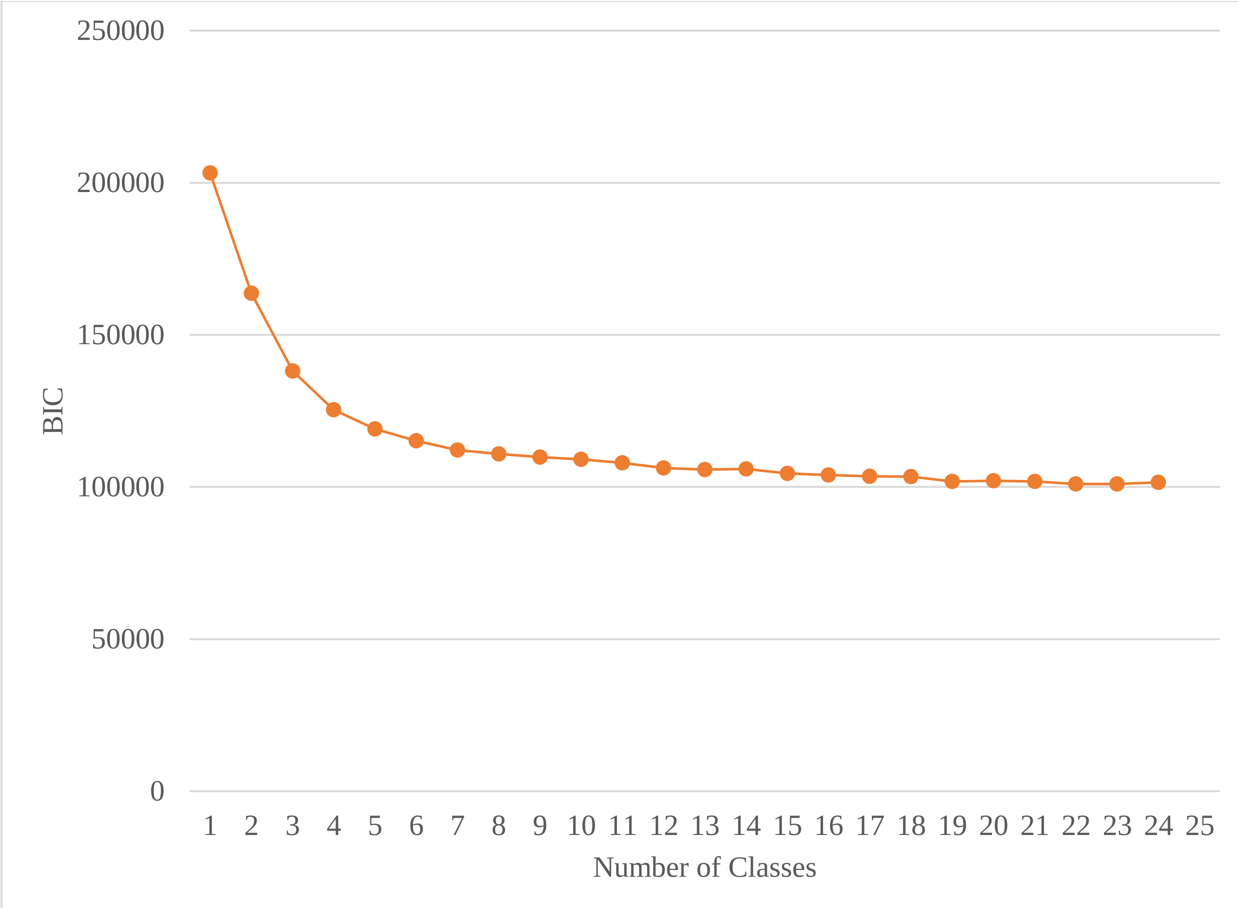
Figure A1. Values of the Bayesian Information Criterion (BIC)



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