

Sentencing Risk Assessment: A Follow-up Study of the Occurrence and Timing of Re-Arrest among Serious Offenders in Pennsylvania

Submitted to

The Pennsylvania Commission on Sentencing

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Contents

Executive Summary	3
Introduction	5
Social Science and the Law	10
Smart Sentencing: The Missouri Approach	12
Research on the Development of a Risk Assessment in Criminal Justice Settings	14
Expected Associations with Recidivism	17
Data and Methods	22
<i>Analysis Plan</i>	26
<i>Coding and Variable Definitions</i>	27
Findings	29
<i>Descriptive Statistics</i>	29
<i>Kaplan-Meier Survival Analysis</i>	37
<i>Cox Proportional Hazards Models</i>	41
<i>Predictive Validity: Comparing the Area Under the Curve</i>	46
<i>Risk Assessment Scoring and Classification</i>	49
<i>Kaplan Meier Survival Plots of Recidivism by Risk Groups</i>	53
References	59
Appendices	67
<i>Appendix A</i>	68
<i>Appendix B</i>	74
<i>Appendix C</i>	78

Executive Summary

The purpose of this report is to inform efforts by the Pennsylvania Commission on Sentencing (PCS) to develop a risk assessment instrument for judges to use at sentencing. Risk factors for recidivism are identified in a group of serious (level 5) offenders sentenced and released in Pennsylvania. Focusing on information judges have at sentencing, this study analyzes the relationship between offender and case characteristics and likelihood of recidivism up to an eleven and a half year period.

- Risk assessments are consistently shown to predict outcomes more accurately than clinical judgment.
- A sentencing risk assessment instrument compiles factors judges currently use at sentencing and presents it in a structured format.
- The majority (66 percent) of serious offenders are sentenced for a violent crime. About 40 percent have a previous conviction, for any type of crime, on their record.
- The overwhelming (69 percent) majority of level 5 offenders are sentenced to prison. About 23 percent and 8 percent are sentenced to jail and community-based sanctions, respectively.
- Almost two-thirds (62 percent) of all offenders recidivated within the study period. Of all the offenders who recidivate, 44 percent do so within the first year.
- This study identifies three risk groups: low, medium, and high based on likelihood and timing to recidivism.
- About 45 percent of offenders in the low risk group recidivated, while offenders in the highest risk group recidivated almost twice as much (85 percent).
- Risk groups are categorized based on eight case and offender characteristics that significantly and consistently predict recidivism:
 - Male
 - Offender is under 30 years of age at sentencing
 - A prior record score (PRS) of 1 or above
 - Juvenile arrest record
 - 12 or more prior arrests
 - Current offense is a sex crime
 - Current offense is a drug crime (predicts less recidivism)

- Offense gravity score of 11 or above (predicts less recidivism)
- Number of previous arrests is the strongest and most consistent predictor of risk.
- Offenses gravity score (OGS) was found to have a consistently significant and negative effect on recidivism, meaning that offenders who committed more serious crimes were less likely to recidivate.

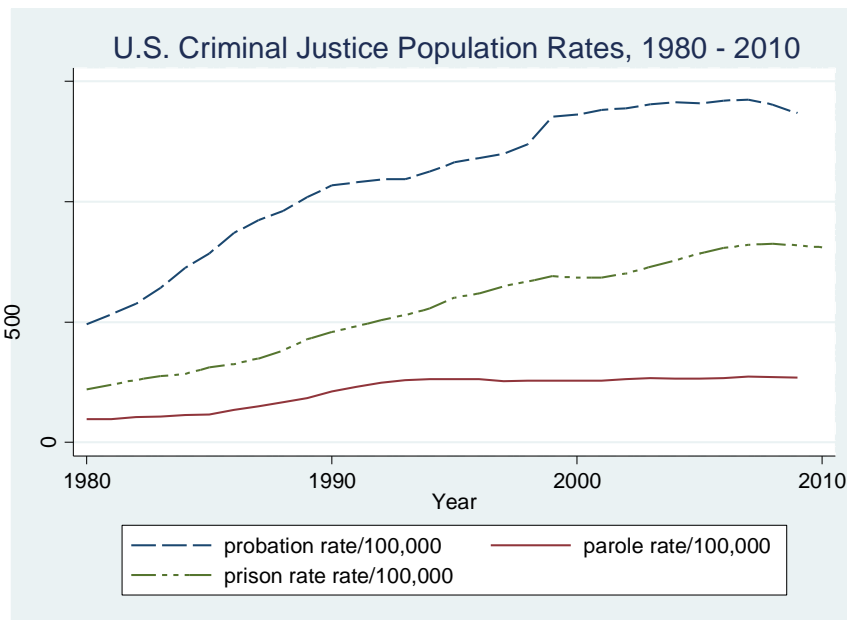
Introduction

Criminal sentencing is one of the most serious governmental powers in a democratic state. Important issues to consider when punishing is the distribution and effectiveness of sentences. Judges make sentencing decisions based on the severity of the current offense, the length and seriousness of the offender's previous record, and their perceptions of the offender's dangerousness to public safety (Albonetti, 1991; Spohn, 2009; Tonry, 1996). Sentences are intended to balance retribution, deterrence, incapacitation, and rehabilitation. Judges have fairly broad discretion when making sentencing decisions (Savelsberg, 1992) and display a significant amount of variation (Nagin and Snodgrass, 2012), despite constraints related to sentencing guidelines. The federal government and many state governments have enacted sentencing guidelines to establish a uniform set of sentencing standards and to reduce sentencing disparity. In Pennsylvania, sentencing guidelines are voluntary; however judges sentence within the guidelines about 90 percent of the time (Kramer, 1995; Pennsylvania Commission on Sentencing, 2012). Even more recently, a host of scholars, judges, and sentencing professionals have called for the adoption of evidence-based sentencing (Bergstrom, 2010). Evidence-based sentencing is the process of using evidence-based practices to sentence offenders in the most effective way possible (Gottfredson, 1999; Missouri Sentencing Advisory Commission, 2010a, 2010b; Silver and Chow-Martin, 2001; Virginia Criminal Sentencing Commission, 2001; Vigorita, 2003). The National Center for State Courts has called for states to 'get smarter about sentencing' by using risk assessments and predictive instruments to assist judges to select sentencing options that protect the public, hold offenders accountable, and reduce recidivism.

The push for smarter criminal justice decision making reflects a growing reliance on social science analysis to make better use of scarce correctional resources (Bergstrom and

Mistick, 2010; Chaneson, 2003, 2005). At least since the mid-1970s, states have sentenced more offenders to prison for longer periods of time (Garland, 2001; Wacquant, 2002). These sentencing patterns have resulted in more than 2 million incarcerated adults and nearly five million adults on probation and parole. The Pew Center on the States (2009) surveyed the states and found that 1 in 31 adults are on some form of correctional supervision, and they demonstrated that growth in correctional spending has outpaced all other forms of public sector spending. Figure 1 is a graph of criminal justice population rates - using Bureau of Justice Statistics (BJS) data - from 1980-2010 within the U.S. in which probation, prison, and parole populations have all risen. Evidence based sentencing and corrections are attempts to stem the growth of the correctional population while maintaining public safety.

Figure 1: U.S. Criminal Justice Population Rates per 100,000, 1980-2010*

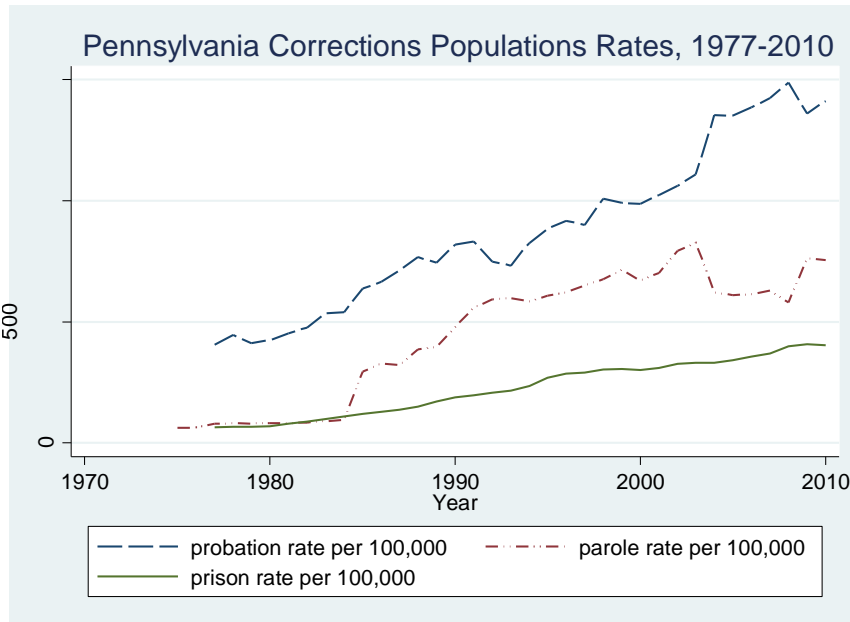


*Data compiled by the authors from the Bureau of Justice Statistics' online correctional database.

The situation in Pennsylvania is similar to the rest of the country with steady growth among correctional populations. Figure 2 is a graph of probation, parole, and prison rates for

Pennsylvania from 1977-2010 and reflects growth patterns very similar to what has occurred across the country (using BJS data).

Figure 2: Pennsylvania. Criminal Justice Population Rates per 100,000, 1980-2010*



*Data compiled by the authors from the Bureau of Justice Statistics' online correctional database.

This report was sponsored by the Pennsylvania Commission on Sentencing (PCS) and Penn State University's Justice Center for Research to inform efforts to develop a judicial risk assessment instrument. The Pennsylvania legislature mandated for PCS to develop a sentencing risk assessment instrument with the passage of Senate Bill 1161. Pennsylvania sentencing guidelines provide suggested punishment ranges according to broad offense types that range from level one to level five. The PCS has compiled several recidivism studies of individuals sentenced within levels three and four (<http://pcs.la.psu.edu/>). Our analysis focuses on offenders convicted at the highest possible sentencing guideline level in Pennsylvania, and reflects the

population most likely to have the greatest impact upon correctional populations.¹ Level five offenders, for the most part, are considered the most dangerous or serious given the nature of their crimes. Consequently, they face the longest sentences and will place the greatest burden on the correctional system. This report will fit within the prior research from PCS studying recidivism with lower level offenders, and is intended to provide a glimpse into the correlates of rearrest among this population.²

In this report, we provide analysis of outcome data from Pennsylvania using level 5 offenders sentenced between 2001 and 2005. The purpose of this report is to inform sentencing and criminal justice professionals about the relationship between offender characteristics available at sentencing and re-arrest. The three overarching research questions are:

1. What offender characteristics are associated with recidivism?
2. How are individual and offense characteristics associated with the timing to rearrest?
3. Can offenders be grouped according to their combinations of risk factors to predict recidivism?

Appropriate statistical techniques are used to answer these questions, and criminological theories guide the analyses. The recidivism analysis reported here includes 10,002 offenders with up to 11 years and 8 months of follow-up data. The most serious current offense is used to describe the offender's current conviction. That is, many individuals are convicted for multiple offenses, and the PCS includes an indication of the offense that is considered the most serious within that judicial proceeding. Using the most serious current offense, we find that two-thirds

¹ Level 5 does not include Murder 1 and Murder 2 offenses, which fall outside of the sentencing guidelines. These offenders receive either lifetime imprisonment or the death penalty, and therefore are not included in the analysis.

² The dependent variable is a composite of rearrest and parole violations resulting in revocation and we refer to these failures as recidivism. Arrest records were obtained from the Pennsylvania State Police and include all arrests recorded in Pennsylvania only. We did not conduct a national records check for arrests in other states.

(66 percent) of the sample have a current violent offense, 16 percent have a current drug offense, 13 percent have a current sex offense, and the remainder have a property or and “other” current conviction.³ Among offenders who recidivated, the longest survival period was 10 years and 10 months, with a means survival time of nearly 1 year and 9 months.

The report is structured in the follow manner. First, we position risk assessment within the evidence-based practices movement, and discuss the benefits and implications of using social sciences methods in corrections and sentencing. Second, we provide a brief example of the implementation of smart sentencing in Missouri. Third, we discuss the research behind developing a risk assessment for use in criminal justice settings. Fourth, we outline the associations between offender characteristics and recidivism. Fifth, we introduce our methods, data, and analysis strategy. Sixth, we present descriptive statistics and regression findings. Seventh, we develop a risk classification schema and compare recidivism rates based on risk scores. Lastly, we conclude this report with discussion of the policy implications and recommendations for future sentencing research.

Correctional resources are limited, which necessitates the use of available tools to improve the efficiency of sentences and the accuracy of prediction. To date, criminologists have worked to develop smart policing (Sherman, 1998; Weisburd, Telep, Hinkle, and Eck, 2010) and evidence-based community corrections policies (Andrews, Zinger, Hoge, et al., 1990; Gendreau, Little, and Goggin, 1996; MacKenzie, 2006), but evidence-based sentencing has received less attention (for exception, see Kleiman, Ostrom, and Cheeseman, 2007). The current research is

³ A total of 13,285 Level 5 offenders were sentenced during 2001-2005, but 2,880 had yet to be released from prison, which prevents them from being in our recidivism study. Further, we restricted the analysis to offenders that had at least a six month window of time in which they could recidivate (i.e., a release date of no later than March, 1, 2012 with a September 1, 2012 follow-up period). More is said about this in the Data & Methods section.

intended to address this gap in knowledge and practice by demonstrating the relationship among recidivism and offender characteristics that judges have access to at sentencing.

Social Science and the Law

Before discussing the methods and findings from the data analysis, we situate this research within a broader movement occurring within the criminal justice policy community. Most criminal justice researchers, policy makers, and practitioners are familiar with the notions of “what works,” evidence-based practices, and data driven policies (see Andrews, Zinger, Hoge, et al., 1990; Andrews and Bonta, 2006; Gendreau, Little, and Goggin, 1996; Lowenkamp, Latessa, and Holsinger, 2006; MacKenzie, 2006; Taxman, 2008). These terms refer to the use of social science methods to identify cost-effective criminal justice solutions. Evidence-based initiatives have occurred mainly in law enforcement and corrections fields, with emerging support within the courts (Chaneson, 2003; Hyatt Bergstrom, and Chaneson, 2011; Warren, 2007).

Actuarial risk assessments, such as those commonly used in correction settings can cause some concern for judges and court professionals. Risk assessment tools, similar to sentencing guidelines, are a way to formalize and standardize judicial decision making, which may raise concerns of discounting professional perspectives and expertise. However, risk assessments can also be looked at as a structured way to collapse judicial “intuition” (Tonry, 1987). That is, judges already consider risk of recidivism when making sentencing decisions. But, this consideration is unsystematic and based on perceptions of the relationships between general offender characteristics (e.g., age, gender) and recidivism. Sentencing risk assessments can fit into this structure by integrating social-science knowledge and provide a standardized way for

judicial actors to assess the relevant factors related to an offender's risk of recidivism (Kleiman et al. 2007; Vigorita, 2003). According to Hyatt et al., "In order to better use the predictive value of such information, as well as ensure uniformity in its application, the nature and mechanics of risk assessment should become a standard part of sentencing procedure" (2011: 266).

Actuarial (i.e., formalized) decision making has been found to improve outcomes in human services professions at least since Meehl's (1956; Grove and Meehl, 1996) review of research on statistical risk prediction. A growing body of literature also suggests that actuarial assessments offer an improved approach to predict future offender behavior (Gottfredson, 1999; Monahan, 2006; Monahan and Walker, 2011; Tonry, 1987). Such approaches are not intended "to control judicial decision making, but rather to better inform judges about the potential outcomes of sentencing" (Hyatt et al., 2011: 266). Social science cannot determine appropriate sentences. Rather, it will take human assessment to answer "normative questions [that] remain beyond the reach of science" (Moore, 2002: 42). Standardized risk assessments can be blended with judicial wisdom and equity under the law to improve the effectiveness and fairness of criminal sentences.

Several notable legal scholars have commented on the usefulness of incorporating scientific study into the judicial process. Chanenson (2003: 1) pointed out that "data can help legislatures and sentencing commissions more intelligently address such crucial issues as setting or revising mandatory minimums and molding the contours of criminal history categories." And, Hyatt and colleagues (2011) state that the use of risk assessment at sentencing "underscores an overall shift in the purposes of sentencing" by replacing the traditional sentencing orientation of proportionality, uniformity, and concerns of disparity, with a "forward looking utilitarian goal" of sentencing according to risk (266). In this sense, the utility of a sentencing risk assessment is

not limited to sentencing decisions, but can be used to restructure the modern-day courtroom into one driven by data and outcomes.

Smart Sentencing: The Missouri Approach

There are several states currently using or exploring the use of sentencing risk assessment tools (Minnesota, Oregon, Virginia, etc.). In Missouri, diverting non-violent criminal from incarceration has been a goal of the sentencing risk assessment. Michael Wolff (2008), Supreme Court Judge of Missouri, stated that “we have begun to look at the question of sentencing outcomes from an overall perspective, as well as to look at which sentences – for which categories of offenders – produce positive results in terms of avoiding recidivism” (2008: 320). He identified that nearly half of state prisoners are sentenced for nonviolent crimes, and 97 percent of all state prisoners are going to be released at some point (Petersilia, 2004; Wolff, 2008). Below, we provide a brief description of Missouri’s judicial system development and successful implementation of a risk assessment instrument (MSAC, 2010a, 2010b).

Missouri, similar to Pennsylvania, is a sentencing guidelines state. Their guidelines are nonbinding, in which a judge does not have to provide any justification for disregarding the guidelines (Chanenson, 2005). (Similarly, Pennsylvania judges are free to depart from the guidelines; however they must provide a reason for doing so.) They have developed an integrated risk assessment approach to structure both sentencing and release decisions. The MSAC’s approach to sentencing assessment development recognized the importance of providing judges with information about potential outcomes related to multiple sentencing options. For this reason, the MSAC developed a risk assessment instrument that includes three sentencing ranges: presumptive, aggravated, and mitigated. The presumptive sentence is the most

typical or modal sentence handed out within the state for a particular offense and individual. The second sentence range allows for considering aggravating circumstances that necessitate a more punitive response. And, third, the mitigated sentencing option is one in which “the circumstance of the crime or the risk presented by the offender justify a less severe sentence” (MSAC, 2010b, p. 2).

MSAC sought to inform all criminal justice actors involved in commitment and release decisions—judges, probation, parole, attorneys, and prison officials. They did a three-year follow up of offenders to determine the differences in recidivism rates among certain lower level felonies sentenced to community sanctions compared to those given institutional sentences. MSAC focused on offender criminal history to determine the most severe sentences. In an effort to incorporate a holistic understanding of the impact of sentencing options on offender behavior, the recommended punishments are provided to judges as part of the pre-sentence investigation report—referred to as a Sentencing Assessment Report (SAR). The SAR is a comprehensive information packet about the individual offender that focuses on: the current offense, offender risk factors, suggested management plan, Commission recommendation, and release guidelines for the Parole Board to consider (Wolff, 2006, p.95). This sentencing approach provides central sentencing decision makers with crucial information that they may not have had or considered previously, while still maintaining full discretion to implement the recommendations or alter them when making sentencing decisions. Since implementing the new guidelines and assessment instrument, Missouri has experienced a decline in their prison population (Wolff, 2006).

Research on the Development of a Risk Assessment in Criminal Justice Settings

Researchers study ways to increase the accuracy and efficiency of organizational actors and incorporate research findings into the courtroom (see Monahan and Walker, 2011). For example, Paul Meehl (1954) demonstrated the efficacy of statistical methods to predict future behavior over clinical judgment. In a later meta-analysis, Groves and Meehl (1996; Groves, Zald, Lebow, Snitz, and Nelson, 2000) analyzed 136 research studies and found that decisions guided by statistically-derived tools provided a more accurate result than clinical assessment. In an ideal world, the judiciary would be able to easily identify the difference between individuals that will recidivate and those that will not. However, recidivists and dangerous individuals cannot be identified by sight or surface level characteristics alone.

The use of risk assessment tools to guide criminal justice actors' decision-making is not new. In fact, Burgess (1928) worked with the Illinois State Parole Board to develop a parole release instrument that relied on an additive binary assessment instrument of 21 factors to predict which offenders were most likely to succeed and fail on parole. As a comparison, three trained psychiatrists also made predictions on a subsample of the 3,000 offenders involved in Burgess' study. The clinicians were found to be slightly more precise at identifying parole successes, but significantly less accurate in predicting parole failures. Reviewing Burgess' research, Groves and Meehl (1996, p. 293) stated that the "conclusion was clear that even a crude actuarial method such as this was superior to clinical judgment in accuracy of prediction."

The judiciary (and all criminal justice positions for that matter) present researchers developing theoretically guided risk assessment instruments with particular challenges due to the need to sentence individuals according to specific legally defined rules. While this is the case, others have pointed out that using actuarial risk assessments can increase sentencing uniformity,

consistency, and objectivity while enabling judicial actors to “manage resources more efficiently by directing them toward the higher risk cases” (Silver and Miller, 2002, p. 143). Gottfredson (1999, p. 110) suggested that sentencing rationality improves “when sentencing theory incorporates risk as a relevant and justifiable consideration.” Risk assessment instruments should be perceived as tools to assist decision making, not instruments meant to limit courtroom actor agency.

Criminological theory and research provides strong evidence that there are similar pathways to chronic criminal lifestyles that are rooted in structural characteristics (Morenoff and Sampson, 1997; Sampson and Groves, 1989), social-psychological characteristics (Gottfredson and Hirschi, 1990), and these characteristics supersede the specific technical aspects of any criminal activity (Sutherland, 1937). It is unreasonable to expect judicial actors to consistently apply both their knowledge of the particular individual’s legal rights and needs, as well as situate this individual within larger offender populations to form a complete picture of how a particular sanction will likely shape this person’s future behavior. Instead, risk assessment instruments allow professionals to integrate specific technical knowledge of a field (e.g., legal philosophy), with the merits of any particular situation (i.e., the particular offender to be sentenced) and situate the individual within larger groups.

In the case of SB 1161, the Pennsylvania Legislature has made it clear that while conserving the resources of the criminal justice system is important, public safety is paramount. This calls for differentiating, and possibly diverting, lower-risk offenders who pose little threat to the public from higher-risk offenders who may need to be incapacitated. In the former situation, a community or mixed sanction might be most appropriate, whereas a more severe institutional sanction might be used for high-risk offenders. Recently, the Virginia Criminal Sentencing

Commission (VCSC, 2001) worked with the National Center for State Courts (Kleiman et al., 2007) to evaluate a sentencing risk assessment instrument used to differentiate among low- and high-risk offenders suitable for non-incarcerative sanctions, and to increase the amount of time served by violent offenders and those with a prior record of violent offenses. Similar to SB 1161, the VCSC was mandated to respond to policy development within Virginia mandating the preparation of guidelines for sentencing courts to identify appropriate candidates for diversion from incarceration, based on the relative risk that a felon will become a threat to public safety (Kleiman et al., 2007, p. 107). The risk assessment fits within Virginia's voluntary sentencing guidelines.

Kleiman et al. (2007, p.120) found that the risk assessment instrument as a whole - the total risk score - provides a significant capability to differentiate recidivists from nonrecidivists. This research is essential for differentiating and effectively sanctioning low versus high-risk offenders. Prior research has found that low-risk offenders who receive more severe punishments designed for high-risk offenders have higher recidivism rates than expected (Lowenkamp, Latessa, and Holsinger, 2006; Lowenkamp, Latessa, and Smith, 2006). Risk assessment instruments use groups of factors that covary with reoffending to form classification schemes to place offenders into groups that have little within-group variation on reoffense rates, but have significant between-group variation on reoffense rates (Kleiman et al., 2007). This is not to suggest that every offender placed into a certain group will have identical behavioral outcomes, but rather it is an approach to reduce data into theoretical categories based upon empirical facts. The use of risk assessment has been cited by many as not only cost effective and more accurate, but also better at achieving criminal justice goals related to punishment (e.g., Pew Center on the States, 2009).

Expected Associations with Recidivism

The research reported here is intended to provide information about offender outcomes after release based on information available at sentencing. Our analysis is intended to contribute to the ongoing efforts of the PCS to work toward developing a risk assessment instrument by analyzing a sample of individuals who are convicted at the highest sentencing level within Pennsylvania. Sentencing level is determined by a combination of two factors: the offense gravity score (OGS) and the prior record score (PRS), which measure the offense seriousness and the seriousness and quantity of the offenders previous convictions, respectively. These items tap into two important concepts related to criminal punishment. First, there is a strong connection between perceptions of offense severity and the public's desire for punishment, in that crimes that are more serious are often punished more severely. Second, longer sentences are given out to offenders who have prior convictions, and in particular, to those who have a serious prior record (Roberts, 2008). These items provide measures of two central issues that judges consider when sentencing, and that sentencing commissions weigh when making sentencing recommendations. The question we investigate, however, is to what degree these measures are related to offender outcomes? We also go beyond the prior record score and the offense gravity score to look at research relevant demographic and case characteristics.

The PCS has completed six interim reports investigating risk and the development of risk assessment instruments at sentencing that are publically available on the PCS website.⁴ In their first report, PCS gathered information on the current use of risk assessments by other jurisdictions, identified risk factors used in other instruments, and the availability of information that is gather at the pre-sentence investigation phase in 25 Pennsylvania counties (Pennsylvania

⁴ The PCS maintains a publication series at <http://pcs.la.psu.edu/publications-and-research/research-and-evaluation-reports/risk-assessment>

Commission on Sentencing, Report 1). The second report included a sample of level 3, 4, and limited number of level 5 offenders to show the relationship between the OGS and PRS scores (Pennsylvania Commission on Sentencing, Report 2). They demonstrated that lower OGS and higher PRS scores are associated with shorter survival times (i.e., higher recidivism). The third report extended PCS' previous research and used logistic regression analysis to find significant positive relationships between recidivism and number of prior arrests, prior property and prior drug arrests. They found negative relationships with OGS, age at sentencing, and sentenced in a rural county (Pennsylvania Commission on Sentencing, Report 3). In this report, PCS also found that, although many offenders commit a broad spectrum of types of crimes, there is a tendency for a smaller subset of offenders to specialize in certain types of crimes.

In the fourth report, PCS scored individual attributes using three approaches – Burgess, weighted Burgess, and Predictive attribute analysis – and found all three to have similar predictive utility (Pennsylvania Commission on Sentencing, Report 4). But, they found the Burgess approach to be the easiest to implement, understand, and use in the field. In their fifth interim report, the PCS, provided analysis to classify offenders in two different ways: using two groups (i.e., high versus low) and three groups (i.e., high, medium and low). They determined choice of grouping approach is a matter selecting how one prefers to balance false positive (i.e., predicting someone as high risk when they do not recidivate) or false negative rates (i.e., incorrectly predicting someone to be low risk that recidivates), as each of these approaches had nearly identical predictive accuracy (Pennsylvania Commission on Sentencing, Report 5). In their sixth interim report, they found the risk assessment instrument was best at identifying lower risk offenders (Pennsylvania Commission on Sentencing, Report 6). Finally, Report 7 tested the validity of their risk scores on a sample of level 3 and 4 offenders with mostly drug and property

convictions. The current report builds upon these previous efforts by PCS to identify correlates of recidivism among higher risk offenders to inform sentencing decision making.

Prior research routinely finds associations between crime and demographic characteristics. Three of the strongest relationships between individual characteristics and crime are gender, race and age. First, males are known to commit the overwhelming majority of crime, and they typically have shorter crime free periods once released into the community. It is regularly found that despite temporal or spatial location men have higher rates of violence, aggression, and criminality (Archer, 2004; Simons and Burt, 2011). Criminological research and crime incidence data demonstrates that males are significantly more likely to engage in crime, be under some form of criminal justice control, and be a victim of crime.

Second, many researchers have found that minorities, especially blacks have higher crime rates (Kleiman et al., 2007). The over-representation of minorities in correctional populations has been studied for a long time and linked to the structural limitations to which minorities are typically exposed (Shaw and McKay, 1942; Sampson and Groves, 1989; Wilson, 1987). Specifically, researchers have identified the effects of social characteristics related to disadvantage and inequality that minority races and ethnic groups experience. Kleiman et al. (2007) found that being black explained a significant portion of the variance in recidivism, but there are obvious ethical considerations when using race as a predictor to make sentencing decisions (Tonry, 1987).

Third, the age-crime curve is one of the more generally agreed upon relationships within the criminology, as individuals commit more crime when they are younger (i.e., the age-crime curve follows a normal distribution from 12 to around 25 years of age). Some suggest, that as people move through life, informal control mechanisms and stakes in conformity reduce their

rate of offending (e.g., marriage, work) (Laub and Sampson, 1993; Toby, 1957). Others (e.g., Terrie Moffitt, 1993) accept a more psychological perspective, which suggests that crime and delinquency proclivity fits along two developmental paths: adolescence limited and life-course persistent. Moffitt's research and others suggests that criminal propensity for most people is age-graded, and only in about 5%-10% of study samples is crime a more persistent behavior. Although as Laub and Sampson (2003) have pointed out, everyone eventually ages out of crime. More recently, Frank Cullen (2011, p. 310) offered further support for age-graded criminology by stating that "Life-course criminology (LCC) is criminology" (Laub, 2006).

Research often shows that past behavior is the best predictor of future behavior, and criminologists also find that individuals with previous criminal offenses are more likely to commit future crimes (Andrews and Bonta, 2006). The number of misdemeanors, felony arrests, and convictions are related to future criminal involvement (Kleiman, 2007; Silver and Chow-Martin, 2002). Both arrest and convictions are important because conviction indicators are affected by process issues related to obtaining a conviction (e.g., charges may be dropped due to lack of evidence or police misconduct), whereas arrest provides a more general indication of the level of criminal involvement. Most individuals arrested as adults were arrested as juveniles, but most individuals arrested as juveniles do not go on to be arrested as adults (Blumstein, Cohen, and Visher, 1986). Among samples of offenders, having a juvenile arrest record is a strong predictor of recidivism. Similarly, the younger a person is involved with the criminal justice system the more likely they are to continue their criminality into adulthood (Piquero, Brame, and Lynam, 2004).

Along with demographics and prior criminal involvement, characteristics of current and prior offenses are also an important indicator of risk of re-offense. Prior research has found that

differences in recidivism rates exist for sex, violent, property, and drug offenders. For example, property crimes are committed more often than personal crimes (Blumstein and Cohen, 1979), so the re-offense rates of property offenders are likely to be higher than other types of offenders. Federal data shows that property offenders consistently recidivate at a higher rate than other types of offenders (Beck and Shipley, 1989; Langan and Levin, 2002). Despite public concern, several studies find that the rate of overall recidivism is lower for sex offenders than other types of offenders (Langan, Smith, & Durose, 2004; Sample & Bray, 2003; Hanson, Scott & Steffy, 1995). The research on drug offenders and violent offenders is mixed. Lo, Kim, and Cheng's (2008) retrospective study suggest that both drug and violent offenders are more likely to experience long periods of no arrest. Data from the Bureau of Justice Statistics (Langan and Levin, 2002) shows that drug offenders are less likely to recidivate than property offenders, but more likely to recidivate than other types of offenders. However, studies on serious drug offenders suggest that they are more likely to recidivate than other types of offenders (e.g., Spohn and Holleran, 2002). Likewise, some studies on violent offenders show that they are less likely to return to prison than non-violent offenders (Schwaner, 1998), while other studies show that violent offenders have a lengthy criminal history compared to non-violent offenders and commit a disproportionate amount of crime (Moffitt, 1989; Farrington, 2003).

An interesting line of criminological research is to determine the proclivity of individuals to specialize in specific crime types. Some individuals may commit only certain types of crime (specialists), whereas others are willing to commit a general range of crimes. Several criminologists have suggested that criminal offenders operate more like a "cafeteria menu," committing a little of many types of crimes depending on opportunity structures (Gottfredson

and Hirschi, 1990). It is likely that generalists will have a higher recidivism rates because their opportunity structures are broader.

Another important criminal offense characteristic is the seriousness of the offense. While offenders with more serious offenses (i.e., offenses that cause more harm) are likely to get harsher sentences, the relationship between offense gravity and recidivism is more complicated. For example, the PCS's Report 2 found that the relationship between offense gravity and recidivism was negative; meaning that those sentences for more serious crime were less likely to commit another offense. Other risk assessments research has also found that lower-level offenses are linked with a higher recidivism rate (e.g., Texas Parole Board, Ohio-ORAS). Lower level crimes, such as burglary or drug use, require a level of pre-meditation and are often done by younger, risk-seeking individuals that are likely to recidivate. Sex and violent offenses are considered the most serious in terms of harm, but are not related to a higher risk of recidivism in this and other risk assessment studies. Other markers of offense seriousness, such as weapon and/or gun possession also have mixed research findings. For example, Huebner, Varanos, and Bynum (2007), found that gun use was not associated with an increased risk of post-release recidivism, while Daniel (2010) found that firearm involvement increased the risk of recidivism for gang offenders only.

Data and Methods

Three datasets are used to conduct this study: a sentencing dataset provided by the Pennsylvania Commission on Sentencing (PCS), an incarceration dataset from the Pennsylvania Department of Corrections, and an arrest dataset provided by Pennsylvania State Police (PSP). The PCS data includes sentencing data from 2001 to 2005 for all offenders sentenced in

Pennsylvania courts. Each data year has over 100,000 sentencing cases, separated by offender State ID (SID) numbers, which are unique to every offender. The DOC dataset includes the date an offender was released from prison and/or sent back to prison for a probation or parole failure. Arrest data (e.g., rap sheets) from Pennsylvania State Police (PSP) provides an indicator of whether the offender has recidivated and all previous arrest data.

Our level of analysis is the individual offender. Pennsylvania relies on a unique SID for each offender, as well as a unique number for each judicial proceeding (JP). The SID number is used to track individuals across different branches of the Pennsylvania criminal justice system (e.g., courts, corrections, and police). The JP number is used to differentiate offenders who had multiple court cases over the course of the 5-year period of interest.

As mentioned above, the PA sentencing system has five levels to indicate the severity of the offender and the offense, with level 1 being the lowest level and 5 being the highest sentencing level. These levels correspond to the sentencing guideline range. Our study is interested in the recidivism patterns and predictors of level 5 offenders only. Previous research (mentioned above) by the PCS analyzed recidivism patterns and predictors for offense levels 3 and 4. The PCS, in response to legislative mandate 1161, wants to understand offender behavior across all sentencing levels. That is, it is important to determine if different types of offenders have varying recidivism patterns. The purpose of this report is to detail the recidivism patterns for a large set of level 5 offenders sentenced between 2001 and 2005 in Pennsylvania.

Years 2001-2005 were selected for several reasons. First, level 5 offenders, for the most part, face long incarceration sentences, which necessitated using a set of years that allowed for enough time for offenders to be released. We found that 2,880 out of 14,026 level 5 offenders sentenced between 2001 and 2005 were still incarcerated during our study. Obviously, we cannot

calculate recidivism patterns for these individuals. However, calculating recidivism rates for individuals sentenced to long (10+ years) sentences is less important for the purposes of this study. Because crimes these individuals receive fall on the far end of the sentencing spectrum, shorter sentences or incarceration alternatives are rarely considered anyway.⁵

The second reason we selected these years is because the PCS made changes to their data collection system in year 2000 — moving over to a computer based system. According to PCS representatives, 2001 was the first year in which accurate and complete data could be easily retrieved. Third, these years provide us with five years of sentencing data, which lends further credibility that our findings are not unduly biased by unobservable temporal trends.

Our study began with a PCS dataset of all levels of offenders for 2001 to 2005, in which there were 624,035 total entries. We restrict these cases to level 5 sentences only, which resulted in 26,111 judicial proceeding and 14,026 unique individuals. In order to obtain one record per individual, we further restricted the dataset to obtain the most serious offense in the most recent judicial proceeding between 2001 and 2005. (Concurrent offenses were controlled for in our models of offense history.) This allowed us to have 14,026 unique offenders, with one current offense per individual. Next, cases were removed that had excessive missing or incomplete records, if the offenders had died, were transferred, escaped, or were still incarcerated. Lastly, we removed offenders that had not been released for at least six months (n=360). Given that offenders can enter the study at different times (i.e., staggered entry), we wanted to ensure that offenders had the ability to be in the community and hence measured as recidivating for a minimum period of time. Therefore, we removed offenders that had been released between March and September, 2012.

⁵ This is an interesting methodological issue in that individuals that remain incarcerated are considered the most dangerous. While analysis of this subpopulation would be theoretically interesting, it nonetheless, would have little policy-relevance.

Table 1: Sample Development of Level 5 Offenders Sentenced in Pennsylvania, 2001-2005

Total Level 5 Sentencing Events	26,111
Unique offenders⁶	14,026
Missing in State Police Data	232
Missing in DOC Data	269
Died ⁷	178
Escaped from Prison	43
Trf. to a Mental Hospital	19
Still incarcerated	2,880
Not out at least 6 months	360
Illogical entries	43 ⁸
Final Sample	10,002

The PCS sentencing data was matched with the Pennsylvania Department of Corrections to obtain the release date for offenders sentenced to prison (70 percent). In order to determine release dates for those sentenced to jail (22 percent), we followed PCS procedures by using the minimum jail sentence date. The majority of offenders sentenced to jail are let out on probation before or when they reach their minimum sentence; therefore this is the best predictor of how long an offender actually serves in jail (Pennsylvania Commission on Sentencing, Report 2). Offenders sentenced to probation (7 percent) and intermediate punishment (<1 percent) began their recidivism period at date of sentence. These data are matched by SID with data the Pennsylvania State Police arrest data, which provides us with arrest records for each offender.⁹ After removing missing data, offenders that had died, escaped, or were transferred, and those still incarcerated, we retain a sample of 10,002 offender. This sample will be used to calculate recidivism rates.

⁶ We used most current offense and most serious offense within a judicial proceeding.

⁷ These offenders died either while serving out their sentence or within a year of release.

⁸ The bulk of these individuals were deleted due to date entries in which the sentencing or arrest date occurred before the date of birth.

⁹ A limitation of the dataset is that our dependent variable is restricted to arrests within Pennsylvania. We did not conduct a national records check to determine if individuals had been arrested in other states.

Analysis Plan

Our analysis strategy starts with descriptive statistics and bivariate relationships of the entire dataset ($n = 10,002$). Next, we split the total sample into three subsamples: training, validation, and test samples. These samples are developed randomly and intended to minimize the likelihood that the findings are a matter of over-fitting the data (i.e., the findings are simply due to idiosyncrasies peculiar to the sample) (Hastie, Tibshirani, and Friedman, 2008). The training sample consists of 50 percent ($n = 5,001$) of the total sample and the test and validation samples are 25 percent of the entire sample ($n = 2,501$ and $n = 2,500$, respectively). Splitting the sample in this way allows for a more rigorous test of what variables to use to classify individuals by their propensity to reoffend. Our strategy uses standard statistical testing procedures in which we advance simple models including only demographic characteristics and include additional criminal history and offense related characteristics to later models. A final model is tested with each sample that includes the variables that achieved statistical support in the prior models. Final variable selection is made by selecting indicators that received the greatest support across the three samples. More is said below when we describe the Cox regression models.

After providing descriptive statistics of the entire sample, we turn to a series of regression analyses to predict the occurrence of recidivism using survival analysis methods. Our regression analysis is directed by theory and prior criminological findings, with the goal being to find the most parsimonious and practical set of covariates that maximize predictive validity. That is, this research is to assist the PCS' work toward development of a sentencing risk assessment instrument, which necessitates that we keep in mind the utility of our findings. For this reason, we restricted our variable selection to items that judges either currently have access to, or could easily gain access to, before the sentencing decision is made. Many of these items are basic

demographics, such as offender's age and gender. Others, such as the offender's criminal history, can be obtained from the pre-sentence report. To further the utility of this research, we wanted to identify as few items as possible that maintained predictive power to allow court personnel to provide judges with a short set of predictive attributes.

Coding and Variable Definitions

Our dependent variable is a new arrest or parole revocation following release from prison, jail, or while on probation. We were able to obtain parole revocations from the DOC records, however this includes only offenders whose parole revocation resulted in a return to prison, not jail. Technical violations are not criminal offenses, per se, but they are a significant driver of incarceration populations. We only include technical violations that result in a return to prison (e.g., the most serious violations). The recidivism variable is constructed in two formats. First, it is a binary indicator of whether a person recidivated (=1) or not (=0) during the follow-up period, which ended in September 1, 2012. Second, the outcome is recorded as the duration between entry into the study – i.e., release from prison or jail and start of probation – and either recidivating (i.e., arrest, revocation) or not (i.e., right censored, surviving) as a continuous measure of time recidivism. Table 2 includes a description of variable labels and coding.

The analysis measures the association between recidivism, a set of individual characteristics, and nature of prior and current criminal offenses. We include demographic characteristics such as sex, race, and age at sentencing. The type of current offense (violent, sex, property, drug, and other) and the nature and seriousness of offenses in their criminal history are included. (See Appendix A and B for a list offenses in each category.) The PCS uses the prior record score (PRS) to indicate the number and seriousness of the offender's criminal history, as well as an offense gravity score (OGS) to indicate the seriousness of the offender's current

offense. The number of total arrests is also included, as well as an indicator of a juvenile arrest. Finally, we developed indicators to measure the criminal career patterns of offenders convicted of at least two offenses. By using a specialization threshold we divided criminal specialists — that is, offenders who have committed 75 percent or more of their crimes in the same category — from those that have committed a variety of different crime types (<75 % in the same category).¹⁰ This provides some measure of the relationship between the variety of an offender’s criminal history and their likelihood to re-offend. This technique mirrors those done in previous specialization research (see Cohen, 1986; Harris et al., 2009; Miethe et al. 2006; Tracy and Kempf-Leonard, 1996; Wikstrom, 1991).

Case characteristics were also included with measures of whether the offense was completed, whether the individual faced multiple counts and whether the offender possessed or used a deadly weapon or gun during the commission of the crime.

Table 2: Coding and Variable Definitions

1. Black: = 1
2. Male: = 1
3. Age30+: 30 years old or older at time of sentencing=1
4. PRS0: PRS score of 1 or more =1
5. OGS11+: OGS score of 11-14 =1
6. Juvenile Arrest: first arrest was under 18 years of age =1
7. C[Offense type]: current conviction is for a violent (reference), sex, property, drug or other crime
8. Prior[Offense type]: a prior conviction of violent (reference), sex, property, drug or other crime
9. Arrests12+: offender has 12 or more arrests =1
10. Specialization: offender is a specialist, generalist, or first-time offender
11. Complete: the most recent conviction is for a completed crime =1
12. Multiple Counts: convicted for multiple offenses within the most current judicial proceeding =1
13. Gun Possession: possession of a gun during the commission of the most recent crime =1

¹⁰ We use prior convictions as a proxy for criminal incidents. Specialists and generalists are offenders who have committed at least two offenses.

Findings

Descriptive Statistics

The descriptive statistics are provided in table 3. The outcome variable – recidivism – is a measure of a new arrest or return to prison for a technical violation, and 62 percent (n = 6,255) of the offenders recidivated within the study period. This was more than 11 years for some offenders. The mean length of months free for those recidivating was nearly 22, with a maximum length of 130 months. Our data shows that 27 percent (n = 2,739), 41 percent (n = 4,153), and 49 percent (n = 4,971) of all offenders recidivated by years 1, 2, and 3, respectively.¹¹ The remainder of recidivists (n = 1,284) did so after the first three years. These temporal patterns are explored later in the survival analysis. Further, it should be noted that out of offenders who recidivated, 44% did so in the first year.

Table 3: Descriptive Statistics of Level 5 Offenders Sentenced in Pennsylvania, 2001-2005
N=10,002

	N	(%)	Mean	Min	Max	#Recid (%) ¹²
Recidivism	6,255	62.54	21.9 months	<1	130	
No Recidivism	3,747	37.46	67.0 months	6	139	
<i>Gender</i>						
Male	9,135	91.33				5,839 (63.9)
Female	867	8.67				416 (47.9)
<i>Race</i>						
Black	4,447	44.46				3,026 (68.0) ¹³
White	4,373	43.72				2,613 (59.7)
Hispanic	916	9.16				470 (51.3)
Other	266	2.66				146 (54.8)

¹¹ These figures represent the percentage of all cases included in the final sample (n = 10,002), but the rate by which offenders recidivate is more stark when considering the percentage compared to the number of offenders at risk which goes down as offenders drop out of the sample.

¹² Over the 11.5 year period.

¹³ For analysis, this variable has been dichotomized as Black and Other Race (Hispanic, White, and Other).

Table 3 (continued): Descriptive Statistics of Level 5 Offenders Sentenced in Pennsylvania, 2001-2005 N=10,002

	N	(%)	Mean	Min	Max	#Recid (%)
<i>Age</i>						
Age at Sentencing			30.13	14.77	78.63	
Juvenile Arrest	2,332	23.32				1,777 (76.2)
<i>Current Offense</i>						
Violent	6,661	66.60				4,145 (62.2)
Sex	1,284	12.84				928 (72.2)
Property	213	2.13				163 (76.5)
Drug	1,689	16.89				908 (53.7)
Other	155	1.55				111 (71.6)
<i>Prior Offense</i>						
Violent	855	8.55				587 (68.6)
Sex	120	1.20				75 (62.5)
Property	747	7.47				550 (73.6)
Drug	2,179	22.79				1,472 (67.5)
Other	2,054	20.54				1,467 (71.4)
<i>Criminal Career Pattern</i>						
Prior arrest #			6.50	1	63	3,691 (80.4) ¹⁴
Specialist	694	6.94				438 (63.1)
Generalist	3,121	31.21				2,169 (69.4)
Prior Record Score			1.72	0	7	1,694 (69.9) ¹⁵
<i>Case Condition</i>						
Completed offense	9,310	93.08				5,850 (62.8)
Multiple charges	3,179	31.78				1,970(61.9)
Offense Gravity Score			9.89	1	14	946 (51.3) ¹⁶
Gun possession	1,024	10.24				632 (61.7)

The overwhelming majority of the sample is male (91 percent), however there are enough females in the sample (n=867) for statistical analysis. The sample is split between black (44 percent) and white (44 percent) offenders, with non-white Hispanic offenders accounting for about 9 percent of the total sample. The average age of the offender at the time of sentencing is

¹⁴ Prior arrest # = number recidivate with an arrest 12+ (mean + 1 standard deviation) (\bar{x} = 6.5, sd = 5.6 = 12.1; n = 3,691)

¹⁵ PRS = number recidivate with a PRS 1+ (based on differentiating offenders who have prior convictions from those who don't)

¹⁶ OGS = number recidivate with OGS 11+ (mean + 1 standard deviation) (\bar{x} = 9.9, sd = 1.4 = 11.3; n = 904)

30 years old, with almost 23 percent of the sample having been arrested as a juvenile (i.e., under 18 years old).

At sentencing, judges will have access to current and prior criminal history information. Such factors are routinely found to be associated with criminal behavior. Table 3 provides prior and current conviction information about each offender. The current sample is composed of two-thirds (n = 6,661) of individuals in which a violent offense is the most serious current offense. Drug offenders account for 16 percent (n = 1,689), sex offenders account for 13 percent (n = 1,284), and property offenders account for two percent (n = 213). This shows that level five offenders in Pennsylvania are mostly convicted for serious (i.e., violent) crimes. A small portion (2 percent) of offenders had crimes that could not be categorized into one of the previously mentioned categories and were included in an “other” offense category.

The seriousness and nature of the current offense is an important consideration at sentencing, but so are prior convictions. The prior offense category in table 3 indicates the total number of offenders with a previous conviction, or convictions, in any of the five offense categories.¹⁷ Nearly 40 percent of these offenders have at least one prior conviction (n=6,083), with the majority being in the drug (23 percent) category. Less than nine percent of the total sample of offenders had a prior conviction for a violent offense (n = 855) or a property offense (n=747). Less than two percent had a prior conviction for a sex crime. Contact crimes are rare events and it appears that even in a sample of serious offenders, a previous conviction for a violent or a sex crime is less common than non-contact crimes.

Specialization and generalization measures (detailed in the Data Description section) are included in the analysis. A 75 percent threshold is used to define specialists and generalists

¹⁷ These figures do not add to 100 percent because any one offender could have prior convictions across several categories, or no prior conviction at all (60 percent of the sample).

among those with more than one conviction. Specialists are 7 percent ($n = 694$) of the total sample (i.e., those repeatedly committing a similar type of crime), and nearly one-third of the total sample ($n = 3,121$) are considered generalists — meaning they commit a variety of crimes over their offending career. This is similar to previous research showing that the majority of offenders are versatile criminals (Farrington, Snyder, and Finnegan, 1988; Harris, Smallbone, Dennison, and Knight, 2009; Simon, 1997).

Along with measures for specialization, other aspects of the offender's criminal history are explored. The average number of arrests is 6.5, with a range of 1 to 63. The arrest is treated as a binary variable in later analysis to compare those with many prior arrests (12 or more) to those without a lengthy arrest record. The prior record score (PRS) is a seven point measurement of the number and seriousness of prior convictions, with this sample having an average PRS score of 1.7.¹⁸ We dichotomized this variable into those with PRS scores of 0 and 1 or above. This was done because the largest difference in recidivism rates occurred between offenders who had no prior convictions to those that had any prior convictions.

Finally, we include different measures for the seriousness of the crime. The offense gravity score (OGS) ranges from 0 to 14 and provides a measure of the seriousness of the current crime. The average OGS score for this sample is almost 10. We dichotomized this variable into groups of scores of 1-10 and 11-14. Nearly all of the convictions were for completed (as opposed to inchoate) offenses (93 percent), and nearly one-third ($n = 3,351$) had multiple charges as part of their case. About 10 percent ($n = 1,024$) of the total sample used a gun during commission of the crime.

¹⁸ The PRS actually ranges from 0-5 with additional indicators measuring repeat offender categories, which collapsed to extend the range (REFEL = 6 and REVOC = 7).

Figure 3: Recidivism Rates by Sex, Race, and Youth Arrest

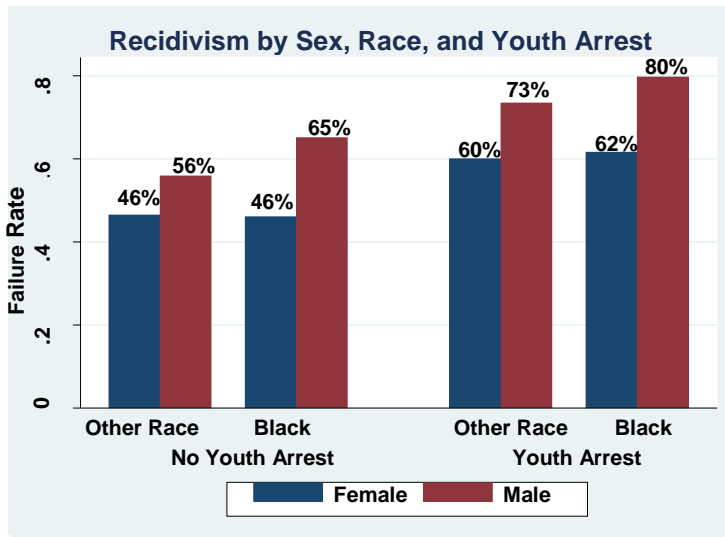


Figure 3 shows the difference in overall recidivism rates over the course of the 11.8-year follow-up period between males and females, blacks and non-blacks, and individuals that were arrested as a juvenile and those who had no youth arrests. Without controlling for other factors, males recidivate at a higher rate than females in all four comparisons (10 to 19 percent more). This difference is particularly stark between black females and black males (18 to 19 percent more). It is also interesting that black females recidivate at only a slightly higher rate than non-black females (0 to 2 percent more) whether they were arrested as juvenile or not, but black males recidivate at a rate that is 7 to 9 percent higher than males of other races. We also see that having been arrested as a youth consistently increases the rate of recidivism when offenders are matched on race and gender. The 80 percent recidivism rate for black males who have had a youth arrest is higher than most any other combination of demographic factors.

Figure 4: Overall Recidivism Rates by Current Offense

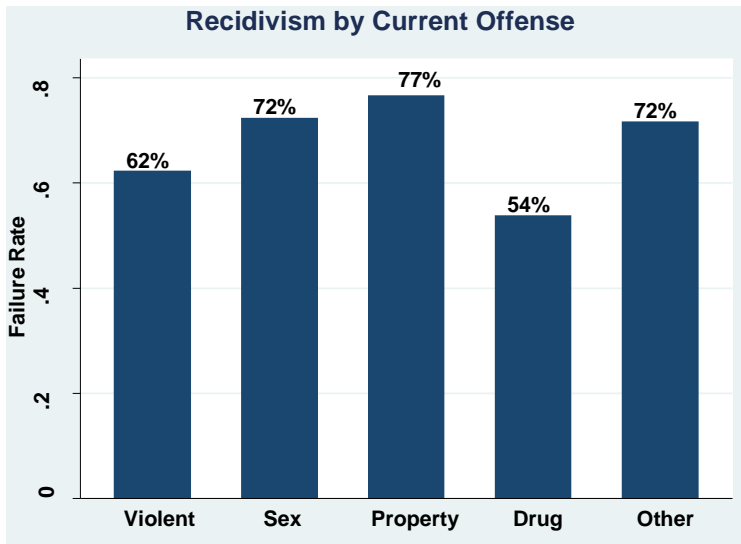
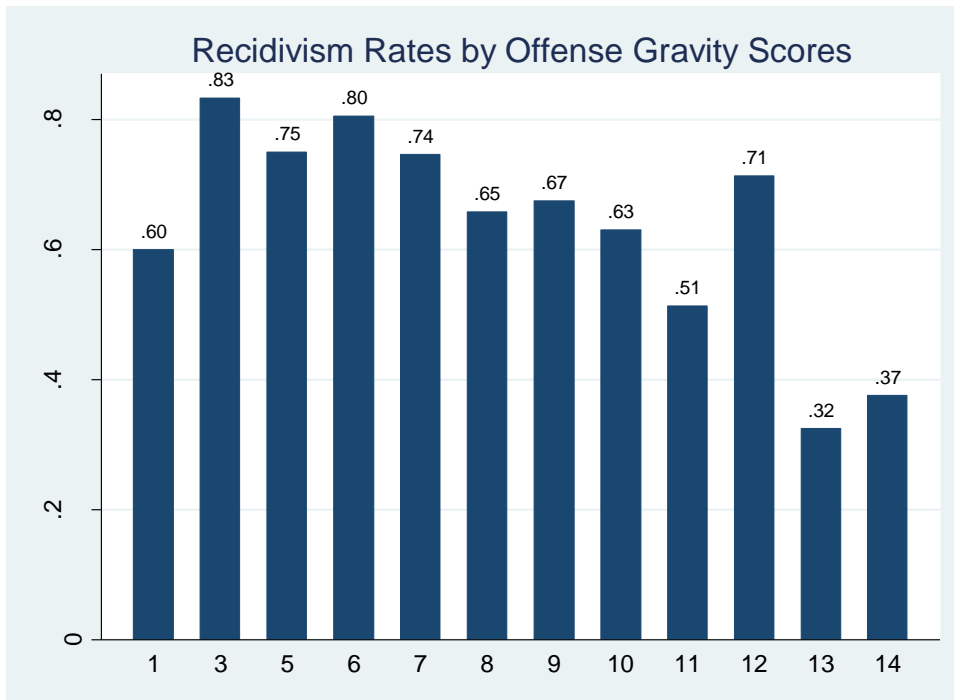


Figure 4 includes the overall recidivism rates over the 11.5-year recidivism period by most serious current offense. Offenders with drug crime as their most serious current offense have the lowest rate of arrest or parole revocation (54 percent), while property offenders have the highest overall rates of failure (77 percent). Sex offenders have a higher than expected recidivism rate at 72 percent, which is about 10 percent higher than the rate for violent offenders. Finally, offenders who committed an offense that did not fit into the sex, violent, drug, or property categories have a 72 percent recidivism rate.

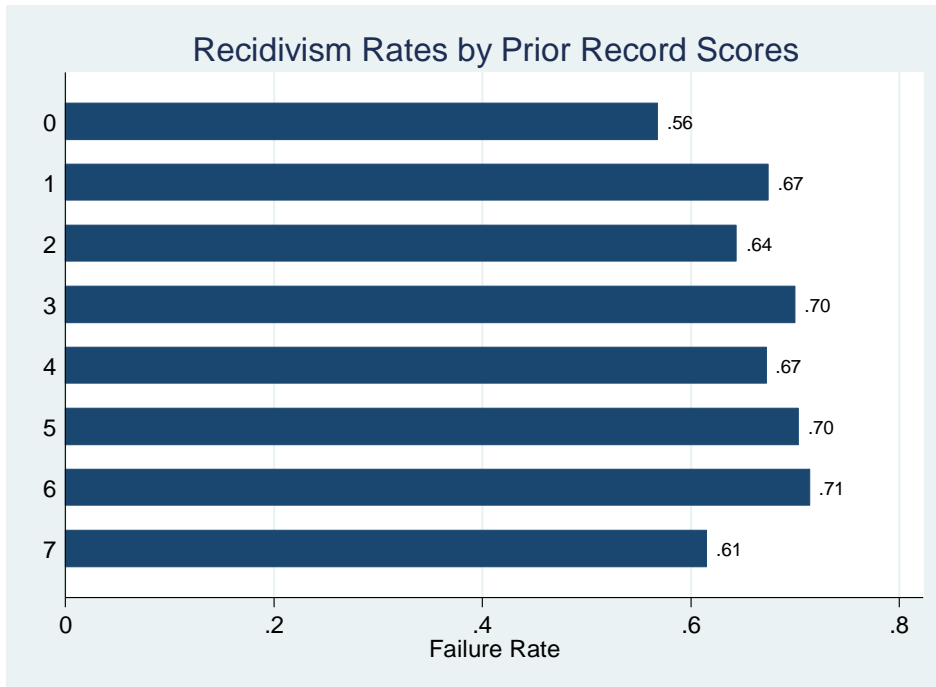
Figure 5: Overall Recidivism Rates by Offense Gravity Scores



The OGS is a 14-point scale developed by the PCS as a way to quantify the severity of an individual's current offense, with a higher score denoting a more serious offense.¹⁹ While the OGS may be a useful indicator of the severity of the offense, our calculations show that it is a non-intuitive predictor of recidivism — in that a more serious offense is associated with lower recidivism. Figure 5 shows that there is a relatively strong negative ($r = -.12, p < .000$) relationship between failure and OGS, as those with the highest OGS scores have the lowest rates of recidivism.

¹⁹ Sentencing levels 2 and 4 are not represented in our sample of serious offenders.

Figure 6: Overall Recidivism Rates by Prior Record Scores



PRS is a 7 point scale used to measure the seriousness of the offender’s criminal record, with a higher score indicating a higher number of convictions and/or more serious past convictions. Repeat felony offenders (REFL) and repeat violent offenders (REVOC) are given the designations of 6 and 7, respectively, and are given longer sentences. Offenders who have no prior convictions are given a score of 0. Figure 6 shows that prior records scores have a positive relationship with recidivism ($r = .11, p < .000$) rates, meaning that offenders who have a more serious criminal record are more likely to recidivate. The biggest spike in recidivism rates occurs when an offender goes from having no prior convictions (PRS=0) to having a PRS of 1. Also, repeat violent offenders (7), while often being given the longest sentences, show a lower recidivism rate than almost all other offenders with lower PRSs. However, there are only 13 offenders who have the REVOC designation.

Associations with Time: Survival Analysis

To provide some understanding of the patterning of recidivism over time we report survival regression models. Survival analysis (also referred to as hazard and event history analysis) is commonly used by criminologists to measure timing to recidivism (Allison, 1984; Chung, 1991, Schmidt, and Witte, 1991). This method received its name because it is commonly used by medical researchers predicting patient survival under various conditions. The purpose is to measure the influence of covariates in the time until an event occurs by treating time as a study variable ranging from 0 to the end of the follow-up period, which in this analysis was up to 11 years and 8 months. The longest follow-up time for a recidivist was 10 years and 10 months.

As is common in many event history analyses our sample is right-censored because we are not able to observe each offender until the event of interest (e.g., recidivism) occurs. This is because many offenders were arrest free during the follow-up period. An important survival analysis assumption is that the censored data are “noninformative” and “unlikely to bias estimates of the effects of independent variables” (Kruttschnitt, Uggen, and Sheldon, 2000: 70, footnote #10). That is, censoring occurs randomly, and the offenders with censored observations are not different from those with uncensored observations with respect to their chance of experiencing recidivism in a given time period. Survival analysis is ideal for dealing with staggered entry times of participants because it deals only in study time (i.e., offender’s time at risk). Each offender’s study time begins upon their release date, starts at time = 0, and continues until they fail or are censored at the end of the follow-up.

Kaplan-Meier Survival Analysis

Kaplan-Meier survival analysis shows relationships between offender attributes and survival at specified times (i.e., at 1, 3, and 5 years out) The results in Table 4 provide estimates

of the probability of survival (not recidivating) at 1, 3, and 5 years for all the covariates, independent of each other. In this analysis, survival refers to the probability that an offender with certain characteristics *will not* recidivate (i.e., survive, censored) at a given time period (t), assuming they have not already failed (i.e., probability of surviving longer than time t) and *not* controlling for other covariates. Time (T) is treated as a continuous random variable,²⁰ and the survival function will have a decreasing shape over time as offenders recidivate. This can be written as $S(t|x_i) = P(T_i \geq t)$.

Turning to table 4, we see that the probability of surviving 1 year is .71 for men and .84 for women. This means that men had a 71 percent chance of not recidivating before 365 days, versus 84 percent for women. This can also be thought of as a 29 percent probability of failure (recidivism) for men and a 16 percent probability of failure for women at the one-year mark. By year 5, men have a 36 percent chance of surviving, compared to 57 percent for women. The log-rank test shows that these differences are significantly different at the .05 level.²¹ This means that females recidivate at a lower rate than males. To get a better sense of what these paths look like, as well as the number of people at risk in each year, the KM survival curves for each covariate are included in Appendix C.

Recidivism rates are higher for males, blacks, and those with a juvenile arrest record relative those without these characteristics. Offenders under 30 at time of sentencing are more likely to recidivate. Offenders with a current conviction for a property offense have lower survival rates compared to those with a current conviction for a sex, violent, drug, or other current offense. Those with a violent, sex, property, drug, or other type of crime in their criminal

²⁰ Study time is calculated from the time someone is released from prison or jail, or placed on probation until their recidivistic event or the end of the study period.

²¹ All differences in survival rates in the table are statistically significant ($p < 0.05$) with the exception of prior sex offense (vs no prior sex offense). This means that all but one covariate is predictive of recidivism.

record recidivate at a higher rate than those who don't have that particular crime type (but may have another type of crime). The difference is most stark between offenders who have a crime in the catch all "other" category and those who don't – with 25 percent vs 41 percent surviving after 5 years, respectively. Offenders with 12 or more arrests are much more likely to recidivate than those with less. Generalists recidivate at a lower rate than specialists. Having a complete offense, multiple charges or using a gun during the commission of a crime is also associated with a higher rate of recidivism. Having a higher OGS is associated with a lower rate of recidivism, however. These bivariate relationships are explored further within the multivariate analysis provided next.

Table 4: Kaplan Meier Survival Functions by Covariates and 1, 3, and 5 Year Rates
N=10,002

	<u>1 year</u>	<u>3 year</u>	<u>5 year</u>
<u>Gender</u>			
Male	.71	.47	.36
Female	.84	.66	.57
<u>Race</u>			
Black	.69	.42	.31
Other Race	.71	.46	.35
<u>Age</u>			
Juvenile Arrest	.61	.32	.21
No Juvenile Arrest	.76	.54	.43
Age at Sentencing <30	.70	.53	.43
Age at Sentencing >30	.75	.63	.55
<u>Current Offense</u>			
Violent	.73	.48	.37
Sex	.62	.42	.32
Property	.60	.31	.22
Drug	.80	.58	.47
Other	.65	.39	.33

Table 4 (continued): Kaplan Meier Survival Functions by Covariates and 1, 3, and 5 Year Rates, N=10,002

	<u>1 year</u>	<u>3 year</u>	<u>5 year</u>
<i>Prior Offense</i>			
Violent	.65	.37	.28
No Violent	.73	.5	.39
Sex			
No Sex	.66	.42	.35
	.73	.49	.38
Property			
No Property	.64	.34	.25
	.73	.5	.39
Drug			
No Drug	.67	.40	.29
	.74	.51	.4
Other			
No Other	.63	.35	.25
	.75	.52	.41
<i>Criminal Career Pattern</i>			
12+ Arrests	.55	.23	.13
1-11 Arrests	.75	.53	.43
Specialist			
Generalist	.69	.45	.35
	.65	.38	.27
1 + Prior Record Score ²²			
0 Prior Record Score	.67	.4	.3
	.78	.57	.46
<i>Case Condition</i>			
Complete Offense	.71	.48	.37
Inchoate Offense	.81	.57	.44
Multiple Charges			
One Charge	.72	.47	.36
	.72	.50	.39
11-14 Offense Gravity Score			
1-10 Offense Gravity Score	.75	.55	.45
	.72	.46	.36
Gun Possession			
No Gun Possession	.72	.44	.33
	.73	.49	.39

Log-rank tests of group equality were used to determine significant differences between group survival times. All of the groups had significantly different survival times ($p < 0.05$), with the exception of the prior sex offense and no prior sex offense.

²² This includes offenders who are Repeat Violent Offenders and Repeat Felony Offenders.

Cox Proportional Hazards Models

The Kaplan Meier analyses are instructive to identify individual factors that are related to recidivism. These analyses are restricted to assessing single factors at a time, and we use Cox proportional hazards models to explore the relationship among several factors simultaneously. The Cox model is a flexible, non-parametric technique used to analyze the determinants of failure or event time and does not require researchers to make any assumptions about the shape of the baseline hazard function as parametric techniques require (Box-Steffensmeier and Jones, 2004; Cox and Oakes, 1984). This is a semi-parametric technique that allows for analyzing the predictors of survival time with censored observations (Cox and Oates, 1984). The hazards function refers to the effect of time (after controlling for the covariates in the model) on the risk of experiencing the event of interest at any given point in time. For example, regardless of individual characteristics, offenders may be inherently more (or less) likely to recidivate as time passes due to unobservable influences.²³ Failing to control for such an effect may bias the results of a survival analysis. Most survival analysis techniques deal with this issue in different ways. One class of models, generally referred to as parametric models (e.g. Weibull, exponential, log-normal, gamma), require the researcher to make some assumptions about the effect of time on the risk of failure (or survival). The Cox model has the added benefit of controlling for the effects of time without requiring researchers to impose assumptions about the temporal patterns and thus is often preferred by analysts for this reason (Box-Steffensmeier and Jones, 2004; Cox and Oates, 1984).

²³ These unobservables could be individual idiosyncrasies or external forces that change over time that are not included in this design.

The Cox proportional hazards regression models are reported in table 5.²⁴ The modeling approach relies on theory and prior research to advance a baseline model (not reported) including black (=1, all other races =0), male, years of age at sentencing, PRS1, and OGS11+. We advance the baseline model by including sets of variables to account for current conviction, prior offenses, criminal career, and case characteristics. Table 5 includes the hazards ratios from the test subsample. The models were developed using three randomly drawn samples by splitting the sample in half for a training sample, and then dividing the other half of the sample into validation and test samples that are each 25 percent of the total sample. The findings between these samples were nearly identical, which led us to estimate the final set of models in table 5 using the test sample.

The model building procedure resulted in seven models estimated using theoretically-relevant sets of predictors of recidivism (the baseline model is not reported here). We used the training (50 percent, n = 5,001) and validation (25 percent, n = 2,501) samples to test each of the sets of variables, and applied a standard 95 percent confidence interval (i.e., standard confidence needed to suggest that the relationship is not a matter of chance) to determine the variables to test in the “Full” model. The goal is to identify a parsimonious model of characteristics that have high predictive validity with recidivism. Therefore, we test the models across three samples to provide a stringent examination of relationships for the training and for the validation sample tables for the Cox regression analysis. There were overall consistent findings across all three samples, but there were some slight differences. The training sample included one model in which prior drug offense was significant, but this was not found in any of the other samples. And, prior other offense is only significant in the test sample (reported below, models 3 and 6).

²⁴ Log-rank tests and univariate Cox models were run to confirm that categorical and continuous covariates met the proportional hazards assumption inherent to Cox regression.

The generalist offender measure was significant in all three of the “Career Criminal” models (#4), but never reached significance in the full models in each of the three samples. PRS was found significantly related to recidivism in all models that did not include number of prior arrests. The prior arrest variable is the strongest indicator of recidivism.

Therefore, the full model includes a refined set of variables that are routinely found to be significant in previous tests. The tables report hazard ratios, with those exceeding 1 indicative of a positive effect on hazard and those below 1 indicative of a negative effect on hazard.

Table 5: Test Sample: Cox Regression Models, N = 2,500

	Onset	Current	Criminal	Career	Case	Full
Black	1.174**	1.291***	1.143*	1.195***	1.188***	1.222***
Male	1.586***	1.470***	1.617***	1.623***	1.616***	1.420***
Age<30	1.286***	1.514***	1.657***	1.459***	1.464***	1.522***
PRS1	1.498**	1.622***	1.318***	1.497***	1.554***	1.358***
OGS11+	0.915	0.801***	0.949	0.912	0.913*	0.822***
Juvenile Ar.	1.406***					1.359***
Current Sex		1.960***				2.098***
Current Property		1.446				1.310
Current Drug		0.742***				0.761**
Current Other		1.163				0.965
Prior violence			0.980			
Prior sex			0.950			
Prior prop			0.977			
Prior drug			0.938			
Prior other			1.229**			1.296**
Arrests 12+			2.035***			2.003***
Specialist				0.774*		1.049
First-Time				0.904		1.111
Complete offense					1.132	
Multiple counts					1.074	
Gun possession					0.966	

Reference categories: non-black, female, age>30, PRS 0, OGS 1-10, no juvenile arrest, current violent offense, no prior violence, sex, property, drug, or other conviction, prior arrests 0-11, generalist, inchoate offense, charged with one count, no gun possession.

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

In table 5, model 1, being black and male is related to a 17 and 59 percent higher hazard rate relative to non-blacks and females, respectively. Both of these variables continue to have a statistically significant effect on crime throughout the models. Offender age at sentencing are found to have strong associations, and a prior record score of 1 or more (PRS1+) is a significant predictor of recidivism in five of the six models reported. Having an offense gravity score of 11 or more (OGS 11+) has a consistent significant and negative relationship with recidivism, meaning that offenders with more severe crimes (as they are currently defined by PCS) are less likely to recidivate. This finding is similar to previous PCS reports. The first column in table five lists the hazard ratios for juvenile arrest as a binary measure of whether an individual was arrested prior to turning 18 years of age, and the analysis shows that individuals with a juvenile arrest (under 18 years of age) are 41 percent more likely to recidivate.

The second model in table 5 reports the current offense measures. This model shows that current sex offenders have a significantly higher rate of recidivism, whereas drug offenders have a significantly lower recidivism rate. In fact, sex offenders are 96 percent more like and drug offenders are 26 percent less likely to recidivate, relative to violent offenders (the reference category).

The third model in table 5 reports the effect of particular priors on recidivism, as well as arrest. The only prior that is significant is a category called “other” which includes crimes that could not be easily put into the sex, violent, property, or drug categories. Offenders are more likely to recidivate if they have a prior in the “other” category. Also, those with 12 or more prior arrests (i.e., mean + 1 standard deviation) have a 123 percent greater likelihood of recidivism.

The career criminal model (column 4, table 5) indicates that specialist offenders have significantly lower odds of recidivating. However, none of the case characteristics in model 5 have a significant effect on recidivism.

The full model (column 6, table 5) provides a robust set of relevant predictors to consider in sentencing risk assessment development. We included all variables found to be significant in the previous model. The only variables that diminished in significance were current drug conviction; however it is still significant at the .01 level. We then move all consistently predictive variables to the final model in table 6. Prior other was not included because it was not found to be significant in the training and validation samples.

Table 6 provides the Cox regression model of results from the final sample that reaffirms the findings from the analyses reported previously. The eight variables below were found to have consistently strong and significant relationships with recidivism and they provide a basis of static measures to predict recidivism. Males are nearly 40 percent more likely to recidivate than females, and people less than 30 years of age at sentencing were nearly 60 percent more likely than those 30 or older.

Table 6: Test Sample: Cox Regression Final Model, N = 2,500

Hazard Ratios				
	HR	z	P>z	95% C.I
Male	1.38	3.21	0.001	1.134 - 1.684
Age <30	1.56	7.36	0.000	1.389 - 1.763
PRS1+	1.30	4.70	0.000	1.166 - 1.454
OGS11+	.820	-3.12	0.002	.7248 - .929
Juvenile Ar.	1.51	6.71	0.000	1.344 - 1.716
Current				
Sex	1.86	7.92	0.000	1.597 - 2.173
Drug	.791	-3.11	0.002	.6831 - .9171
Arrest12+	2.35	11.98	0.000	2.048 - 2.711

Those with a PRS score of 1 or more, meaning those with any prior record, were 30 percent more likely to recidivate compared to those with a zero score. Individuals with a juvenile arrest have a 51 percent greater chance of recidivating than individuals that had their first arrest as an adult. For the analysis in table 6, the current offense variables were recoded as dummy variables of current sex (=1) and current drug (=1) compared to those with a different current offense (=0). Sex offenders have a nearly 90 percent higher probability of recidivating and drug offenders have a nearly 20 percent lower probability of recidivating compared to individuals with a violent, property, or “other” current offense. The prior number of arrests indicator continues to be the strong predictor of recidivism as those with 12 or more prior arrests have a 135 percent greater likelihood of recidivating.

The analyses thus far have focused on how each of the predictors are related to recidivism, net of the other covariates in the models, but risk assessment development requires developing these factors into composite scores to determine how sets of important factors are related to recidivism. Before presenting our risk scoring procedures, we provide brief analysis using Receiver Operator Characteristics (ROC) to estimate the Area Under the Curve (AUC) statistics comparing the predictive power of each of the three subsamples used to develop the risk attributes. After comparing the AUCs, the significant variables from the final model are used to estimate risk scores from which we can classify offenders into risk groups, and plot the probability of recidivism across the different risk groups.

Predictive Validity: Comparing the Area Under the Curve

The area under the curve (AUC) estimates from the receiver operating characteristics (ROC) analysis demonstrate the predictive validity of the full models and final model to provide comparative statistics between the training, validation, and test samples. ROC analysis is a plot

of the sensitivity (i.e., offenders predicted to recidivate who do so within the study period) and 1-specificity (i.e., offenders predicted to recidivate who do not recidivate during the study period) pairs that are produced as a single decision threshold is moved from lowest to highest possible values. Sensitivity is the true positive rate and 1-specificity is the false positive rate, and these rates are the probability of positive prediction among cases with or without a failure, respectively. ROC estimates provide a way to compare the relative predictive validity of each of the regression models from the test, training, and validation samples.

The challenge of prediction is often represented with a contingency table similar to the one below. Column 1, row A demonstrate the true positive rate, or hit rate: individuals the model predicted to recidivate who actually did so. And, Column 2, row A reports the false positive rate or the false alarm rate, which includes individuals predicted to recidivate who did not. Row B, column 1, shows the false negative rate, or offenders who were predicted to *not* recidivate, but did so. And, finally, the true negative rate is reported in row B, column 2, which are offenders predicted to *not* recidivate who survived throughout the entire follow-up (i.e., censored cases).

Table 7: Contingency Matrix of Observed and Predicted Recidivism

	Column 1 Recidivism	Column 2 No Recidivism
Row A Predict Recidivism	True Positive	False Positive
Row B Predict No Recidivism	False Negative	True Negative

The goal of any prediction exercise is to maximize the true positive and true negative rates. In a perfect sentencing scenario, for instance, this would mean that judges would identify all the offenders who never commit another crime (true negative) and all the offenders who reoffend (true positive). Unfortunately, such perfect prediction is impossible, but ROC estimates provide a measure of how well each model balances true positives (i.e., benefits) and false positives (i.e., costs).

The AUC estimate the probability that a classifier, which differs by model, will rank a randomly chosen positive instance higher than a randomly chosen negative instance. It varies from 0.5 (accuracy is not improved over chance) to 1.00 (perfect accuracy). In table 8, the AUCs are reported from the training, validation, and test samples using the full model and the final model from the training sample (table 6). The analysis shows a consistently high predictive validity across the samples (69.7-70.7 percent accuracy) to suggest that the findings are not a matter of chance or peculiarities of any one sample drawn. There are at least two other important findings revealed from this analysis. First, the AUC estimates are significant at the 95 percent confidence level in each of three samples, indicating that each predicts recidivism statistically better than chance. And, second, the AUCs are nearly identical suggesting that our findings are not the result of over-fitting, but rather are indicative of real relationships between level 5 offenders and recidivism.

Table 8: Comparing Predictive Accuracy of Training, Validation, and Test Final Cox Proportional Hazards Models

	<u>AUC</u>	<u>S.E.</u>	<u>95% C.I.</u>
Train Full	0.707	0.007	0.693 - 0.722
Validation Full	0.697	0.010	0.676 - 0.717
Test Full	0.705	0.010	0.685 - 0.727
Test Final	0.701	0.010	0.680 - 0.722

Risk Assessment Scoring and Classification

The analysis to this point has identified robust relationships between certain offender characteristics and recidivism. However, risk assessment development requires aggregating these characteristics in different ways. Development a risk assessment instrument requires that researchers make decisions regarding what issues are most important to practitioners —there must be a balance between public safety, over prosecution, ethical concerns, and practicality. Burgess' (1928) method of using unweighted binary factors to classify offenders has been embraced by several researchers, and the PCS found this scoring approach predicted equally as well as a weighted version and a more advanced statistical approach (also, see Monahan, Steadman, Silver, Appelbaum, et al., 2001). This approach maximizes practicality because it relies on summing binary (0, 1) indicators across factors, and identifying different cutoffs related to recidivism. Additionally, recent research by the Pennsylvania Department of Corrections has found a similar approach using only static items to predict recidivism as well as more complicated risk assessments (i.e., Level of Service Inventory-Revised).

The survival analysis identified a set of indicators that were scored (0, 1) and summed so that larger values were related to recidivism. Table 9 provides a description of our coding scheme for developing the risk scores. Risk assessment development requires that researchers make practical judgments related to ethics and practical necessity. For this reason, offender race is not included in the scoring procedure.²⁵ Gender (male = 1) and age at sentencing, which is coded as a binary factor of below the mean age at sentencing (< 30 years old = 1) and above the mean age sentencing (=> 30 years old = 0) are included in the scoring procedure. A PRS score of

²⁵ Using race as a risk factor for recidivism is not in line with many other goals of the criminal justice system, such as reducing minority over-representation and racial bias.

0 (=1) is included in the scoring procedure and an offense gravity score of 11 or higher (OGS11+), which had a consistently negative association with recidivism.

Table 9: Coding and Variable Definitions

1. Male=1
 2. PRS1+: Prior record score of 1 or above = 1
 3. Juvenile Arrest: First arrest <18 =1
 4. Age < 30 = 1
 5. Arrests12+: Offender had 12 or more arrests = 1
 6. Current Offense: drug offense = 0, violent, property, and other offenses = 1, and sex offense = 2
 7. OGS < 11 = 1
-
-

Juvenile arrest and 12 or more arrests (mean plus one standard deviation) were each scored as 0,1 positive indicators. Two offense types were consistently related to recidivism in the survival analyses: current sex conviction and drug convictions. Current sex conviction is positively related to recidivism, and drug conviction was found to be negatively related to recidivism. To provide some weighting for these relationships between current offense and recidivism, the following coding scheme was used: drug =0, violent, property, and other = 1, and sex =2. The risk classification method has a potential range of 0-8.

Figure 7 and table 10 show the positive linear relationship between recidivism and risk score. Figure 7 shows the percent failing by each risk score and table 9 gives a breakdown of how many offenders are in each group. The individuals scoring 0 (i.e., female drug offenders without any of the other risk factors) have less than an 8 percent failure rate, with 2 of these 26 people failing. The failure rates increase to 30 percent and 39 percent for those with scores between 1 and 2, respectively, which is nearly half the overall failure rate. The failure rates peak

at 84 percent and 88 percent for those scoring between 6 (494/587) and 7 (81/92) points, respective.

Figure 7: Recidivism Rates by Overall Risk Score for the Entire Sample, 10,002

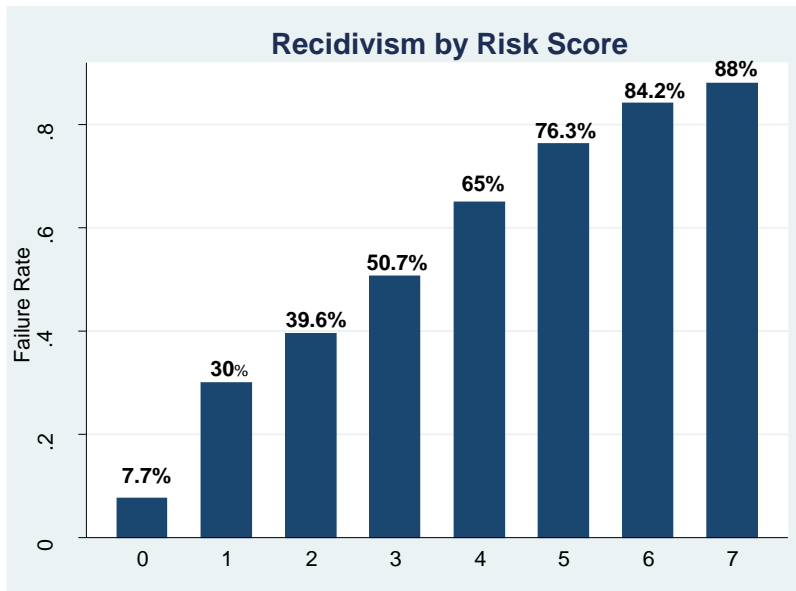


Table 10: Raw Risk Scores for the Entire Sample, 10,002

Risk Score	0	1	2	3	4	5	6	7	Total
#Survived	24	219	570	1,039	1,191	600	93	11	3,747
%Survived	92.31	69.97	60.45	49.29	35.03	23.69	15.84	11.96	37.46
#Recidivated	2	94	373	1,069	2,209	1,933	494	81	6,255
%Recidivism	7.69	30.03	39.55	50.71	64.97	76.31	84.16	88.04	62.54
Total	26	313	943	2,108	3,400	2,533	587	92	10,002

These raw scores serve as the basis for developing risk group classifications. These scores were collapsed into low (0-3), medium (4-5), and high (6-7) groups based upon their failure rates. In table 11 we report the risk group classifications and recidivism rates. Table 11 reports the failure rates by risk group in which 45 percent (1,538/3,390), 70 percent

(4,142/5,933), and 85 percent (575/679) of the low, medium, and high risk groups recidivated during this study, respectively.

Table 11: Risk Classifications and Recidivism for the Entire Sample, 10,002

Risk Group	Low	Medium	High	Total
#Survived	1,852	1,791	104	3,747
% Survived	54.63	30.19	15.32	37.46
#Recidivated	1,538	4,142	575	6,255
% Recidivism	45.37	69.81	84.68	62.54
Total	3,390	5,933	679	10,002

These descriptive statistics provide initial support for the factors selected and the scoring procedures used to develop the risk classifications. In table 12, we report univariate Cox regression models to provide further evidence of the association between these groups and recidivism. The hazard ratios provide an initial exploration of the relationship between the risk groups and recidivism for the test, validation, and training sample.²⁶ Compared to offenders in the low risk group (reference category) the medium risk group is 95 percent to 126 percent more likely to recidivate. Offenders in the high risk group are 223 percent to 341 percent more likely to recidivate than the low risk group.

Table 12: Cox Proportional Hazards Regression Analysis of Risk Groups and Recidivism

	<u>Test</u>	<u>Validation</u>	<u>Training</u>
Low (reference)			
Medium	2.244***	1.953***	2.260***
High	4.056***	3.228***	4.407***
BIC	49521.8	22614.2	22277.2

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

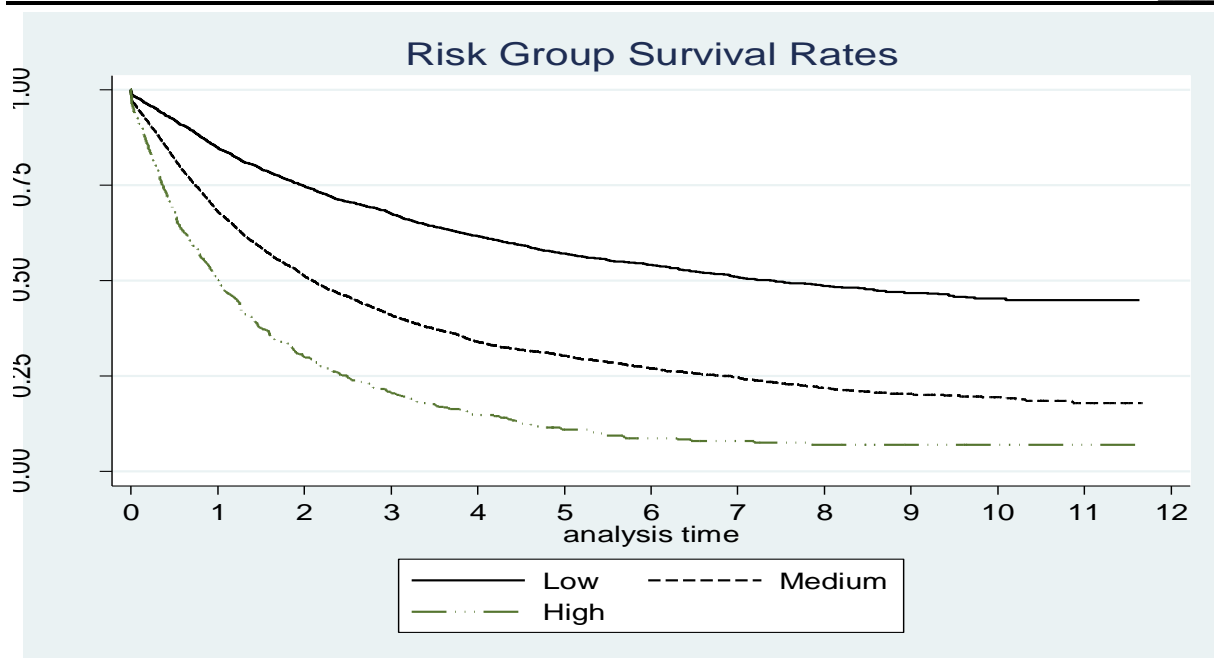
²⁶ A similar cross validation technique was used for the analysis in table 11, but the three random samples were redrawn because we do not want to test the risk groups on the same samples as was used for development.

Kaplan Meier Survival Plots of Recidivism by Risk Groups

A final step in the analysis is to consider the survival plots across the three risk groups. One of the added benefits of Kaplan Meier survival analysis is the ability to provide easy to interpret graphs about the performance of groups over time regarding the outcome variable. In figures 3, we plot the survival probability estimates for the three risk groups to provide a visual of how each group performs over time with regard to recidivism. All individuals enter the study at $t = 0$ and there is a 100 percent survival at that time (as can be seen at the upper left-hand corner of each of the figures).

Figure 8 shows the survival rates that individuals in the low risk (solid line) group have a much higher survival probability throughout the study than those in the other three groups. In fact, the differences here are rather stark, and start immediately upon entering the study, which means that low risk offenders not only have a lower chance of recidivating, but when they do recidivate, they do so at a slower rate.

Figure 8: Kaplan Meier Survival Estimates for Risk Groups



Conclusions

The analyses are a first step in understanding the long-range recidivism patterns among offenders sentenced at the highest sentencing level in Pennsylvania. Our statistical approach was rooted in prior research and criminological theory to locate a parsimonious set of factors which predicted recidivism. While we were constrained to using factors that judges had at the sentencing stage, all of the factors studied and selected are strongly related to recidivism. The case and offenders characteristics identified are factors that judges currently use to make decisions. The assessment process compiled these factors into a structured instrument that has the potential to make judges more aware of the relationship between offender characteristics and recidivism.

The research reported here incorporated criminological theory and prior research findings with a detailed analytical plan. The data is composed of offenders sentenced at level 5 in Pennsylvania between 2001 and 2005, who were released for at least 6 months at the start of the study.²⁷ The outcome variable was gathered from PA state police arrest records and from the PA Department of Corrections (i.e., parole revocations). The analysis started with descriptive statistics of the entire dataset ($n = 10,002$) before we split the sample into training, development, and test samples to follow advanced approaches in statistical learning for cross-validation (Hastie et al., 2006). Kaplan-Meier survival analysis and Cox Proportional Hazards regression analysis were used to identify covariate patterns with recidivism. The Cox regression models advanced a baseline model by estimating an additional five models in which the covariates that met the standard 95 percent confidence level ($\alpha = .05$) and had practical validity were included in the final regression analyses.

²⁷ Some offenders recidivated before 6 months, but all were given the potential to recidivate for at least 6 months.

The analyses were performed on all three datasets using the following steps. First, we explored associations and model strength with the training sample. Second, we verified the results with the validation sample, and when we found inconsistencies, we returned to the training sample for continued analysis. Third, we continued to go back and forth between the training and validation samples until we found highly consistent results. Fourth, we estimated all models with the test dataset. The only adaptations made with the test sample were minor, and namely involved recoding certain variables. ROC analysis was used to estimate AUC coefficients across the three samples in which we found nearly identical estimates, with all estimates predicting significantly better than chance. The statistical approach we used relied on survival analysis to allow for a staggered entry to the study time and control for right censoring (i.e., those not recidivating), but we also performed discrete time logistic regression analyses (that are unreported) to confirm that the results were not dependent on particular time periods.

These analyses resulted in the development of three risk classification groups using a risk scale composed of 8 characteristics. These items are static criminal justice and demographic factors. The characteristics used to classify offenders are:

1. Male=1
2. PRS1+: Prior record score of 1 or above = 1
3. Juvenile Arrest: First arrest <18 =1
4. Age <30 = 1
5. Arrests12+: Offender had 12 or more arrests = 1
6. Current Offense: drug offense = 0, violent, property, and other offenses = 1, and sex offense = 2
7. OGS < 11 = 1

Hyatt and Bergstrom (2011) point out that sentencing is a matter of balancing art and science, and risk assessment development must also maintain such a balance. Thus, we made several decisions to select factors and to score individuals into different risk groups. These

decision were made in consultation with PCS and by following precedents set in risk assessment literature. However, ultimately, research cannot speak to the legality or the morality of these decisions. First, we followed conventional ethical norms and excluded race as a consideration in the risk scoring procedures. Race was controlled for in the statistical analyses, although it would have also improved classification if included in the risk scoring procedure. Second, we have decided to include OGS in the final risk scale. A higher OGS was found to have a consistent negative relationship with recidivism, which replicates what PCS has found with less serious offenders. However, it should be noted that practitioners may take issue with a risk assessment that puts offenders with more serious crimes into lower risk categories — particularly if this instrument is used to divert lower risk offenders away from prison. Third, while race was left out, age and gender were included in the risk assessment scoring procedure. Offenders have no control over their age or gender, thus criticism has been put forth about whether these factors should be included in a risk assessment, and particularly whether this is a legal practice. These are issues that research cannot answer and that the PCS will need to explore as they move forward with this mandate. On a more practical note, interaction terms between PRS and OGS were considered, but ruled out because such measures move away from the ease and practical utility of the ten items that were selected. A surprise is that current sex offense conviction was found to be significant and positively related with recidivism, despite past literature to the contrary. Initially, it was thought this might be a matter of over-fitting, but this finding was supported across both cross-validation samples (and in numerous unreported analyses). We suggest further research into this finding, as it stands in contrast to much sex offender recidivism literature.

As with any research project, this study has limitations. First, the outcome measure is broad and captures any arrest or revocation. In the future, it would be interesting to look at the nature of the recidivism offense, especially as it relates to violent recidivism. Separating outcomes by arrests, revocation, and reconviction would also show different pathways of recidivism for offenders — particularly as this relates to type of current offense. Second, the study does not consider the potential differences in the covariate pattern of predictors for females (i.e., this resulted in some female offenders scoring zero, but recidivating). The findings signal a need for more nuanced study of gender differences to tease out the different recidivism pathways for women and men. Third, the analyses do not account for within individual changes, or organizational, legal, and cultural changes that occurred during the time of the study that potentially influenced the results. Analyses are needed that provide a more intricate investigation of time-varying covariates and the nested nature of offenders within broader social contexts. Finally, and perhaps most importantly, this report does not provide guidance on how to best use a risk assessment tool at sentencing. Risk of recidivism is only one consideration that judges use to make sentencing decisions and our analysis cannot speak to the relative importance of other considerations, such as retribution or rehabilitation potential. These issues become particularly salient for a state like Pennsylvania because sentencing guidelines already prescribe the intended punishment without consideration of risk. Interested parties in Pennsylvania will have to decide the logistics of adopting a sentence risk assessment instrument as per SB 1161. Despite these limitations, the analysis provides a glimpse into the covariate patterns of level five offenders and an initial risk assessment scoring procedure that can be integrated with previous research and enhanced by future endeavors.

The use of risk assessment tools has gained prominence within the corrections field. In fact, many jurisdictions require probation and parole officers to conduct general assessments, substance abuse assessments, and specialized assessment for sex or domestic violence offenders. And, in several states prisons rely on intake units to conduct a battery of assessments when new inmates are admitted. Regardless of the setting, however, these assessments are used with the hopes of improving offender outcomes by reducing recidivism, and maximizing resources by not over supervising low risk offenders or placing offenders in inappropriate programs.²⁸ There are several reasons for the increased use of risk assessments in corrections, but one overriding reason is related to the consistent finding that desired outcomes are more likely to be achieved when actuarial decision making is used. Meehl's (1954) well-known review of research nearly 60 years ago provided a strong footing for such a claim. And, numerous criminologists have since supported the use of risk assessment in corrections because they are related to improved outcomes for offenders (Andrews and Bonta, 2006; MacKenzie, 2006).

Criminal justice professionals make difficult decisions every day. These decisions have implications for public safety, justice, and the civil liberties of offenders. Currently, there is potential to blend social science methods into the sentencing decision making process in order to give the courts more information at sentencing. We have completed this report with the hopes of contributing to this literature, and providing the PCS with initial research into level five offenders.

²⁸ Researchers have found that placing low risk individuals in treatments designed for high risk offenders tends to increase recidivism (Lowenkamp et al., 2006).

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Appendices

Appendix A Current Offense Coding

Violent Offenses

Aggravated Assault - Cause S.B.I.

Aggravated Assault - Attempt S.B.I.

Aggravated Assault - Cause S.B.I. Police, etc.

Aggravated Assault - Attempt S.B.I. Police, etc.

Aggravated Assault - Cause or Attempt B.I. Police, etc.

Aggravated Assault - Cause or Att B.I. w/Deadly Weapon

Aggravated Assault - Fear S.B.I.

Neglect Care-dependent Person (Cause S.B.I.)

Arson - Endangering Persons; Person in Bldg. or B.I. results

Arson - Endangering Persons; Nobody in Bldg. and no B.I.

Assault by Prisoner

Burglary - Home: Person Present

Murder Inchoate - Conspiracy - no S.B.I.

Murder of The Third Degree

Murder Inchoate - Conspiracy with S.B.I.

Murder Inchoate - Attempt with S.B.I.

Murder Inchoate - Attempt - no S.B.I.

Murder Inchoate - Solicitation - no S.B.I.

Terroristic Threats

Robbery - Inflicts S.B.I.

Robbery - Threatens S.B.I.

Robbery - Commit/Threaten any F1 or F2

Robbery - Inflicts or Threatens B.I.

Unlawful Restraint-Victim <18 yrs old

Robbery of Motor Vehicle - with S.B.I.
Robbery of Motor Vehicle - without S.B.I.
Discharge of Firearm into an Occupied Structure
Voluntary Manslaughter
Endangering Welfare of Children - Course of conduct
Suicide, Causing or Aiding as Homicide - Murder 3
Intimidation of Witness/Victim-Listed Factors
Intimidation of Witness/Victim-Listed Factors/F-1 or Murder
Kidnapping
Murder of an Unborn Child - Murder 3
Simple Assault

Drug Offenses

Acquisition of C.S. by Fraud: Sch II Prescr. pills (Narcotic) (51 - 100 pills)
Acquisition of C.S. by Fraud: Sch II Prescr. pills (Narcotic) (> 100 pills)
Acquisition of C.S. by Fraud: Sch II Prescr. pills (Coc/Meth/PCP) (51-100 pills)
Acquisition of C.S. by Fraud: Sch II Prescr. pills (Any Other) (51 - 100 pills)
Acquisition of C.S. by Fraud: Sch II Prescr. pills (Any Other) (> 100 pills)
Acquisition of Controlled Substance by Fraud: Cocaine (100 - 1000 g)
Contraband - Provide controlled substance to inmate
Contraband - Possession of controlled substance by inmate (8/25/97)
Drug Delivery Resulting in Death
Possession With Intent to Deliver: Schedule IV
Possession With Intent to Deliver: Narcotic (10 - < 50 g)
Possession With Intent to Deliver: Narcotic (50 - < 100 g)
Possession With Intent to Deliver: Narcotic (100 - 1000 g)

Possession With Intent to Deliver: Narcotic (> 1000 g)

Possession With Intent to Deliver: Methamphetamine (2.5 - < 10 g)

Possession With Intent to Deliver: Methamphetamine (10 - < 50 g)

Possession With Intent to Deliver: Methamphetamine (50 - < 100 g)

Possession With Intent to Deliver: Methamphetamine (100 - 1000 g)

Possession With Intent to Deliver: Methamphetamine (> 1000 g)

Possession With Intent to Deliver: PCP (2.5 - < 10 g)

Possession With Intent to Deliver: PCP (10 - < 50 g)

Possession With Intent to Deliver: PCP (50 - < 100 g)

Possession With Intent to Deliver: PCP (100 - < 1000 g)

Possession With Intent to Deliver: Cocaine (< 2.5 g)

Possession With Intent to Deliver: Cocaine (2.5 - < 10 g)

Possession With Intent to Deliver: Cocaine (10 - < 50 g)

Possession With Intent to Deliver: Cocaine (50 - < 100 g)

Possession With Intent to Deliver: Cocaine (100 - 1000 g)

Possession With Intent to Deliver: Cocaine (> 1000 g)

Possession With Intent to Deliver: Drug Unknown

Acquisition of Controlled Substance by Fraud: Drug Unknown

Acquisition of Controlled Substance by Fraud: Heroin (50 - < 100 g)

Acquisition of Controlled Substance by Fraud: Heroin (100 - 1000 g)

Acquisition of Controlled Substance by Fraud: Narcotic (10 - < 50 g)

Acquisition of Controlled Substance by Fraud: PCP (100 - 1000 g)

Possession w/ Intent to Deliv.: Marijuana (10 - < 50lbs.)

Possession w/ Intent to Deliv.: Marijuana (21- <50 plants)

Possession With Intent to Deliver: Heroin (< 1 g)

Possession With Intent to Deliver: Heroin (1 - < 10 g)

Possession With Intent to Deliver: Heroin (10 - < 50 g)

Possession With Intent to Deliver: Heroin (50 - < 100 g)

Possession With Intent to Deliver: Heroin (100 - 1000 g)

Delivery by practitioner: Cocaine (50 - < 100 g)

Delivery by practitioner: Drug Unknown

Delivery by practitioner: Heroin (> 1000 g)

Delivery by practitioner: Narcotic (100 - 1000 g)

Delivery by practitioner: Narcotic (> 1000 g)

Sex Offenses

Statutory Sexual Assault

Involuntary Deviate Sexual
Intercourse

IDSJ with a Child < 13 yrs.

Incest

Rape

Rape of a Child <13 yrs.

Sexual Abuse of Children - Taking
Photo

Sexual Assault

Aggravated Indecent Assault

Aggravated Indecent Assault of a
Child

Property Offenses

Access Device Fraud - Att./obtain \$500>

Burglary - Home: No One Present

Catastrophe - Intentionally Causing

Failure to Remit Sales Tax

Theft - Unlawful Taking; > \$100,000
Theft - Unlawful Taking - During Disaster
Theft - Unlawful Taking; Firearm
Theft - Unlawful Taking; > \$2,000 - \$25,000/Auto-
etc.
Tax Violations
Theft - Deception; Firearm
Firearms; Sale or Transfer - Subsequent Offense
Owning/Operating a Chop Shop

Undetermined Offenses

Homicide by Vehicle While DUI
Aggravated Assault by Vehicle While DUI
Criminal Attempt-Unspecified
Corrupt Organizations
Criminal Conspiracy-Unspecified
Firearms; Possessed by Former Convict (eff.
2/14/00)
Firearms-Loaded; Persons Not To Possess, Use, etc.
Firearms-Unloaded; Persons Not To Possess, Use,
etc.
Solid Waste: Management of Hazardous Waste
Escape - Other Escapes; this Subsection
Failure to Register (lifetime)
Firearms; Altering I.D.
Failure to Verify (lifetime)
Failure to Verify
False Identification to Law Enforcement Authorities

Homicide by Vehicle (w/DUI Conviction)

Involuntary Manslaughter

Involuntary Manslaughter - victim < 12 yrs.

Appendix B Prior Offense Coding

Prior Violence Convictions

Murder and inchoate murder

Voluntary manslaughter

Kidnapping

Arson (F-1)

Robbery SBI

Robbery/motor vehicle/SBI

Aggravated assault (SBI)

Burglary (house and person)

Ethnic intimidation

Arson (F-1/no person)

Robbery

Robbery/motor vehicle/ no SBI

Prior aggravated assault (att. SBI)

Simple assault

Murder and inchoate murder

Voluntary manslaughter

Kidnapping

Arson (F-1)

Robbery SBI

Robbery/motor vehicle/SBI

Aggravated assault (SBI)

Burglary (house and person)

Intimidation of witness

Assault by life prisoner

Ethnic intimidation

Simple assault (<12 years of age)

Prior Drug Convictions

Drug delivery causing death

Felony drug (>50 g)

Other felony drug

Drug delivery causing death

Felony drug (>50 g)

Other felony drug

Prior Sex Convictions

Rape

Involuntary deviant sexual intercourse

Aggravated indecent assault

Sexual assault

Luring child into vehicle

Indecent assault

Indecent exposure

Corruption of minor

Rape

Involuntary deviant sexual intercourse

Aggravated indecent assault

Incest

Sexual assault

Luring child into vehicle

Indecent assault (<13 age)

Indecent exposure (<16)

Corruption of minor

Unlawful contact with minor

Prior Property Convictions

Burglary

Burglary

Prior Undetermined Convictions

Inchoate to 4 point F-1

Felony-1

Felony-2

Felony -3

Involuntary manslaughter

Homicide by vehicle

Possessing an instrument of crime

Prohibited offensive weapon

Possession of weapon on school
property

Possession of weapon on court
property

Endangering welfare of children

Dealing infant children

Violation of uniform firearms act

M-1 DUI

Weapons of mass destruction

Aggravated jury tampering

Other 4 point offenses

Inchoate to 4 point F-1

Other felony-1

Felony-2

Felony -3

Involuntary manslaughter

Accidents involving death

M-1 involving death

Possessing an instrument of crime

Prohibited offensive weapon

Electronic incapacitation

Possession of weapon on school
property

Possession of weapons on court
property

Violation of uniform firearms act

M-1 involving weapons

Endangering welfare of children

Dealing infant children

M-1 involving children

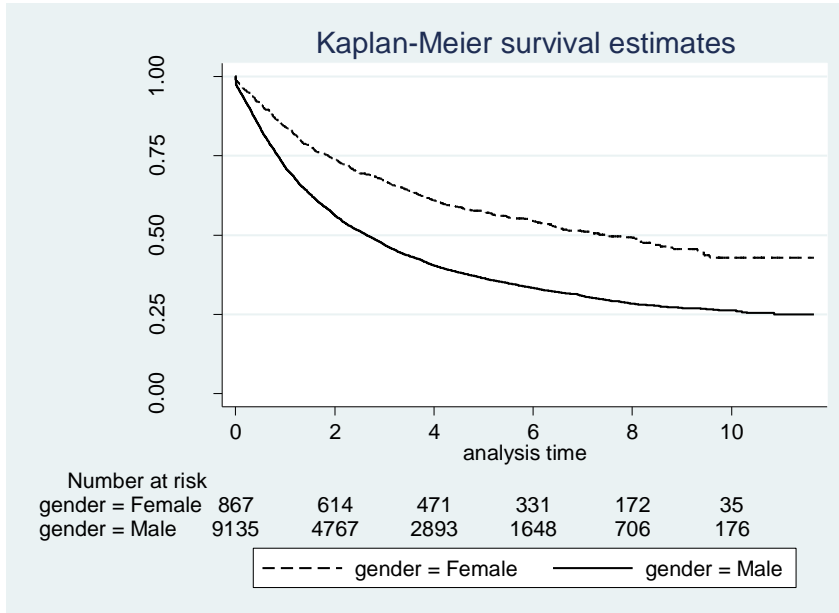
Unclassified DUI

M-2 DUI

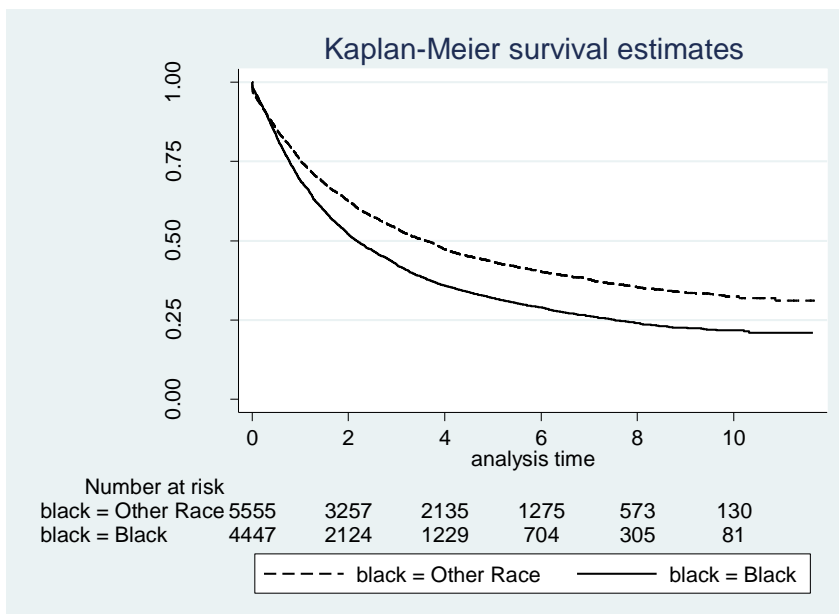
M-1 DUI

Appendix C Kaplan-Meier Survival Curves for Covariates

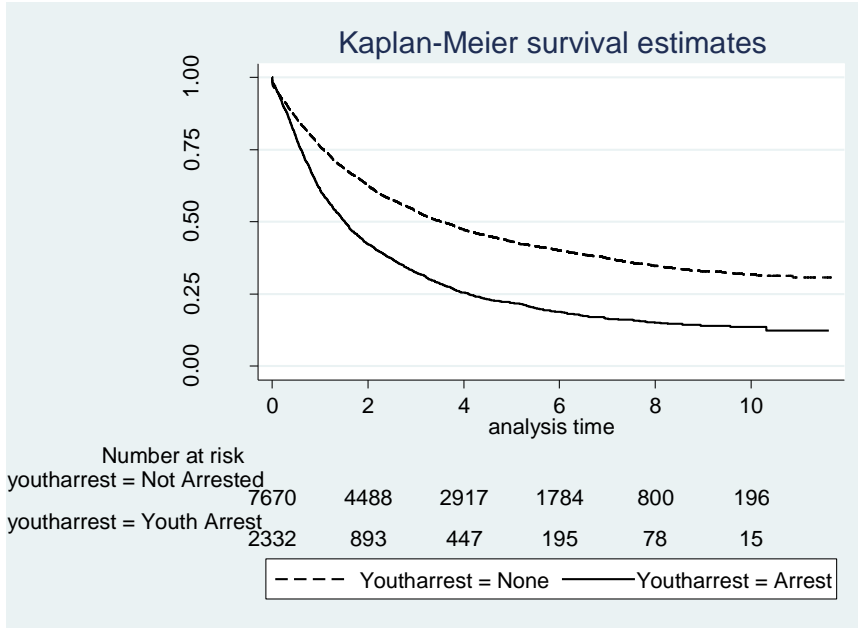
Male and Female



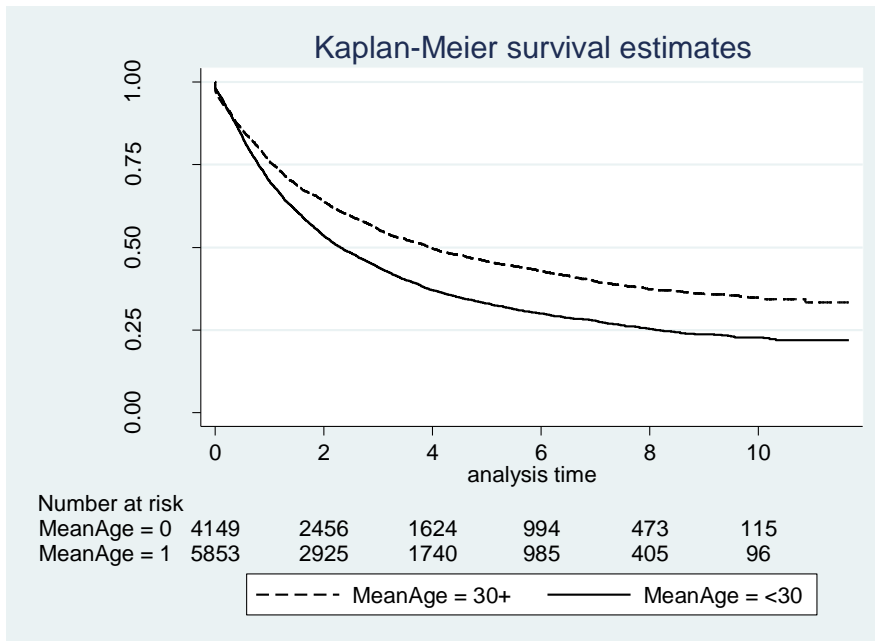
Black and Other Race



Youth Arrest and No Youth Arrest

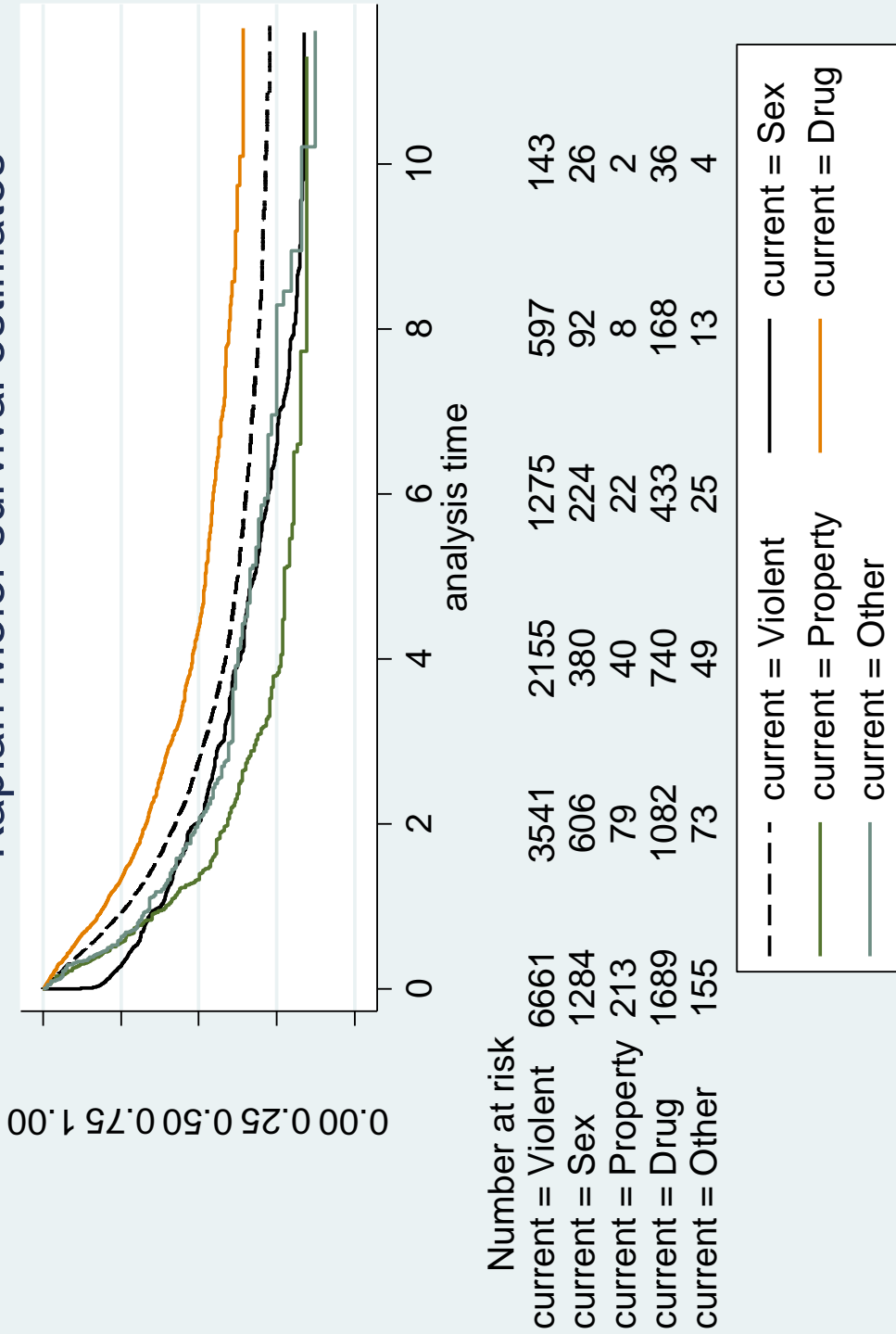


Age at Sentencing 30+ and 30-

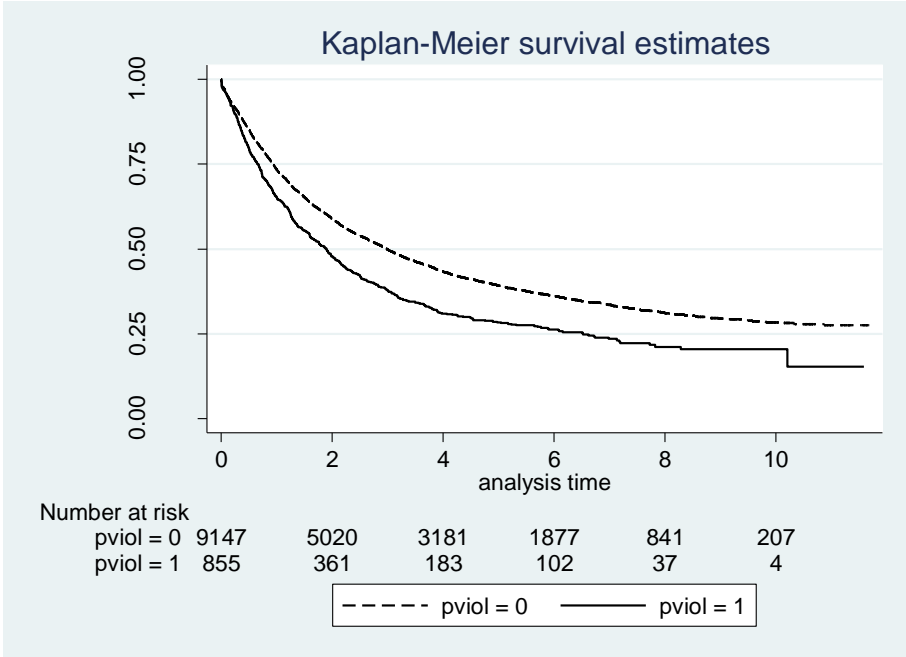


Current Offense

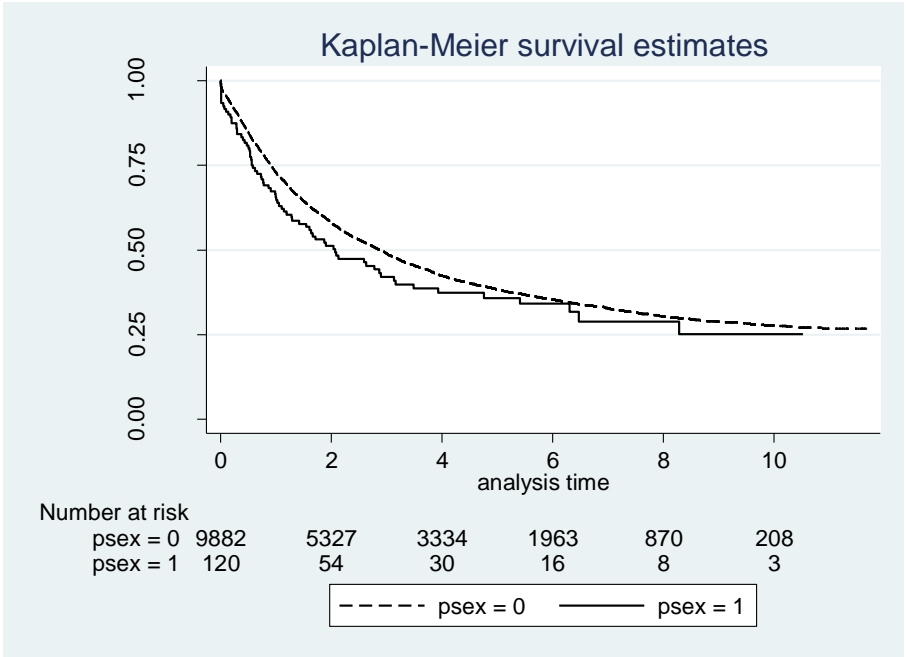
Kaplan-Meier survival estimates



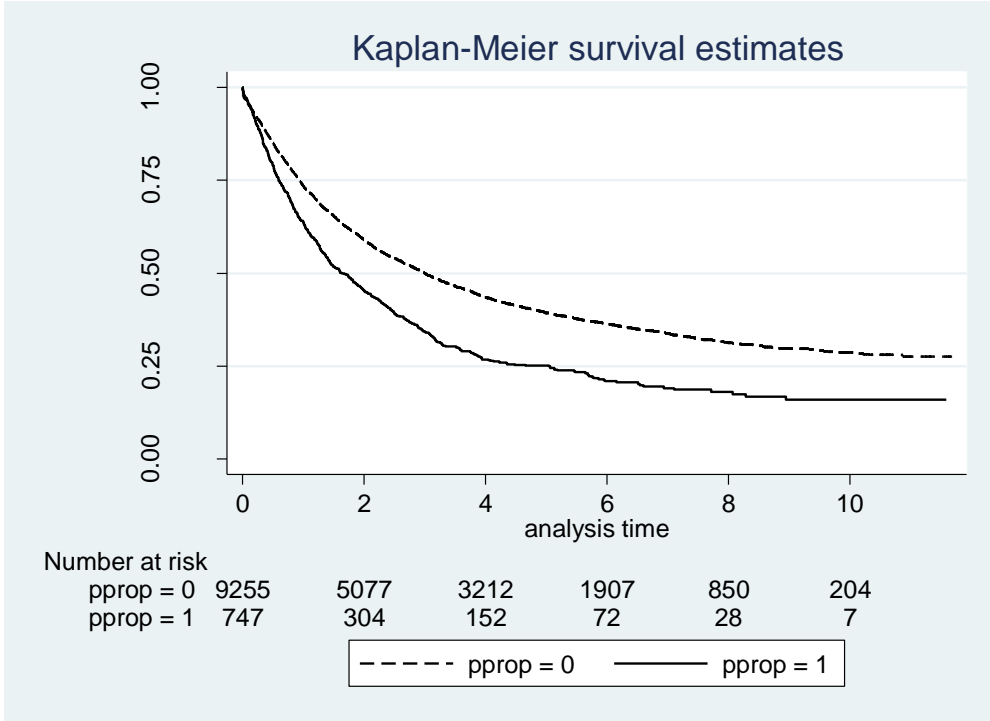
Prior Violent Offense and No Prior Violent Offense



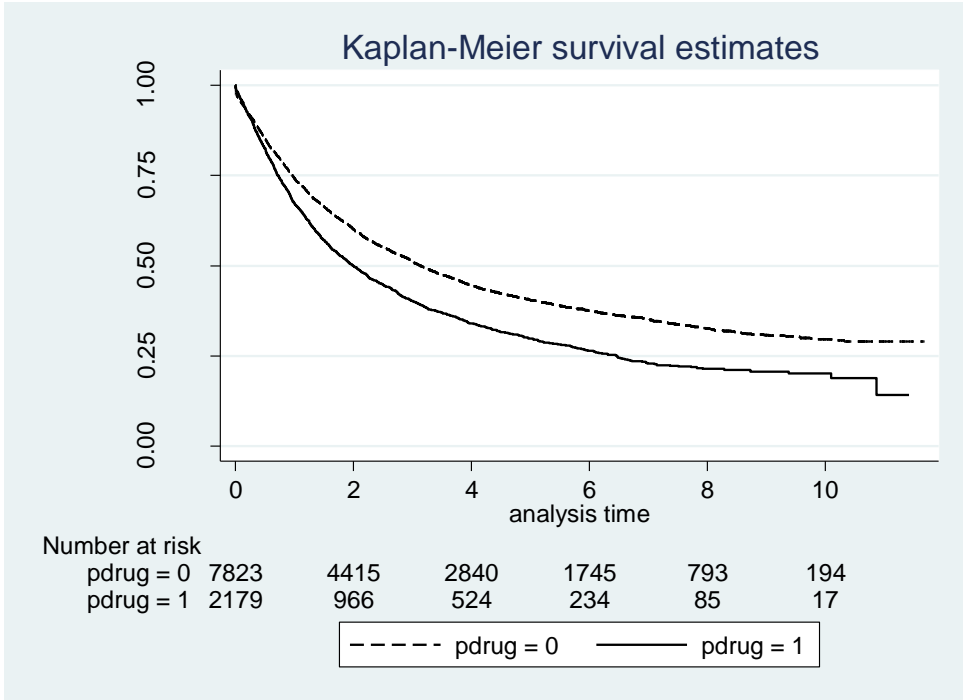
Prior Sex Offense and No Prior Sex Offense



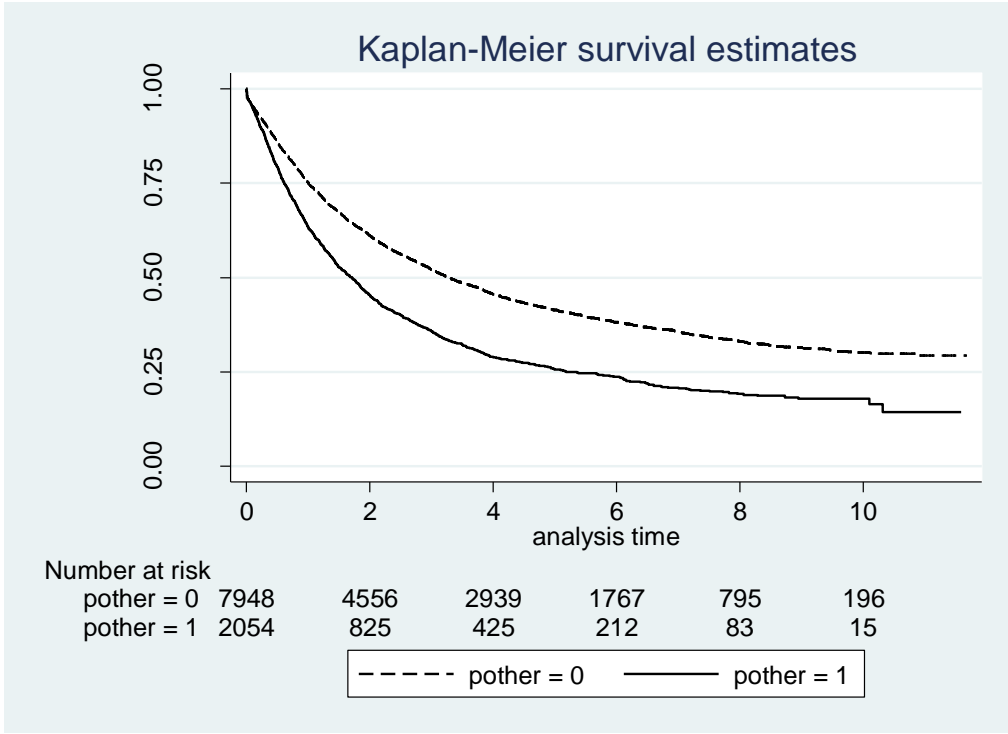
Prior Property Offense and No Prior Property Offense



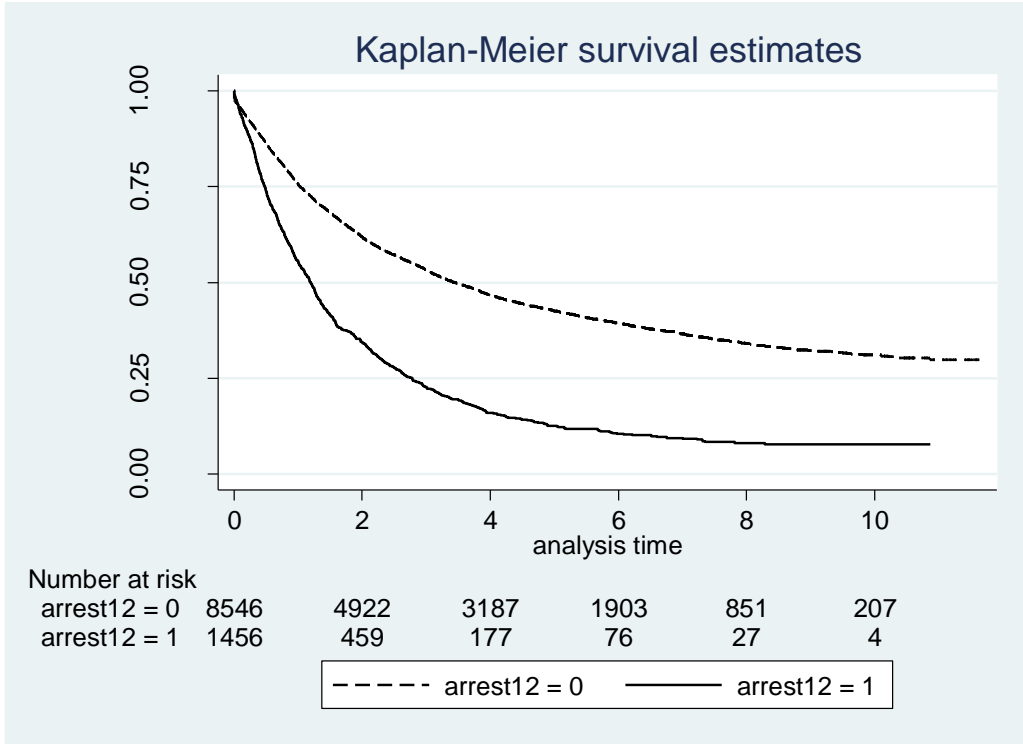
Prior Drug Offense and No Prior Drug Offense



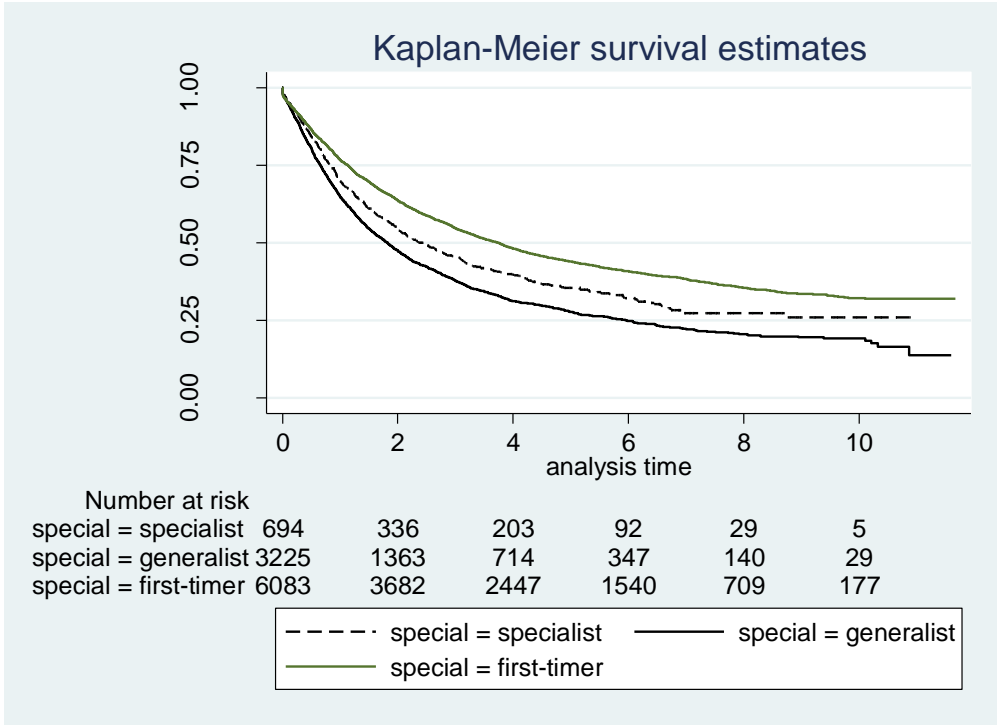
Prior Other Offense and No Prior Other Offense



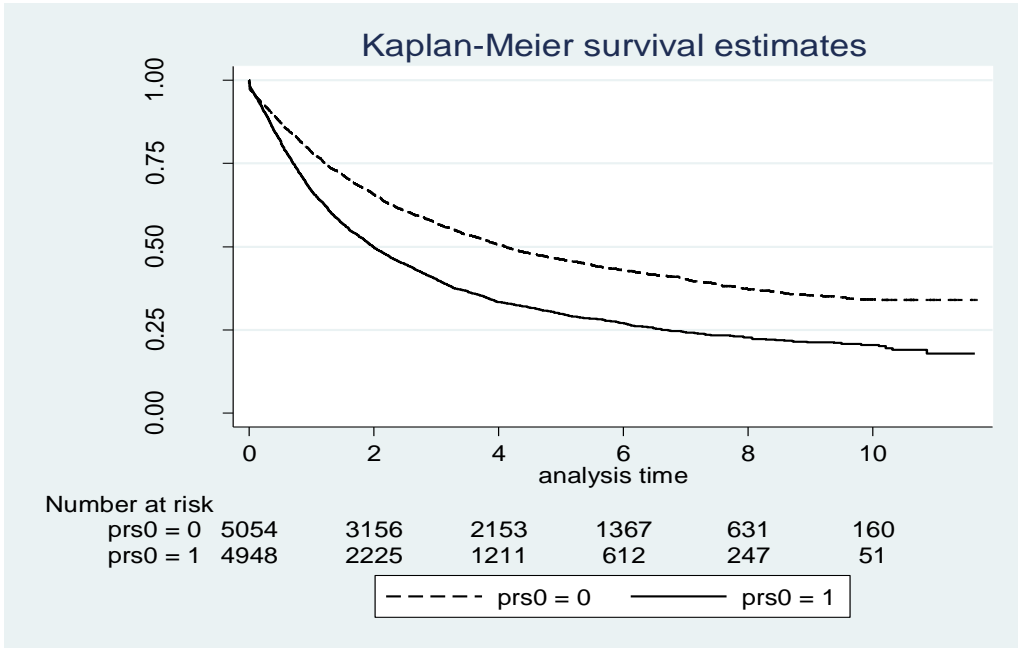
Arrest 12+ and Arrest 1-11



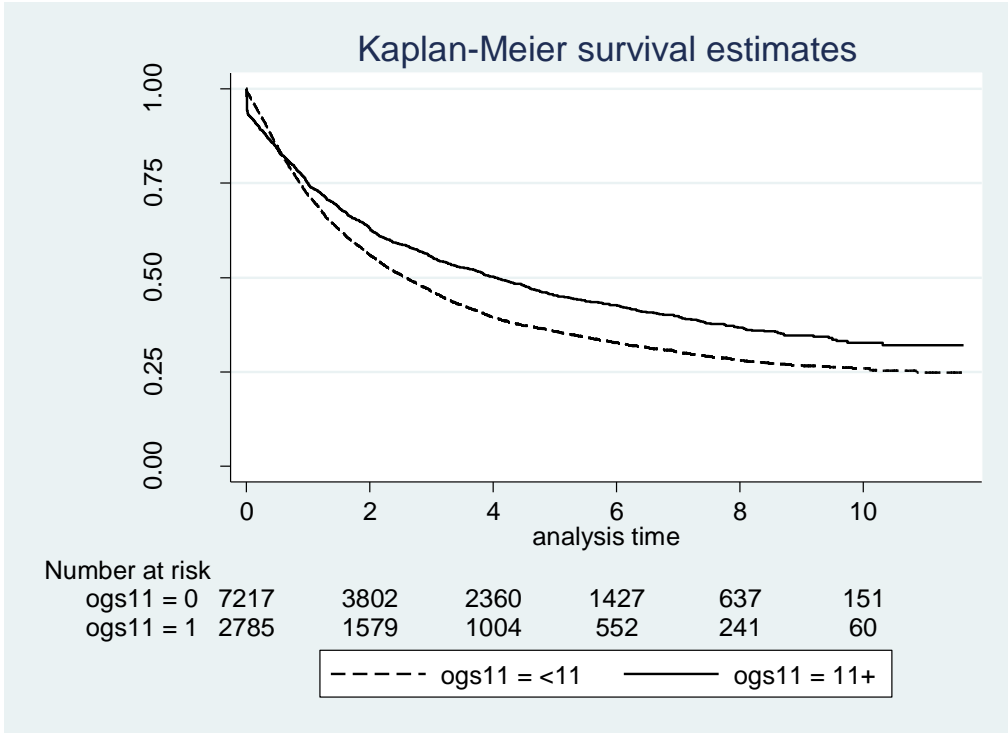
Specialist and Generalist



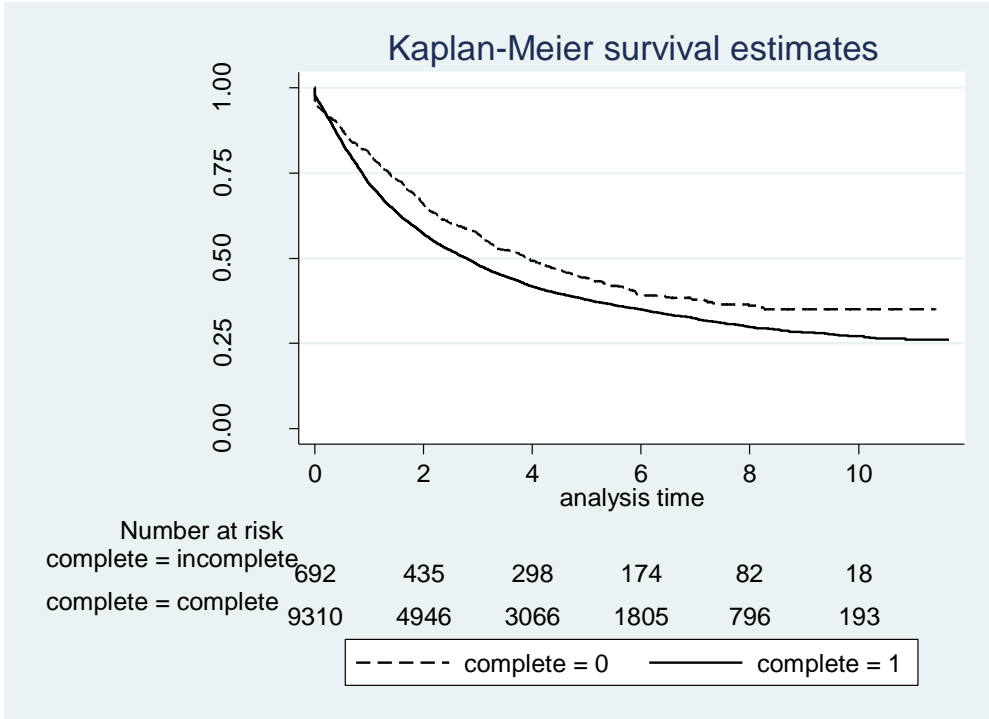
Prior Record Score=0 and Prior Record Score = 1+ (includes REVOC and REFEL)



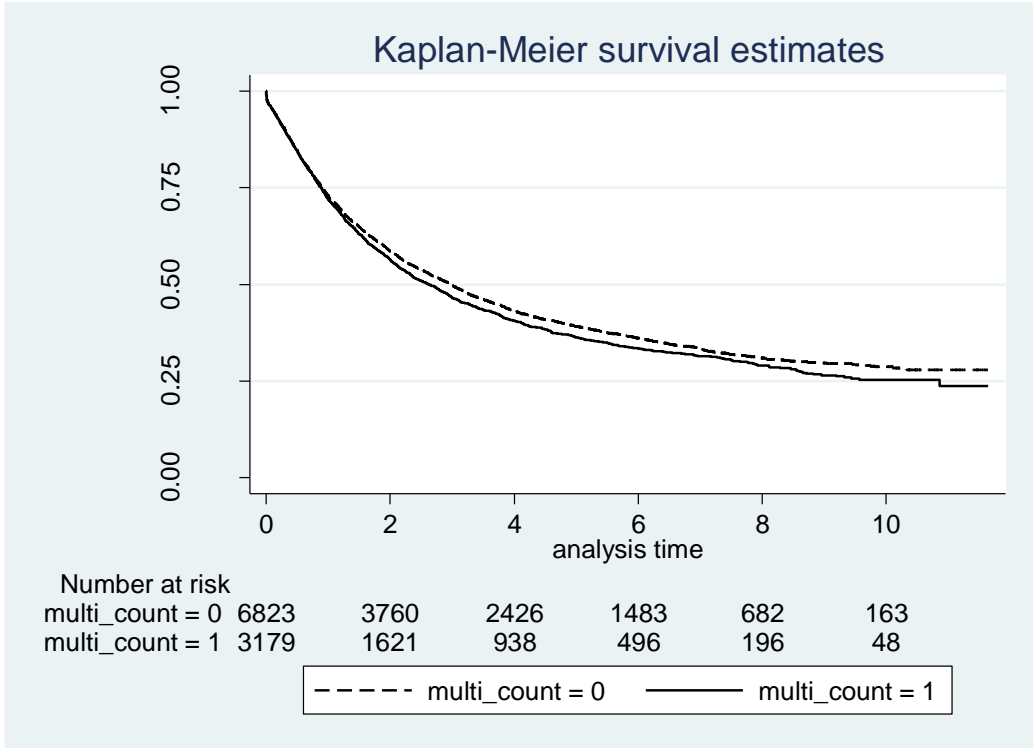
Offense Gravity Score=0-11 and Offense Gravity Score=11-14



Complete Offense and Inchoate Offense



Multiple Count and Single Count During Judicial Proceeding



Gun Possession and No Gun Possession During Commission of Current Offence

