

ABSTRACT

Title of dissertation: RISK-ANTICIPATED COMMUNITY SUPERVISION

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Many offenders are released conditionally to communities in lieu of jails or prisons because, for them, the benefits of sustained social ties and community-based treatment are thought to outweigh any of those brought about by incarceration. There is reason for caution, though, as their release to some extent jeopardizes public safety. Available research, for instance, convincingly suggests a sizeable fraction of offenders enters probation yet fails to comply with release conditions. This steepens the already uphill challenges of offender management and reintegration facing supervision agencies.

The underlying goal of this study is the development and validation of an instrument for informing immediate, risk-anticipated security and treatment assignments among community-supervised offenders in the District of Columbia. The study examines whether probationers in the population test positive, provide a bogus specimen, or fail to appear for any drug testing event as well as whether and, if so, how often they test positive for each of the seven substances (*viz.*, alcohol, methadone, amphetamine, cocaine, marijuana, opiates, and phencyclidine) screened by the Court Services and Offender Supervision Agency for the District of Columbia. It also examines whether offenders are ultimately convicted given an arrest for a new crime. Analyses also center on how often supervision- and drug-related violations occur as well as the probabilities and rates of ultimately terminating unsuccessfully.

These processes are estimated among a random sample of approximately 200 probationers having terminated their community sentences during the interval beginning on January 1, 2004, and ending on December 31, 2004. From well over 200 theoretically plausible predictors, this study identified a very small set that provide the agency with advance notice of the most challenging groups of offenders. This set of characteristics includes (a) the age at the time of assessment, (b) the expected length of supervision, (c) the number of substances ever used, (d) whether the probationer had ever used opiates or phencyclidine, (e) the number of weapons-related convictions, (f) the SFS-98 score, (g) the recommended sentence, (h) the impression of recidivism risk on the supervising CSO, and (i) local rates of arrests for drug-related and public order crimes.

RISK-ANTICIPATED COMMUNITY SUPERVISION

by

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RISK-ANTICIPATED COMMUNITY SUPERVISION

Many offenders are released conditionally to communities in lieu of jails or prisons because, for them, the benefits of sustained social ties and community-based treatment are thought to outweigh any of those brought about by incarceration. There is reason for caution, though, as their release to some extent jeopardizes public safety. Available research, for instance, convincingly suggests a sizeable fraction of offenders enters probation yet fails to comply with conditions of release. This often includes absconding, reoffending, failing to pay fines or restitution, or refusing to attend or complete treatment programs.

Langan and Cunniff (1992) for instance, in following a representative sample of 79,000 felony probationers, found within 3 years nearly two-thirds had either been arrested for new felony charges or charged with violating conditions of supervision. Almost half were either sent to prison or jail or had absconded. Likewise, the Bureau of Justice Statistics (BJS) estimates roughly 18–25% of probationers fail to successfully complete supervision (BJS, 2000, 2002, 2003). Recent estimates indicate the percentage of unsuccessful probationers may be as large as 40% (Glaze & Bonczar, 2006). In summarizing the BJS Annual Probation Survey for yearend 2004, Glaze and Bonczar found on average about 16% of probationers are returned to incarceration, a slightly smaller fraction fails with other outcomes, and roughly 4% abscond. Even successfully completed terms are punctuated with repetitious violations. For instance, both Clear, Harris, and Baird (1992) and Bork (1995) found between one-fourth and one-half of probationers that do successfully complete community supervision were not fully compliant with release conditions (see also, Bonczar, 1997; Glaze & Palla, 2004; Gray, Fields, & Maxwell, 2001; Mayzer, Gray, & Maxwell, 2004; Petersilia, Turner, Kahan, & Peterson, 1985; Petersilia, 1985a, 1985b, 1998).

This steepens the already uphill challenges of offender management and reintegration facing supervision agencies. With limited resources, these agencies must identify the most effective

strategies and services for managing and reintegrating an endless stream of offenders. This is a tremendous task and one replete with uncertainty. Grappling with such issues is the theme of this research.

Choices facing supervision agencies often necessitate judgments about the future behaviors of those under their charge, yet research has traditionally provided limited guidance in the early identification of potentially noncomplying probationers. Recently though several studies have enriched the understanding of the compliance process by identifying poor performance markers (see, Gray et al., 2001; Langan & Levin, 2002; MacKenzie & Li, 2002; Mayzer et al., 2004; Minor, Wells, & Sims, 2003; Silver & Chow-Martin, 2002; F. P. Williams III, McShane, & Dolny, 2000). This study draws heavily on these recent studies.

The underlying goal of this study is the development and validation of an instrument for informing immediate, risk-anticipated security and treatment assignments among community-supervised offenders in the District of Columbia. While representing more in some instances, less in others, here risk represents the propensity for classes of supervised offenders to engage in negative supervision performance (NSP) which, here, encapsulates key features of community supervision split across two domains: legal and supervision-specific.

Elements in the legal¹ domain include substance use and criminogenic behaviors. This study examines whether probationers in the population test positive, provide a bogus specimen, or fail to appear for any drug testing event as well as whether and, if so, how often they test positive for each of the seven substances (*viz.*, alcohol, methadone, amphetamine, cocaine, marijuana,

¹The term “legal” is used generally for categorizing like behaviors. One element in particular, adult alcohol use, is legally acceptable; however, grouping this behavior within the legal category maintains continuity within the literature review and the methodological discussions and it allows for cleaner discrimination between deviant behaviors and procedural missteps. A fine line separates legal and illegal alcohol intake—it is, of course, illegal under certain circumstances. It is assumed here, as only a fraction of offenders are screened for alcohol use, the justification for such screens is inherently deviance-related.

opiates, and phencyclidine) screened by the Court Services and Offender Supervision Agency for the District of Columbia (CSOSA). It also examines whether offenders are ultimately convicted given an arrest for a new crime during the supervision period and the follow-up period.

Supervision-specific elements include two salient features of supervision performance: condition violations, both supervision- and drug-related, and termination modes. Supervision-related violations include violations of general and special conditions; drug-related violations include only the subset of conditions specifically involving alcohol and illegal substances. Analyses center on how often supervision- and drug-related violations will occur. Probabilities of terminating unsuccessfully² are also estimated as are factors associated with early failures.

Population processes are estimated using both individual- and environmental-level predictors. Individual-level predictors comprise both background and legal characteristics, where background characteristics include indicators such as age, education and employment patterns, residential stability, substance use, physical and mental health, and social and family attributes; legal predictors tap criminal history, aspects of the instant offense, and characteristics of the instant sentence. While these predictors capture offender-specific influences, environment-level forces capture those potentially affecting clusters of offenders. These include demographic and socioeconomic measures, such as population density, concentrated poverty, and ethnic heterogeneity. Objective crime patterns, using both overall and crime-disaggregated indices, are also incorporated as are measures of residential and commercial land use.

This prelude introduces the problem—developing an instrument for assessing risk of NSP for guiding immediate custodial and treatment decisions—and, in the next few chapters, I begin linking it with large bodies of theoretical literature and empirical research. I open Chapter 2 by describing risk assessments in corrections then highlighting conceptual explanations of criminal-

²Potential termination modes include satisfactory expiration or termination, unsatisfactory expiration or termination, revocation followed by sanctions, revocation followed by reincarceration, absconsion, and death.

ity, recidivism, and NSP. I synthesize these patterns in Chapter 3 when describing and justifying the methods and procedures used in the present study. I describe the results from these procedures in Chapter 4, and, in the final chapter, summarize these as well as draw out their implications and caveat these with a discussion of the limitations in this study.

LITERATURE REVIEW

Identifying factors contributing to crime rates, understanding the origin, nature, or characteristics of criminal offending, and ascertaining the causes and correlates of recidivism are core criminological pursuits. Many studies have isolated contributors to varying regional crime rates; likewise, criminological research is rich with studies identifying general and offense-specific correlates of criminal behavior. Correlates are wide-ranging. They include both individual- and structural-level characteristics drawn variously from biologic, psychologic, sociologic, demographic, ecologic, and economic sources. Many are consistently associated with, most pertinently, negative supervision performance (NSP).³

The goal is developing a risk-anticipated instrument for guiding immediate security and treatment decisions facing the Court Services and Offender Supervision Agency for the District of Columbia (CSOSA). It draws heavily on literature and research linking both individual- and structural-level characteristics with subsequent behaviors and relies on a substantial assessment opportunity provided by information readily available to the CSOSA early in the custodial process. A plan to take advantage of these opportunities is developed in the next chapter. Here, I provide conceptual justifications by highlighting where the weight of the theoretical literature and empirical research falls with respect to these correlates. Before descending into these details a background is provided to contextualize this study within its intellectual and methodological heritage. It opens with an identification of the purposes of risk assessments then briefly traces their footing in the field over time.

Though risk assessments are at the height of fashion today (P. R. Jones, 1996; van Voorhis & Brown, 1997), forecasting which sets of individuals are most likely to initiate, persist, escalate,

³The term NSP is used here to encapsulate problem behaviors, be they criminogenic or supervision-specific, posed by supervised offenders.

or desist offending—discovering predictors of future criminality—is far from a recent development. These are traditional concerns. Throughout corrections history risk assessments have been instrumental in their achievement. For instance, they have helped to understand and classify, to inform decisions bearing on and, invariably, to enhance surveillance and control over corrections populations (Brennan, 1987; Champion, 1994; Farrington & Tarling, 1985b; S. D. Gottfredson & Gottfredson, 1985). They have helped isolate the dangerous, the violent, and the insane; they have helped predict likely delinquents from non-, parole successes from failures, and chronic, habitual offenders from their counterparts (Burgess, 1928; Coccozza & Steadman, 1976; Glueck & Glueck, 1930, 1950; Greenwood & Abrahamse, 1982; Link, Andrews, & Cullen, 1992; Monahan, 1981). They have provided considerable value to corrections and, by most accounts, will continue to do so.

They are specifically valued among community supervision agencies for their ability to both formalize and guide decisions which mutually tighten agency accountability and augment public safety and offender reintegration efforts. Risk assessments lend themselves to the development of consistent, equitable, efficient, and verifiable decision calculi that can then be evaluated, updated, modified, and refined—perpetually adjusting to, and consequently curtailing, error. Risk assessments identify and thereafter classify offenders across various measures of risk and need thus speeding appropriate control and therapeutic responses. They identify special populations, such as violent, chronic offenders, for whom unique services and control mechanisms are available. In a similar fashion, they identify minimal risks. This helps ensure only minimally restrictive mechanisms sustain conformity. They also identify those with special needs, such as educational or mental health, which then suggests appropriate therapeutic responses. Codified decision rules, accurate identification and classification, and timely matching of services and control mechanisms each increase agency accountability, public safety, and offender reintegration.

Isolated examples of criminological risk assessments appear as early as the 1920s (e.g., Bruce, Burgess, & Harno, 1928; Burgess, 1928; Glueck & Glueck, 1930; Hart, 1923; Warner, 1923), but it was not until the 1950s, a period Cullen and Gendreau (2001) depict as ripe with correctional optimism, that they begin appearing all together (see also, Farrington & Tarling, 1985b). The earliest of these, described variously as anamnestic or idiographic methods (see, Melton, Pettila, Poythress, & Slobogin, 1997; Morris & Miller, 1985), were largely informed by intuition or personal experience and were thus highly subjective. Based primarily on case studies, idiographic methods find justification in stability: past behaviors under certain conditions are indicative of future behaviors under similar conditions. Past behaviors were, after all, once future behaviors themselves. It is no surprise then to find they are among the strongest behavioral predictors. Still, despite their intuitive charm, idiographic predictions were nonetheless limited first by the strictly individualized approach—generalizable no further than the case under study—and second by their exclusive situational approach—restricted only to conditions having already been observed.

Later methods, though still largely subjective, were increasingly analytic and thus countered some of the problems with earlier models. Known broadly as clinical assessment, this tradition, heavily imbued in professional training and experience, was the criminological norm through the 1950s—a time coinciding with the beginning of the tenebrious end of correctional optimism (Brennan, 1987; Cullen & Gendreau, 2001). Like idiographic methods, clinical assessments were also based on case-by-case observations and they, too, were highly subjective. Most often they were conducted by a single clinician who, by piecing together information derived from unstructured interviews and detailed case reports, estimated likelihoods a particular case might experience a given outcome. Because of this single-case method, risk factors for one case could, and in many instances did, vary widely across cases and even within cases assessed by multiple ob-

servers. Distinctive is their embodiment of professional—particularly psychological—guidance. Clinical assessments were based on measures deemed relevant by the observing clinician. Though at times they incorporated batteries of psychometric tests they were, for the most part, neither standardized nor quantified (Brennan, 1987; Grove & Meehl, 1996; Grove, Zald, Lebow, Snitz, & Nelson, 2000; Morris & Miller, 1985). And while they represent a more formal approach than idiographic methods, they too were mired in problems. Indeed, success among both idiographic and clinical assessments pales in comparison to success found among the statistical assessments that soon came to dominate the field (for review see, Cocozza & Steadman, 1976; P. R. Jones, 1996; Kahneman & Tversky, 1973; Lidz, Mulvey, & Gardner, 1993; Meehl, 1954; Menzies, Webster, McMain, Staley, & Scaglione, 1994; Monahan & Steadman, 1994; Monahan, 1981; Mossman, 1994; Quinsey & Maguire, 1986).

The clinical assessment heyday coincides with a period Cullen and Gendreau (2001) say viewed the notion of criminal rehabilitation most favorably. Many accepted the notion that dangerous, chronic, habitual offenders could be pre-identified and early selected for special control and therapeutic strategies. The considerable support for the rehabilitation of offenders on one hand coupled with a general willingness to identify and classify offender subgroups on the other created conditions risk assessments naturally satisfy: they bridge the stated goals of corrections with a means to do so.

While optimistic through the 1950s, the atmosphere later turned increasingly critical. It was during the decades that followed when evidence challenging extant correctional practice began prompting many to reconsider correctional mainstays. Rehabilitation was among the most notable of these (Cullen & Gendreau, 2001). The theme resonating was that correctional treatment was ineffective. For some, the interventions were at fault (Bailey, 1966; D. Lipton, Martinson, & Wilks, 1975; Martinson, 1974; Robinson & Smith, 1971). Others blamed the setting (Foucault, 1977;

Irwin & Cressey, 1962; Sykes & Messinger, 1960). Regardless, a shared disdain for correctional treatment was taking hold. Prisons became conspicuous targets. From within, violent inmate uprisings began attracting attention to inequities and injustices. Outside their walls, academics began pointing to pervasive racial disparities and wide sentencing variabilities (R. L. Austin & Allen, 2000; D'Alessio & Stolzenberg, 2003; D. A. Smith, Visher, & Davidson, 1984; Spohn, 2000; Zatz & Hagan, 1985; Zatz, 1984).

Along with attacks on the rehabilitative front, fear was rising as a result of both real and perceived crime increases. This generated a growing sense of intolerance toward crime and criminals begetting later demands for coherent and consistent identification, processing, sentencing, and control of serious, persistent offenders (Brennan, 1987; Fogel, 1975; von Hirsch, 1976; P. R. Jones, 1996). By the 1970s, these sentiments, well-founded or not, were firmly established. The passing of this decade witnessed the development of a new correctional mindset and the near abandonment of one its core ideals. Rehabilitation lost its foothold, its public favor; as it fell, inextricable praxes, like risk assessments, followed—not only because embracing them tacitly embraced the philosophy in which they were grounded, but also because evidence of their ostensible inadequacies was mounting. In place of rehabilitation corrections began instead emphasizing retribution and crime control. This shift was in a large way reflective of increasingly conservative politics.

The 1980s confluence of rising crime and economic constraint fostered a conservative political shift. Crime was booming, the economy was busting, and this together began pushing many into advocating tougher and less expensive crime control strategies. The long-term consequences have been enormous. It essentially triggered a pervasive burden still overwhelming corrections. Of particular interest is the ironic sparking of continued research into the effectiveness of cor-

rectional treatment, non-standard methods of offender management, and statistical prediction of which I describe next.

To rehabilitation, the American industry had collectively turned a blind, skeptical eye. Despite the benumbing nihilism rehabilitation research continued (see, Cullen & Gendreau, 2001). This was continued mainly at the hands of a minority of rehabilitation adherents trained in psychology and measurement (e.g., Lipsey, Cordray, & Berger, 1981; T. Palmer, 1975) and was, for the most part, of Canadian origin. It was, nonetheless, largely overshadowed by the unfortunate American emanation.

Skepticism persisted at least until the late-1980s when the findings aired by persevering rehabilitation adherents were becoming increasingly difficult to ignore. Proponents consistently affirmed the contrary of much of the dialogue that had provided rehabilitation's deathblow only decades earlier (D. A. Andrews et al., 1990; Cullen & Gilbert, 1982; Gendreau, Goggin, & Paparozzi, 1996; Gendreau & Ross, 1979, 1987). Rather than accepting the nihilistic view on pure faith, many began gradually adopting—once again—an optimistic stance. Theoretical advances in rehabilitation began slowly reemerging across the country (Cullen & Gendreau, 2001).

Springing from these advances was an increasingly clear understanding of risk factors and the distinctions among them, a greater understanding of offending and recidivism, and growth in rigorous assessment methods. Traditionally, distinctions have been made between static and dynamic risk factors (D. Andrews & Bonta, 1998). On the one hand, static risk factors are either aspects of offenders or their past that are predictive of criminality but not subject to change (e.g., age, gender, early family factors, and, often one of the strongest factors, criminal history; D. Andrews and Bonta; S. D. Gottfredson and Gottfredson). These have been and will doubtlessly continue to be longtime staples of corrections research. On the other, dynamic risk factors reflect circumstances, attitudes, and behaviors that are mutable and, consequently, likely targets for

intervention (D. Andrews & Bonta, 1998). Dynamic factors are subdivided respective to their association with criminal behavior: criminogenic dynamic risk factors (or simply criminogenic needs; e.g., antisocial personality, substance abuse, or low self-control) have been empirically linked to criminal behaviors; non-criminogenic needs (e.g., low self-esteem) have not.

Both static risk factors and criminogenic needs are linked to criminality. Further, studies show criminogenic needs predict criminal behaviors as well as static factors do (Champion, 1994; Gendreau, Goggin, & Paparozzi, 1996; Glover, Nicholson, Hemmati, Bernfeld, & Quinsey, 2002). They differ, however, in their expected responsiveness to treatment. It is this difference that makes static factors less desirable than criminogenic needs for guiding treatment plans. Because they cannot, for the most part, change readily in response to treatment, static risk factors are unlikely intervention targets. There is simply little expected utility in targeting them. Criminogenic needs, because they can change readily, are indeed likely intervention targets (D. Andrews & Bonta, 1998). They are related to criminality and reasonably responsive to treatment; targeting them is expected to provide at least some rehabilitative benefit.

It is precisely this mutability, however, that makes them less attractive for immediate custodial decisions than static risk factors (cf., Quinsey, Coleman, Jones, & Altrows, 1997; Zamble & Quinsey, 1997). Assessing criminogenic needs implies both longitudinal data and substantial observation. This is likely unavailable when making immediate decisions. For these decisions, information is typically limited to the readily accessible such as that available from police records, Presentence Investigation report (PSI) reports, court documents, jail or prison profiles, and previous supervision information.

As these conceptual distinctions were becoming well-understood, criminologists continued investigating factors implicated in the offending and recidivism process. This prompted continued experimentation with innovative offender management strategies. Early studies of persistent of-

fending (e.g., Wolfgang, Figlio, & Sellin, 1972) had established the notion that a small number of offenders were disproportionately responsible for crime. Given large differences in individual offending rates, strategies targeting only high-risk offenders for incarceration appeared viable. The problem thus became identifying and controlling serious, persistent offenders.

Selective incapacitation strategies became widely accepted justifications for incarceration and continued to be seen as such as more studies replicated the findings of Wolfgang et al. (1972). In the very least, though intuitively appealing, identifying chronic, high-risk offenders proved elusive. Worse, it had the potential to and, by most accounts, did create more problems than it solved (see, Bernard & Ritti, 1991). Prisons and ultimately all corrections populations distended as the stream of inmates sent “up the river” became progressively larger and less manageable. Community supervision agencies were expectably burdened—not only by sheer numbers but also by economic constraint. The number of offenders agencies managed was rising; their budgets were not (Petersilia, 1985b). This prodded many agencies to search for alternatives for meeting increasing service demands (P. R. Jones, 1996).

Unlike the prison industry community corrections agencies were unable to build themselves out of the crisis. Boxed in, they could acquiesce by, for instance, pragmatically shifting interests toward offender management rather than treatment (Feeley & Simon, 1992). Or they could innovate. They could, for instance, increase the development of and subsequent reliance on non-traditional correctional practices.

Boot camps or intensive supervision programs are among these innovations (for comprehensive reviews, see MacKenzie, 2000; Petersilia, 1998). These and the many strategies not mentioned share a common thread with risk assessments. Namely, the compromise between public safety and public cost. Balancing the two is something for which risk assessments are vital; they allow agencies to allocate resources efficiently by reserving extensive surveillance and control

mechanisms for those presenting the highest risk and more costly treatment programs for those presenting the greatest need. As it turned out, risk assessments reemerged in the 1990s as vogue correctional tools (see, P. R. Jones, 1996; van Voorhis & Brown, 1997). Much of this attraction was epiphenomenal.

While conceptual developments were broadening and more corrections agencies were toying with non-standard means of offender management, methodological advances were leading to increasingly precise assessment and classification tools (Champion, 1994). The seeds were planted in the 1950s when pitfalls associated with existing instruments were urging for more rigorous methods (Glaser, 1987; S. D. Gottfredson & Gottfredson, 1979; Meehl, 1954; Sawyer, 1966). As increasingly precise methodologies began appearing, clinical assessments became nearly universally rejected by criminologists. An alternative, more formal approach, known interchangeably as statistical, mechanical, or actuarial assessment, began its ascent. These methods, characterized mainly by their objectivity and formality, markedly improved practice consequently contributing to a greater acceptance of risk assessments (Brennan, 1987) at just the time a newfound attraction to correctional rehabilitation was emerging. As criminology began embracing—once again—the rehabilitation philosophy, the scope and precision of risk assessments were both increasing. Where early efforts were largely driven by security concerns, contemporary efforts encompass security as well as programmatic goals. Along those lines, contemporary risk assessments—unlike earlier models—explicitly incorporated characteristics that are related to criminal behavior, changeable, and thus amenable to treatment. By the 1990s, this broader variant had made its way into prevailing fashion (Champion, 1994; P. R. Jones, 1996).

Characterized by objectivity, formality, and empirical rigor, statistical risk assessments are undoubted advancements over earlier tools (D. M. Gottfredson, 1987; Meehl, 1954; Monahan et al., 2001; Mossman, 1994; Quinsey, Harris, Rice, & Cormier, 1998; Rice & Harris, 1995; Sawyer,

1966; van Voorhis & Brown, 1997). Assessments are largely derived from objective evaluations of predictors following predefined rules. Predictors typically comprise a set of fixed risk factors (e.g., age, gender, age of onset) and a range of criminal history variables (e.g., versatility, frequency, prior parole failure, security classification, offense severity, sentence length, offense type; see, Brown, 2002). Decision rules define how predictors are selected and mathematically weighted with the ultimate goal of maximizing the statistical association with the criterion. Compared to clinical assessments, when validated and implemented properly, statistical assessments are more accurate and the instruments on which they are based demonstrate higher reliabilities (Brennan, 1987; Cocozza & Steadman, 1976; Grove & Meehl, 1996; Grove et al., 2000; P. R. Jones, 1996; Lidz et al., 1993; Meehl, 1954; Menzies et al., 1994; Monahan & Steadman, 1994; Monahan, 1981; Morris & Miller, 1985; Mossman, 1994; Quinsey & Maguire, 1986).

Up to this point, I have contextualized risk assessments within corrections research, described their historical trends, and sketched out current methods. The next section turns to an examination of individual-level factors consistently correlated with criminality, recidivism, and NSP. After reviewing the individual factors, contextual factors are discussed.

Individual-level predictors

This section is divided into two groups, the first describes personal and social attributes of offenders that are associated with crime, recidivism, and negative supervision performance (NSP), such as age, education, employment, residential mobility, substance use, health, and family factors, and the second describes criminal and supervision histories and highlights how these characteristics are linked to future NSP. Net of other characteristics, findings from empirical studies imply NSP will be more prevalent among younger, poorly educated offenders having unstable employment and residential histories, alcohol and substance abuse problems, strained early and

current family relationships, those with health problems—particularly with injuries resulting from assaults, those with the earliest and most extensive involvement with the juvenile justice system, those with lengthy histories of criminal justice involvement, and those whose supervision is the longest and most intensive. NSP will also be more common among probationers residing in communities characterized by economic disadvantage, ethnic heterogeneity, immigration concentration, residential instability, high crime, mixed-use land patterns, and high alcohol availability. Discussion opens with evidence bearing on the link between age and offending, recidivism, and NSP.

Age

Age is linked inextricably with both offending and recidivism in such a way as to expect higher levels of NSP among the most youthful offenders. Two issues are entwined. First, an early onset of problem behaviors, conduct disorders, and delinquency predict persistent offending. Second, younger offenders are disproportionately represented in age distributions of offenders, recidivists, and failing supervisees. The focus for now is on the latter issue; discussion of the former is deferred to a later section describing how juvenile and criminal histories anticipate NSP.

As a nearly undisputed criminological mainstay, criminal behavior is concentrated among adolescence and young adults ages 12 to 30 (Dembo et al., 1995; Farrington, 1986; Gendreau, Little, & Goggin, 1996; M. R. Gottfredson & Hirschi, 1986; Hoffman & Beck, 1984; Matza, 1964; Osgood, Johnston, O'Malley, & Bachman, 1989; Sampson & Laub, 1993; Wolfgang, Thornberry, & Figlio, 1987). It increases gradually with age then tapers through young adulthood. Along these lines, the likelihood of NSP is highest among younger offenders and studies consistently find unsuccessfully completing community sentences is more likely among younger offenders (Clarke, Lin, & Wallace, 1988; Cloninger & Guze, 1973; Dembo, Williams, Schmeidler, et al.,

1991; Harer, 1994; Harrison & Gfroerer, 1992; Irish, 1989; Morgan, 1993; Rhodes, 1986; Sims & Jones, 1997; Whitehead, 1991; cf., Benedict & Huff-Corzine, 1997).

Some argue this reflects a natural inclination toward and an ultimate “burn-out” or “maturational reform” from criminal participation (Hoffman & Beck, 1984; Matza, 1964). Others point to the age-graded changes in social influences and institutions (e.g., Sampson & Laub, 1993). It may also indicate, as some suggest, less effective adjustment to the requirements and demands of supervision, such as sustaining contact with supervision officers, among younger offenders (MacKenzie, Shaw, & Souryal, 1992; F. P. Williams III et al., 2000; cf., McReynolds, 1987; Schwaner, 1997).

Characteristics associated with age ultimately place younger offenders at greater risk of NSP. The predictor discussed in the next section is partly dependent on youthfulness and, like age, is also a prominent and well-established correlate of offending and NSP.

Education

Educational performance, commitment to educational goals, and educational attainment are inversely associated with criminal justice involvement. Schools are secondary socializing institutions acting to reinforce social values and a large body of research suggests those performing poorly in early academic settings are involved more so in offending than their counterparts (Hindelang, 1973; Hirschi, 1969; Kruttschnitt, Heath, & Ward, 1986; Sampson & Laub, 1993; Ward & Tittle, 1994; and see, Horney, Osgood, & Marshall, 1995).

Poor performance weakens commitment to conventional educational goals which in turn limits the strength of otherwise inhibiting control mechanisms (Hirschi, 1969). As A. K. Cohen (1955) argued, to the extent these goals are positively valued, the inability to achieve status and acceptance in the educational sphere might generate negative affect. This distances youth from conventionality. Those exhibiting the least commitment to educational goals are the most crime

prone (Agnew & White, 1992; Kruttschnitt et al., 1986; Sampson & Laub, 1993; L. Zhang & Messner, 1996). Brezina concurs. He argues those experiencing such affect cope using an array of cognitive, behavioral, and emotional strategies, increased offending being one such mechanism (see, Agnew, 1985, 1989, 1992; Brezina, 1996; Farnworth & Leiber, 1989; Thornberry, Moore, & Christenson, 1985a).

The least committed also face higher risks of dropping out of high school, truncating, often immutably, their educational attainment (see, Farrington, 1997; Harrison & Gfroerer, 1992; Jarjoura, 1996; Thornberry, Moore, & Christenson, 1985b). This is relevant as research indicates the likelihood of criminal involvement decreases as educational attainment increases (Beck et al., 1993; S. D. Gottfredson & Gottfredson, 1979; Quinsey et al., 1998; Thornberry et al., 1985b) It is a decisive predictor of NSP (Gray et al., 2001; Harer, 1994; Irish, 1989; Landis, Merger, & Wolff, 1969; Mayzer et al., 2004; Morgan, 1993; Rhodes, 1986; Roundtree, Edwards, & Parker, 1984; Silver & Chow-Martin, 2002; Sims & Jones, 1997). Silver and Chow-Martin (2002), for example, found the likelihood of rearrest within five years was well-predicted by whether offenders finished high school.

Educational characteristics are thus important factors in assessing risk of NSP. Stemming partly from a tenuous hold on conventional values, something instilled early in life and reinforced by the educational system, poor performance early in the educational process, a lack of commitment to its goals, and lowered levels of attainment are expected to increase risk. A similar effect is expected throughout adulthood in the legitimate employment sector, which is the topic of the next section.

Employment

Certain employment characteristics are consistently associated with NSP. Unemployment and job instability in particular are both associated with elevated offending (Farrington, 1986; Thornberry & Christenson, 1984; Thornberry & Farnworth, 1982) and recidivism (Uggen, 2000). This is widely replicated and, by most accounts, offenders sharing these attributes present a higher risk of NSP.

The legitimate labor force is a conventional setting that Sampson and Laub (1993) note likely encourages conformity (also see, Warr, 1998). Thornberry and Christenson (1984) continue that a commitment to these conventional goals reduces criminal involvement by simultaneously increasing its costs and decreasing both available time for, and any rewards likely generated from, nonconformity. As involvement in illegal activities increases, legitimate opportunities shrink. This interchange suggests unemployment will have a positive effect on NSP and that this effect should become increasingly stronger as unemployment spells become more frequent.

Being unemployed is associated with rearrests, technical violations, and absconding (J. Austin & Litsky, 1982; Gray et al., 2001; Harer, 1994; Irish, 1989; M. Jones, 1995; Landis et al., 1969; MacKenzie & Li, 2002; Morgan, 1993; Silver & Chow-Martin, 2002; Sims & Jones, 1997; F. P. Williams III et al., 2000; cf., Roundtree et al., 1984). Irish (1989) for instance examined a randomly sampled cohort of probationers discharged in 1982 and found unemployment was associated with higher rearrest rates. Among a subsample of $n = 562$ probationers ($n = 349$ [62%] of whom were employed; $n = 213$ [38%] were unemployed) he distilled information bearing on offender characteristics, program adjustment, and supervision outcomes from a wide array of sources, such as PSIs, supervision case records, and police arrest reports. Criteria included rearrest, supervision violation, and supervision adjustment. Out of all the predictors, unemployment was one of the most influential. Specifically, offenders unemployed at the time of arrest or sen-

tencing had higher probabilities of arrest while supervised or shortly after supervision had ended than their counterparts. In addition, probationers unemployed during their sentence were more likely to violate supervision conditions.

Employment instability increases the chances of NSP. For instance, numerous job changes and frequent unemployment spells have been linked to both offending (Farrington, 1997) and recidivism (S. D. Gottfredson & Gottfredson, 1979; D. M. Gottfredson, Wilkins, & Hoffman, 1978). As unstable work histories are characteristically shared among the criminally active (Laub & Lauritsen, 1994), this will likely affect supervision performance. Landis et al. (1969) examined adult felons in California ($n = 791$) and found among those failing probation, employment instability was a decisive predictor. Similarly, F. P. Williams III et al. (2000) found employment instability was among the most important predictors of absconsion among a relatively large, random sample of parolees in California ($n = 4047$). In fact, stability measures in general were the most influential predictors of absconsion within the first year of parole. These included occupational and residential stabilities (and see, J. Austin & Litsky, 1982; MacKenzie & Li, 2002; Mayzer et al., 2004).

Sampson and Laub (1993) argue that beyond mere stability, the quality of employment moderates its impact on offending. Specifically, higher wage, higher quality, and more satisfying occupations are those in which conforming values are most likely instilled (see, Allan & Stefensmeier, 1989; Huiras, Uggen, & McMorris, 2000). Naturally, selection artifacts are potential explanations. As Uggen and Staff warn, "...the best recidivism risks may be most likely to self-select into higher quality jobs, but they would be less likely than other people to recidivate even in the absence of employment" (2001, p. 3). Nevertheless, the evidence bearing on the interrelationship among employment status, stability, and offending suggests it is a clear factor when assessing risk of NSP. In terms of continued substance use, convictions, violations, and modes of termina-

tion, employment instability will likely exert the strongest effect on convictions, violations, and modes of termination. A measure with a similar focus on continuity also shown to correlate with offending and recidivism is residential mobility.

Residential stability

The frequency with which offenders move is related to offending and supervision performance. This likely involves underdeveloped informal social controls (see, Kasarda & Janowitz, 1974; Sampson, 1988), as those changing residences often are unlikely to develop strong interpersonal ties with their neighbors and other members of their community. They are also less likely to have a wide opportunity—and, perhaps, willingness—to participate in community activities and organizations (Sampson, 1988). This social isolation is thought to leave unchecked pressures to deviate otherwise dampened by informal social controls.

Using data derived from the British Crime Survey, Sampson (1988) examined (a) the relationship of community residential stability on local friendship ties, community attachment, and social activity patterns and (b) the influence of community characteristics on individual behavior. In ways Hirschi (1969) anticipated, Sampson found among $n = 10905$ residents and $n = 238$ localities, those with the longest tenure in the community were more likely to have developed dense local friendships, to be strongly attached to their community, and to participate more often in community organizations.

Residential stability is also associated with NSP. For instance, F. P. Williams III et al. (2000) found parolees with unstable living arrangements were more likely to abscond. Among the sample ($n = 4047$) they examined, roughly one-fourth ultimately absconded. Modeling abscon- sion within the first year of supervision, the most influential characteristics were (a) unstable living conditions, (b) frequent unemployment, (c) previous parole violations, (d) low stakes in confor-

mity, (e) frequent prior arrests, (f) being single, and (g) having previous felonies. J. Austin and Litsky (1982) corroborate these findings, at least among probationers. They examined $n = 12526$ offenders supervised in Nevada. Of these, $n = 338$ eventually absconded. For probationers, initial assessment scores were predictive of later absconion the main contributors to which included frequent address changes, low motivation for change, youthfulness, unemployment, prior probation sentences, and prior revocations (and see, Mayzer et al., 2004).

It is expected then that residential instability will be key in discriminating probationers by risk of NSP. Another set of factors consistently able to discriminate among high and low risk offenders are measures of substance use and abuse.

Substance use

Use and abuse of both alcohol and illegal substances are consistently associated with offending and NSP. I discuss both in this section beginning with the former.

Alcohol is empirically bound with offending, including aggression and violence, as well as with general criminality, recidivism, and NSP. Linking mechanisms include both individual- and structural-level characteristics, where processes at the individual level bear primarily on indirect pharmacological consequences of consumption; at the structural-level, on ecological inducements implicated in criminality.

Intoxication has known pharmacological antecedents. Contemporary research suggests these effects are complicated within a host of mediating and moderating factors (see, Fagan, 1990; Miczek et al., 1994; Reiss & Roth, 1993). Behavioral consequences are contingent on qualities of use, such as habituation and intensity, tolerances, concentrations in the brain, and whether these concentrations are rising or falling. They also depend on individual attributes, such as personali-

ties, behavioral histories, and expectancies and on endocrinological, genetical, and neurobiological characteristics.

It is implicated in a large fraction of crimes and, as expected, a large fraction of offenders are alcohol consumers (Greenfeld, 1998). The most common crimes committed by intoxicated offenders are public-order offenses and assaults, both of which are prevalent among probationers (see, Bonczar, 1997; Glaze & Palla, 2005; Greenfeld, 1998). Based on analyses of administrative records and personal interviews, Mumola and Bonczar (1998) report up to 40% of probationers were under the influence of alcohol at the time of their instant offense.

Cognitive distortions may intensify already heightened aggressive predispositions thus amplifying combativeness (Miczek et al., 1994). This might explain research finding aggression is a more frequent recourse among non-abstainers than abstainers (Boyum & Kleiman, 1995): there is a strong, statistical association between alcohol and both aggression and violence. Indeed, intoxication is a central antecedent to murder, assault, and rape (see, Reiss & Roth, 1993; Q. Zhang, Loeber, & Stouthamer-Loeber, 1997).

Alcohol intoxication is thus expected to predict aggressive and violent aspects of NSP. This is, understandably, where the bulk of alcohol-crime research is centered. Just as clearly, studies link alcohol with other crime types including, obviously, driving while intoxicated, public intoxication, and liquor law violations as well as offenses void inherent alcohol characteristics, such as public-order and property crimes and certain offending patterns.

Public-order crimes comprise almost one-third of all crimes reported to the police (Greenfeld, 1998; Stitt & Giacopassi, 1992), and, generally, higher levels of use are associated with increased offending (see, Seltzer & Langford, 1984; Shupe, 1954; Stitt & Giacopassi, 1992; Q. Zhang et al., 1997). Alcohol is similarly implicated in property crimes. For instance, in analyzing detailed case histories of convicted property offenders, Cordilia found consumption was often implicated

in the “unplanned, low-profit, high-risk crime” characteristic of casual property offenders (1985, p. 170). Not only was alcohol more accepted among casual offenders, it was verily encouraged, as, for them, it was functional. It bunched the loose-knit groups, helped sustain criminal activity, and facilitated repetitious offending.

Consumption and intoxication, while empirically linked with crime and NSP are, unfortunately, unlikely candidates for predicting NSP as this process depends so strongly on situational factors. There is, however, evidence suggestive of the less situational linkage between alcohol and NSP.

Suggestive of the high prevalence of alcoholism among convicted property offenders, Cordilia (1985) notes that the lifestyles of many leads them into a downward spiral of alcoholism, eventual exclusion from organized offending groups and, ultimately, homelessness or prison. Also, among known violent offenders, both alcohol use and abuse are disproportionately high and, likewise, violent crimes are unexpectedly prevalent among those with alcohol dependencies (Miczek et al., 1994).

There is also evidence suggesting specific crime patterns, such as persistent offending and repeated probation violations, are linked with alcohol. Higher consumption is generally associated with greater risk (J. Austin & Litsky, 1982; Cordilia, 1985; Farrington & Hawkins, 1991; S. D. Gottfredson & Gottfredson, 1979; Harer, 1994; MacKenzie, Browning, Priu, Skroban, & Smith, 1998; MacKenzie & Li, 2002; Rice & Harris, 1995; Schmidt & Witte, 1988, 1989).

Among an entry cohort of felony probationers in Virginia ($n = 125$), MacKenzie and Li (2002) found those drinking excessively were more likely to persist offending. Similarly, in an analyses of both self- and officially-reported behavior among $n = 126$ probationers, MacKenzie et al. (1998) found offending increased during months characterized by heavy alcohol use. These patterns are widespread among abusers. Among federal parolees ($n = 1205$), for instance, Harer

(1994) found 3-year recidivism rates were higher among those reporting alcohol dependency compared to their counterparts. And among parolees and, especially, probationers in Nevada ($n = 12526$), J. Austin and Litsky (1982) found absconders had substantially higher levels of alcohol abuse compared to non-absconders. Similarly, in their analysis of North Carolina releasees, Schmidt and Witte (1988) found alcoholism was an important characteristic common among reincarcerated parolees.

Thus, among supervised populations, those with problem consumption patterns may pose greater risks. This may be seen in increased alcohol-related as well as public-order and property crimes. As well, problem drinkers are more likely to be persistent offenders, repeat probation violators, and absconders.

Closely paralleling these findings are those describing the interplay among illegal substances, offending, and NSP. Illegal substance use and abuse is a pervasive American problem (Substance Abuse and Mental Health Services Administration [SAMHSA], 2002). Beyond its inherent unlawfulness, research strongly links illegal substances with criminality (M. R. Chaiken & Chaiken, 1987; Nurco, 1979). Drug use in general is associated with higher offending levels (Anglin & Speckart, 1988; Clayton & Tuchfeld, 1982; D. C. McBride & McCoy, 1981; McGlothlin, 1979; Stacy & Newcomb, 1995). Recreational users, for example, are more crime prone than abstainers (Dembo et al., 1995; Elliott, Huizinga, & Menard, 1989; L. Gardner & Shoemaker, 1989; Newcomb & Bentler, 1986; Stice, Myers, & Brown, 1998). Addiction and dependency as well are linked to both offending (Bland, Newman, Thompson, & Dyck, 1998; Inciardi, 1980; McGlothlin, 1979; Speckart & Anglin, 1985) and recidivism (S. D. Gottfredson & Gottfredson, 1979; J. Palmer & Carlson, 1976; Wish & Johnson, 1986) levels (and see, Dembo, Williams, Getreu, et al., 1991; Dobinson & Ward, 1986; Greenfield & Weisner, 1995; Guze, Wolfgram, McKinney, & Cantwell, 1968; Swanson, Holzer, Ganju, & Jono, 1990).

This implies prevalent drug use among incarcerated and supervised offenders, which is supported by research (Mumola, 1999; Mumola & Bonczar, 1998). Drug use and abuse have also been linked to recidivism and NSP. For example, findings from analyses of pretrial releases suggests those testing positive for drugs at arrest posed heightened rearrest risks (D. A. Smith & Polsenberg, 1992). Among probationers, Benedict and Huff-Corzine (1997) found a history of drug use—especially higher levels—was related to increased risk of rearrest (see also, MacKenzie et al., 1998; MacKenzie & Li, 2002; Silver & Chow-Martin, 2002). Likewise, MacKenzie et al. (1998); MacKenzie and Li (2002); Silver and Chow-Martin (2002) found probation absconders had higher drug use levels (and see, Baird, Storrs, & Connelly, 1984; Gray et al., 2001; Harer, 1994; Schmidt & Witte, 1988).

In summarizing, alcohol and drug use and abuse have both been linked with criminality and NSP. Use and abuse histories will thus inform assessments of supervision performance, where, namely, those probationers either currently or with a history of using and abusing alcohol or illegal substances are expected to present greater risks of NSP.

Childhood and family factors

This section describes literature and research regarding the linkages among childhood and family factors, criminality, and NSP beginning with the earliest factors. Certain childhood experiences, such as early economic conditions and family practices, influence later experiences, like family relationships; aspects of both are associated with supervision performance.

Ample research connects certain early life influences with problem experiences in childhood, adolescence, and into adulthood. To this end, there is considerable stability in behaviors. As, among others, M. R. Gottfredson and Hirschi (1990) contend, childhood experiences have life long consequences (see also, Wilson & Herrnstein, 1985). This is not to say, however, that these

influences are irreversible (see, Sampson & Laub, 1993). Nevertheless, I draw attention here to lowered economic conditions and early family characteristics and discuss how these are expected to inform assessments of NSP.

For Merton (1957), success is a value shared across American culture. The means for achieving success, however, are only narrowly accessible to those in the lower strata. Anomic adaptations are likely when these aspirations go unmet. Resorting to unconventional means for achieving success, such as criminality, are among such adaptations.

Yet, motivation and aspiration alone do not fully account for adaptive behaviors. The impact of this is expressed in Cloward and Ohlin's (1960) classic blending of anomie and differential association traditions. They point out that, just as it is for legitimate opportunities, illegitimate opportunities are themselves structured unevenly and, further, the values and skills needed to take advantage of these opportunities must be learned within the environment.

Minority boys especially those in the lower classes bear the brunt of this, as they are the ones most likely deprived of educational and occupational opportunities, exposed to high levels of deviance, and to have little at stake inhibiting deviance. This makes them most susceptible to early delinquent onset. If illegitimate opportunities do arise and they acquire the skills to take advantage of them, deviance likely represents the least costly and most rational alternative to conventionality. Moreover, such criminal precociousness is one of the strongest predictors of persistence as I demonstrate in later section.

The family is a learning context and, easily, exposure to deviance in the family contributes to the learning of necessary skills and motivations for deviance. Parent criminality disrupts family functioning in more way than one. It obstructs the development of strong parent-child ties; moreover, it might limit—or, in the case of incarceration, even remove—the capacity of one or both parents to monitor and supervise their children (Farrington, 2000; Hirschi, 1983). Even more,

M. R. Gottfredson and Hirschi (1990) expect criminally involved parents will limit their involvement in parenting; Sampson and Laub (1993) expect, if they are involved, their child rearing skills are likely severely limited. So, in addition to providing an environment conducive to learning criminality, deviant parents may also fail to inculcate safeguards promoting conventionality. This likely explains evidence that those having criminally involved parents are more likely themselves to become criminal (see, McCord, 1979; Robins, 1978).

Other early family aspects associated with later criminality are large family size (Farrington, 1997; Hirschi, 1994; and see, Gove, Hughes, & Galle, 1979; Sampson & Laub, 1993; Stark, 1987), family conflict and dissolution (Farrington, 2000; Kolvin, Miller, Fleeting, & Kolvin, 1988; Thornberry, Smith, Craig Rivera and, & Stouthamer-Loeber, 1999; Wells & Rankin, 1991; cf., Kruttschnitt et al., 1986), and maltreatment (Dembo et al., 1995; Dembo, Williams, Schmeidler, et al., 1991; Kazdin, 1995; Kruttschnitt et al., 1986; C. Smith & Thornberry, 1995; Widom, 1989).

Immediate family characteristics, such as marital quality and family involvement, are also associated with offending NSP. In general, such investments in conventional society insulate against offending (Farrington, 1989; Sampson & Laub, 1990; Sampson, Raudenbush, & Earls, 1997). Lower offending levels are found among married versus non-married offenders (Horney et al., 1995; Laub, Nagin, & Sampson, 1998; Sampson & Laub, 1990, 1993; West, 1982); yet, the linking mechanism is somewhat cloudy.

For one, evidence suggests it is not merely being married but also the quality of the relationship that matters (Laub et al., 1998; Sampson & Laub, 1993). Sampson and Laub (1993) contend marital cohesiveness and strong bonds of affection are more influential than is the status (and see, Glueck & Glueck, 1950). More generally, marriage may only signify a more basic attribute, such as self-control (M. R. Gottfredson & Hirschi, 1990; and see, Wilson & Herrnstein, 1985). Those most prone to criminality may chose not to marry, be unable to find a willing mate, or be able to

sustain a marriage. Those most heavily involved in criminality may be unwilling to enter into or sustain marriages. For instance, M. R. Gottfredson and Hirschi (1990) assert, to the extent such relationships impinge on criminality, offenders likely eschew or abandon conventional ties. This includes those with spouses and children. The institution itself may influence offending in other ways. For instance, rather than functioning through informal social controls, it could function by insulating one from unconventional opportunities and learning environments (see, Warr, 1993, 1998).

Conceptual ambiguities notwithstanding, risk of NSP is lower among married versus non-married offenders (Clarke et al., 1988; Landis et al., 1969; Morgan, 1993; Sims & Jones, 1997; cf. Gray et al., 2001; Mayzer et al., 2004; Roundtree et al., 1984). Successful supervision performance is thought to depend as much or more on having an agreeable marital climate, one characterized by mutual trust and obligation, than simply on being married (Laub et al., 1998). Sharing a residence with a spouse suggests an agreeable climate. Being married and cohabiting is associated with reduced criminality. For instance, MacKenzie and Li (2002) found probationers living with their spouses were less likely to commit non-drug related crimes than their counterparts. Among federal inmates, Harer (1994) similarly found married releasees cohabiting with their spouses posed less recidivism risk than those living under different arrangements (see also, Petersilia, 1985a).

Of the instant family factors, marriage and family relations are implicated in the production of NSP. Given conceptual ambiguities, how precisely key processes are captured will surely dictate predictive merit. Still, strained family relations and a diminished social support system likely influence violations and termination modes. And even though relatively little research has examined early childhood factors among supervision populations, these too are likely salient factors in anticipating NSP.

Health

Certain health-related characteristics anticipate performance while supervised. The two dimensions considered here are physical and mental health. Aspects of both associate positively with offending and recidivism, but the strength of the evidence bearing on these latter is more prevalent and thus more compelling.

Empirical findings suggest the less healthy and more injury prone are involved more so criminally than their counterparts. To begin, the prevalence of certain communicable diseases is higher among correctional populations (National Commission on Correctional Health Care, 2002). In addition, there is evidence that injuries and accidents are more common among the crime prone population (Shepherd, Farrington, & Potts, 2002). The injuries having the strongest relationship with subsequent criminality are those resulting from assaults (Farrington, 1995).

Evidence—notwithstanding want—indicates less healthy people may pose higher supervision risks. Unfortunately, physical health and supervision performance have not been adequately investigated. Implicitly measures of physical health and especially those related to assaultive injuries will vary with supervision performance. Although the evidence bearing on physical health and offending is limited, research on mental health and crime abounds.

An often disputed assertion is that those with mental disorders are more likely to engage in criminal behaviors than those without such disorders (see, Link, Andrews, & Cullen, 1992; Monahan, 1992). This is an extremely difficult relationship to confirm, yet one indeed meriting attention. Research since the mid-1960s suggests those diagnosed with any of the major forms of mental illness are more likely than their non-diagnosed counterparts to become crime involved (Bland et al., 1998; Estroff, Dackis, Gold, & Pottash, 1985; Johnston & O'Malley, 1986; Lin et al., 1996; Link, Andrews, & Cullen, 1992; Link, Cullen, & Wozniak, 1992; Monahan, 1992; Teplin, Abram, & McClelland, 1996; Teplin, 1990).

The Bureau of Justice Statistics (BJS) reports mental disorders tend to be fairly common among corrections populations (Ditton, 1999). Roughly 16% each of state prisoners, jail inmates, and probationers are mentally ill. Considering the research connecting it with criminality, there will likely be a link between mental health and supervision performance although, as a risk factor, its influence may be moderate at best compared to the effect associated with other factors.

The health factors discussed here included physical and mental health. There is little reason to ignore either in making risk assessments, though substantially more empirical work has been devoted to the link between mental health and crime. Even so, there is reason to expect its predictive ability will be overshadowed. Some of this, as alluded to earlier, stems from strong empirical relationships with other personal characteristics. Indeed, the rest will likely stem from criminal history and instant sentence characteristics that will likely bubble up as the most influential predictors. These are discussed next.

Criminal history

Discussion thus far has centered on offender attributes. It shifts slightly here and centers on their past behaviors and, particularly, any criminal justice responses these might have elicited. I describe characteristics empirically associated with offending and NSP beginning with earliest of these, such as early and extensive involvement with the juvenile justice system, then moving toward more recent characteristics, such as previous criminal justice involvement and behavior while under custody, and qualities of the instant supervision sentence.

Past behavior is axiomatically the best predictor of future behavior. Behavioral patterns from early childhood, through adolescence, and well into adulthood are often quite similar (see, M. R. Gottfredson & Hirschi, 1990; Sampson & Laub, 1993), and researchers invariably find previous delinquency and criminality are among the strongest predictors of future offending (Irish,

1989; Roundtree et al., 1984). Nevertheless, in a well described paradox, most delinquents do not become adult criminals (Robins, 1978). There are, however, early offending characteristics that well-discriminate likely persisting youths from their counterparts. In particular, those offending the earliest are most likely to persist and escalate; moreover, extensive delinquency involvement foreshadows serious adult criminality (Baird et al., 1984; Dean, Brame, & Piquero, 1996; Laub & Lauritsen, 1994; Piquero & Buka, 2002; Piquero & Chung, 2001).

This is true for NSP as well. For instance, Roundtree et al. (1984) found significant differences in probation outcome with respect to age at first arrest. They compared probationers having been arrested at ages 18 and younger to those without such early arrests and found a larger proportion of revokees among those with younger ages at first arrest. J. Austin and Litsky (1982) found a similar pattern regarding absconsion among parolees and probationers. Likewise, MacKenzie et al. (1992) found those younger at first exposure to the criminal justice system performed poorer while supervised than did their counterparts. In addition, when examining a randomly sampled exit cohort of probationers discharged from probation in 1982 in Nassau County, New York, Irish (1989) found probationers having the most extensive juvenile records were among those performing the poorest both during and after community sentences. Silver and Chow-Martin (2002) similarly found extensive juvenile records predict both rearrest and reincarceration. Taken together, these findings suggest early and extensive involvement with the juvenile justice system will foreshadow NSP.

Past arrests are often used predictors of later criminal involvement. Measured typically by an item dichotomously capturing whether an offender was arrested or not either ever in the past or during some finite temporal window or by a measure summing the number of prior arrests. Given the lowered standards of proof, arrests are only suggestive. Convictions, because of the more stringent burden of proof, are arguably better measures (see, Maltz, 1984). They demonstrate that

not only was crime was committed but also that the given offender was implicated. A high number of previous convictions strongly indicates patterned criminality (Petersilia, 1985a; Quinsey et al., 1998; Silver & Chow-Martin, 2002; Whitehead, 1991). In some studies, convictions dominate among explanations. For example, M. Jones (1995) found the number of previous misdemeanor convictions was one of the strongest predictors of probation failure (see also, Mayzer et al., 2004). Similarly, Schwaner (1997) found having more adult and juvenile convictions was associated with increased likelihoods of absconding (see also, J. Austin & Litsky, 1982; J. Austin, Quigley, & Cuvelier, 1989).

Dispositions have unique predictive abilities of their own. For the most part, risk of NSP increases as histories of incarcerations or community sentences lengthen. For example, Silver and Chow-Martin (2002) found as the number of prior incarceration sentences increased, so too did risk of recidivism. For instance, Schwaner (1997) found that parolees with lengthier incarceration histories had greater chances of absconding. And chances of a absconding also increase as the number of previous supervision sentences increase (J. Austin & Litsky, 1982).

Other criminal history aspects are also telling, such as specializing in particular crime types and engaging in more serious types of offenses. Chronic property offenders, for instance, are more likely to specialize in continued, property-related offending than other crime types (Bartell & Thomas, 1977; Petersilia et al., 1985). In fact, Bartell and Thomas (1977) found the number of past arrests for burglary is one of the strongest predictors of probation failures. Similarly, Petersilia et al. (1985) found property offenders returned to crime faster and more often than those whose sentencing offenses included robbery or drug-related offenses (see also, Cunniff, 1986; Irish, 1989; McGaha, Fichter, & Hirschburg, 1987; Sims & Jones, 1997; Vito, 1987). The seriousness of previous criminal involvement is also important. This is usually measured by non-violent to violent or misdemeanor to felony comparisons among arrests and convictions. In general, offenders with

histories of violence present lower risks of reoffending than do, say, chronic property offenders. Morgan (1993), for instance, found histories of felonious offending were linked to lowered probation success. Both Mayzer et al. (2004) and F. P. Williams III et al. (2000) found similar results.

Regarding performance while in custody, institutional and post-release behaviors are often quite similar. Misconduct while incarcerated, for instance, is a strong predictor of subsequent recidivism (Brown, 2002; Harer, 1994). Among released federal inmates, higher levels of institutional misconduct were associated with higher levels of post-release recidivism (Harer, 1994). Also, Mayzer et al. (2004) found as the number of condition violations increased, so did the likelihood of revocation and absconsion among supervised offenders. Further, the timing of violations discriminated between these groups, where absconders were more likely to experience violations early in supervision (Mayzer et al., 2004). Having previously failed while supervised in the community has been linked with later supervision performance. J. Austin et al. (1989), for example, found those with previous parole or probation revocations were more likely to be rearrested and to abscond during the instant sentence. One's criminal justice status at the time of arrest is also linked with NSP. For instance, federal inmates under community supervision when committing the crimes for which they were sentenced were more likely to be rearrested upon release than their counterparts not under community supervision (Harer, 1994).

With respect to the triggering offense, both technical violations and continued offending are more likely among offenders sentenced to violent crimes. Bork (1995) for example found offenders serving community sentences for robbery were more likely to violate probation conditions. Gray et al. (2001) similarly found probationers serving sentences for assaultive crimes were more likely to commit technical offenses and had a higher probability of committing new crimes. And Harer (1994) found among federal prison releasees, those sentenced for crimes against persons

(i.e., robbery, homicide, manslaughter, sex offenses) had the highest rates of returning to crime upon release; those sentenced for fraud or drug trafficking, the lowest.

Qualities of community sentences, such as intensity and treatment exposure, are also associated with supervision performance (see, Benedict & Huff-Corzine, 1997; MacKenzie, 1991; Mayzer et al., 2004; Rhodes, 1986). Benedict and Huff-Corzine (1997) found, at least among whites, the more intensive and rigorous the supervision, the higher was the risk of failure. Longer and more stringent probation requirements were linked similarly by Mayzer et al. (2004) with increased risk of later absconson or revocation. And, MacKenzie and Souryal (1994) note increased levels of both self- and officially-reported crimes during months where the supervision officers contacted the families and employers of the offenders. Much recidivism research indicates risk increases as sentences lengthen (Kronick, Lambert, & Lambert, 1998; MacKenzie et al., 1992; Morgan, 1993; Roundtree et al., 1984; Sims & Jones, 1997; cf., Benedict & Huff-Corzine, 1997). Kronick et al. found years of sentence to be associated with revocations among parolees, where longer sentences increased the likelihood of violating. Also, examining the months elapsed until community sentence ended, Sims and Jones found those having longer terms had higher probabilities of failing. Similarly, MacKenzie et al. found those with longer community sentences adjusted more poorly than their counterparts. There is also evidence suggesting longer community sentences may enhance the likelihood of absconding (McReynolds, 1987).

Treatment exposure has been linked with NSP as well. Minor et al. (2003) for instance, found offenders ordered to mental health treatment were more likely to subsequently violate conditions. This may reflect similarities among offenders sharing such orders, something that places them as a group at higher risk. It might also be that the conditions were so demanding that it nearly assured unattainability. On the other hand, MacKenzie et al. (1998) found among those ordered to drug treatment, self-reported crime increased in months where treatment was missed.

Throughout this section I highlighted the considerable stability in behaviors over time and described how the relationships between past behaviors and their consequent responses will influence NSP. In particular, those with the highest risks of NSP are likely the ones with the earliest exposure to and most extensive involvement with the juvenile justice system. The salience of adult arrests and, more importantly, convictions and dispositions was introduced, with the bulk of research suggesting those with lengthier conviction and custodial histories will likely pose the highest risk of NSP. Patterns within these histories, such as chronic property offending, engaging in more serious offense types, and custodial misconduct, also anticipate NSP. Finally, evidence bearing on aspects of the instant sentence, such as triggering offense, intensity, and treatment exposure, were discussed with the weight of evidence suggesting these factors are salient for risk assessments.

Contextual predictors

A compositional explanation of local crime sees increases developing in areas disproportionately comprising residents manifesting characteristics known to correlate with criminality and NSP, such as those introduced in the foregoing section. Another side sees the behaviors of residents not as a cause but rather a consequence of environmental characteristics. I introduce a few of these in this section. These are, namely, local sociodemographic, economic, crime, and commercialization characteristics.

Sociodemographic and economic characteristics

Sociodemographic and economic characteristics associated with crime and NSP include (a) dense population, (b) high racial and ethnic heterogeneity, (c) disproportionate age structure, (d) high family disruption, (e) residential instability, (f) unemployment, and (g) income inequality.

I begin this section with a discussion of population density and its expected influence on social interaction, the prevalence of deviant values, and the development of moral cynicism.

Generally, offending increases commensurately with relative population (Galle, Gove, & McPherson, 1972; Freedman, 1975). Such densities vary positively with specific crime forms, such as violent (Kposowa, Breault, & Harrison, 1995; Sampson & Lauritsen, 1994; D. A. Smith & Jarjoura, 1988; Stack, 1983) and property (Jackson, 1984; Schuerman & Kobrin, 1984; Stack, 1983). As area populations become inordinately dense residents may be more able to cloak themselves in anonymity making for less personal social interactions undermining the development of the strong informal social ties thought to exist in cohesive neighborhoods (Sampson et al., 1997). Residents are less willing to participate in community organizations, monitor their neighbors, supervise local children, intervene when crimes are committed, or request assistance from the police which, in turn, diminishes collective efforts to maintain crime-free communities. At the same time, increases in population densities strain public resources, which, itself, undermines the crime inhibiting force otherwise felt through formal mechanisms of control (Sampson et al., 1997).

The environment structures the content of social interactions and the presence of criminogenic attitudes and definitions are unavoidably high when relative populations are dense (see, Akers, 1998). It is not just that denser areas tend to have more deviant residents and thus a higher presence of prodeviant definitions, as Stark (1987) contends they do, but also that the high concentration of people in places leads to a heightened awareness among the residents about one another (see also, Sampson & Raudenbush, 2004). It is simply harder, Stark contends, to conceal deviance when others so easily witness or learn of morally discreditable behaviors. Sims and Jones's (1997) and Harer's (1994) research, for instance, demonstrate that as the relative size of the population in which offenders live or are released into increases, success while supervised becomes less likely. In some studies, relative population emerges as one of the strongest predictors

of recidivism among supervised offenders (Silver & Chow-Martin, 2002). Inextricably connected to dense populations is an expected increase in racial and ethnic diversity. As I discuss next, this too is a likely influence on NSP.

Heterogeneity—typically operationalized as the relative number of Black or non-white residents within the population (Bursik, 1986; Sampson, 1986)—is regularly linked with regional crime and offending patterns (Harries, 1974; Messner, 1983). Certain forms of crime appear more susceptible to such shifts. Areas with higher concentrations of Black residents, for example, tend to have higher rates of violent crime (Sampson, 1986; Sampson & Raudenbush, 2004). Some have explained these shifts as culturally-induced phenomena (Wolfgang & Ferracuti, 1967; and see Curtis, 1975; Fischer, 1978; Gastil, 1971; Hackney, 1969; Loftin & Hill, 1974; Messner, 1983; Silberman, 1978). Others contend heterogeneity impedes the establishment of common values and that cultural conflicts or inconsistencies underlie differential offending patterns (Sellin, 1938; D. A. Smith & Jarjoura, 1988; Wirth, 1956/1964).

Given evidence linking age with offending, it is not surprising that crime rates emulate size changes in the proportion of teens and young adults composing the population (Loftin & Hill, 1974; Pogue, 1975; Wilson & Herrnstein, 1985). Regardless of their ages, though, offenders living in areas disproportionately comprising teens and young adults might be at higher risk of NSP. This is thought to be influenced less so by the direct effect of the disproportionate presence of a high crime group and more so by the indirect influence it has on other community processes and, ultimately, on the strength of crime inhibiting social controls. It might influence, for instance, family structure, mobility patterns, and employment and income characteristics.

Family structure is typically conceptualized in terms of either generalized intactness, often measured by the divorce rate, or in terms of control-contributiveness, often measured by the proportion of single- and female-headed households. A high prevalence of family disorder is thought

to undermine community efforts to realize common goals, like staving off encroaching crime and disorder. Sampson (1986) has shown that these areas have weakened non-coercive means of self-regulation because participation levels in networks such as friendship and community organizations, thought to mediate formal controls, are less prevalent; those existing, less forceful (and see, Sampson & Raudenbush, 2001). Supervised offenders residing in areas characterized by high family disruption, because they are bound less by social control mechanisms are freer to engage in NSP than those living in areas characterized by greater family cohesion. Not too distant from this control-theoretic framework is the notion that family structure influences routine activities. In particular, it typifies an aspect of guardianship (see, L. Cohen & Felson, 1979). Single-headed compared to partnered households contribute at most half as much guardianship potential. With only one family member there will be less contact with other residents, less supervision exercised over peer groups, and less intervening for the sake of community goals. Consistent with this, researchers have shown that as the proportion of divorced residents increases, offending does as well (Choldin & Roncek, 1976; Land, McCall, & Cohen, 1990; Sampson, 1986). At times it exerts considerable unique impact (e.g., Messner & Tardiff, 1986).

Neighborhood transience is a related concept that is also likely implicated in the production of NSP. Its expected effects are similar to those stemming from disrupted families in that both are thought to undermine non-coercive means of informal social control. It has typically been measured as the proportion of residents living in the same dwelling for the last five years or as a function of the ratios of renters to owners (e.g., Heitgerd & Bursik, 1987; Sampson, 1986; Sampson et al., 1997). It is an often included structural covariate on the grounds that high levels are thought to disrupt primary relationships and inhibit the development of strong institutional ties. It weakens community integration by limiting friendship and organizational participation and, as a consequence, by reducing collective regulatory efforts (Bursik & Grasmick, 1993). High

transience areas will be less able to secure and mobilize resources and will thus be less able to favorably affect policy, such as local business and policing practices. Likewise, residents are less likely to develop and sustain strong attachments and they are less likely to intervene for the common good. Residents of areas having high levels of mobility tend to have the highest offending levels; likewise, areas characterized by high levels of mobility tend also to have the highest rates of offending (Sampson & Lauritsen, 1994; D. A. Smith & Jarjoura, 1988). NSP is also expected to vary with local economic factors as they, too, have shown to vary with regional crime and offending rates.

Regional unemployment rates vary positively with offending (see, Cantor & Land, 1985; Carroll & Jackson, 1983). The evidence bearing on this issue, however, is of uncertain significance as many studies have been unable to isolate unemployment-offending effects (e.g., Danziger & Wheeler, 1975) and few studies have examined the impact of local unemployment on NSP. An exception is Harer's (1994). He found as the size of unemployed residents in a region grew, the likelihood of recidivism among parolees released into those areas increased (see also, Kubrin & Stewart, 2006). More compelling research links crime, at least certain forms, with aspects of relative wealth, such as income inequality. I describe this next.

Wealth is unevenly distributed across society and, largely, as it becomes more disparate regional crime rates increase. Some find, for instance, residential areas having the highest aggregated incomes tend to have relatively lower crime rates (LaFree & Drass, 1996; Sampson, 1986; M. D. Smith & Parker, 1980) or, similarly, that areas having higher concentrations of lower income residents tend to have higher crime rates (Crutchfield, Geerkin, & Grove, 1982; D. A. Smith & Jarjoura, 1988). Some studies, however, have either been unable to identify a relationship between wealth and offending (Messner & Tardiff, 1986; Patterson, 1991) or have found contradicting evidence (Messner, 1983; Rosenfeld, 1986).

Insight anent this uncertainty is gleaned from studies disaggregating the effects of income differentials by crime types. Income inequality is associated with higher levels of violent offending (Loftin & Parker, 1985; Messner & Tardiff, 1986; Patterson, 1991; Taylor & Covington, 1988) and, to a lesser extent, property offending (Crutchfield et al., 1982).

It is thought then that NSP will be more common among those probationers residing in densely populated areas, as these areas increase anonymity and impersonalized social interaction, exposure to deviant values, and moral cynicism. Higher levels of NSP are also expected among probationers whose residential areas are characterized by high racial and ethnic heterogeneity, a disproportionate presence of teens and young adults, a disrupted family structure, and residential instability. Finally, NSP is expected more so among those residing in areas having high unemployment levels or income inequality than their counterparts. Another likely contextual influence on NSP is the presence of local crime. I discuss relevant literature and research in the next section.

Objective crime measures

Ample research indicates criminal activities cluster in place and time (e.g., Sherman, Gartin, & Buerger, 1989). Compositional explanations suggest this reflects the spatial distribution of predisposed individuals (e.g., Wilson & Hernnstein, 1985), but environmental characteristics are also likely implicated. Mentioned thus far are certain sociodemographic and economic characteristics. The argument continues by pointing out likely influences on NSP stemming from local crime levels. I begin by introducing a simple and, in most cases, rightfully avoided explanation, that residents of high-crime communities are also those that are responsible for a large fraction of the local crime, then provide reasons for not wholly avoiding ecological inference. I then describe direct influences on NSP expected from exposure to criminal activities as well as indirect influences

expected through stigmatization, increased crime tolerances, and weakened formal and informal controls.

A simple explanation posits those residents of high-crime communities are also those that are responsible for a large fraction of the local crime. This is presumptuous. Moreover, inferences such as these invariably knuckle under criticisms: they assume each resident within a community shares those characteristics represented by the community as a whole. This fallacy is widely known and, for inferential work, should be approached cautiously. On the other hand, these are much less prohibitive concerns in risk assessments. Not all residents of an area are criminally active. Rather, a small group of active offenders likely accounts for a large fraction of crime. There is persuasive evidence suggesting supervised offenders, as they have each been implicated criminally in one way or another, are members of this small but active group.

Although a non-ignorable amount of crime in an area is committed by outsiders (Rand, 1986), Bursik and Grasmick (1993) show offenders commit a large fraction of their crimes within their own communities. It could reflect, as Reiss (1986) suggests, offenders seeking to minimize costs associated with offending including those associated with target selection and rarely venture into unfamiliar areas to offend (and see, Boggs, 1965; Carter & Hill, 1978; Gould, 1969; Reppeto, 1974). There is reason then to expect that, first, at least some neighborhood crime is generated by its own residents and, second, that supervised offenders are likely among the criminally active.

More complex explanations turn on direct influences from exposure to criminal activities and indirect influences through stigmatization, increased crime tolerances, and weakened formal and informal controls. Community crime greatly affects the likelihood of learning criminal behaviors. Akers (1998) argues the clustering of crime reflects the extent sociocultural traditions and control systems provide learning environments conducive to deviance. Structural characteristics underlie offending variabilities, but, importantly, they do so by affecting the process by which indi-

viduals learn to commit or refrain from criminal acts. Residents of crime-ridden areas more likely witness or hear of law violations than those living in less crime-ridden areas and the perceptions residents attach to these behaviors influences their own. How rewarding or justifiable one sees criminality, how certain one believes the consequences, and how strongly one identifies with those committing or espousing definitions favorable to crime each influence the probability of engaging in criminal behavior (Akers, 1998). Thus, the level of crime in an area might influence subsequent NSP directly by providing a learning context conducive to criminal behaviors. Indirect effects are also likely.

High crime rates stigmatize communities and degrade the moral standing of its residents and potentially undermines strong social ties (Stark, 1987). They also influence tolerances for deviance, which vary regionally. There may be areas where crime flourishes, areas where it dies off quickly, and areas where it somehow never germinates. Deviant patterns somehow come to dominate social interactions. It may be, like the incivilities hypothesis suggests (see, Kelling & Coles, 1996; Taylor, 1999; Wilson & Kelling, 1982), disorder creeps into areas, most likely those with insufficient social capital to resist its growth, and eventually overwhelms them. Left unchecked, disorder begets continued disorder and, ultimately, makes conditions ripe for rising crime.

This stigma may also influence local law enforcement practices. As areas become more crime entrenched, the law becomes differentially enforced. Police, knowing elimination is unlikely, might come to tolerate higher levels of crime in some areas hoping at the very least for containment (D. A. Smith, 1986). This sets off an enduring trend of localization of both offending and offenders: it signals criminality's general tolerance, entices motivated non-residents, and compels conventional residents to disinvest (Stark, 1987).

Local crime patterns may thus prove critical in assessing supervised offenders for risk of NSP. Being the likely participants of community crime and being surrounded by negative stigma,

criminal attitudes and definitions, and high tolerances for crime, puts a mechanistic explanation behind why those from high crime areas might be higher risks of NSP than those residing in communities with lower crime areas. Another regional aspect deserving attention is commercialization patterns, which I discuss next.

Commercialization patterns

This section describes literature and research bearing on commercialization patterns and offending then draws inferences regarding how these characteristics might contribute to NSP. The focus is on the relative densities of businesses within geographic space and, because they are thought to uniquely influence NSP, I make the distinction between businesses of a general nature and those primarily involved in the sale or distribution of alcohol.

There are intrinsic, crime generating characteristics in areas wherein residential units are coexistent with or adjacent to commercial areas. Such mixed-use areas manifest higher rates of deviance, disorder, and crime, and this is mainly attributed to its influence on social control mechanisms, criminal attitudes and opportunities, and perceptions of neighborhoods and residents.(see, Kelling & Coles, 1996; Reiss, 1986; Sampson & Raudenbush, 2001; Skogan, 1992; Stark, 1987; Taylor, 1999; Wilson & Kelling, 1982).

As residential areas begin taking on a more commercial constitution a higher proportion of non-residents intermingle with residents who, as anonymity increases, become less able or willing to exert control over and thus contribute to order maintenance (Sampson, 1986, 1988). Mixed-use areas invite a greater blend of people than otherwise expected were it not for the commercial draw. This overwhelms formal means of control (Sampson & Raudenbush, 1999, 2001).

They also tend to have denser, less stable, and less economically advantaged populations and, by most accounts, are the least desirable and most affordable residential areas (Stark, 1987).

Tending toward dilapidation, this feature is adopted by the residents and ascribed by those with whom residents interact (see, Sampson & Raudenbush, 2004; Stark, 1987). Those residing in mixed-use areas have fewer reasons to conform; those ascribing, fewer reasons to interact. Mixed-use areas likely elevate exposure to deviant people and patterns. Exposure to deviance greatly affects the likelihood of learning such behaviors. Its residents are more likely witness or hear of deviance; this can influence the probability of engaging in criminal behavior (Akers, 1998). Be they patrons, the businesses themselves, or even the architectural design of the areas, mixed-use areas also present more criminal opportunities. They provide motivated offenders with easily accessible and attractive targets and living close to these areas provides them with intimate knowledge of areas having the highest criminal opportunities and the lowest risk of detection (Stark, 1987).

There is reason to believe an alcohol-related component of some businesses will further influence the production NSP. Crimes, many of which are alcohol-related, cluster in time and space and much of this coincides with densely available alcohol (see, Cochran, Rowan, Blount, Heide, & Sellers, 1998; Costanza, Bankston, & Shihadeh, 2001; D. M. Gorman, Speer, & Gruenewald, 2001; Gyimah-Brempong, 2001; R. Lipton & Gruenewald, 2002; Scribner, Cohen, Kaplan, & Allen, 1999; Scribner, MacKinnon, & Dwyer, 1995; Sherman et al., 1989; Speer, Gorman, Labouvie, & Ontkush, 1998; Stitt & Giacomassi, 1992).

A greater presence of alcohol retailers indulges non-abstainers. Unfettered proclivity and near-ubiquitousness increases their chances of consumption which in turn raises the potential for uncharacteristic behaviors (see, Gruenewald, Ponicki, & Holder, 1993; cf. Fitzgerald & Mulford, 1993). Nonetheless, alcohol-related problems are simply not explained fully via pharmacological effects à la disinhibition (see, Room & Collins, 1983). Rather, they hinge on the combination of

these effects with situational and sociocultural characteristics (see, Bushman, 1997; Fagan, 1990; Gustafson, 1994; Parker & Rebhun, 1995; Reiss & Roth, 1993).

Alcohol-related businesses increase criminal opportunities. Some offenders might savvily prey on intoxicated victims. Roncek and Maier (1991), for instance, highlight the expectedness that patrons may have cash or other desirable items and, further, that intoxicating effects may diminish the abilities of these patrons to protect themselves and others. Social norms delineate acceptable behavior with respect to alcohol consumption and intoxication (Linsky, Colby, & Straus, 1986; Parker & Auerhahn, 1998; Skog, 1985; Wiseman, 1991). These norms may encourage or discourage either (Parker, 1993). As MacAndrew and Edgerton eloquently state, “The way people comport themselves when they are drunk is determined not by alcohol’s toxic assault upon the seat of moral judgment, conscience, or the like, but by what their society makes of and imparts to them concerning the state of drunkenness” (1969, p. 165). An unmixed presence of alcohol-related businesses may signal to residents and outsiders alike that consumption and intoxication are acceptable if not encouraged and the greater visibility of taverns, bars, and liquor stores—and, naturally, of consumption and intoxication—minimizes alcohol-related stigma.

To iterate, the goal here is developing a risk-based instrument for guiding immediate security and treatment decisions facing the CSOSA, and, up to this point, I have contextualized such instruments within corrections research, described their historical trends, and sketched out the current methods. I then spent the bulk of the chapter on conceptual justifications for including certain individual- and structural-level characteristics as part of this instrument. These include, in particular, age, education, employment, residential stability, substance use, childhood and family factors, health, and criminal history as well as contextual characteristics such as sociodemographic and economic characteristics, objective crime measures, and commercialization patterns. In the next chapter I describe the methods and procedures used in the present study.

METHODOLOGY

The present task is describing the linkage between the methods and procedures used in developing an instrument for informing immediate, risk-anticipated security and treatment assignments among community-supervised offenders in the District of Columbia and the literatures and researches discussed in the previous chapter. It begins with the research design. To preface, measures will not and, for that matter, rightly cannot be manipulated. Nor are any treatments or interventions implemented. Of interest instead are the population relationships subordinated in the production of negative supervision performance (NSP). The correlational design used here is appropriate as it lends itself to explorations of such complex systems and aids in disentangling the relative importance of involved predictors.⁴ What follows is a description of the participants, the data sources and measures, and the procedures.

Participants

Appropriate samples in assessment studies are representative of the population for whom inferences are made. This differs, naturally, from samples representative of the general population (see, S. D. Gottfredson & Gottfredson, 1986), and it suggests those for whom estimates apply are unambiguous (see, J. M. Chaiken, Chaiken, & Rhodes, 1994). Considering these two points the population for this study was confined to only the most typical probationers yet to be supervised

⁴These designs are nevertheless weaker than, say, experimental or prospective, longitudinal designs. Internal validity can be questionable and the magnitude that observed rather than omitted predictors influence variation in the criterion can be difficult, if not impossible, to unravel. Likely, the most momentous consequence is the inability to infer causation. Correlational designs merely attest to associations; neither can antecedent or consequential relationships be identified nor can assurances of nonspuriousness be drawn. Despite these weaknesses correlational designs are attractive (see, Holmes & Taggart, 1990). One reason for this centers on their high level of external validity as, assuming appropriate sampling and modeling techniques, derived conclusions tend to generalize well. Their potential contributions to both theoretical literature and predictive research are also attractive—particularly when limiting predictors to those that are *theoretically* causal. The extent to which predictors and criteria covary is estimable and findings, in turn, inform both theory and research.

by the Court Services and Offender Supervision Agency for the District of Columbia (CSOSA).⁵ Because it was a theoretical population an enumeration was impossible. Estimates were instead derived from observed behaviors among a sample of probationers having already served their sentences. In the next few passages I describe the procedures that ensured, as much as possible, the sample adequately represented the population.

The underlying goal was guiding immediate, risk-anticipated custodial and treatment decisions facing the CSOSA by developing an instrument applicable to the majority of incoming offenders. The majority of offenders supervised by the agency are Black males having been sentenced to regular probation;⁶ the sampling frame was thusly restricted to this group and, because of this, the instrument developed here provides a general assessment tool.

Such precautions, while limiting, especially cross-jurisdictional, generalizeability, reduced variability in and thus size requirements for the sample. This stems from the constraining effect on the number of covariate patterns.⁷ At the same time they also militated against both the presence of and the techniques for accommodating missing data: offenders sentenced to the most common forms of supervision tend to have fewer data inconsistencies than those sentenced to special and, especially, less intensive forms of supervision.

⁵The CSOSA is an independent federal executive branch agency that was established under §11232 of the National Capital Revitalization and Self-Government Improvement Act of 1997. Its mission is to increase public safety, prevent crime, reduce recidivism, and support the fair administration of justice in close collaboration with the community. It comprises the Pretrial Services Agency and the Community Supervision Programs which, together, provide pretrial and community supervision services to over 15,000 DC residents serving probation, parole, and supervised release sentences.

⁶The term “regular” defines a specific, indeed, the most common, sentence among those supervised by the CSOSA. Compared to sentences typical among “special” sentences, such as those imposed on sex offenders, those with mental or physical disabilities, or those supervised as part of the interstate compact—none of which are included in this study—regular sentences stand out in their generality. Demographic and supervision level data describing the 2004 exit cohort are available upon request.

⁷These and other technical points are discussed further in a later section.

The sampling frame was also restricted to only those having already terminated sentences. An exit cohort enabled observation at least until sentences terminated, and, as emphasized previously, the processes underlying how probationers ultimately concluded their sentences was central to this assessment.

Another restriction relates to exposure. Focal criteria occurred largely within the observation period which comprises the supervision period, which is, formally, the interval beginning on the first day of an offender's sentence and ending on the last day of the sentence, and the post-supervision period, the interval beginning on the day after the last day of the sentence and ending on the last day of observation period.

To maximize exposure, the lower limit of the observation period reached as far as possible into agency history and, as it turned out, this reach was bounded by the second issue: data quality. As it coordinated new with existing functions the CSOSA felt growing pains in several areas. Data integrity was one.

A migration from an early to their current case management system was attempted during which the agency suffered isolated yet substantial data loss; information predating this migration is of dubious quality. As such, their analyses would be dicey. Direct population of data in the current case management system, Supervision and Management Automated Record Tracking (SMART), began regularly by the first few months of 2002, and, given an average sentence for Black, male probationers hovering near 2 years, the exit cohort selection parameter had to be at least 2 years after this to adequately capture data from the beginning of the supervision period.

To minimize risks associated with problematic data and at the same time allow for the longest possible follow-up, probationers were selected from among those terminating sentences during the interval beginning January 1, 2004, and ending December 31, 2004. They were fol-

lowed until December 31, 2006. This allowed between 23 and 35 months of post-supervision observation.

Two related qualifications follow. The first bears on sample size requirements; the second, case selection. Risk assessments require large samples for optimal performance and, while obviously subjective, approximate guidelines defining large exist nonetheless. Some suggest at least 500 cases are required (e.g., P. R. Jones, 1996). This assumes, however, a general population. As I discussed earlier, because the studied population was relatively homogenized, a smaller, randomized sample was adequately representative. Even more, the absolute sample size—at least for the modeling strategies used here—is of lesser concern than, say, the number of events either per covariate pattern or per parameter (Hosmer & Lemeshow, 2000; Peduzzi, Concato, Kemper, Holford, & Feinstein, 1996). As a general rule, at least 10 events are needed per covariate pattern (Hosmer & Lemeshow, 2000; Peduzzi et al., 1996). Here, the expected sample size was $N \approx 200$ Black male probationers⁸ and I ensured the ratios of events to covariate patterns were within these rules of thumb.

Models developed here were validated by bootstrapping, a validation technique outclassing both of the more common validation approaches: data splitting and cross-validation techniques (Efron & Tibshirani, 1993). Like cross-validation, bootstrapping is a resampling technique. It involves estimating expected variability from numerous, random samples drawn with replacement from the same, original sample (Efron, 1983; Efron & Tibshirani, 1993; S. D. Gottfredson & Gottfredson, 1986; Linnet, 1989; Monahan et al., 2001). When bootstrapping regression models, population parameters are estimated by first repetitively sampling observed data, with replacement, estimating the parameter among each, then calculating intervals around statistics by pooling

⁸As this is comparatively modest given P. R. Jones's (1996) suggestions, an explanation is necessary. Much of the analytic work here relies on information derived from Presentence Investigation reports (PSIs), which, as I show in the next section, do not readily lend themselves to analysis; incorporating more than a handful is unapproachable.

and averaging subsample estimates (Efron, 1979, 1982, 1983; Efron & Tibshirani, 1991, 1993; Fox, 1997). Done this way, bootstrapping provides nearly unbiased estimates of predictive accuracy, is more efficient than cross-validation, makes full use of available data, and allows for post-estimation optimization adjustments (see, Harrell & Lee, 1985; Harrell, Lee, & Mark, 1996). It is thus preferable among alternative measures of internal validity.⁹

The restricted population, randomized sample, and validation techniques offset, at least partially, the concern regarding the relatively small sample. To iterate, the population is limited to the most typical offenders yet to be supervised in the District of Columbia by the CSOSA. These are, namely, Black males sentenced to regular probation. Population estimates are bootstrapped from characteristics observed among a random sample of roughly 200 probationers having terminated their sentences during the interval beginning on January 1, 2004, and ending on December 31, 2004. With the description of the participants complete attention turns now to the remaining methodological elements including the data, measures, and procedures, and I pick this up with a description of the data sources and the measures derived thereof.

Data and Measures

Both individual- and environmental-level data were gathered.¹⁰ Individual-level data describe aspects unique to each probationer; environmental-level data describe contextual aspects that are, potentially, shared among probationers.¹¹

⁹Monahan et al. (2001) recently used this approach when examining $n = 939$ patients from the MacArthur Risk Assessment Study. Their criterion was serious violence in the community within 20 weeks of discharge. So as not to limit the data available for analyses, they bootstrapped parameter estimates. This entailed constructing 1,000 subsamples from their original data, fitting their model to each subsample, then summarizing across estimates.

¹⁰To link these two levels, the primary residence of each probationer was recovered from the CSOSA housing data and then geocoded to a point within the x - y space defining the DC. Each of these points were in turn aggregated to the U.S. Census Bureau (Census) block-group (BG) level defined by the Census, and it is precisely this level at which the environmental data were summarized.

¹¹At least, that is, among those living within the same BG. And, indeed, there were 75 offenders living in the same BG as at least one other offender.

Measures were obtained from three broad sources including (a) the CSOSA, (b) the Census, and (c) local regulatory and criminal justice agencies. These sources along with the measures derived from each are described next beginning with individual-level measures.

Individual-level measures

Individual-level measures were obtained from the CSOSA and included (a) the Risk-needs Screener, (b) Presentence Investigation reports, and (c) Supervision and Management Automated Record Tracking database.

Risk-needs Screener. The Risk-needs Screener (RNS) is an instrument originally designed by the Community Supervision Services (CSS) and Community Justice Programs (CJP) offices of the CSOSA. It is described fully in Appendix A; the specific measures used here are shown in Table 1. As readily seen, the RNS encapsulates many of the individual-level features described in Chapter 2 to well-predict NSP such as age, educational level, and employment stability. It gropes in the dark, however, when it comes to operationalizing these features. Because of this, I relied heavily on data recovered from the PSIs.

Missingness was a relatively minor issue with respect to the RNS yet one still needing pre-modeling attention. Three offenders were completely missing the RNS data; a 4th offender was missing a single RNS value—the item capturing original offense $msOO_i$ —which was proxied from the PSI. One of the 3 with completely missing screener data was simultaneously missing the PSI completely. This offender was dropped from analyses thus reducing the sample to $n = 199$ Black male probationers. Most items for the other two offenders were proxied from data in either the PSI or the SMART database. I elaborate on this next.

Table 1

Description and representation of items comprising the CSOSA Risk-needs Screener.

Symbol	Description	Coding
<i>rnsAge_i</i>	Age at the time of assessment	[0, 100)
<i>rnsEdu_i</i>	Educational level	^a
<i>rnsSSN_i</i>	Significant relationships	0 = None, 1 = One, 2 = Two or more
<i>rnsRL_i</i>	Recent loss	1 = Yes, 0 Otherwise
<i>rnsEmp_i</i>	Employment changes/year	^b
<i>rnsRes_i</i>	Residential moves/year	^b
<i>rnsPV_i</i>	Prior violent offense	0 = None, 1 = One, 2 = Two or more
<i>rnsNPA_i</i>	Prior adult arrests	^c
<i>rnsPS_i</i>	Prior supervision failures	0 = None, 1 = One to two, 2 = Three or More
<i>rnsFA_i</i>	Frequency of arrests/year	0 = None, 1 = One, 2 = Two or more
<i>rnsAF_i</i>	Age at first arrest	^d
<i>rnsPC_i</i>	Prior convictions	0 = None, 1 = One to five, 2 = Six or more
<i>rnsCSA_i</i>	Current substance abuse	1 = Yes, 0 Otherwise
<i>rnsHSA_i</i>	Prior substance abuse	1 = Yes, 0 Otherwise
<i>rnsCMD_i</i>	Current mental disorder	1 = Yes, 0 Otherwise
<i>rnsHMD_i</i>	History of mental disorder	1 = Yes, 0 Otherwise
<i>rnsImp_i</i>	CSO Impression	1 = Low, 2 = Medium, 3 = High
<i>rnsLOC_i</i>	Level of cooperation	1 = Fully, 2 = Non-, 3 = Restrained
<i>rnsOO_i</i>	Originating offense	1 = Drug-related, 2 = Non-violent, 3 = Violent
<i>rnsPD_i</i>	Physical disabilities	1 = Yes, 0 Otherwise

^a 1 = 10th or Below, 2 = 11th, 3 = High School or GED, 4 = Some college.

^b 0 = Currently or recently incarcerated or in a shelter; 1 = Two or fewer; 2 = Three or more.

^c 1 = Two or less, 2 = Three to four, 3 = Five, 4 = Six or more. ^d 1 = Ages 15 and younger, 2 = Ages 16 to 17, 3 = Ages 18 to 25, 4 = Ages 26 and older.

Specifically, for $i = 1, 2$ offenders with missing educational data, education level $rnsEdu_i$ was replaced with

$$rnsEdu_i = \begin{cases} psiEduGrdCm_i \leq 10, & 10\text{th or below;} \\ psiEduGrdCm_i = 11, & 11\text{th;} \\ psiEduGrdCm_i = 12 \\ \text{or } psiEduGED_i = \text{true}, & \text{HS/GED;} \\ psiEduGrdCm_i > 12, & \text{Some college;} \end{cases}$$

where $psiEduGrdCm_i$ captures the highest grade completed and $psiEduGED_i$ captures whether, if not a high school graduate, a GED was earned.¹²

Significant relationships $rnsSSN_i$, having original levels of no relationships, relationship with 1 person, and relationships with 2 or more people, was replaced with

$$rnsSSN_i = \begin{cases} x_i < 1, & \text{no relationships;} \\ x_i = 1, & \text{relationship with 1 person;} \\ x_i > 1, & \text{relationship with 2 or more people;} \end{cases}$$

where x_i represents the sum of the PSI variables capturing whether the PSI writer finds a supportive social network $psiFamSSN_i$, whether the offender has sustained contact with his mother $psiFamCntm_i$ or father $psiFamCntf_i$ until the instant arrest or, if either is deceased, until their time of death.¹³

¹²Unless otherwise noted, values of true and false are coerced to integers as $\frac{\text{true}}{\text{false}} \mapsto \frac{1}{0}$ throughout.

¹³Unless otherwise noted, values of yes and no are coerced to integers as $\frac{\text{yes}}{\text{no}} \mapsto \frac{1}{0}$ throughout.

Residential changes within the previous year $rnsRes_i$ was replaced with

$$rnsRes_i = \begin{cases} h_i + i_i \geq 1, & \text{Currently/recently incarcerated;} \\ x_i > 2, & \text{3 or more moves;} \\ x_i \leq 2, & \text{2 or fewer moves;} \end{cases}$$

where h_i and i_i are calculated from SMART housing tables and indicate, respectfully, the instant supervision period began within 30 days of either a discharge from a halfway house or a custodial sentence; x_i reflects the number of unique addresses for each offender within a backwards 2-year window available in the SMART housing tables.

Employment changes/year $rnsEmp_i$ was replaced with

$$rnsEmp_i = \begin{cases} \left. \begin{array}{l} h_i + i_i \geq 1, \\ psiEmpCurm_i \geq 12 \text{ or} \\ \left(\begin{array}{l} psiEmpCurm_i < 12 \\ \text{and } psiEmpLess_i = \text{FALSE} \\ \text{and } psiEmpSta_i \\ \ni \{ \text{Unemployed, Erratic/Odd jobs} \} \end{array} \right) \end{array} \right\}, & \begin{array}{l} \text{Currently/recently incarcerated;} \\ \\ \text{2 or fewer jobs ;} \end{array} \\ psiEmpSta_i \in \{ \text{Unemployed, Erratic/Odd jobs} \}, & \text{3 or more jobs/unemployed;} \end{cases}$$

where h_i and i_i are calculated from the SMART housing tables and indicate, respectfully, the instant supervision period began within 30 days of either a discharge from a halfway house or a custodial sentence; $psiEmpCurm_i$ ¹⁴ captures the number of months at the current job; $psiEmpLess_i$ captures whether there are any jobs within the previous year with a duration of less than 30 days; $psiEmpSta_i$ best characterizes employment status at time of instant offense.

¹⁴The item $psiEmpCurm_i$ was dropped from the analyses as it was missing values for $111/199 = 0.56$ of the offenders. Luckily, it was non-missing for the 2 offenders missing $rnsEmp_i$.

Prior violent offense $rnsPV_i$ was replaced with

$$rnsPV_i = \begin{cases} vc_i < 1, & \text{None;} \\ vc_i = 1, & 1; \\ vc_i > 1, & 2 \text{ or More;} \end{cases}$$

where vc_i represents the sum of the number of adult convictions $psiCrmAdlCnvVio_i$ and juvenile offenses $psiCrmJuvVio_i$ involving violence.

Prior adult arrests $rnsNPA_i$, having original levels of 2 or less, 3 to 4, 5, and 6 or more, was replaced with a categorical transformation of the PSI item capturing the number of adult cases $psiCrmAdlCasn_i$, where

$$rnsNPA_i = \begin{cases} 0 \leq psiCrmAdlCasn_i \leq 4, & 2 \text{ or less;} \\ 4 < psiCrmAdlCasn_i \leq 8, & 3 \text{ to } 4; \\ 8 < psiCrmAdlCasn_i \leq 12, & 5; \\ 12 < psiCrmAdlCasn_i, & 6 \text{ or more.} \end{cases}$$

Prior convictions $rnsPC_i$, having original levels of None, 1 to 5, and 6 or more, was replaced with the PSI measure capturing the number of adult convictions $psiCrmAdlCnv_i$,

$$rnsPC_i = \begin{cases} psiCrmAdlCnv_i < 1, & \text{None;} \\ 1 \leq psiCrmAdlCnv_i \leq 7, & 1 \text{ to } 5; \\ 7 < psiCrmAdlCnv_i, & 6 \text{ or more.} \end{cases}$$

Prior supervision failures $rnsPS_i$, having original levels of None, 1 to 2, and 3 or more, was replaced with

$$rnsPS_i = \begin{cases} psiSupRev_i < 1, & \text{None;} \\ 1 \leq psiSupRev_i \leq 2, & 1 \text{ to } 2; \\ 2 < psiSupRev_i, & 3 \text{ or more;} \end{cases}$$

where $psiSupRev_i$ captures the number of previous supervision failures.

Current substance abuse $rnsCSA_i$, recorded as either Yes or No, was replaced with the minimum of either $dtmsPos_i$ or 1 [$rnsCSA_i = \min(dtmsPos_i, 1)$], where $dtmsPos_i$ represents the sum of the number of positive drug screens taken 30 days before and after the screener interview. Values greater than zero were mapped to Yes.

Prior substance abuse $rnsHSA_i$, also coded as either Yes or No in the screener, was replaced with $rnsHSA_i = \min(psiEU_i, 1)$ where $psiEU_i$ represents the sum of the PSI variables capturing whether the offender admits to ever using alcohol $psiSubAlEU_i$, amphetamines $psiSubAmEU_i$, cocaine $psiSubCoEU_i$, opiates $psiSubHeEU_i$, marijuana $psiSubMaEU_i$, opiates $psiSubOpEU_i$, or PCP $psiSubPcEU_i$.

History of mental disorder $rnsHMD_i$ was replaced with the PSI item capturing whether the offender has been diagnosed with a mental illness $psiMedMdDx_i$. If so, $rnsHMD_i = \text{Yes}$.

Physical disabilities $rnsPD_i$ was replaced with

$$rnsPD_i = \begin{cases} psiPD_i \geq 1, & \text{Yes;} \\ psiPD_i \not\geq 1, & \text{No;} \end{cases}$$

where $psiPD_i$ is the sum of the number of disabilities $psiMedDis_i$ and injuries $psiMedInj_i$.

Current offense $rnsOO_i$, having original levels of drug-related, non-violent, or violent, was replaced with

$$rnsOO_i = \begin{cases} O_i = \text{any violent}, & \text{Violent;} \\ O_i = \text{Otherwise, any drug-related}, & \text{Drug-Related;} \\ \text{Otherwise,} & \text{Non-violent;} \end{cases}$$

where O_i represents an item taken from SMART categorizing > 2000 offense codes into 1 of roughly 30 broad offense groups.

Proxies were unavailable for the RNS items capturing recent loss $rnsRL_i$, level of cooperation during the interview $rnsLOC_i$, current mental disorder $rnsCMD_i$, age at first arrest $rnsAF_i$,

frequency of arrests/year $rnsFA_i$, and the impression of risk on the officer administering the interview $rnsIMP_i$. All were imputed using methods described next.

Missing values for $rnsRL_i$, $rnsLOC_i$, $rnsCMD_i$, $rnsAF_i$, $rnsFA_i$, and $rnsIMP_i$ were estimated and imputed using random draws from the conditional distributions of the nonmissing values on each given the values across the other screener variables. Specifically, 5 imputes were derived from random draws from the conditional distributions of the nonmissing values of each target measure given the values across the other variables. This resulted in a 5-length vector of imputes for each probationer-value. This vector represents, for each offender, the “best guess” estimate of the true value with an added stochastic component. This random residual is added in such a way that conditional variances for the target variable are comparable to those of the nonmissing values. For descriptive purposes the average of these imputes are reported; when modeling, each impute is used and the resulting coefficients and standard errors are adjusted for imputation.

There were further adjustments made to the RNS variables for all $i = 1, 2, \dots, N$ probationers. For example, The items $rnsOO_i$ and $rnsPD_i$ were excluded in favor of measures collected from the PSIs. The items $rnsRes_i$ and $rnsEmp_i$ were coded near-identically—each having three levels, the first for both capturing whether the offender was currently or recently released from incarceration or was residing in a shelter at the time of the screening. As including both would likely introduce redundancy and needlessly absorb degrees of freedom, these two items were collapsed into one summary measure $rnsSta_i$. The item $rnsSta_i$ reflects whether either of $rnsRes_i$ or $rnsEmp_i$ indicated the offender was currently or recently released from incarceration or was residing in a shelter at the time of the screening, in which case $rnsSta_i \mapsto 0$; both $rnsRes_i$ and $rnsEmp_i$ indicated the offender had experienced 2 or fewer changes in either condition, in which case $rnsSta_i \mapsto 1$; and, otherwise, if either of $rnsRes_i$ or $rnsEmp_i$ indicated the offender had experienced 3 or more such changes, then $rnsSta_i \mapsto 2$.

The two items capturing current $rnsCSA_i$ and past $rnsHSA_i$ substance abuse were significantly related.¹⁵ A large proportion ($167/199 = 0.84$) of offenders admit prior substance abuse as compared their counterparts ($32/199 = 0.16$). This imbalance was less pronounced as it concerned current substance abuse where the proportion of offenders admitting abuse ($78/199 = 0.39$) was considerably smaller than that among those not admitting ($121/199 = 0.61$). These two items were collapsed into a single measure capturing whether the i th offender had a history of substance abuse. If not, $rnsDrg_i \mapsto 0$. Otherwise, if the offender did have a history of substance abuse but no indication of current substance abuse then $rnsDrg_i \mapsto 1$; if the offender had both a history of and indications of current substance abuse then $rnsDrg_i \mapsto 2$.

A similar reduction was used for the items capturing a history of $rnsHMD_i$ and a current $rnsCMD_i$ mental disorder. Here, though, the offenders having either condition was extremely rare: $10/199 = 0.05$ reported a history of and $6/199 = 0.03$ a current mental disorder. A single indicator was created capturing whether the i th offender had either a history of or a current mental disorder and, if so, $rnsMH_i \mapsto 1$; Otherwise, 0.

The item $rnsLOC_i$ was collapsed into a dichotomous indicator $rnsFullCoop_i$. Most offenders ($170/199 = 0.85$) were classified as fully cooperative; very few as either noncooperative ($6/199 = 0.03$) or restrained ($23/199 = 0.12$). Given this, the last two levels of $rnsLOC_i$ were combined resulting in an indicator of whether offenders were fully cooperative or not.

The last two levels of $rnsNPA$ were collapsed thus dividing the sample into probationers with 2 or less $68/199 = 0.34$ 3 to 4 $45/199 = 0.23$ or 5 or more $86/199 = 0.43$ prior adult arrests. Similarly, the last two levels of $rnsPS$ were collapsed thus dividing the sample into probationers having none $120/199 = 0.60$ versus 1 or more $79/199 = 0.40$ prior supervision failures.

¹⁵ $\chi^2 = 8.8893$, $df = 1$, $p = 0.00$.

Presentence Investigation report. The PSIs provide an unmatched picture of personal and social aspects and the most comprehensive description available of both the triggering event and the criminal and supervision histories.¹⁶ Typically they describe (a) general and demographic attributes; (b) information about the instant offense; (c) the defendant's statement about the instant offense; (d) criminal and supervision histories; (e) educational, vocational, and employment characteristics; (f) family and social backgrounds; (g) health profile; (h) substance use, abuse, and treatment histories; and (i) both sentencing recommendations and any notable features that might inform such decisions. Fortunately, all PSIs¹⁷ are securely stored on the agency network. Their unseemly format, however, makes incorporating more than a handful unapproachable: they are literally disjoined from remaining agency functions, authored largely without content or structure prescription, and are thus less conformable to warehousing than those data derived from, for example, surveys or realtime data. They are seen primarily as output and, once complete, are essentially buried in the agency network.¹⁸ This overlooks an opportunity for informing agency decisions.¹⁹

Their richness warrants recovering as much information as feasible. To this end, an instrument was developed for extracting the most common PSI features that have also been shown to vary with NSP. In the next few passages I describe the specific items obtained from the PSIs.²⁰

¹⁶For most sentenced offenders the CSOSA provides the sentencing authority with a PSI. Because of their intensiveness, these reports are not typically ordered for minor offenders.

¹⁷At least those ordered by the sentencing authority on or after the first few months of 2002

¹⁸PSI authors save reports in a subfolder within the agency network share identified, typically, by the author's last name. The reports themselves are often either Microsoft Word documents or Adobe Portable Document Formats with filenames comprising case numbers or other identifiers.

¹⁹There are, of course, sophisticated text-mining applications capable of squeezing out much of the information contained in these reports. There are no plans for using these procedures here. The reasoning stems from, first, a project that focuses precisely on extracting PSI information is concurrent with the present study. Any efforts done here would be redundant—and, likely, inferior. Second, there are plans to integrate the PSI authoring and recording within, or closer to, SMART. Once implemented, the reports will be more easily incorporated into quantitative studies.

²⁰There were originally close to 200 items extracted from the PSIs, but roughly half were either completely missing or constant across all offenders and were thus excluded.

Two sets of 6 items were obtained from the PSIs to capture whether the i th offender ever used ($j = 1$) and, if so, admitted to a problem with ($j = 2$) each K substance

$$k = \left\{ \begin{array}{l} 1, \text{ alcohol;} \\ 2, \text{ amphetamine;} \\ 3, \text{ cocaine;} \\ 4, \text{ marijuana;} \\ 5, \text{ opiates; and} \\ 6, \text{ phencyclidine} \end{array} \right.$$

as $psiSub_{ikj}$. For each, 1 = Yes, 0 Otherwise.

Summary measures were derived to capture the number of drugs out of the 7 the i th offender ever used $psiSubEU1_i$, which ranged $[0, +\infty)$, and whether or not (1 = Yes, 0 Otherwise) the offender ever used any of the 7 $psiSubEU2_i$, and, likewise, the number of drugs out of the 7 that the offender admits to having a problem with $psiSubAP1_i$, which ranged $[0, +\infty)$, and whether or not (1 = Yes, 0 Otherwise) the offender admits to a problem with any of the 7 $psiSubAP2_i$.

Juvenile adjudication and confinement characteristics were also recovered from the PSIs. These were, specifically, the number of juvenile cases $psiCrmJuvCasn_i$, the number of juvenile adjudications $psiCrmJuvAdj_i$, and the number of juvenile confinements of length greater than 30 days $psiCrmJuvCon_i$. Each of these items took on values within the interval $[0, +\infty)$.

Criminal history measures include the total number of adult cases $psiCrmAdlCasn_i$, the number of adult convictions $psiCrmAdlCnvn_i$, and $k = 1, 2, \dots, 5$ crime-disaggregated measures

across

$$k = \begin{cases} 1, & \text{violence;} \\ 2, & \text{property;} \\ 3, & \text{drugs;} \\ 4, & \text{weapons; and} \\ 5, & \text{NSP} \end{cases}$$

as $\psi_{CrmA}C_{nk}$. These last items potentially range within the interval $[0, +\infty)$.

Additional items captured the nature of the originating offense.²¹ These individual items were reduced before model estimation to a hierarchical measure, triggering offense $\psi_{Offense}_i$, capturing whether the instant offense involved (a) violence, or, if not, (b) weapons, or, if not, (c) property, or, if not, (d) drugs, or, if not, (e) public order, or, if not, (f) sex crimes, or, otherwise, (g) unclassified crimes.

PSI authors provide accounts of the originating offense from the perspectives of both the arresting authority as well as the offender and, typically, note any discrepancies. Several items were constructed to capture this including whether the offender agrees with the arresting authority account ψ_{StaAgr}_i . Also, if the offender denies responsibility, whether intoxication $\psi_{StaBlad}_i$,

²¹These included whether the instant offense involved absconson ψ_{inspa}_i , bail-reform charges ψ_{NspBra}_i , bail jumping $\psi_{NspJump}_i$, or other NSP charges ψ_{NspOth}_i ; using drugs $\psi_{OffDrgus}_i$, buying drugs $\psi_{OffDrgbu}_i$, possessing drugs $\psi_{OffDrgpo}_i$, selling drugs $\psi_{OffDrgse}_i$, drug paraphernalia $\psi_{OffDrgpa}_i$, or some other, uncategorized, drug offense $\psi_{OffDrgot}_i$; theft $\psi_{OffProth}_i$, autotheft $\psi_{OffProat}_i$, burglary $\psi_{OffProbu}_i$, stolen property $\psi_{OffProsp}_i$, destruction of property $\psi_{OffProd}_i$, forgery $\psi_{OffProfo}_i$, or some other property offense $\psi_{OffProot}_i$; disorderly conduct $\psi_{OffPubdi}_i$, gambling $\psi_{OffPubga}_i$, vagrancy $\psi_{OffPubva}_i$, public drunkenness $\psi_{OffPubpd}_i$, or some other public order crime $\psi_{OffPubot}_i$; prostitution $\psi_{OffSexpr}_i$ or some other sex crimes $\psi_{OffSexot}_i$; murder $\psi_{OffViomu}_i$, rape $\psi_{OffViora}_i$, robbery $\psi_{OffVioro}_i$, arson $\psi_{OffProar}_i$, assault $\psi_{OffVioas}_i$, or some other violent offense $\psi_{OffVioot}_i$; or discharging a gun $\psi_{OffWeadi}_i$ or some other gun-related offense $\psi_{OffWeaot}_i$. For each, 1 = Yes, 0 Otherwise.

injury $psiStaBlai_i$, mental disorder $psiStaBlam_i$, the police $psiStaBlap_i$, self $psiStaBlas_i$, or the victim $psiStaBlav_i$ was blamed for the offense instead. For each, 1 = Yes, 0 Otherwise.

Additional items captured whether the police suspected the i th offender was under the influence of drugs $psiOffDrgSus_i$ or alcohol $psiOffIntSus_i$ at the time of the arrest and whether drug $psiOffDrgVer_i$ or alcohol $psiOffIntVer_i$ use was field-verified; whether the offender tested positive for $psiSubLuPosA_i$ or drugs $psiSubLuPosD_i$ at lock-up; whether someone other than the offender was physically injured as a result of the offense $psiOffInj_i$; and whether the police recovered money from the offender or the area wherein the crime occurred $psiOffMon_i$. For each, 1 = Yes, 0 Otherwise.

Two items capture—given a previous incarceration sentence—whether any screens were positive for alcohol $psiSubInPosA_i$ or other substances $psiSubInPosD_i$, 1 = Yes, 0 Otherwise.

A notable feature recovered from the PSIs is the Salient Factor Score (SFS) which is the recidivism prediction instrument used by the United States Parole Commission (USPC) (see, Hoffman & Beck, 1974). The SFS has been extensively validated and is known to be quite accurate (Blumstein, Cohen, Roth, & Visher, 1986; Janus, 1985). SFS 98—the most recent revision—is calculated here as $psiSFS_i$ and used as a comparative tool (see, United States Parole Commission [USPC], 2003). Its calculation is described in Appendix B.

The recommended sentence $psiSR_i$ was also recovered from the PSIs. Such recommendations took on values of either incarceration, probation, or split-sentence.

Data bearing on sentence and supervision histories were collected from the PSIs. This included information about criminal justice status at the time of arrest, previous community supervision and incarceration sentences, and previous acts of NSP. These items are shown in Table 2. Also obtained were times capturing the number of times (values ranged within $[0, +\infty)$) the i th offender was referred to drug $psiSupTxdri_i$, detoxification $psiSupTdx_i$, and mental health

Table 2

Presentence Investigation report, sentence and supervision histories.

Symbol	Description	Coding
$psiSupSta_i$	Status, time of instant arrest	a
$psiCrmAdlSupNpr_i$	Number, previous probation sentences	$[0, +\infty)$
$psiCrmAdlSupNpa_i$	Number, previous parole supervision sentences	$[0, +\infty)$
$psiCrmAdlInc_i$	Number, ICs ^b	$[0, +\infty)$
$psiSupRev_i$	Number, previous supervision failures	$[0, +\infty)$
$psiSupAbs_i$	Number, previous supervision absconsions	$[0, +\infty)$
$psiSupWar_i$	Number, previous supervision warrants	$[0, +\infty)$
$psiAdlSupRev_i$	Number, previous supervision revocations	$[0, +\infty)$

^a Either fugitive, probation, parole, or free from control.

^b Incarceration sentence for length greater than 30 days.

$psiSupT xmh_i$ treatment and whether the i th offender had previously been exposed to either drug or alcohol treatment $psiSubTXAny_i$, 1 = Yes, 0 Otherwise.

Family characteristics obtained from PSIs capture early and current family structure and support. Parent marital status at birth, their involvement through childhood, and whether there is sustained contact, for example, are among those shown in Table 3. The item capturing parent marital status at birth $psiFamBir_i$ had sparse levels. At birth, parents of offenders were largely either married and living together ($92/199 = 0.46$), unmarried and living apart ($78/199 = 0.39$), or unmarried but cohabiting ($27/199 = 0.14$). The parents of the remaining $199 - (92 + 78 + 27) = 2/199 = 0.01$ offenders were married and living apart and divorced and living apart. This item was reduced to

$$psiFamMarBir_i = \begin{cases} 0, & \text{not cohabiting, married or unmarried;} \\ 1, & \text{cohabiting, unmarried,;} \\ 2, & \text{cohabiting, married,.} \end{cases}$$

where cohabiting collapses the levels Married-living together and Unmarried-cohabiting; married collapses levels Married-living together, Married-living apart, and Divorced-living apart.

Several indicators were created to reduce the dimensionality in the data. For example, the indicator *parentInvolve* was created to represent whether either mother, father, or both were uninvolved in parenting or that both were involved 1 = Yes, 0 Otherwise. The indicator *parentAlive* was created to represent whether both parents were alive, 1 = Yes, 0 Otherwise. The indicator *parentContact* was created to represent whether there was sustained contact with both parents, 1 = Yes, 0 Otherwise. *raisedBy* was created to indicate that the offender was raised by either a single mother, single father, or an extended family, 1 = Yes, 0 Otherwise. The items *psiFamAbuNG*, *psiFamAbuPH*, and *psiFamAbuSX* were summarized with the indicator *anyAbuse*, 1 = Yes, 0 Otherwise. Finally, *psiSocMarSta* and *psiSocMarDiv* were represented by the indicator *psiSocMar* to represent whether the offender was cohabiting, either married or unmarried, or not.

Certain social characteristics were also obtained. These items, shown in Table 4, capture marital status, dependents, and whether the *i*th offender lives with dependent children.

There were also several educational characteristics obtained from the PSIs. These included for $i = 1, 2, \dots, N$, highest grade attempted *psiEduGrdAt_i* and completed *psiEduGrdCm_i* educational years and, if not a high school graduate, whether a GED was earned *psiEduGED_i* (1 = Yes, 0 Otherwise).

A pair of items capture whether in the previous year there were any employment stints of less *psiEmpLess_i* or more *psiEmpMore_i* than 30 days (1 = Yes, 0 Otherwise).

Limited health characteristics were also obtained including measures of substance use and of physical and mental disabilities, injuries, and illnesses. These are shown in Table 5.

Table 3

Presentence Investigation report, family characteristics.

Symbol	Description	Coding
<i>psiFamBir_i</i>	Parent marital status at birth	1 = Yes, 0 Otherwise
<i>psiFamNow_i</i>	Parent marital status now	1 = Yes, 0 Otherwise
<i>psiFamNowfb_i</i>	Father alive at birth	1 = Yes, 0 Otherwise
<i>psiFamInvm_i</i>	Mother involved in parenting	1 = Yes, 0 Otherwise
<i>psiFamInvf_i</i>	Father involved in parenting	1 = Yes, 0 Otherwise
<i>psiFamRaism_i</i>	Raised by single mother	1 = Yes, 0 Otherwise
<i>psiFamRaisf_i</i>	Raised by single father	1 = Yes, 0 Otherwise
<i>psiFamRaixf_i</i>	Raised by extended family	1 = Yes, 0 Otherwise
<i>psiFamRai ff_i</i>	Raised by foster family	1 = Yes, 0 Otherwise
<i>psiFamNowfn_i</i>	Father alive now	1 = Yes, 0 Otherwise
<i>psiFamAlimn_i</i>	Mother alive now	1 = Yes, 0 Otherwise
<i>psiFamCntf_i</i>	Sustained contact with father	1 = Yes, 0 Otherwise
<i>psiFamCntm_i</i>	Sustained contact with mother	1 = Yes, 0 Otherwise
<i>psiFamSibAl_i</i>	Number, siblings	[0, +∞)
<i>psiFamSibbn_i</i>	Number, blood-siblings	[0, +∞)
<i>psiFamSibsn_i</i>	Number, step-siblings	[0, +∞)
<i>psiFamSsn_i</i>	PSI author finds a supportive social network	1 = Yes, 0 Otherwise
<i>psiFamAbuph_i</i>	Physical abuse	1 = Yes, 0 Otherwise
<i>psiFamAbusx_i</i>	Sexual abuse	1 = Yes, 0 Otherwise
<i>psiFamAbung_i</i>	Neglect/abandonment	1 = Yes, 0 Otherwise

Table 4

Presentence Investigation report, social characteristics.

Symbol	Description	Coding
<i>psiSocMarSta_i</i>	Marital status	^a
<i>psiSocMarDiv_i</i>	Ever divorced	1 = Yes, 0 Otherwise
<i>psiSocChl_i</i>	Children, same residence	^b
<i>psiSocHouFa_i</i>	Lives with relatives ^c	1 = Yes, 0 Otherwise
<i>psiSocChlBil_i</i>	Number, biological children ^d , same residence	[0, +∞)
<i>psiSocChlBin_i</i>	Number, biological children ^d	[0, +∞)
<i>psiSocChlStn_i</i>	Number, step-children ^d	[0, +∞)
<i>psiSocTon_i</i>	Number, children total ^c	[0, +∞)

^a 5 = Married, living together; 4 = Married, living apart; 3 = Divorced, living apart; 2 = Single, cohabiting; 1 = Single, living alone; 0 = Widowed. ^b 0 = No children under 18, 1 = Children under 18, not all same residence, 2 = Children under 18, all same residence.

^d Ages 18 or younger. ^c i.e., parents, siblings, aunts, uncles, cousins, or grandparents.

Table 5

Presentence Investigation report, health characteristics.

Symbol	Description	Coding
<i>psiMedMdDis_i</i>	Number, disabilities	[0, +∞)
<i>psiMedInj_i</i>	Number, injuries	[0, +∞)
<i>psiMedMdDx_i</i>	Ever diagnosed with a mental illness	1 = Yes, 0 Otherwise
<i>psiMedMdDr_i</i>	Takes prescribed psychotropic medications	1 = Yes, 0 Otherwise
<i>psiMedMdHo_i</i>	Number, previous mental health hospitalization	[0, +∞)
<i>psiMedMdSu_i</i>	Ever attempted suicide	1 = Yes, 0 Otherwise
<i>psiSubSM_i</i>	Self-medicating with alcohol or drugs	1 = Yes, 0 Otherwise
<i>psiMedWougun_i</i>	Number, gunshot wounds	[0, +∞)
<i>psiMedWoustb_i</i>	Number, stabbing wounds	[0, +∞)

As the range of potential predictors obtained from the PSIs was quite large, that missingness would compromise analytics was expected at the outset. In contrast to those captured in the RNS, missingness was more widespread with respect to the PSI data and strategies similar to those taken for the RNS were used to minimize this problem. $63/118 = 0.53$ were missing less than 5 values; $20/118 = 0.17$ were missing 5 to 9 values; $18/118 = 0.15$, 10 to 14; $9/118 = 0.076$, 15 to 20; and $8/118 = 0.068$ were missing 20 or more. Missing values were imputed based on nonmissing values among other individual-level measures. Specifically, 5 imputes were derived from random draws from the conditional distributions of the nonmissing values of each target measure given the values across the other variables. This resulted in a 5-length vector of imputes for each probationer-value.

Supervision and Management Automated Record Tracking. In addition to those in the RNSs and PSIs, data provided by the CSOSA also include information contained throughout its SMART database, a relational database comprising over 350 individual tables. Nearly every piece of information pertaining to probationers is contained within SMART. Prominent characteristics include the beginning $beginDt_i$ and ending $outTrmDt_i$ dates of the supervision period, the actual $daysSupAct_i$ and expected $daysSupExp_i$ number of days supervised, and the supervision level $supLvl_i$ (i.e., minimum, medium, maximum, or intensive).

The observation period subsumes both the supervision period—the interval spanning from the supervision period begin date $beginDt_i$ to the supervision period termination date $outTrmDt_i$ ²² and the post-supervision period—the interval spanning from $outTrmDt_i$ to the follow-up close date. For all sampled offenders, the follow-up close date is December 31, 2006.

What I discuss next are those items bearing on performance, such as drug screening, conviction and violation histories, and termination modes.

²²For most offenders this is the date on which the supervision period ended in one of three modes: successful, unsuccessful, or revoked. For absconders, termination date is the date of the first of a series of contact losses. For offenders that died while supervised, termination date is the date of death.

Results from drug testing events include which, if any, of the 7 potentially screened substances were positive at each J event for the $i = 1, 2, \dots, N$ probationers. For clarity, these substances are mapped to the index k as

$$k = \begin{cases} 1, & \text{alcohol;} \\ 2, & \text{methadone;} \\ 3, & \text{amphetamine;} \\ 4, & \text{cocaine;} \\ 5, & \text{marijuana;} \\ 6, & \text{opiates; and} \\ 7, & \text{phencyclidine.} \end{cases}$$

The specific data used here include the date of the j th event for the i th probationer $outDrgdt_{ji}$ and two sets of indicators. The first, $outDrgScr_{1ji}, outDrgScr_{2ji}, \dots, outDrgScr_{kji}$, capture whether the k th substance was screened during the j th event, and, if so, the second set, $outDrgPos_{1ji}, outDrgPos_{2ji}, \dots, outDrgPos_{kji}$, capture whether the result was positive. For both, 1 = Yes, 0 Otherwise.

The item $outS_{1i}$ summarizes these items in capturing whether the i th probationer ever tested positive, provided a bogus specimen, or failed to appear for a drug testing event. The variables $outDrgTotScr_{1i}, outDrgTotScr_{2i}, \dots, outDrgTotScr_{7i}$ capture the total number of drug screens for the k th substance and $outDrgTotPos_{1i}, outDrgTotPos_{2i}, \dots, outDrgTotPos_{ki}$ capture the total number of positive screens for the k th substance; $piPos_{ki}$ capture the proportion of positive screens for the k th substance.

Conviction data are available in SMART as part of a data sharing agreement with the Superior Court of the District of Columbia, a trial court with general jurisdiction over virtually all

local legal matters. This agreement allows the CSOSA to identify its offenders and determine the outcomes of prosecution, trial, and sentencing processes. The specific measures recovered include for every J conviction event involving each $i = 1, 2, \dots, N$ probationers, the conviction date $outCnvdt_{ji}$, the date of arrest leading to the conviction $outCnvArrdt_{ji}$, and the type of charge on which the conviction is made $outCnvCg_{ji}$. Here, charge types are broadly classified into one of five categories (see, Appendix C) and are mapped to the index m as

$$m = \begin{cases} 4, & \text{violent;} \\ 3, & \text{drug- or alcohol-related;} \\ 2, & \text{property;} \\ 1, & \text{public disorder; and} \\ 0, & \text{other.}^{23} \end{cases}$$

The next measures bear on whether and, if so, how often during the observation period rearrests resulted in convictions. Criteria include $outC1_i$, which captures whether the i th probationer was arrested and subsequently convicted for any offense during the supervision period; and $outC2_i$, which captures whether the i th probationer was arrested and subsequently convicted for any offense during the post-supervision period. For each, 1 = Yes, 0 Otherwise.

Violations and modes of termination data were also obtained from SMART. Following agency definitions, condition violations are classified as either supervision- or drug-related, where supervision-related violations include violations of general and special conditions (see, Table D1 and Table D2); drug-related violations include only those specifically involving illegal substances. The date $outViodt_{ji}$ and broken condition $outVioCond_{ji}$ were recovered for every J violation event involving the $i = 1, 2, \dots, N$ probationers. The variable $outVioTyp_{ji}$ summarizes the j th event for

the i th probationer as

$$outVioTyp_{ji} = \begin{cases} 1, & \text{Drug-related;} \\ 0, & \text{Supervision-related.} \end{cases}$$

Two criteria were constructed: $outV1_i$, which captures the total number of times the i th probationer violated a supervision-specific condition and $outV2_i$, which captures the total number of times the i th probationer violated a drug-related condition.

The termination mode $outT1_i$ and the date of termination $outT2_i$ are obtained from SMART for the i th probationer. Termination modes capture the process by which probationers completed their sentence. Possible modes are detailed in Appendix E. Briefly, these are

$$outT1_i = \begin{cases} 1, & \text{death;} \\ 2, & \text{successful;} \\ 3, & \text{unsuccessful and terminated;} \\ 4, & \text{revoked; and} \\ 5, & \text{absconsion.} \end{cases}$$

However, sparse categories necessitated collapsing levels into either successful or unsuccessful termination. As such, $outT1_i$ was recoded into an indicator of failure (i.e., unsuccessful, revoked, or absconsion).

Contextual measures

The RNSs, the PSIs, and the information housed within SMART describe characteristics unique to each probationer. To describe their environments data were also obtained from five other sources including an agency maintaining local geospatial data,²⁴ the U.S. Census Bureau (Census),

²⁴Among other roles the Office of the Chief Technology Officer for the District of Columbia maintains for the District of Columbia (DC) point, polyline, and polygon data describing streets and administrative and political boundaries.

the local police department, and two agencies responsible for business regulation. These environmental data are discussed next beginning with sociodemographic and economic characteristics obtained from the Census.

Sociodemographic and economic characteristics. Several items were obtained from the 2000 Census Summary File 3 (SF3) to capture the contextual aspects shown in Chapter 2 to relate well with NSP, which are, namely, wealth and poverty, race and ethnicity, immigration, employment, age and family structure, and residential stability. The SF3 comprises sample data from roughly 1:6 U.S. households receiving the Census 2000 long-form questionnaire. The measures derived here, summarized for each $k = 1, 2, \dots, 436$ block-group, are shown in Table 6.

Missingness resulted from an absence of data bearing on areas outside of the DC: 3 offenders lived each within separate census tracts of neighboring Prince George's county, Maryland; recovering data for these BGs was uncomplicated as they were all obtainable from the Census.

Objective crime measures. A data sharing agreement between the CSOSA and the MPDC allows CSOSA access to local arrest data. Locations of arrest events are geocoded thereby coordinating each within x - y space then aggregated by crime category within BG. The obtained measures include the number of arrests for violent $arrVio_k$, property $arrPro_k$, drug- and alcohol-related $arrDrg_k$, public-order $arrPub_k$, and otherwise unclassified $arrOth_k$ crimes. I then created density measures of each type of arrests as $arrVio.d_k$, $arrPro.d_k$, $arrDrg.d_k$, $arrPub.d_k$, and $arrOth.d_k$, respectfully.

These data will be used in linking environmental-level data with probationer residences. I obtained street-level information which then provided a means for both coordinating points within x - y space and for aggregating these points within BGs. Note, a Census block-group (BG) consists of all census blocks having the same first digit of their four-digit identifying numbers within a census tract and generally contain between 600 and 3,000 residents (see, United States Census Bureau [Census], 2004, A-8). It is precisely this level that all environmental-level data were summarized.

Table 6

U.S. Census, sociodemographic characteristics, 2000, by Census block-group, $k = 436$.

Symbol	Description	Coding
<i>piBlk</i>	<u>Population, Black</u> Population	[0, 1]
<i>piDif</i>	<u>Population^a, different house in 1995</u> Population ^a	[0, 1]
<i>piEdu</i>	<u>Population^b, less than a high school diploma or equivalency</u> Population ^b	[0, 1]
<i>piFHH</i>	<u>Households, female, no husband present</u> Households	[0, 1]
<i>piFor</i>	<u>Population, foreign born</u> Population	[0, 1]
<i>piHis</i>	<u>Population, Hispanic or Latino</u> Population	[0, 1]
<i>piPov</i>	<u>Population^c, income in 1999 < poverty level</u> Population ^c	[0, 1]
<i>piPub</i>	<u>Households, public assistance income</u> Households	[0, 1]
<i>piRnt</i>	<u>Housing units, renter occupied</u> Occupied housing units	[0, 1]
<i>piUne</i>	<u>Population^d, unemployed</u> Population ^d	[0, 1]
<i>rtAK</i>	<u>Children^e</u> Adults ^f	[0, 1]
<i>popDens</i>	<u>Population</u> land area m ²	[0, ∞)

Note. Data are provided by the U.S. Census Bureau, Summary File 3, 2000.

^a Population 5 years and over. ^b Population ages 25 and older.

^c Population for whom poverty status is determined. ^d Population 16 years and over.

^e Population under age 18. ^f Population ages 18 and older.

Access to objective crime measures was just short of nonexistent for the 3 non-DC BGs wherein sampled offenders resided. Strategies similar to those taken among the individual-level measures were used to adjust for missingness, but before doing so as much information as possible was replaced with data provided by the local police department with arresting jurisdiction.

An arrangement with the Prince George's County Police Department (PGPD) was established which enabled recovering the number of arrests for both violent and property crimes within

each of the 3 Maryland BGs.²⁵ The two remaining arrest summaries capturing, respectfully, drug and alcohol $arrDrg_i$ and public order $arrPub_i$ crimes were imputed.

Specifically, missing values were imputed based on non-missing values across those remaining. Five imputes for each were derived from random draws from the conditional distributions of the nonmissing values of each target given the values across the other variables. This resulted in a 5-length vector of imputes for each measure per BG.

Commercialization patterns. Data describing the concentrations of businesses within BGs were collected from the Department of Consumer and Regulatory Affairs for the District of Columbia (DCRA), the regulatory agency charged with licensing as well as monitoring and enforcing compliance with commercial regulations in DC. I obtained the location and type of all licensees in DC, geocoded their locations, then summarized types within BG. The specific measures derived from these data capture the total number of licenses for employment services; entertainment services; general businesses; housing; public health; and sales, service, and repair. To represent commercialization I calculated a summary measure $busDens_k$ capturing the density of all licensees²⁶ per 1,000 residential housing units within BG.

I also obtained data specifically addressing retail alcohol licensees. The Alcoholic Beverage Regulation Administration for the District of Columbia (ABRA) provides data describing alcohol retailers in DC. This agency issues licenses as well as monitors and enforces compliance with regulations among liquor stores, brewpubs, nightclubs, restaurants, taverns, hotels, and other establishments that manufacture, sell, or serve alcoholic beverages in DC. I summarized the location, class, and type of every alcohol retail licensee in DC. Licensees were then classified by license

²⁵These values were, for Block Group 2, Census Tract 8019.01: $arrVio_i = 24$ and $arrPro_i = 261$; for Block Group 1, Census Tract 8012.05: $arrVio_i = 37$ and $arrPro_i = 442$; and for Block Group 4, Census Tract 8012.02: $arrVio_i = 90$ and $arrPro_i = 506$.

²⁶excluding retail alcohol outlets

type, which were one of either (a) off-premises sale of beer, wine, and spirits; (b) off-premises sale of beer and wine only; (c) on-premises sale of beer, wine, and spirits; or (d) on-premises sale of beer and wine only. Densities of each licensee were calculated per square meter of BG land area for each $k = 433$ as, respectfully, $alcBWS1_k$, $alcBW1_k$, $alcBWS2_k$, and $alcBW2_k$. A summary measure $alcDens_k$ was also calculated representing the density of all licensees per 1,000 square meter of BG land area.

None of the measures capturing commercialization patterns were available for the 3 Maryland BGs and these, too, were imputed using the same procedures as outlined above.

Described thus far are the data sources and the measures derived from these sources. Broadly, these include (a) the RNS, (b) the PSI, and (c) the SMART database, which are each provided by the CSOSA; objective crime measures, which are derived from data provided by the local police agency; densities of local businesses, and, in particular, alcohol retailers, which are derived from data provided by local regulatory agencies; and various social, economic, and housing summaries, which are derived from data provided by the Census. Among described measures were predictors, both individual- and contextual-level, as well as the legal and supervision-specific criteria operationalizing NSP. In the next few passages I review NSP—as defined by the criteria—while also describing the specific models, each estimated with various General Linear Models (GLMs) (see, Dobson, 2001; McCullagh & Nelder, 1989), in which these criteria were central.

Procedure

NSP itself is unmeasurable. It is a simplifying concept used to succinctly describe a broad set of related characteristics. As described previously, NSP encapsulates behaviors classified into legal and supervision-specific domains. Criteria in the legal domain capture substance use and rearrests resulting in convictions; supervision-specific criteria include condition violations and

termination modes. Because of its multifarious nature, multiple measures are needed to get an understanding of NSP in the population and thus, here, separate models are estimated for each embedded feature. The procedures used in estimating these models are described throughout this section beginning with those related to substance use.

Model **MS1** estimates factors associated with the probabilities that probationers in the population will ever fail a drug-testing event while supervised. The criterion for this model was *outS1*. Models **MS2A**, **MS2B**, . . . , **MS2G** estimate factors associated with how often probationers in the population will test positive for the *k*th screened substance. The criterion for these models were, respectfully, *outDrgTotPos_{ik}*.

Models **MC1** and **MC2** estimate the probabilities that probationers in the population will be convicted for new crimes given an arrest. Model **MC1** does this for convictions during the supervision period; Model **MC2**, the post-supervision period. The criteria were, respectfully, *outC1_i* and *outC2_i*.

Model **MV1** estimates factors associated with how often probationers in the population will violate supervision-related conditions and Model **MV2** estimates factors associated with how often probationers in the population will violate drug-related conditions. The criteria were *outV1_i* and *outV2_i*, respectfully.

Model **MT1** estimates likelihoods probationers in the population will terminate sentences in one of three unsuccessful modes (i.e., unsuccessful, revoked, or absconsion); Model **MT2** estimates how soon either are likely to occur. The criteria were, respectfully, *outT1* and *outT2*.

The procedures used in estimating risk of NSP as operationalized by the criteria involved, first, developing a general model to predict each criterion using predictors identified in the review as likely influences. Models were reduced to binary trees using recursive partitioning analysis (RPA) (Breiman, Friedman, Olshen, & Stone, 1984; Clark & Pregibon, 1992; Therneau & Atkin-

son, 1997)²⁷ and then pruned back to account for replacement optimism based on an AIC-like pruning scheme (see, Venables & Ripley, 2002; Ciampi, Negassa, & Lou, 1995). A multivariable GLM was then developed using the pruned-tree predictors with any parameterization and functional form adjustments necessary to normalize marginal distributions. Standard errors were corrected using robust variance estimators following procedures outlined by (Huber, 1967; Rogers, 1993; H. White, 1980; R. L. Williams, 2000).

After models were estimated I turned to evaluation and validation. Model performance was evaluated in terms of calibration and discrimination and models were validated by bootstrapping (see, Appendix F).

²⁷Using the R library RPART (Therneau & Atkinson, 1997).

RESULTS

Analytic results are presented in this chapter. In the first section I describe the central characteristics moving, generally, from the individual- to the contextual-level then follow with presentations of model estimates. Detailed discussions are held off until the following chapter.

Description

Descriptions of measures are presented in this section beginning with characteristics of the sample in terms of supervision-specific measures and then those bearing on individual- and contextual-level predictors. Descriptions of the criteria are presented along with the model estimates.

Supervision level $supLvl_i$ took on one of four values:²⁸ $109/199 = 0.54$ were supervised at the maximum level and $47/199 = 0.24$ were supervised at the intensive level. The remaining offenders were supervised at medium $32/199 = 0.16$ and minimum $11/199 = 0.055$ levels.

The majority of offenders began supervision between calendar years 2002 ($53/199 = 0.27$) and 2003 ($92/199 = 0.46$); $31/199 = 0.16$ began in 2004; $14/199 = 0.07$ began in 2001; and $8/199 = 0.04$ began in 2000.²⁹ The shortest supervision period was 2 weeks and 2 days; the longest was 6 years and 29 days. Median length of supervision was 1 year and 47 days; the 0.25 and 0.75 quantiles span from 42 weeks to 2 years. On average, sampled offenders served between 109 and 166 (95%CI) fewer days than expected given the expiration date in the original full term sentence. As a function of the sampling all offenders terminated sentences during the interval spanning January 1, 2004 to December, 31, 2004.³⁰ Supervision period begin dates $beginDt_i$,

²⁸With the exception of one offender whose supervision level remained undetermined. Supervision level for this offender was recoded from TBD to the sample mode, MAX.

²⁹One offender began supervision in 1998—1 year and 289 days before the next earliest begin date. This offender is excluded from Figures 1 and 2.

³⁰One offender officially terminated supervision in 2004, but is treated as though he terminated in June, 2003. Within three months after beginning supervision in April, 2003 this offender absconded. A warrant was issued and his super-

Table 7

CSOSA Risk-needs Screener, social characteristics, $n = 199$.

Symbol	Description	Level	95% CI/Proportion
<i>rnsAge</i>	Age at the time of assessment		[31.6, 34.6]
<i>rnsEdu</i>	Educational level	<i>10th or below</i>	$\frac{48}{199}$ 0.24
		<i>11th</i>	$\frac{35}{199}$ 0.18
		<i>HS/GED</i>	$\frac{78}{199}$ 0.39
		<i>Some college</i>	$\frac{38}{199}$ 0.19
<i>rnsSSN</i>	Significant relationships	<i>No relationships</i>	$\frac{10}{199}$ 0.0503
		<i>Relationship with one person</i>	$\frac{16}{199}$ 0.0804
		<i>Relationship with two or more people</i>	$\frac{173}{199}$ 0.87
<i>rnsRL</i>	Recent loss	<i>Yes</i>	$\frac{37}{199}$ 0.19
<i>rnsSta</i> ^a	Instability	<i>Currently/Recently incarcerated/shelter</i>	$\frac{61}{199}$ 0.31
		<i>Two or fewer changes</i>	$\frac{77}{199}$ 0.39
		<i>Three or more changes</i>	$\frac{61}{199}$ 0.31

^a Derived from RNS items *rnsEmp* and *rnsRes*.

expected termination dates $outTrmDtExp_i$, termination dates $outTrmDt_i$, and termination modes $outTrmMod_i$ are shown in Figures 1 and 2.³¹

The Risk-needs Screener (RNS) items are described in Table 7 through Table 9. Items capturing demographic and social characteristics, including age, education, significant relationships, recent loss, and instability are shown in Table 7. Those capturing criminal histories are shown in Table 8. Substance abuse, mental health, and agency responsiveness to offenders—including impressions of risk and cooperation—are shown in Table 9.

Items obtained from the Presentence Investigation report (PSI) as well as those derived therein are shown in Tables 10–19. Table 10 summarizes substance use and abuse measures. Crim-

vision status was changed to reflect that monitoring was no longer possible, but it was not until March, 2004, that his supervision period was officially terminated. Delayed termination in this case captures more administrative than behavioral effects and, thus, I treat the date of termination for this offender (as well as that for the only other absconder) as the date of the first of an unending series of contact losses.

³¹Plots are shown by supervision level $supLvl_i$ only to ease digestion: no relationship is implied.

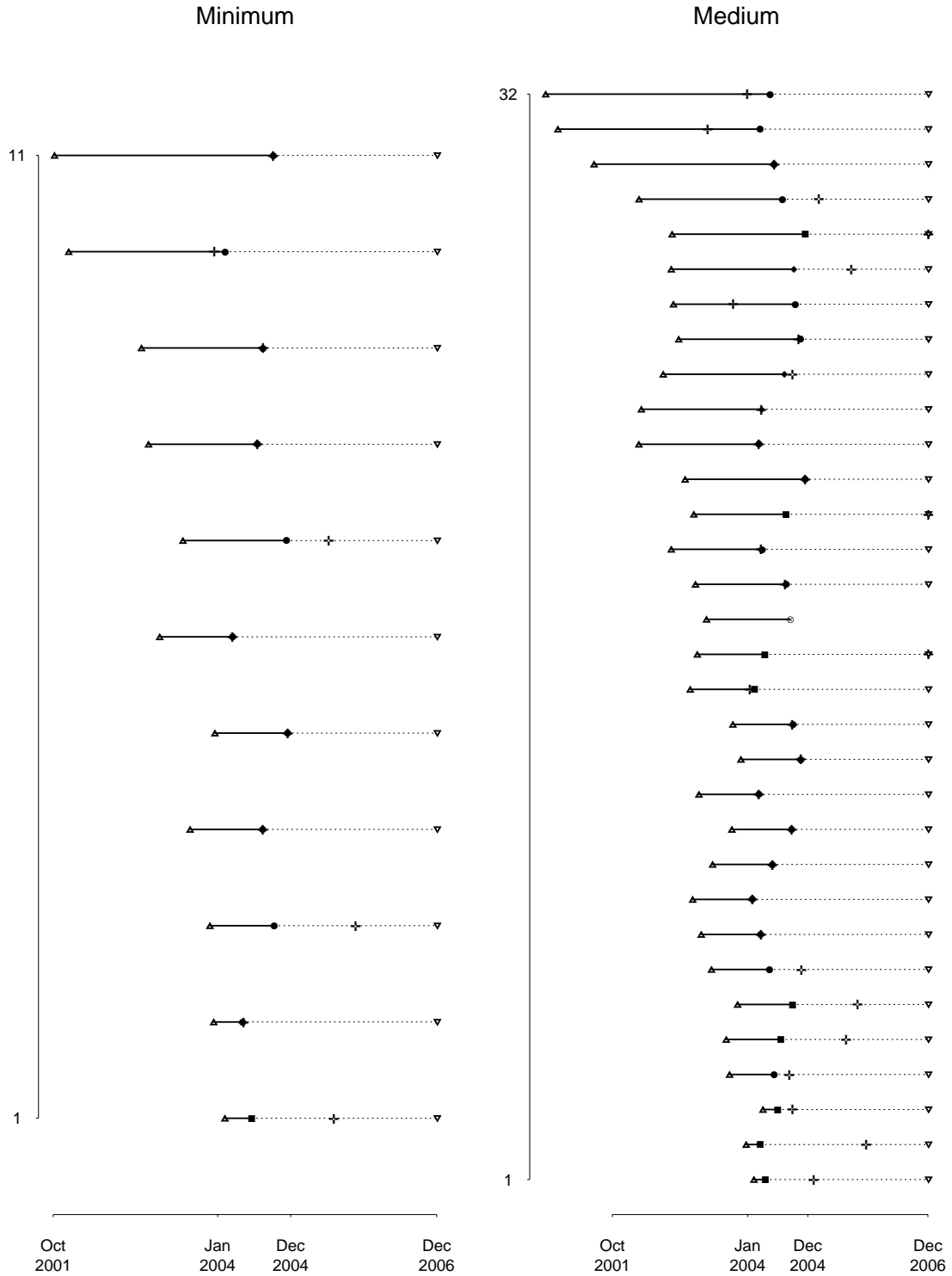


Figure 1. Begin date $beginDt_i$ (Δ), expected termination date $outTrmDtExp_i$ (+), and termination date $outTrmDt_i$ marked by termination mode $outTrmMod_i$ [absconscion (\oplus), death (\otimes), revocation (\blacksquare), successful (\bullet), and unsuccessful (\blacklozenge)], and follow-up close dates (∇) by supervision level for minimum ($n = 11$) and medium ($n = 32$) supervision levels.

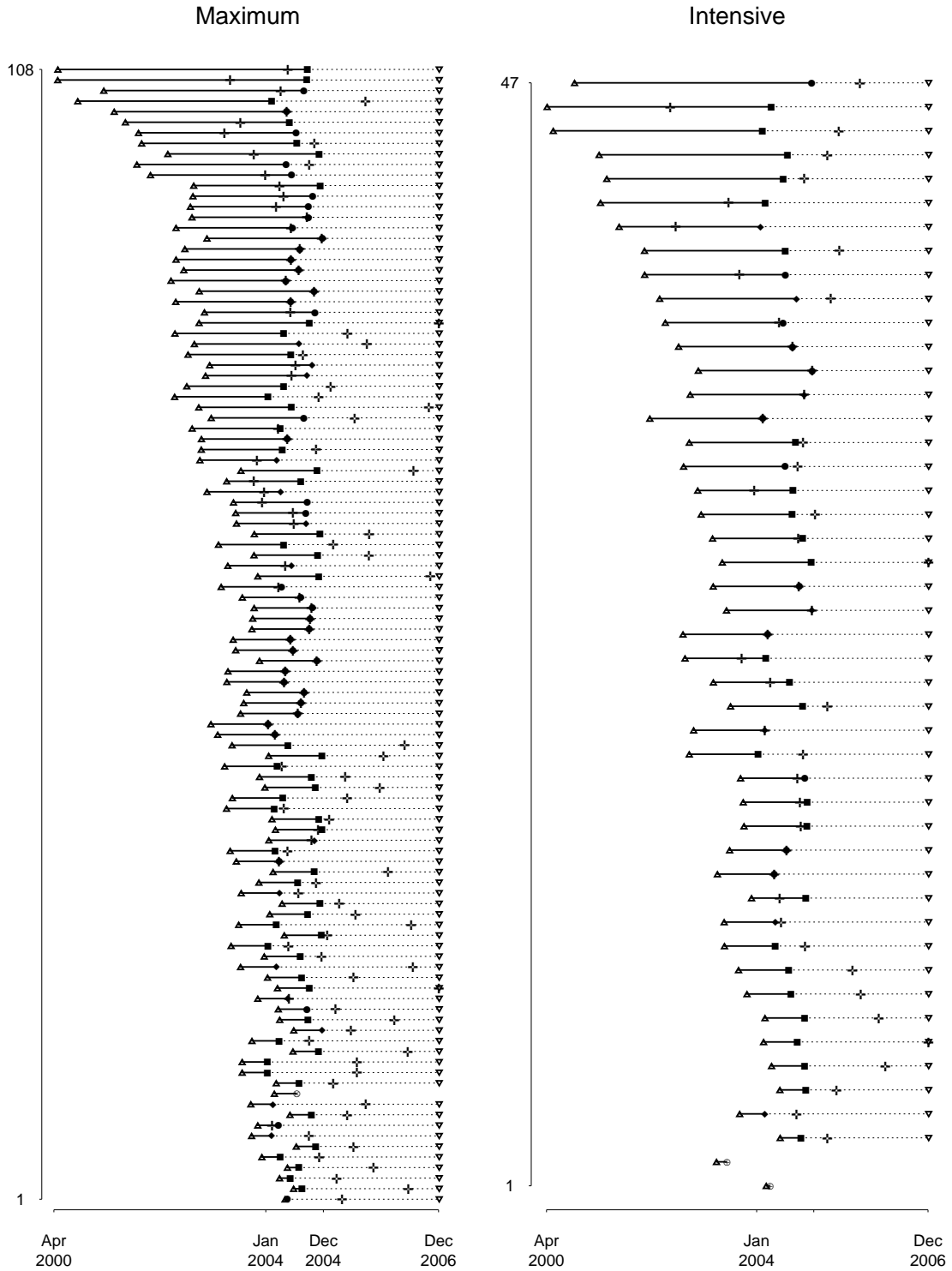


Figure 2. Begin date $beginDt_i$ (Δ), expected termination date $outTrmDtExp_i$ (+), and termination date $outTrmDt_i$ marked by termination mode $outTrmMod_i$ [absconscion (\oplus), death (\otimes), re-conviction (\blacksquare), successful (\bullet), and unsuccessful (\blacklozenge)], and follow-up close dates (∇) by supervision level for maximum ($n = 109$) and intensive ($n = 47$) supervision levels.

Table 8

CSOSA Risk-needs Screener, criminal history characteristics, $n = 199$.

Symbol	Description	Level	Proportion
<i>rnsPV</i>	Prior violent offense	<i>None</i>	$\frac{124}{199}$ 0.62
		<i>One</i>	$\frac{41}{199}$ 0.21
		<i>Two or More</i>	$\frac{34}{199}$ 0.17
<i>rnsNPA</i>	Prior adult arrests	<i>Two or less</i>	$\frac{68}{199}$ 0.34
		<i>Three to Four</i>	$\frac{45}{199}$ 0.23
		<i>Five</i>	$\frac{12}{199}$ 0.0603
		<i>Six or more</i>	$\frac{74}{199}$ 0.37
<i>rnsPS</i>	Prior supervision failures	<i>None</i>	$\frac{120}{199}$ 0.6
		<i>One to Two</i>	$\frac{66}{199}$ 0.33
		<i>Three or more</i>	$\frac{13}{199}$ 0.065
<i>rnsFA</i>	Frequency of arrests/year	<i>None</i>	$\frac{84}{199}$ 0.42
		<i>One</i>	$\frac{78}{199}$ 0.39
		<i>Two to Four</i>	$\frac{37}{199}$ 0.19
<i>rnsAF</i>	Age at first arrest	<i>15 and younger</i>	$\frac{28}{199}$ 0.14
		<i>16 to 17</i>	$\frac{37}{199}$ 0.19
		<i>18 to 25</i>	$\frac{112}{199}$ 0.56
		<i>Over 26</i>	$\frac{22}{199}$ 0.11
<i>rnsPC</i>	Prior convictions	<i>None</i>	$\frac{54}{199}$ 0.27
		<i>One to Five</i>	$\frac{121}{199}$ 0.61
		<i>Six or more</i>	$\frac{24}{199}$ 0.12

inal histories are described through Tables 11–14. Treatment histories are described in Table 15. Family characteristics are shown in Table 16. Social characteristics are shown in Table 17. Educational and employment characteristics are shown in Table 18. Health characteristics obtained from the PSIs are shown in Table 19.

What I move into next is a generalization of the geopolitical characteristics of the areas in which sampled offenders reside. It begins with a description of the geographical unit, the U.S.

Table 9

CSOSA Risk-needs Screener, substance use, mental health, and agency responsiveness, $n = 199$.

Symbol	Description	Level	Proportion
<i>rnsDrg</i> ^a	Substance use	<i>rnsHSA=NO</i>	$\frac{32}{199}$ 0.16
		<i>rnsHSA=YES & rnsCSA=NO</i>	$\frac{94}{199}$ 0.47
		<i>rnsHSA=YES & rnsCSA=YES</i>	$\frac{73}{199}$ 0.37
<i>rnsMH</i> ^b	History or current mental disorder	<i>Yes</i>	$\frac{11}{199}$ 0.055
<i>rnsImp</i>	CSO Impression	<i>Low</i>	$\frac{53}{199}$ 0.27
		<i>Medium</i>	$\frac{94}{199}$ 0.47
		<i>High</i>	$\frac{52}{199}$ 0.26
<i>rnsFullCoop</i> ^a	Fully cooperative	<i>Yes</i>	$\frac{170}{199}$ 0.85

^a Derived from RNS items *rnsCSA* and *rnsHSA*. ^b Derived from RNS items *rnsCMD* and *rnsHMD*.

Census Bureau (Census) block-group (BG), then moves into a summary of how the contextual predictors vary across these units.

The BG was chosen because, unlike the census tracts within which they are nested, they were intentionally designed to represent near-neighborhoods and, unlike the smaller clusters of blocks they encompass, their sample data is publicly available from the Census.³² Among the $k = 436$ BGs, $122/436 = 0.28$ were occupied by sampled offenders: $75/436 = 0.17$ were occupied by only 1, $27/436 = 0.06$ by 2, and $20/436 = 0.05$ by 3 or more. There were 3 BGs having 5 offender residents each.

³²There are 433 DC BGs, but, all in all, there are $k = 436$ BGs included in this discussion. A data integrity slippage resulted in the inclusion of 3 residents of neighboring Prince George's county, Maryland, in the sample of Black, male probationers. Usually, non-DC residents supervised by the CSOSA are done so pursuant to the the Interstate Compact (Court Services and Offender Supervision for the District of Columbia [CSOSA], 2004) which provides the DC "may enter into a compact with any of the United States for the mutual helpfulness in relation to persons convicted of crimes or offenses who may be on probation or parole." Non-DC resident offenders are usually classified not as regularly supervised but rather as interstate compact offenders. As the sample frame for this study included only regularly supervised probationers, a decision was made to include these 3 non-DC residents in the study sample after weighing costs associated with data loss in an already-limited sample against those of introducing both artifacts due to their unlikeness vis-à-vis the population and difficulties in recovering comparable environmental characteristics.

Table 10

Presentence Investigation report, ever used and admits to problem with substances, by substance
 $n = 199$.

Symbol	Description	Level	Proportion
<i>psiSubAlAP</i>	Admits to problem, alcohol	Yes	$\frac{17}{199}$ 0.085
<i>psiSubAlEU</i>	Ever use, alcohol	Yes	$\frac{98}{199}$ 0.49
<i>psiSubAmAP</i>	Admits to problem, amphetamines	Yes	$\frac{3}{199}$ 0.015
<i>psiSubAmEU</i>	Ever use, amphetamines	Yes	$\frac{13}{199}$ 0.065
<i>psiSubCoAP</i>	Admits to problem, cocaine	Yes	$\frac{36}{199}$ 0.18
<i>psiSubCoEU</i>	Ever use, cocaine	Yes	$\frac{106}{199}$ 0.53
<i>psiSubMaAP</i>	Admits to problem, marijuana	Yes	$\frac{43}{199}$ 0.22
<i>psiSubMaEU</i>	Ever use, marijuana	Yes	$\frac{159}{199}$ 0.8
<i>psiSubHeAP</i>	Admits to problem, opiates	Yes	$\frac{29}{199}$ 0.15
<i>psiSubHeEU</i>	Ever use, opiates	Yes	$\frac{48}{199}$ 0.24
<i>psiSubPcAP</i>	Admits to problem, PCP	Yes	$\frac{22}{199}$ 0.11
<i>psiSubPcEU</i>	Ever use, PCP	Yes	$\frac{79}{199}$ 0.4
<i>psiSubEU1</i> ^a	Number ever used, substances out of 7	[0, 3)	$\frac{95}{199}$ 0.48
		3	$\frac{59}{199}$ 0.3
		[4, 7]	$\frac{45}{199}$ 0.23
<i>psiSubEU2</i>	Ever used any of 7 substances	Yes	$\frac{187}{199}$ 0.94
<i>psiSubAP1</i> ^a	Number admit to problem, substances out of 6	0	$\frac{125}{199}$ 0.63
		1	$\frac{31}{199}$ 0.16
		[2, 5]	$\frac{43}{199}$ 0.22
<i>psiSubAP2</i>	Admits to problem with any of 6 substances	Yes	$\frac{74}{199}$ 0.37

^a Discretized for presentation.

Table 11

Presentence Investigation report, juvenile and adult offending histories, $n = 199$.

Symbol	Description	Level	Proportion
$psiCrmJuvCasN$	Number, juvenile cases	None	$\frac{133}{199}$ 0.67
		One	$\frac{21}{199}$ 0.11
		Two or more	$\frac{45}{199}$ 0.23
$psiCrmJuvAdj$	Number, adjudications	None	$\frac{152}{199}$ 0.76
		One or more	$\frac{47}{199}$ 0.24
$psiCrmJuvCon$	Number, juvenile confinements	None	$\frac{182}{199}$ 0.91
		One or more	$\frac{17}{199}$ 0.085
$psiCrmAdlCasN^a$	Number, adult cases	[0, 4)	$\frac{65}{199}$ 0.33
		[4, 7)	$\frac{38}{199}$ 0.19
		[7, 13)	$\frac{50}{199}$ 0.25
		[13, 37]	$\frac{46}{199}$ 0.23
$psiCrmAdlCnvN^a$	Number, convictions	[0, 2)	$\frac{79}{199}$ 0.4
		2	$\frac{29}{199}$ 0.15
		[3, 6)	$\frac{45}{199}$ 0.23
		[6, 18]	$\frac{46}{199}$ 0.23

^a Discretized for presentation.

The DC is the most densely populated of the U.S. with roughly 3,600 people per km². The 95%CI around mean block-group population spans [1250, 1401]; around mean households, [536, 614]; and around mean family units, [254, 285]. Not all geographic units in the DC have residential populations. Several in fact have populations, households, or family units equal to zero.³³

A majority ($\frac{347214}{578133} = 0.60$) of the residents are Black; a small proportion ($\frac{73904}{578133} = 0.13$) is foreign born; and an even smaller proportion ($\frac{45151}{578133} = 0.078$) is Hispanic. The ratio

³³Specifically, there are zero populations in census tracts 54.02, 57.02, 62.02, 89.05; zero housing units in tracts 54.02, 57.02, 62.02, 73.08, 89.05, and 98.09; and zero family units in tracts 2.01, 54.02, 57.02, 62.02, 73.08, 89.05, 95.01, and 98.09. Measures drawn from the Summary File 3 (SF3) that rely on these units are thus incalculable, and, as imputation would be meaningless, such units are dropped from estimation when necessary.

Table 12

Presentence Investigation report, adult conviction histories, by conviction type $n = 199$.

Symbol	Description	Level	Proportion
<i>psiCrmAdlCnvVio</i>	Number, violent convictions	None	$\frac{147}{199}$ 0.74
		One	$\frac{34}{199}$ 0.17
		Two or more	$\frac{18}{199}$ 0.09
<i>psiCrmAdlCnvNsp</i>	Number, NSP convictions	None	$\frac{158}{199}$ 0.79
		One	$\frac{32}{199}$ 0.16
		Two or more	$\frac{9}{199}$ 0.045
<i>psiCrmAdlCnvWea</i> ^a	Number, weapons convictions	0	$\frac{162}{199}$ 0.81
		[1, 9]	$\frac{37}{199}$ 0.19
<i>psiCrmAdlCnvPro</i>	Number, property convictions	None	$\frac{133}{199}$ 0.67
		One	$\frac{30}{199}$ 0.15
		Two or more	$\frac{36}{199}$ 0.18
<i>psiCrmAdlCnvDrg</i>	Number, drugs convictions	None	$\frac{85}{199}$ 0.43
		One	$\frac{45}{199}$ 0.23
		Two or more	$\frac{69}{199}$ 0.35

^a Discretized for presentation.

of residents ages 17 and younger to those ages 18 and older is $\frac{115634}{462499} = 0.25$. Less than a quarter ($\frac{86071}{388982} = 0.22$) of the residents ages 25 and older failed to earn a high school diploma. One-half ($\frac{272935}{545475} = 0.50$) of the residents ages 5 and older have been living in the same house for 5 years or more. The majority ($\frac{147585}{250525} = 0.59$) of occupied housing units are occupied by renters rather than owners. $\frac{47784}{250745} = 0.19$ of the households comprise female householders with no husband present. Officially, $\frac{109837}{547312} = 0.20$ of the population for whom poverty status is known are impoverished; only $\frac{13683}{250745} = 0.055$ of the households receive public assistance. Among the population ages 16 and over in the civilian labor force, $\frac{31937}{297719} = 0.11$ are unemployed. Following Sampson et al. (1997), the items *piPov*, *piPub*, *piFHH*, *piUne*, *rtAK*, *piBlk*, *piHis*, *piFor*, *piRnt*, and *piDif* were summarized with factor scores. Loadings after oblimin rotation are shown in Table 20.

Table 13

Presentence Investigation report, triggering offense, $n = 199$.

Symbol	Description	Level	95% CI/Proportion
<i>psiOfense</i>	Triggering offense	<i>Drug-related</i>	$\frac{118}{199}$ 0.59
		<i>Violent</i>	$\frac{37}{199}$ 0.19
		<i>Property</i>	$\frac{19}{199}$ 0.095
		<i>Non-violent, weapons</i>	$\frac{16}{199}$ 0.0804
		<i>Other</i>	$\frac{9}{199}$ 0.045
<i>psiStaAgr</i>	Agrees with offense account?	<i>Yes</i>	$\frac{166}{199}$ 0.83
<i>psiStaBlaD</i>	Does the offender blame drugs?	<i>Yes</i>	$\frac{25}{199}$ 0.13
<i>psiStaBlaM</i>	Blames mental disorder?	<i>Yes</i>	$\frac{1}{199}$ 0.005
<i>psiStaBlaP</i>	Does the offender blame police?	<i>Yes</i>	$\frac{9}{199}$ 0.045
<i>psiStaBlaS</i>	Does offender blame self?	<i>Yes</i>	$\frac{51}{199}$ 0.26
<i>psiStaBlaV</i>	Does the offender blame victim?	<i>Yes</i>	$\frac{11}{199}$ 0.055
<i>psiOffInj</i>	Someone physically injured?	<i>Yes</i>	$\frac{28}{199}$ 0.14
<i>psiOffMon</i>	Police recovered money?	<i>Yes</i>	$\frac{77}{199}$ 0.39
<i>psiNSPBra</i>	Instant offense is bail-reform	<i>Yes</i>	$\frac{16}{199}$ 0.0804
<i>psiOffDrgSus</i>	Police suspect influence of drugs	<i>Yes</i>	$\frac{11}{199}$ 0.055
<i>psiOffDrgVer</i>	Drug use verified	<i>Yes</i>	$\frac{11}{199}$ 0.055
<i>psiOffIntSus</i>	Police suspect influence of alcohol	<i>Yes</i>	$\frac{4}{199}$ 0.0201
<i>psiOffIntVer</i>	Intoxication verified	<i>Yes</i>	$\frac{1}{199}$ 0.005
<i>psiSubLuPosA</i>	At lock-up, positive for alcohol	<i>Yes</i>	$\frac{4}{199}$ 0.0201
<i>psiSubLuPosD</i>	At lock-up, positive for drugs	<i>Yes</i>	$\frac{43}{199}$ 0.22
<i>psiCrmAdlSFS</i>	Salient Factor Score		[5.47, 6.28]
<i>psiSR</i>	Recommended sentence	<i>Probation</i>	$\frac{109}{199}$ 0.55
		<i>Incarceration</i>	$\frac{55}{199}$ 0.28
		<i>Split-sentence</i>	$\frac{35}{199}$ 0.18

Table 14

Presentence Investigation report, sentence and supervision histories, $n = 199$.

Symbol	Description	Level	Proportion
$psiSupSta$	Criminal justice status at time of arrest	<i>Fugitive</i>	$\frac{3}{199}$ 0.015
		<i>Probation</i>	$\frac{42}{199}$ 0.21
		<i>Parole</i>	$\frac{4}{199}$ 0.02
		<i>Free</i>	$\frac{150}{199}$ 0.75
$psiCrmAdlSupNPr^a$	Number, probation sentences	0	$\frac{54}{199}$ 0.27
		1	$\frac{54}{199}$ 0.27
		[2, 4)	$\frac{56}{199}$ 0.28
		[4, 9]	$\frac{35}{199}$ 0.18
$psiCrmAdlSupNPa^a$	Number, post-incarceration parole	0	$\frac{167}{199}$ 0.84
		[1, 5]	$\frac{32}{199}$ 0.16
$psiCrmAdlIncn^a$	Number, confinement sentences > 30 days	0	$\frac{74}{199}$ 0.37
		1	$\frac{36}{199}$ 0.18
		[2, 5)	$\frac{48}{199}$ 0.24
		[5, 13]	$\frac{41}{199}$ 0.21
$psiSupRev$	Number, previous supervision failures	<i>None</i>	$\frac{109}{199}$ 0.55
		<i>One</i>	$\frac{43}{199}$ 0.22
		<i>Two or more</i>	$\frac{47}{199}$ 0.24
$psiSupAbs$	Number, previous supervision absconsions	<i>None</i>	$\frac{193}{199}$ 0.97
		<i>One</i>	$\frac{5}{199}$ 0.025
		<i>Two or more</i>	$\frac{1}{199}$ 0.005
$psiSupWar$	Number, previous violation warrants	<i>None</i>	$\frac{169}{199}$ 0.85
		<i>One</i>	$\frac{23}{199}$ 0.12
		<i>Two or more</i>	$\frac{7}{199}$ 0.035
$psiCrmAdlSupRev$	Number, probation or parole revocations	<i>None</i>	$\frac{120}{199}$ 0.6
		<i>One</i>	$\frac{44}{199}$ 0.22
		<i>Two or more</i>	$\frac{35}{199}$ 0.18

^b Incarceration sentence for length greater than 30 days.

Table 15

Presentence Investigation report, treatment histories, $n = 199$.

Symbol	Description	Level	Proportion
$psiS upT xDr$	Number, drug treatment referrals	<i>None</i>	$\frac{123}{199}$ 0.62
		<i>One</i>	$\frac{43}{199}$ 0.22
		<i>Two or more</i>	$\frac{33}{199}$ 0.17
$psiS upT xDx$	Number, detoxification referrals	<i>None</i>	$\frac{178}{199}$ 0.89
		<i>One</i>	$\frac{19}{199}$ 0.095
		<i>Two or more</i>	$\frac{2}{199}$ 0.0101
$psiS upT xMh$	Number, mental health referrals	<i>None</i>	$\frac{188}{199}$ 0.94
		<i>One</i>	$\frac{10}{199}$ 0.0503
		<i>Two or more</i>	$\frac{1}{199}$ 0.005
$psiS ubT xAny$	Any previous drug or alcohol treatments	<i>Yes</i>	$\frac{78}{199}$ 0.39

There were 19,087 business licensees³⁴ across $k = 1, 2, \dots, 433$ BGs in the District. Densities within BGs ranged between [132, 248] licensees per 1,000 housing units (95%CI). There were 1,663 retail alcohol licensees across BGs. By far, the majority of these retailers were those $983/1663 = 0.59$ licensed for on-premises sales of beer, wine, and spirits. The 95%CI around mean densities of alcohol licensees per 200,000 m² of BG land area are shown in Table 21.

The 95%CI around mean arrest rates are shown in Table 22. Rates capture the number of arrests per 1,000 residents ages 18 and older for violent, property, alcohol and drug, public order, and unclassified crimes as well as an index of all crimes.

In the next section I describe the models operationalizing negative supervision performance (NSP). Criteria are tabulated in Table 23, and in each section that follows I describe the criterion of interest, the steps taken to reduce the pool of potential predictors, and the development of the model. I then present model estimates and conclude each section with an interpretation of these estimates. These findings are discussed in greater detail in the chapter that follows.

³⁴Excluding licensed alcohol retailers.

Table 16

Presentence Investigation report, family characteristics, $n = 199$.

Symbol	Description	Level	Proportion
<i>psiFamMarBir</i>	Parent marital status at birth	<i>Not cohabiting</i>	$\frac{80}{199}$ 0.40
		<i>Cohabiting, unmarried</i>	$\frac{27}{199}$ 0.14
		<i>Cohabiting, married</i>	$\frac{92}{199}$ 0.46
<i>parentInvolved</i>	Either parent uninvolved	<i>Yes</i>	$\frac{94}{199}$ 0.47
<i>parentAlive</i>	Both parents alive	<i>Yes</i>	$\frac{109}{199}$ 0.55
<i>raisedBy</i>	Single mother or father or extended family	<i>Yes</i>	$\frac{108}{199}$ 0.54
<i>psiFamRaixf</i>	Raised by extended family	<i>Yes</i>	$\frac{51}{199}$ 0.26
<i>psiFamRaiFf</i>	Raised by foster family	<i>Yes</i>	$\frac{9}{199}$ 0.045
<i>parentContact</i>	Sustained contact ^a with both parents	<i>Yes</i>	$\frac{104}{199}$ 0.52
<i>psiFamSSN</i>	Supportive social network	<i>Yes</i>	$\frac{82}{199}$ 0.41
<i>psiFamSibAl^b</i>	Number of siblings	[0, 3)	$\frac{67}{199}$ 0.34
		3	$\frac{37}{199}$ 0.19
		[4, 7)	$\frac{62}{199}$ 0.31
		[7, 24]	$\frac{33}{199}$ 0.17
		<i>anyAbuse</i>	Any report of abuse
<i>psiFamNowFb</i>	Father alive at birth	<i>Yes</i>	$\frac{191}{199}$ 0.96
<i>psiFamSibBn^b</i>	Number of blood-siblings	[0, 3)	$\frac{74}{199}$ 0.37
		3	$\frac{34}{199}$ 0.17
		[4, 6)	$\frac{42}{199}$ 0.21
		[6, 24]	$\frac{49}{199}$ 0.25

^a Until instant offense. If deceased, until time of death. ^b Discretized for presentation.

Estimation

Substance use

Model **MS1** estimates factors associated with population probabilities of ever testing positive, providing a bogus specimen, or failing to appear for a drug-testing event while supervised and Models **MS2A**, **MS2B**, . . . , **MS2G** estimate factors associated with how often probationers test positive for the k th screened substance.

Table 17

Presentence Investigation report, social characteristics, $n = 199$.

Symbol	Description	Level	Proportion
<i>psiS ocMar</i>	Cohabiting	<i>Yes</i>	$\frac{149}{199}$ 0.75
<i>psiS ocHouFa</i>	Lives with extended family ^a	<i>Yes</i>	$\frac{109}{199}$ 0.55
<i>psiS ocTon</i> ^b	Number, children ^c total	0	$\frac{72}{199}$ 0.36
		1	$\frac{68}{199}$ 0.34
		2	$\frac{33}{199}$ 0.17
		3	$\frac{13}{199}$ 0.0653
		[4, 12]	$\frac{13}{199}$ 0.0653
		<i>psiS ocChlBil</i>	Number, biological children ^c living with
<i>One</i>	$\frac{23}{199}$ 0.11		
<i>Two or more</i>	$\frac{15}{199}$ 0.075		
<i>psiS ocChlBin</i>	Number, biological children	<i>None</i>	$\frac{53}{199}$ 0.27
		<i>One</i>	$\frac{60}{199}$ 0.3
		<i>Two</i>	$\frac{39}{199}$ 0.2
		<i>Three or more</i>	$\frac{47}{199}$ 0.24
<i>psiS ocChlStn</i>	Number, step-children	<i>None</i>	$\frac{192}{199}$ 0.96
		<i>One</i>	$\frac{2}{199}$ 0.01
		<i>Two or more</i>	$\frac{5}{199}$ 0.025

^a Including parents, siblings, aunts, uncles, cousins, or grandparents, for instance.

^b Discretized for presentation. ^c Ages 18 and younger.

Sampled offenders had, on average, just over one year of drug testing data ($M = 14.7, SD = 9.86$) with about 5 drug testing events monthly, $M = 4.69, SD = 1.57$. Not all of the 7 substances were screened at each event: offenders³⁵ were screened for at least 3 substances and, typically, for 4 or 5. Nearly all offenders were screened at least once for phencyclidine, cocaine, marijuana, and opiates ($\frac{190}{199} = 0.95$, $\frac{194}{199} = 0.97$, and $\frac{194}{199} = 0.97$, $\frac{194}{199} = 0.97$, respectfully). $\frac{67}{199} = 0.34$ of the sample was screened at least once for methadone, $\frac{74}{199} = 0.37$ for alcohol, and $\frac{77}{199} = 0.39$ for amphetamines.

³⁵Excluding $n = 5$ offenders who did not have any drug testing events.

Table 18

Presentence Investigation report, educational and employment characteristics, $n = 199$.

Symbol	Description	Level	Proportion
<i>psiEduGED</i>	Earned GED ^a	<i>Yes</i>	$\frac{33}{199}$ 0.17
<i>psiEduGrdAt</i> ^b	Highest grade attempted	[0, 11)	$\frac{63}{199}$ 0.32
		11	$\frac{46}{199}$ 0.23
		12	$\frac{62}{199}$ 0.31
		[13, 16]	$\frac{28}{199}$ 0.14
<i>psiEduGrdCm</i> ^b	Highest grade completed	[6, 10)	$\frac{53}{199}$ 0.27
		[10, 12)	$\frac{71}{199}$ 0.36
		12	$\frac{51}{199}$ 0.26
		[13, 16]	$\frac{24}{199}$ 0.12
<i>psiEmpLess</i>	Any jobs of duration < 30 days	<i>Yes</i>	$\frac{24}{199}$ 0.12
<i>psiEmpMore</i>	Any jobs of duration > 30 days	<i>Yes</i>	$\frac{155}{199}$ 0.78

^a If not high school graduate. ^b Discretized for presentation.

Table 19

Presentence Investigation report, health characteristics, $n = 199$.

Symbol	Description	Level	Proportion
<i>psiMedDis</i>	Number, physical disabilities	<i>None</i>	$\frac{191}{199}$ 0.96
		<i>One or more</i>	$\frac{8}{199}$ 0.0402
<i>psiMedMdDx</i>	Has the offender been diagnosed with a mental illness	<i>Yes</i>	$\frac{17}{199}$ 0.085
<i>psiMedMdDr</i>	Does the offender take any psychotropic medications?	<i>Yes</i>	$\frac{13}{199}$ 0.065
<i>psiMedMdHo</i>	Times previously hospitalized for mental health	<i>None</i>	$\frac{192}{199}$ 0.96
		<i>One or more</i>	$\frac{7}{199}$ 0.035
<i>psiMedInj</i>	How many injuries are listed?	<i>None</i>	$\frac{145}{199}$ 0.73
		<i>One</i>	$\frac{41}{199}$ 0.21
		<i>Two or more</i>	$\frac{13}{199}$ 0.065
<i>psiMedWouGun</i>	Wounds result from gunshots	<i>None</i>	$\frac{179}{199}$ 0.90
		<i>One or more</i>	$\frac{20}{199}$ 0.10
<i>psiMedWouStb</i>	Wounds resulting from stabbings?	<i>None</i>	$\frac{192}{199}$ 0.96
		<i>One or more</i>	$\frac{7}{199}$ 0.035

Table 20

U.S. Census, subset of sociodemographic characteristics, 3-Factor solution, oblimin, $k = 436$.

Variable	Description	Factor/Loading
		Concentrated disadvantage
<i>piPov</i>	$\frac{\text{Population}^c, \text{ income in 1999} < \text{poverty level}}{\text{Population}^c}$	0.76
<i>piPub</i>	$\frac{\text{Households, public assistance income}}{\text{Households}}$	0.88
<i>piFHH</i>	$\frac{\text{Households, female, no husband present}}{\text{Households}}$	0.89
<i>piUne</i>	$\frac{\text{Population}^d, \text{ unemployed}}{\text{Population}^d}$	0.56
<i>rtAK</i>	$\frac{\text{Children}^e}{\text{Adults}^f}$	0.86
<i>piBlk</i>	$\frac{\text{Population, Black}}{\text{Population}}$	0.67
		Immigrant concentration
<i>piHis</i>	$\frac{\text{Population, Hispanic or Latino}}{\text{Population}}$	0.83
<i>piFor</i>	$\frac{\text{Population, foreign born}}{\text{Population}}$	0.92
		Residential stability
<i>piRnt</i>	$\frac{\text{Housing units, renter occupied}}{\text{Occupied housing units}}$	0.63
<i>piDif</i>	$\frac{\text{Population}^a, \text{ different house in 1995}}{\text{Population}^a}$	0.87

Table 21

One-sided 95% confidence limit below (LCLM) and above (UCLM) mean densities of alcohol licensees per 200,000 m² of BG land area, 2004, $k = 433$.

Variable	Description	LCLM	UCLM
<i>alcBWS1</i>	Off-premises sale of beer, wine, and spirits	0.38	0.64
<i>alcBW1</i>	Off-premises sale of beer and wine only	0.73	1.2
<i>alcBWS2</i>	On-premises sale of beer, wine, and spirits	0.59	1.4
<i>alcBW2</i>	On-premises sale of beer and wine only	0.024	0.17
<i>alcDens</i>	Total licensees	1.9	3.2

Table 22

One-sided 95% confidence limit below (LCLM) and above (UCLM) mean block-group arrests per 1,000 residents ages 18 and older, 2004, $k = 436$.

Variable	Description	LCLM	UCLM
<i>arrVio</i>	Violent	19.5	25.7
<i>arrPro</i>	Property	10.9	20.7
<i>arrDrg</i>	Drug- and alcohol-related	18.9	42.4
<i>arrPub</i>	Public-order	19.3	38.6
<i>arrOth</i>	Unclassified	50.6	93.9
<i>arrDens</i>	Total Arrests	124	217

Table 23

Description of criteria.

Criteria	<i>M</i>	<i>SD</i>	<i>N</i>
Failed a drug testing event while supervised	0.79	0.41	199
Rate of positive screens for alcohol	0.14	0.26	74
Rate of positive screens for methadone	0.02	0.10	67
Rate of positive screens for amphetamines	0.00	0.02	77
Rate of positive screens for cocaine	0.07	0.14	194
Rate of positive screens for marijuana	0.10	0.17	194
Rate of positive screens for opiates	0.03	0.10	194
Rate of positive screens for phencyclidine	0.03	0.10	190
Convicted of new crime during supervision period	0.26	0.44	199
Convicted of new crime during post-supervision period	0.25	0.43	199
Number of supervision-related violations	1.53	2.47	199
Number of drug-related violations	2.40	3.81	199
Terminated unsuccessfully	0.58	0.50	199
Months until termination	17.24	11.41	199

Among those screened, $93/194 = 0.48$ failed at least one screen for cocaine, $41/194 = 0.21$ failed at least one screen for opiates, $33/190 = 0.17$ failed at least one for phencyclidine, $81/194 = 0.42$ failed at least one for marijuana, $33/74 = 0.45$ failed at least one for alcohol, $5/77 = 0.065$ failed at least one for amphetamines, and $4/67 = 0.06$ failed at least one screen for methadone.

MS1. The criterion for **MS1** is whether the i th probationer ever tested positive, provided a bogus specimen, or failed to appear for a drug testing event while supervised (if so, $outS1_i = 1$), and, indeed, a large fraction ($158/199 = 0.79$) of the sampled probationers did so. The 95%CI around mean $outS1$ spanned $[0.74, 0.85]$. Interest centers on the predicted probability of the criterion, $\widehat{\Pr}(outS1_i = 1)$.

Potential predictors were included in a general model which was then recursively partitioned³⁶ into the binary tree shown in Figure 3a.³⁷ This classification tree, since it was likely too complex to validate, was trimmed back to that shown in Figure 3b.³⁸

Predictors having the largest effect on whether probationers ever fail a drug-testing event while supervised included (a) the number of substances out of 7 the offender ever used $psiSubEU1_i$, (b) the expected number of days of supervision $daysSupExp_i$, and (c) the rate of property-related arrests within the block-group $arrPro.d_i$; remaining predictors did not appear in the model.

The resultant model separated sampled probationers into 4 groups. The groups (and predicted values) included (a) probationers having used fewer than 1 substance out of 7 (No); (b) probationers having used 1 or more substances out of 7 and expecting more than 563 days of supervision (Yes); (c) probationers having used 1 or more substances out of 7, expecting less than 563 days of supervision, and living within a BG having a rate of property-related arrests below 25.55

³⁶Using the R library RPART (Therneau & Atkinson, 1997).

³⁷The Gini rule was used for splitting, prior probabilities were set proportional to observed frequencies, and altered priors were used for the loss function.

³⁸Cost-complexity pruning was based on the $1 - SE$ rule among cross-validated data.

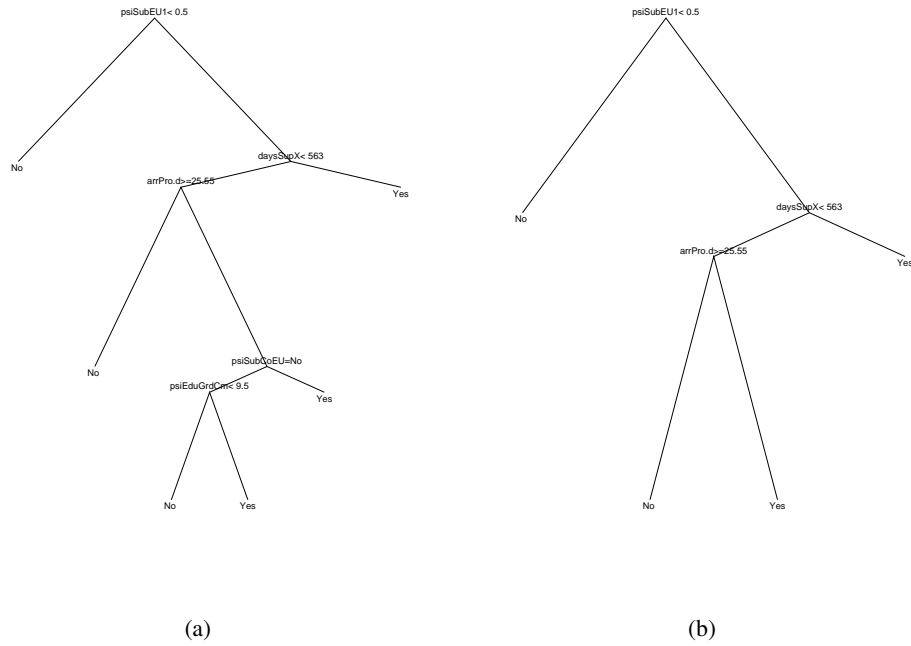


Figure 3. Initial (a) and pruned (b) classification trees predicting $outS 1_i$, **MS1**, $n = 199$.

(Yes); and (d) probationers having used 1 or more substances out of 7, expecting less than 563 days of supervision, and living within a BG having a rate of property-related arrests above 25.55 (No).

An initial model

$$\begin{aligned} \widehat{\Pr}(outS 1_i = 1 | \mathbf{x}_i) &= \frac{1}{1 + \exp[-(\mathbf{x}_i \boldsymbol{\beta})]} \\ &= \frac{1}{1 + \exp[-(\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3})]}, \end{aligned}$$

where $x_{i1} = psiSubEU1_i$, $x_{i2} = daysSupExp_i$, and $x_{i3} = arrPro.d_i$, was fitted to the sample data with the pruned-tree predictors in their original form; parameter estimates are shown in the first column of Table 24.³⁹

³⁹A robust estimator of variance was used in place of the standard estimator to adjust for $k = 122$ block-group clusters (Huber, 1967; Rogers, 1993; H. White, 1980).

Table 24

Parameter estimates, logistic regression of $outS1_i$, **MS1**, $n = 199$.

	b/z	b/z
$psiSubEU1$	0.451*	
	(2.23)	
$daysSupExp$	0.001	
	(1.95)	
$arrPro.d$	-0.011	
	(-1.95)	
$psiSubEU1^*$		0.477**
		(2.69)
$daysSupExp^*$		1.089**
		(2.80)
$arrPro.d^*$		3.401
		(0.79)
α	-0.383	-3.312
	(-0.67)	(-0.88)
Model χ^2	13.669**	15.874**

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

The Wald test⁴⁰ of the hypothesis that all coefficients except the intercept were zero $H_0 : \beta_1 = \beta_2 = \beta_3 = 0$ was rejected, $\chi_W^2 = 13.67$, $df = 3$, $p = 0.00$. The test of $H_0 : \beta_1 = 0$ was rejected ($\chi_W^2 = 4.97$, $df = 1$, $p = 0.03$), but neither test of $H_0 : \beta_2 = 0$ ($\chi_W^2 = 3.81$, $df = 1$, $p = 0.05$) nor of $H_0 : \beta_3 = 0$ ($\chi_W^2 = 3.81$, $df = 1$, $p = 0.05$) were rejected.

The model correctly classified 0.80 of the sample. Its ability to discriminate probationers with respect to the criteria is described succinctly by the area under the receiver operating characteristic curve (ROC) curve (AUC). This statistic suggests how likely it is that a probationer ever failing a drug testing event will have a higher predicted probability than their never failing

⁴⁰The likelihood-ratio chi-square (χ_L^2) test is likely invalid given the robust estimator of variance used to adjust for $k = 122$ block-group clusters.

counterparts. Hosmer and Lemeshow (2000) suggest interpreting AUC as

- AUC = 0.5, Lacks discriminatory power;
- $0.7 \leq \text{AUC} < 0.8$, Acceptable discriminatory power;
- $0.8 \leq \text{AUC} < 0.9$, Excellent discriminatory power;
- $0.9 \leq \text{AUC} < 1$, Outstanding discriminatory power.

In this case the model demonstrated acceptable discrimination, AUC = 0.73.

The model had deviance $(-2 \log L) = D = 178.55$, Akaike's (1973) information criterion (AIC) = 0.937, and Bayesian information criterion (BIC) = -853.643 ; the Hosmer-Lemeshow goodness-of-fit statistic (\hat{c}) suggested the model was empirically consistent, $\chi_{HL}^2 = 4.49$, $df = 8$, $p = 0.81$.

Focus then turned to refining this preliminary model in terms of parametric relationships and scale beginning with the relationship between $outS1_i$ and $psiSubEU1_i$.

A plot of the lowess smoothed logit against linear $psiSubEU1_i$ gave a counterintuitive impression of the influence of $psiSubEU1_i$ on $outS1_i$. There was an apparent near linear increase in the log-odds of $outS1_i$ that peaked at $psiSubEU1_i = 5$ and declined thereafter. This apparent nonlinearity resulted from the poor behavior in the upper tail of the distribution. Although it potentially ranged within $[0, 7]$, only $4/199 = 0.02$ of the sampled probationers reported $psiSubEU1 > 5$. To account for this the last three levels of $psiSubEU1_i$ were collapsed as $psiSubEU1_i^*$. Replotting the smoothed logit against $psiSubEU1_i^*$ gave a more intuitive impression of the influence of $psiSubEU1_i$ on $outS1_i$. In addition, there was no evidence to suggest the between-level spacings were substantially dissimilar.

Attention then turned to the relationship between $daysSupExp_i$ and $outS1_i$. Although the effect of $daysSupExp_i$ was not significantly different from zero (see, column 1 of Table 24), the tree in Figure 3b indicated this might be due to incorrect functional form: it suggested a break

in $daysSupExp_i$ near its median of 548 days. Such a nonlinearity was entirely within reason, as those probationers expecting relatively shorter sentences might be more willing to abstain than those facing relatively longer sentences who might be overwhelmed by abstention.

A plot of the smoothed logit against linear $daysSupExp_i$ showed a clear nonlinearity with the logit dropping sharply until roughly the first quartile ($0.25Q = 365$) then turning sharply upward and continuing essentially linearly. The logit flattened slightly at just over 1,000 days and then reassumed the slope at around 2,000 days. Despite the apparent cupping effect in the right half of the distribution there was little to be gained in modeling it: only $34/199 = 0.17$ of the sampled offenders had $daysSupExp_i$ greater than 1,000 days; only $3/199 = 0.015$ had values greater 2,000. On the other hand, the break at roughly 1 year was theoretically interesting.

I tested whether polynomial terms well-described the relationship, but neither quadratic nor cubic functions⁴¹ were statistically better than a linear term. Nor were first, second, or third degree fractional polynomials.⁴² As an alternative I tested three different piecewise regressions. The first allowed one linear effect for $daysSupExp$ at below 365 days and a different linear effect above. The next allowed one linear effect up to 548 days and a different effect thereafter. The last allowed one linear effect up to 365 days, a second linear effect between 365 days and 548 days, and a third effect from 548 days onward. None of these splines were significantly better than a linear term. Last I explored binary splits representing high and low values of $daysSupExp_i$. I tested separate breakpoints at 548 days and at 365 days. Both represented the data better than a linear term; the latter outperformed the former. Given this, $daysSupExp_i$ was split at 365 days and included in the model as $daysSupExp_i^*$.

I then turned to the relationship between $arrPro.d_i$ and $outS1_i$. A plot of the smoothed logit against linear $arrPro.d_i$ showed a clear negative trend beginning at roughly $arrPro.d \geq$

⁴¹Higher powers were not explored.

⁴²Higher degrees were not explored.

40. The tree in Figure 3b suggests a break in *arrPro.d* at 25.5. Both apparent effects are likely artifacts stemming from poor behavior in the upper tail of the distribution: mean *arrPro.d* was roughly equal to the 0.78 Q , $M = 15.40$, $SD = 38.60$. A normal quantile-comparison plot of *arrPro.d_i* identified several outlying values in the right tail; all 3 were represented by the only 3 non-DC residents in the sample. Although a nonlinear function might reasonably approximate the apparent relationship, given that the arrest densities outside of the District were inessential and that removing non-DC residents essentially linearized the relationship, these 3 cases were temporarily dropped from the regression of *outS 1_i*. A plot of the smoothed logit against *arrPro.d_i^{*}* confirmed this. Still, after making these changes some non-normality was still present and was corrected using the unconditional Box-Cox method. The maximum-likelihood (ML) normalizing transformation parameter λ in x^λ was estimated as $\widehat{\lambda} = 0.178$; the predictor was normalized by applying the transformation $arrPro.d_i^* = (arrPro.d_i + 0.5)^{0.18}$.

Following these changes the effect of *arrPro.d_i^{*}* was not significantly different from zero ($\chi_W^2 = 0.46$, $df = 1$, $p = 0.50$). Thus, so as not to reduce potentially predictive information with respect to the other two predictors in the model, the 3 non-DC cases were re-included and the model was refitted. Parameter estimates for the regression of *outS 1_i* on *psiSubEU1_i^{*}*, *daysSupExp_i^{*}*, and *arrPro.d_i^{*}*

$$\begin{aligned}\widehat{\Pr}(outS 1_i = 1 | \mathbf{x}_i) &= \frac{1}{1 + \exp[-(\mathbf{x}_i\boldsymbol{\beta})]} \\ &= \frac{1}{1 + \exp[-(\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3})]},\end{aligned}$$

where $x_{i1} = psiSubEU1_i^*$, $x_{i2} = daysSupExp_i^*$, and $x_{i3} = arrPro.d_i^*$, are shown in the second column of Table 24.⁴³ The Wald⁴⁴ test of $H_0: \beta_1 = \beta_2 = \beta_3 = 0$ was rejected, $\chi_W^2 = 15.87$, $df = 3$, $p = 0.00$. The test of $H_0: \beta_1 = 0$ was rejected ($\chi_W^2 = 7.22$, $df = 1$, $p = 0.01$), the test of

⁴³A robust estimator of variance was used in place of the standard estimator to adjust for $k = 122$ block-group clusters (Huber, 1967; Rogers, 1993; H. White, 1980).

⁴⁴The χ_L^2 test is likely invalid given the robust estimator of variance used to adjust for $k = 122$ block-group clusters.

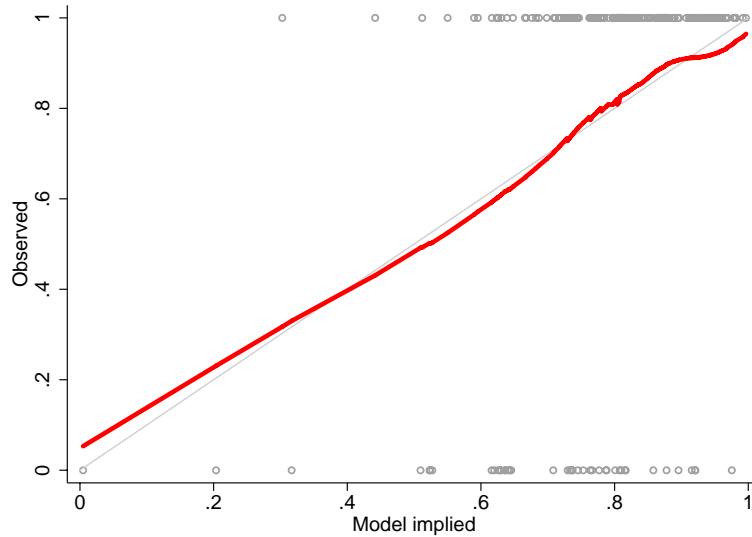


Figure 4. Comparison between model-implied probabilities of experiencing $outs\ 1_i$ and a moving average of the proportion of probationers ever failing a drug testing event, **MS1**, $n = 199$.

$H_0: \beta_2 = 0$ was rejected ($\chi^2_W = 7.84$, $df = 1$, $p = 0.01$). The test of $H_0: \beta_3 = 0$ was not rejected ($\chi^2_W = 0.62$, $df = 1$, $p = 0.43$).

Model calibration and discrimination remained virtually unchanged from the preliminary model. A visual indication of model calibration is given in the plot in Figure 4 which compares predicted probabilities $\hat{\pi}$ from the regression of $outs\ 1_i$ with a moving average of the proportion of probationers having at least one positive drug screen. The thick line represents the fraction of probationers failing a drug-testing event while supervised across levels of predicted probabilities. Close tracking between this and the diagonal line indicates good calibration. That the thick line in Figure 4 indeed tracks closely with the diagonal suggests the model is largely well-calibrated.

Among the sample, 0.80 were correctly classified. The model demonstrated acceptable discrimination, $AUC = 0.72$. It had $D=180.23$, $AIC=0.946$, and $BIC=-851.965$; the \hat{c} suggested it was empirically consistent, $\chi^2_{HL} = 5.74$, $df = 8$, $p = 0.68$.

Table 25

Lower (LCLM) and upper (UCLM) bias-corrected 95% confidence limits, **MS1**, $n = 199$.

	LCLM	UCLM
$psiSubEU1^*$	0.102	0.852
$daysSupExp^*$	0.286	1.893
$arrPro.d^*$	-6.046	12.847

The regression of $outS1_i$ on $psiSubEU1_i^*$, $daysSupExp_i^*$, and $arrPro.d_i^*$ shown in the second column of Table 24 was validated by bootstrapping. Bias-corrected confidence intervals around the estimated parameters are shown in Table 25. As indicated in the table, the effect of $arrPro.d_i^*$ is unlikely to replicate in the population. On the other hand, the effects of both $psiSubEU1_i^*$ and $daysSupExp_i^*$ are likely to be found in the population; interpretations of the model are based on these latter two effects while holding $arrPro.d^*$ at its mean.

Predicted values $\widehat{\pi}$ ranged within the interval [.002, .965], with mean $\widehat{\pi} = 0.794$, $SD = 0.14$. The two most important characteristics influencing $\widehat{Pr}(outS1_i = 1)$ are $psiSubEU1^*$ and $daysSupExp^*$. Holding all else equal, having used 5 or more substances compared to none increases the predicted probability $\widehat{\pi}$ an offender will ever test positive, provide a bogus specimen, or fail to appear for a drug testing event while supervised by 0.47, from 0.42 to 0.89. The effect of $psiSubEU1^*$ is greatest when moving from none to 1, which increases $\widehat{\pi}$ by 0.11, from 0.58 to 0.69. $\widehat{\pi}$ continues to increase with each additional substance ever used at a decreasing rate.

The expected length of supervision also plays a role in whether probationers will ever test positive, provide a bogus specimen, or fail to appear for a drug testing event while supervised. Those probationers expecting longer periods of supervision (i.e., > 1 year) are more likely to fail. Their odds of failing are, in fact, 1.7 times larger. Expecting a supervision period of one year or more versus less than one year is associated with an increase of 0.17 in $\widehat{\pi}$, from 0.71 to 0.88.

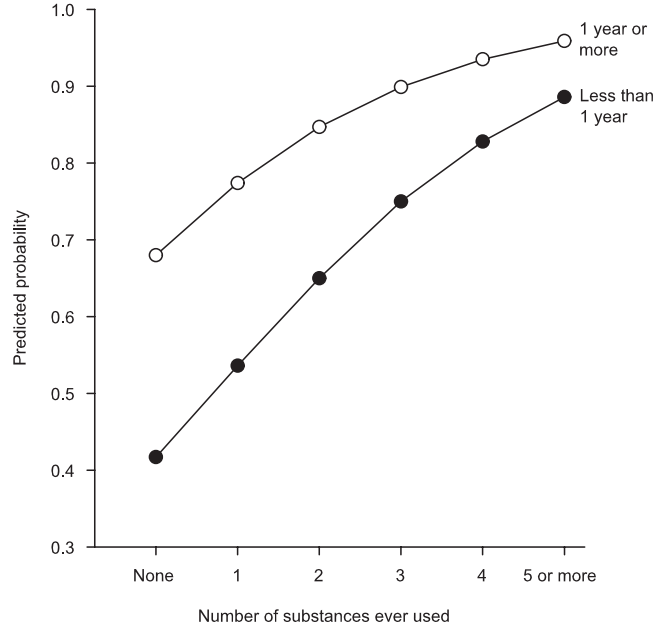


Figure 5. Predicted probabilities an offender in the population will test positive, fail to appear, or provide a bogus specimen for a drug testing event while supervised positive for cocaine, by the number of substances ever used and length of supervision, **MS1**, $n = 199$.

The plot in Figure 5 shows the positive effect of $psiSubEU1_i^*$ on $outS1_i$ and how this effect differs by $daysSupExp_i^*$. When $psiSubEU1_i^*$ is low the effect of $daysSupExp_i^*$ is relatively large, but as $psiSubEU1_i^*$ increases the effect shrinks. For instance, among probationers having used none of the 7 substances, the $\hat{\pi}$ is 0.26 higher among those expecting a supervision period of one year or more versus less than one year. This same difference among probationers having used 5 or more of the 7 substances is 0.07.

MS2A. The criterion for **MS2A** is the number of positive tests for alcohol $outDrgTotPos_{i1}$. The 95%CI around mean $\frac{n_{positives}}{n_{screens}}$ is shown in Table 26. As indicated, screens for alcohol were relatively rare among the sample: just under 3 out of every 8 ($74/199 = 0.37$) probationers were screened. One or more screens were positive for about half ($33/74 = 0.45$) of those screened. As screens for alcohol were relatively uncommon **MS2A** was excluded from the present analysis.

Table 26

One-sided 95% confidence limit below (LCLM) and above (UCLM) mean rate of positive screens, by substance.

Criterion	Description	LCLM	UCLM	n_{screened}
$\frac{outDrgTotPos_{i1}}{outDrgTotScr_{i1}}$	Alcohol	0.0755	0.198	74
$\frac{outDrgTotPos_{i2}}{outDrgTotScr_{i2}}$	Methadone	0.0	0.0444	67
$\frac{outDrgTotPos_{i3}}{outDrgTotScr_{i3}}$	Amphetamine	0.0	0.00655	77
$\frac{outDrgTotPos_{i4}}{outDrgTotScr_{i4}}$	Cocaine	0.0519	0.0908	194
$\frac{outDrgTotPos_{i5}}{outDrgTotScr_{i5}}$	Marijuana	0.0724	0.121	194
$\frac{outDrgTotPos_{i6}}{outDrgTotScr_{i6}}$	Opiates	0.0187	0.0475	194
$\frac{outDrgTotPos_{i7}}{outDrgTotScr_{i7}}$	Phencyclidine	0.0153	0.0427	190

MS2B. The criterion for **MS2B** is the number of positive tests for methadone $outDrgTotPos_{i2}$. Screens for methadone were relatively rare among the sample with only $67/199 = 0.34$ of the sample being screened at least once. Screens were positive one or more times for only $4/67 = 0.06$ of those probationers screened. The 95%CI around mean $\frac{n_{\text{positives}}}{n_{\text{screens}}}$ is shown in Table 26. As screens for methadone were relatively uncommon **MS2B** was excluded from analyses.

MS2C. The criterion for **MS2C** is the number of positive tests for amphetamines $outDrgTotPos_{i3}$. Screens and positive screens for amphetamines were rare. Among the $77/199 = 0.39$ of the sample that was screened, only $5/77 = 0.065$ had one or more positive results. The 95%CI around mean $\frac{n_{\text{positives}}}{n_{\text{screens}}}$ is shown in Table 26. As screens for amphetamines were relatively uncommon **MS2C** was excluded from analyses.

MS2D. The criterion for model **MS2D** is the number times the i th probationer tested positive for cocaine $outDrgTotPos_{i4}$; interest centers on the expected rate of this criterion in the population $\widehat{\mu}_i$. Screens for cocaine occurred 5 times a month, on average, throughout the supervision period, $M = 5.05, SD = 7.2$. $194/199 = 0.97$ of the sample was screened at least once for

cocaine, one or more of which were positive for $93/194 = 0.48$ of those screened. The 95%CI around mean $\frac{n_{\text{positives}}}{n_{\text{screens}}}$ is shown in Table 26.

Potential predictors were included in a general model which was then recursively partitioned⁴⁵ into the binary tree shown in Figure 6a using Poisson-splitting methods (see, Breiman et al., 1984; Therneau & Atkinson, 1997).⁴⁶ This classification tree, since it was likely too complex to validate, was trimmed back to that shown in Figure 6b.⁴⁷

Predictors having the largest effect on the rate of screens for cocaine included (a) age at the time of assessment $rnsAge_i$, (b) the number of substances ever used $psiSubEU1_i$, (c) the total number of children younger than age 18 $psiSocTon_i$, and (d) the expected number of days of supervision $daysSupExp_i$; remaining predictors did not appear in the model.

The resultant model separated sampled probationers into 5 groups. The groups (and predicted values) included (a) those younger than age 33 and having used 3 or fewer substances (0.75); (b) those younger than age 33 and having used more than 3 substances (7.7); (c) those age 33 or older, having 3 or fewer children under age 18, and expecting to serve less than 455 days of supervision (2.3); (d) those age 33 or older, having 3 or fewer children under age 18, and expecting to serve more than 455 days of supervision (11); and (e) those age 33 or older and having more than 3 children under age 18 (27).

Before fitting an initial model, several transformations were made. First, age_i^* was calculated as $age_i^* = \frac{rnsAge_i}{10}^{-1}$ to allow for non-linearities in the effect of age on the rate of positive screens for cocaine. Next, the last three levels of $psiSubEU1_i$ were collapsed as $psiSubEU1_i^*$ to remedy sparse representation in the upper regions of the predictor. Finally, $psiSocTon_i$ was trun-

⁴⁵Using the R library RPART (Therneau & Atkinson, 1997).

⁴⁶The Gini rule was used for splitting, prior probabilities were set proportional to observed frequencies, and altered priors were used for the loss function.

⁴⁷Cost-complexity pruning was based on the $1 - SE$ rule among cross-validated data.

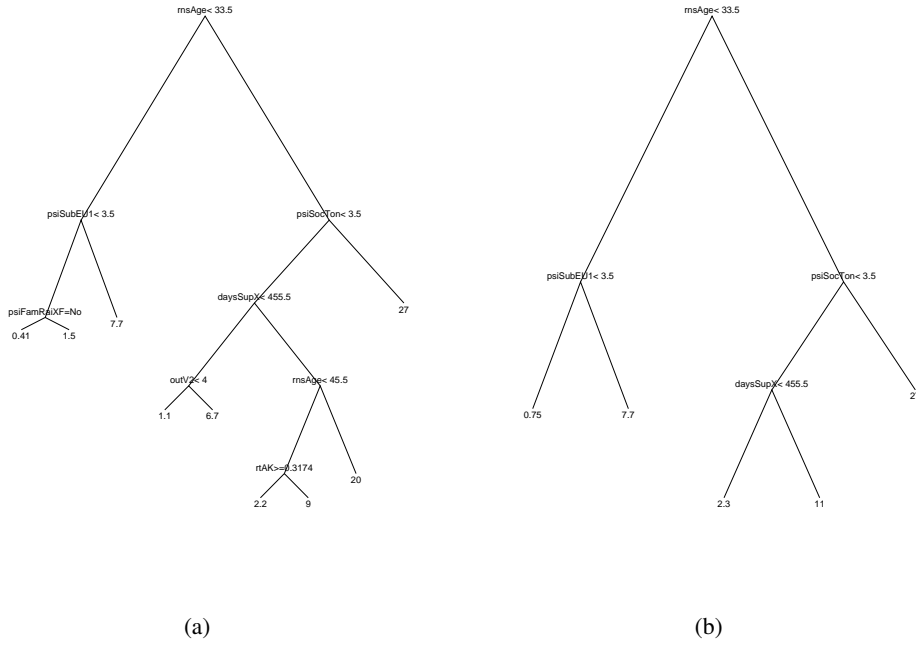


Figure 6. Initial (a) and pruned (b) classification trees predicting $outDrgTotPos_{i4}$, **MS2D**, $n = 194$.

cated at 4 as $psiSocTon_i^*$. This, too, was done in response to sparse representation in the upper levels of the predictor.

An initial model

$$\widehat{\Pr}(outDrgTotPos_{i4} | \mathbf{x}_i) = \frac{\exp(-\mu_i)\mu_i^{outDrgTotPos_{i4}}}{outDrgTotPos_{i4}!}$$

where $\mu_i = \exp(\mathbf{x}_i\boldsymbol{\beta})$ and $x_{i1} = age_i^*$, $x_{i2} = psiSubEU1_i^*$, $x_{i3} = daysSupExp_i$, and $x_{i4} = psiSocTon_i^*$, was fitted to the sample data with the pruned-tree predictors; parameter estimates are shown in the first column of Table 27.⁴⁸

After this initial model was fit there was significant evidence that the observations were overdispersed with respect to the Poisson model, $G^2 = 1153.370$, $p = 0.000$. Thus, **MS2D** was

⁴⁸A robust estimator of variance was used in place of the standard estimator to adjust for $k = 122$ block-group clusters (Huber, 1967; Rogers, 1993; H. White, 1980). Also, to account for varying times-at-risk, the logged number of drug screens $\log(outDrgTotScr_{i4})$ was included and constrained to a coefficient of 1.

Table 27

Parameter estimates, Poisson and negative binomial regressions of $outDrgTotPos_{i4}$, **MS2D**, $n = 194$.

	b/z	b/z	b/z
age^*	-7.698*** (-5.96)	-7.464*** (-6.72)	-7.922*** (-6.39)
$psiSubEU1^*$	0.175 (1.63)	0.482*** (4.62)	0.482*** (4.76)
$psiSocTon^*$	0.190 (1.44)	0.198 (1.66)	0.198 (1.75)
$daysSupExp$	0.000 (0.17)	0.001 (1.65)	
$daysSupExp^*$			0.691 (1.78)
α	-1.096* (-2.08)	-2.460*** (-4.60)	-2.370*** (-4.28)
Overdispersion α		1.051*** (7.86)	1.037*** (7.44)
Model χ^2	56.789***	81.913***	75.001***

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

respecified to include a multiplicative disturbance term v_i to capture unobserved heterogeneity.

The model

$$\widehat{\Pr}(outDrgTotPos_{i4} | \mathbf{x}_i) = \frac{\exp(-\widetilde{\mu}_i)\widetilde{\mu}_i^{outDrgTotPos_{i4}}}{outDrgTotPos_{i4}!}$$

where $\widetilde{\mu}_i = \exp(\mathbf{x}_i\boldsymbol{\beta} + v_i)$ and $x_{i1} = age_i^*$, $x_{i2} = psiSubEU1_i^*$, $x_{i3} = daysSupExp_i$, and $x_{i4} = psiSocTon_i^*$, was then fitted to the sample data. Parameter estimates from this regression are shown in the second column of Table 27.⁴⁹

The model had $D=771.03$, $AIC=4.036$, and $BIC=-219.325$.

⁴⁹A robust estimator of variance was used in place of the standard estimator to adjust for $k = 122$ block-group clusters (Huber, 1967; Rogers, 1993; H. White, 1980). Also, to account for varying times-at-risk, the logged number of drug screens $\log(outDrgTotScr_{i4})$ was included and constrained to a coefficient of 1.

The Wald test⁵⁰ of the hypothesis that all coefficients except the intercept were zero $H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$ was rejected, $\chi_W^2 = 81.91$, $df = 4$, $p = 0.00$. The tests of $H_0 : \beta_1 = 0$ ($\chi_W^2 = 45.16$, $df = 1$, $p = 0.00$) and of $H_0 : \beta_2 = 0$ ($\chi_W^2 = 21.36$, $df = 1$, $p = 0.00$) were rejected, but neither tests of $H_0 : \beta_3 = 0$ ($\chi_W^2 = 2.73$, $df = 1$, $p = 0.10$) nor of $H_0 : \beta_4 = 0$ ($\chi_W^2 = 2.76$, $df = 1$, $p = 0.10$) were rejected.

By comparison, the Poisson regression (PR) shown in the first column of Table 27 performed at its worse in predictions of 0 where it greatly underpredicted counts. The negative binomial regression (NBR) shown in the second column of Table 27 performed at its worse in predictions of counts of 3 where it, too, underpredicted counts albeit on a relatively smaller scale. Overall, the NBR, with mean absolute difference between predicted and observed values $|\Delta_{\widehat{\pi}_o - \widehat{\pi}_p}| = 0.008$, outperformed the PR, with its $|\Delta_{\widehat{\pi}_o - \widehat{\pi}_p}| = 0.078$.

Before moving on, focus turned to refining the model in terms of parametric relationships and scale beginning with the relationship between *outDrgTotPos_{i4}* and *psiSubEU1_i**. In neither plot of lowess smoothed rates of positive screens against linear *psiSubEU1_i** nor of linear *psiSocTon_i** were there substantial departures from linearity. These two predictors were thus left unchanged. On the other hand, a plot of the lowess smoothed rates of positive screens against linear *daysSupExp_i* did suggest a non-linearity. I explored several alternatives to linearity, however, neither quadratic nor cubic functions⁵¹ were statistically better than a linear term. Nor were first, second, or third degree fractional polynomials.⁵² I examined several different splines to account for the non-linearity, but none provided an acceptable fit. Ultimately, *daysSupExp_i* was split at 365 days and included in the model as *daysSupExp_i**.

⁵⁰The χ_L^2 test is likely invalid given the robust estimator of variance used to adjust for $k = 122$ block-group clusters.

⁵¹Higher powers were not explored.

⁵²Higher degrees were not explored.

The model

$$\widehat{\Pr}(outDrgTotPos_{i4} | \mathbf{x}_i) = \frac{\exp(-\widetilde{\mu}_i)\widetilde{\mu}_i^{outDrgTotPos_{i4}}}{outDrgTotPos_{i4}!}$$

where $\widetilde{\mu}_i = \exp(\mathbf{x}_i\boldsymbol{\beta} + v_i)$ and $x_{i1} = age_i^*$, $x_{i2} = psiSubEU1_i^*$, $x_{i3} = daysSupExp_i^*$, and $x_{i4} = psiSocTon_i^*$, was then fitted to the sample data. Parameter estimates from this regression are shown in the third column of Table 27.⁵³

The model had D=769.19, AIC=4.027, and BIC=-221.168.

The Wald test⁵⁴ of the hypothesis that all coefficients except the intercept were zero $H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$ was rejected, $\chi_W^2 = 75.00$, $df = 4$, $p = 0.00$. The tests of $H_0 : \beta_1 = 0$ ($\chi_W^2 = 40.87$, $df = 1$, $p = 0.00$) and of $H_0 : \beta_2 = 0$ ($\chi_W^2 = 22.67$, $df = 1$, $p = 0.00$) were rejected, but neither tests of $H_0 : \beta_3 = 0$ ($\chi_W^2 = 3.18$, $df = 1$, $p = 0.07$) nor of $H_0 : \beta_4 = 0$ ($\chi_W^2 = 3.07$, $df = 1$, $p = 0.08$) were rejected.

A visual indication of model calibration is given in the plot in Figure 7. This plot shows the observed and predicted probabilities of counts zero through 9. As indicated, the model-implied and observed probabilities track closely throughout the distribution, with the poorest fit in counts of 3.

The NBR of *S2D* on age_i^* , $psiSubEU1_i^*$, $daysSupExp_i^*$, and $psiSocTon_i^*$, shown in the third column of Table 27 was validated by bootstrapping. Bias-corrected confidence intervals around the estimated parameters are shown in Table 28. As indicated, the effects of age_i^* and $psiSubEU1_i^*$ were likely to replicate in the population, but neither that of $psiSocTon_i^*$ nor of $daysSupExp_i^*$ were.

⁵³A robust estimator of variance was used in place of the standard estimator to adjust for $k = 122$ block-group clusters (Huber, 1967; Rogers, 1993; H. White, 1980). Also, to account for varying times-at-risk, the logged number of drug screens $\log(outDrgTotScr_{i4})$ was included and constrained to a coefficient of 1.

⁵⁴The χ_L^2 test is likely invalid given the robust estimator of variance used to adjust for $k = 122$ block-group clusters.

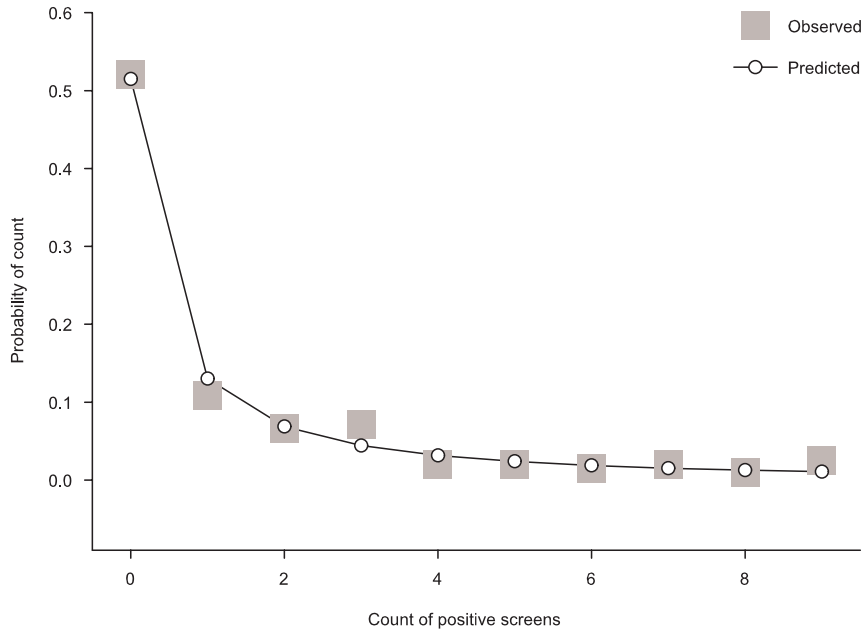


Figure 7. Observed and NBR model-implied counts of $outDrgTotPos_{i4}$, **MS2D**, $n = 194$.

The most important characteristics influencing the rate of positive screens for cocaine included age at the time of assessment $rnsAge_i^*$ and the number of substances ever used $psiSubEU1_i^*$. The expected rate of positive screens for cocaine increases with age. Holding all else constant, the rate of positives for probationers at the lower quartile ($0.25Q \approx 23$) of age is roughly 0.03. It increases to 0.06 for those at the median ($0.5Q \approx 31$) age and to roughly 0.12 for those at the upper quartile ($0.75Q \approx 43$). Holding all other predictors constant each additional substance ever

Table 28

Lower (LCLM) and upper (UCLM) bias-corrected 95% confidence limits, **MS2D**, $n = 194$.

	LCLM	UCLM
age_i^*	-10.6	-5.25
$psiSubEU1_i^*$.27	.694
$psiSocTon_i^*$	-.0753	.472
$daysSupExp_i^*$	-.0811	1.46

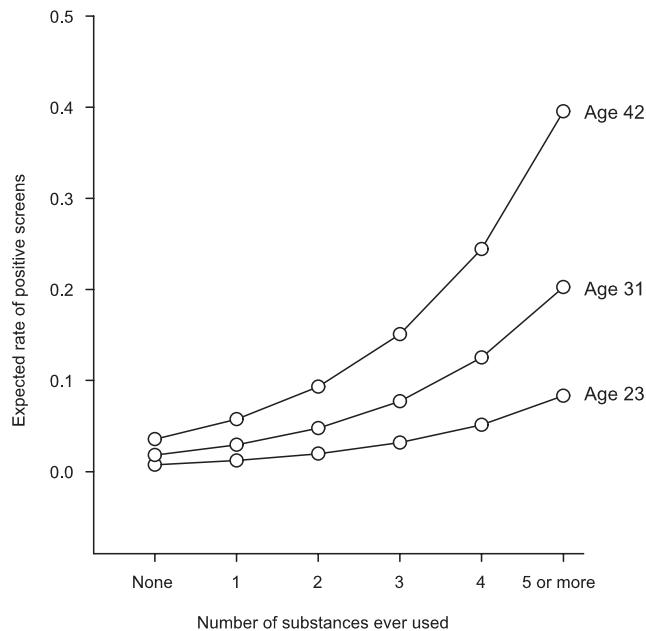


Figure 8. Expected rates of positive screens for cocaine, by the number of substances ever used and age, **MS2D**, $n = 194$.

used increases the expected number of positive screens for cocaine by a factor of 1.6 or roughly 62%.

The plot in Figure 8 shows the effect of age at its $0.25Q$, $0.5Q$, and $0.75Q$ on the rate of positive screens for cocaine across the number of substances ever used. The number of substances ever used is associated with increases in the rate of positive screens for cocaine and these increases vary by age. For probationers having used none of the illegal substances age makes little difference on the expected rate, but as the number of substances ever used increases the expected rates of positives are higher for older versus younger offenders. For instance, holding all else constant the expected rate of positive screens for probationers having used none of the substances is 0.0075 for probationers age 23, 0.018 for those age 31, and 0.036 for those age 42. Rates for those having used 3 substances are 0.032 for probationers age 23, 0.077 for those age 31, and 0.15 for those age 42. For those having used 5 or more substances rates of positives are 0.083 for those age 23, 0.2 for those age 31, and 0.4 for those age 42.

MS2E. The criterion for **MS2E** is the number times the i th probationer tested positive for marijuana $outDrgTotPos_{i5}$; interest centers on the expected rate of this criterion in the population $\widehat{\mu}_i$. Screens for marijuana occurred roughly 5 times monthly, on average, throughout the supervision period, $M = 4.98, SD = 7.19$. $194/199 = 0.97$ of the sample was screened at least once for marijuana; one or more of these were positive for $81/194 = 0.42$ of the probationers. The 95%CI around mean $\frac{n_{positives}}{n_{screens}}$ is shown in Table 26.

Potential predictors were included in a general model which was then recursively partitioned⁵⁵ into the binary tree shown in Figure 9a using Poisson-splitting methods (see, Breiman et al., 1984; Therneau & Atkinson, 1997).⁵⁶ This classification tree, since it was likely too complex to validate, was trimmed back to that shown in Figure 9b.⁵⁷

Predictors having the largest effect on the rate of positive tests for marijuana included (a) age at the time of assessment $rnsAge_i$, (b) population density within the block-group $popDens_i$, and (c) the total number of prior juvenile cases $psiCrmJuvCasn_i$; remaining predictors did not appear in the model.

The resultant model separated sampled probationers into 4 groups. The groups (and predicted values) included (a) those ages 34 and older (0.2); (b) those younger than age 34 and living within a block-group with population density equal to or greater than 3.609 (7.8); (c) those younger than age 34, living within a block-group with population density less than 3.609, and having no prior juvenile cases (9.1); and (d) those younger than age 34, living within a block-group with population density less than 3.609, and having 1 or more prior juvenile cases (30).

⁵⁵Using the R library RPART (Therneau & Atkinson, 1997).

⁵⁶The Gini rule was used for splitting, prior probabilities were set proportional to observed frequencies, and altered priors were used for the loss function.

⁵⁷Cost-complexity pruning was based on the $1 - SE$ rule among cross-validated data.

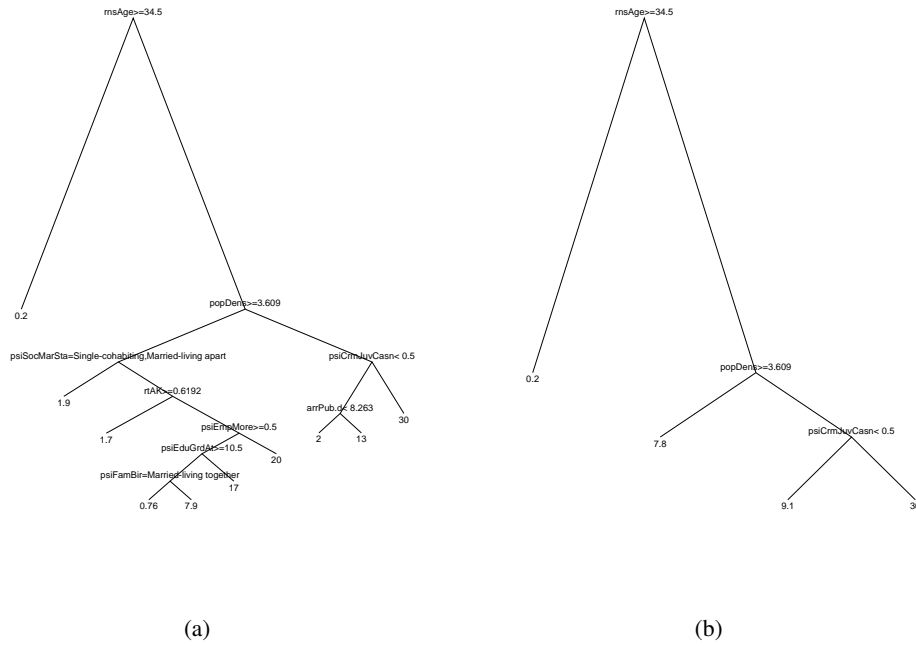


Figure 9. Initial (a) and pruned (b) classification trees predicting $outDrgTotPos_{i5}$, **MS2E**, $n = 194$.

Before fitting an initial model, several transformations were made. First, $rmsAge_i$ was transformed as $age_i^* = \frac{rmsAge_i^3}{10} - 36.33$. Second, as its levels were sparse in the upper tail, $psiCrmJuvCasn_i$ was truncated at 4 as $psiCrmJuvCasn_i^*$.

An initial model

$$\widehat{\Pr}(outDrgTotPos_{i5} | \mathbf{x}_i) = \frac{\exp(-\mu_i)\mu_i^{outDrgTotPos_{i5}}}{outDrgTotPos_{i5}!}$$

where $\mu_i = \exp(\mathbf{x}_i\boldsymbol{\beta})$ and $x_{i1} = age_i^*$, $x_{i2} = popDens_i$, and $x_{i3} = psiCrmJuvCasn_i^*$, was fitted to the sample data with the pruned-tree predictors; parameter estimates are shown in the first column of Table 29.⁵⁸

⁵⁸A robust estimator of variance was used in place of the standard estimator to adjust for $k = 122$ block-group clusters (Huber, 1967; Rogers, 1993; H. White, 1980). Also, to account for varying times-at-risk, the logged number of drug screens $\log(outDrgTotScr_{i5})$ was included and constrained to a coefficient of 1.

Table 29

Parameter estimates, Poisson and negative binomial regressions of $outDrgTotPos_{i5}$, **MS2E**, $n = 194$.

	b/z	b/z	b/z
age^*	-0.038*** (-6.32)	-0.037** (-3.14)	-0.037** (-3.13)
$popDens$	-0.053 (-1.52)	-0.030 (-1.24)	
$psiCrmJuvCasn^*$	0.140 (1.74)	0.113 (1.19)	0.107 (1.14)
$popDens^*$			-0.465 (-1.11)
α	-2.527*** (-10.43)	-2.626*** (-10.93)	-2.465*** (-6.92)
Overdispersion α		1.167*** (6.04)	1.165*** (6.00)
Model χ^2	52.995***	19.691***	17.673***

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

After this initial model was fit there was significant evidence that the observations were overdispersed with respect to the Poisson model, $G^2 = 1239.181$, $p = 0.000$. Thus, **MS2E** was respecified to include a multiplicative disturbance term v_i to capture unobserved heterogeneity.

The model

$$\widehat{\Pr}(outDrgTotPos_{i5} | \mathbf{x}_i) = \frac{\exp(-\widetilde{\mu}_i)\widetilde{\mu}_i^{outDrgTotPos_{i5}}}{outDrgTotPos_{i5}!}$$

where $\widetilde{\mu}_i = \exp(\mathbf{x}_i\boldsymbol{\beta} + v_i)$ and $x_{i1} = age_i^*$, $x_{i2} = popDens_i$, and $x_{i3} = psiCrmJuvCasn_i^*$, was then fitted to the sample data. Parameter estimates from this regression are shown in the second column of Table 29.⁵⁹

⁵⁹A robust estimator of variance was used in place of the standard estimator to adjust for $k = 122$ block-group clusters (Huber, 1967; Rogers, 1993; H. White, 1980). Also, to account for varying times-at-risk, the logged number of drug screens $\log(outDrgTotScr_{i5})$ was included and constrained to a coefficient of 1.

The model had $D=805.31$, $AIC=4.203$, and $BIC=-190.311$.

By comparison, the PR shown in the first column of Table 29 performed at its worse in predictions of counts of 0 where it underpredicted counts. The NBR shown in the second column of Table 29 performed at its worse in predictions of 1 where it overpredicted counts. Overall, the NBR, with mean absolute difference between predicted and observed values $|\Delta_{\widehat{\pi}_o - \widehat{\pi}_p}| = 0.019$, outperformed the PR, with $|\Delta_{\widehat{\pi}_o - \widehat{\pi}_p}| = 0.064$.

I then turned to assessing scale beginning with the relationship involving $psiCrmJuvCasn_i^*$. A plot of the univariable lowess smooth of $outDrgTotPos_{i5}$ versus $psiCrmJuvCasn_i^*$ did not suggest substantial nonlinearity of $psiCrmJuvCasn_i^*$ in the rate of positive screens for marijuana. This predictor was thus left as is. On the other hand, a similar plot of $outDrgTotPos_{i5}$ versus $popDens_i$ did suggests a non-linearity. To account for this $popDens_i$ was replaced with $popDens_i^* = \sqrt{popDens_i/10}$.

The model

$$\widehat{\Pr}(outDrgTotPos_{i5} | \mathbf{x}_i) = \frac{\exp(-\widetilde{\mu}_i)\widetilde{\mu}_i^{outDrgTotPos_{i5}}}{outDrgTotPos_{i5}!}$$

where $\widetilde{\mu}_i = \exp(\mathbf{x}_i\boldsymbol{\beta} + v_i)$ and $x_{i1} = age_i^*$, $x_{i2} = popDens_i^*$, and $x_{i3} = psiCrmJuvCasn_i^*$, was then refitted to the sample data. Parameter estimates from this regression are shown in the third column of Table 29.⁶⁰

The model had $D=805.44$, $AIC=4.203$, and $BIC=-190.187$.

The Wald test⁶¹ of the hypothesis that all coefficients except the intercept were zero $H_0: \beta_1 = \beta_2 = \beta_3 = 0$ was rejected, $\chi_W^2 = 17.67$, $df = 3$, $p = 0.00$. The test of $H_0: \beta_1 = 0$ was rejected

⁶⁰A robust estimator of variance was used in place of the standard estimator to adjust for $k = 122$ block-group clusters (Huber, 1967; Rogers, 1993; H. White, 1980). Also, to account for varying times-at-risk, the logged number of drug screens $\log(outDrgTotScr_{i5})$ was included and constrained to a coefficient of 1.

⁶¹The χ_L^2 test is likely invalid given the robust estimator of variance used to adjust for $k = 122$ block-group clusters.

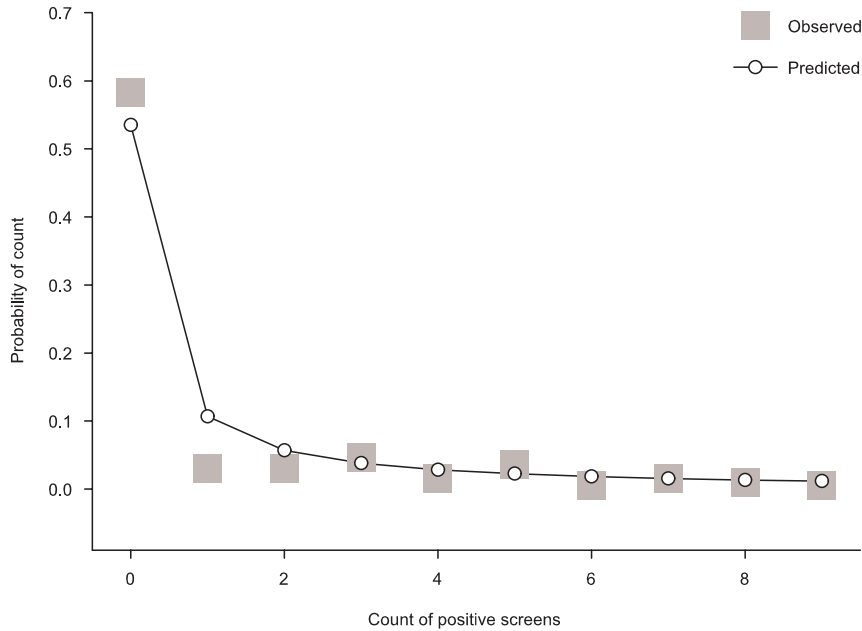


Figure 10. Observed and NBR model-implied counts of $outDrgTotPos_{i5}$, **MS2E**, $n = 194$.

($\chi^2_W = 9.77$, $df = 1$, $p = 0.00$) but neither test of $H_0: \beta_2 = 0$ ($\chi^2_W = 1.22$, $df = 1$, $p = 0.27$) nor of $H_0: \beta_3 = 0$ ($\chi^2_W = 1.30$, $df = 1$, $p = 0.25$) were rejected.

A visual indication of model calibration is given in the plot in Figure 10. This plot shows the observed and predicted probabilities of counts zero through 9. As indicated, the model-implied and observed probabilities do not track well for counts of zero and 1, but track closely thereafter.

The NBR of $S2E$ on age_i^* , $popDens_i^*$, and $psiCrmJuvCasn_i^*$, shown in the third column of Table 29 was validated by bootstrapping. Bias-corrected confidence intervals around the estimated parameters are shown in Table 30. As indicated, only the effect of age_i^* was likely to replicate in the population.

The single most important characteristic influencing the rate of positive screens for marijuana is age at the time of screening. The expected rate of positive screens for marijuana by age is plotted in Figure 11. As indicated, the expected rate decreases near-linearly with age. Holding all

Table 30

Lower (LCLM) and upper (UCLM) bias-corrected 95% confidence limits, **MS2E**, $n = 194$.

	LCLM	UCLM
age_i^*	-.0637	-.00997
$popDens_i^*$	-1.39	.465
$psiCrmJuvCasn_i^*$	-.0988	.314

else constant, for those at the lower quartile ($0.25Q \approx 23$) of age the rate of positives is roughly 0.16. It decreases to 0.08 for those at the median ($0.5Q \approx 31$) age and to roughly 0.02 for those at the upper quartile ($0.75Q \approx 43$). The expected rate flattens thereafter.

MS2F. The criterion this model is the number times the i th probationer tested positive for opiates $outDrgTotPos_{i6}$; interest centers on the expected rate of this criterion in the population $\widehat{\mu}_i$. Screens for opiates occurred roughly 5 times monthly, on average, throughout the supervision period, $M = 5.05, SD = 7.2$. $194/199 = 0.97$ of the sample was screened at least once for opiates; one or more of these was positive for $41/194 = 0.21$ of the probationers. The 95%CI around mean $\frac{n_{positives}}{n_{screens}}$ is shown in Table 26.

Potential predictors were included in a general model which was then recursively partitioned⁶² into the binary tree shown in Figure 12a using Poisson-splitting methods (see, Breiman et al., 1984; Therneau & Atkinson, 1997).⁶³ This classification tree, since it was likely too complex to validate, was trimmed back to that shown in Figure 12b.⁶⁴

Predictors having the largest effect on the rate of positive tests for opiates included (a) having ever used opiates $psiSubHeEU_i$, (b) density of arrests for property crimes within the block-

⁶²Using the R library RPART (Therneau & Atkinson, 1997).

⁶³The Gini rule was used for splitting, prior probabilities were set proportional to observed frequencies, and altered priors were used for the loss function.

⁶⁴Cost-complexity pruning was based on the $1 - SE$ rule among cross-validated data.

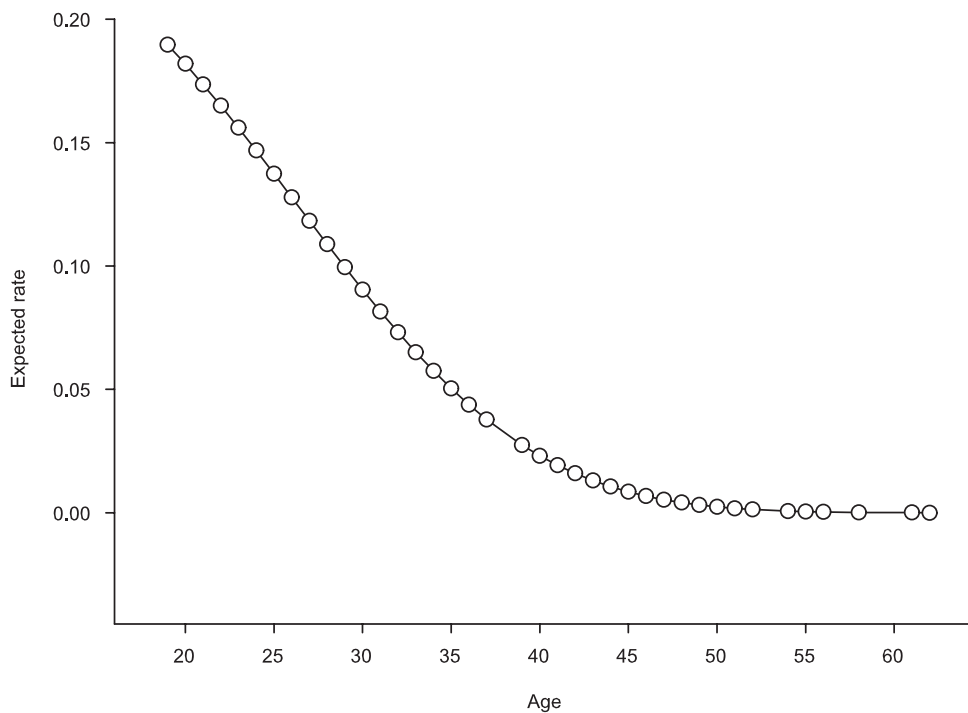


Figure 11. Expected rates of positive screens for marijuana by age at time of screening, **MS2E**, $n = 194$.

group $arrPro.d_i$, and (c) the number of prior adult convictions $psiCrmAdlCnv_i$; remaining predictors did not appear in the model.

The resultant model separated sampled probationers into 4 groups. The groups (and predicted values) included (a) those having never before used opiates (0.14); (b) those having used opiates at least once and living within a block group with rates of arrests for property crimes of 11.46 or higher (0.88); (c) those having used opiates at least once, living within a block group with rates of arrests for property crimes lower than 11.46, and having 8 or more prior adult convictions (2.6); and (d) those having used opiates at least once, living within a block group with rates of arrests for property crimes lower than 11.46, and having fewer than 8 prior adult convictions (13).

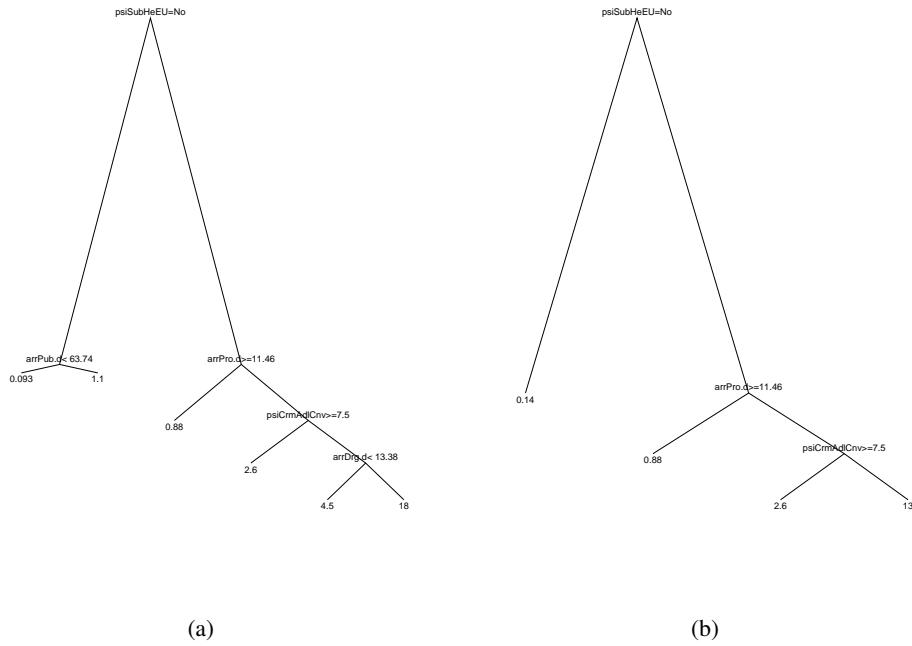


Figure 12. Initial (a) and pruned (b) classification trees predicting $outDrgTotPos_{i6}$, **MS2F**, $n = 194$.

An initial model

$$\widehat{\Pr}(outDrgTotPos_{i6} | \mathbf{x}_i) = \frac{\exp(-\mu_i)\mu_i^{outDrgTotPos_{i6}}}{outDrgTotPos_{i6}!}$$

where $\mu_i = \exp(\mathbf{x}_i\boldsymbol{\beta})$ and $x_{i1} = psiSubHeEU_i$, $x_{i2} = arrPro.d_i$, and $x_{i3} = psiCrmAdlCnv_i$, was fitted to the sample data with the pruned-tree predictors in their original form; parameter estimates are shown in the first column of Table 31.⁶⁵

After this initial model was fit there was significant evidence that the observations were overdispersed with respect to the Poisson model, $G^2 = 249.421$, $p = 0.000$. Thus, **MS2F** was respecified to include a multiplicative disturbance term v_i to capture unobserved heterogeneity.

⁶⁵A robust estimator of variance was used in place of the standard estimator to adjust for $k = 122$ block-group clusters (Huber, 1967; Rogers, 1993; H. White, 1980). Also, to account for varying times-at-risk, the logged number of drug screens $\log(outDrgTotScr_{i7})$ was included and constrained to a coefficient of 1.

Table 31

Parameter estimates, Poisson and negative binomial regressions of $outDrgTotPos_{i6}$, **MS2F**, $n = 194$.

	b/z	b/z
$psiSubHeEU$	4.013*** (9.40)	4.106*** (10.22)
$arrPro.d$	-0.034 (-1.64)	-0.019 (-1.33)
$psiCrmAdlCnv^*$	0.008 (0.11)	0.044 (0.79)
α	-5.871*** (-16.50)	-6.192*** (-20.49)
Overdispersion α		0.780* (2.47)
Model χ^2	120.397***	174.339***

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

The model

$$\widehat{\Pr}(outDrgTotPos_{i6} | \mathbf{x}_i) = \frac{\exp(-\widetilde{\mu}_i)\widetilde{\mu}_i^{outDrgTotPos_{i6}}}{outDrgTotPos_{i6}!}$$

where $\widetilde{\mu}_i = \exp(\mathbf{x}_i\boldsymbol{\beta} + v_i)$ and $x_{i1} = psiSubHeEU_i$, $x_{i2} = arrPro.d_i$, and $x_{i3} = psiCrmAdlCnv_i$, was then fitted to the sample data. Parameter estimates from this regression are shown in the second column of Table 31.⁶⁶

The model had $D=350.81$, $AIC=1.860$, and $BIC=-644.820$.

The Wald test⁶⁷ of the hypothesis that all coefficients except the intercept were zero $H_0 : \beta_1 = \beta_2 = \beta_3 = 0$ was rejected, $\chi_W^2 = 174.34$, $df = 3$, $p = 0.00$. The test of $H_0 : \beta_1 = 0$ was

⁶⁶A robust estimator of variance was used in place of the standard estimator to adjust for $k = 122$ block-group clusters (Huber, 1967; Rogers, 1993; H. White, 1980). Also, to account for varying times-at-risk, the logged number of drug screens $\log(outDrgTotScr_{i7})$ was included and constrained to a coefficient of 1.

⁶⁷The χ_L^2 test is likely invalid given the robust estimator of variance used to adjust for $k = 122$ block-group clusters.

rejected ($\chi^2_W = 104.35$, $df = 1$, $p = 0.00$) but neither test of $H_0: \beta_2 = 0$ ($\chi^2_W = 1.76$, $df = 1$, $p = 0.18$) nor of $H_0: \beta_3 = 0$ ($\chi^2_W = 0.63$, $df = 1$, $p = 0.43$) were rejected.

By comparison, the PR shown in the first column of Table 31 performed at its worse in predictions of zero counts where it overpredicted. The NBR shown in the second column of Table 31 performed at its worse in predictions of counts of 1 where it too overpredicted counts. Overall, the NBR, with mean absolute difference between predicted and observed values $|\Delta_{\widehat{\pi}_o - \widehat{\pi}_p}| = 0.010$, outperformed the PR, with $|\Delta_{\widehat{\pi}_o - \widehat{\pi}_p}| = 0.022$.

I then turned to assessing scale beginning with the relationship involving $psiCrmAdlCnv_i$. A plot of the univariable lowess smooth of $outDrgTotPos_{i6}$ against $psiCrmAdlCnv_i$ suggested the relationship was essentially linear; this predictor was left as is. On the other hand, a similar plot suggested there was substantial non-linearity in the relationship involving $arrPro.d_i$ and $outDrgTotPos_{i6}$. Some of this stemmed from poor behavior in the upper tail of the distribution. There were several extreme outliers ($arrPro.d_i \geq 163$). Several transformations of $arrPro.d_i$ were attempted with and without the outlying cases. None, however, adequately represented the relationship. Ultimately, $arrPro.d_i$ was left as is and thus the model was unchanged.

A visual indication of model calibration is given in the plot in Figure 13. This plot shows the observed and predicted probabilities of counts zero through 9. As indicated, the model-implied and observed probabilities track closely throughout the distribution, with the poorest fit in counts of 1.

The NBR of $S2F$ on $psiSubHeEU_i$, $arrPro.d_i$, and $psiCrmAdlCnv_i$, shown in the second column of Table 31 was validated by bootstrapping. Bias-corrected confidence intervals around the estimated parameters are shown in Table 32. As indicated, only the effect of $psiSubHeEU_i$ is likely to replicate in the population. Those of $arrPro.d_i$ and $psiCrmAdlCnv_i$ are not.

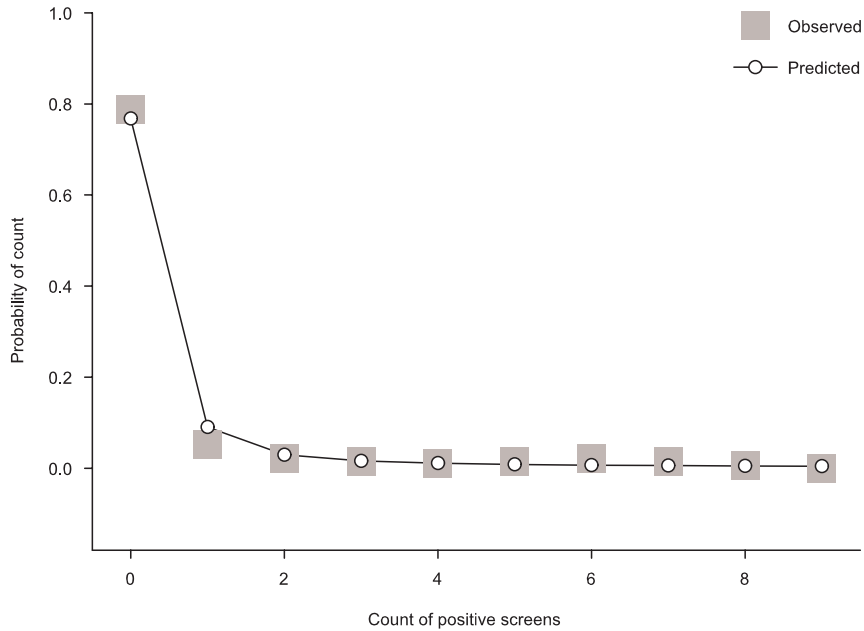


Figure 13. Observed and NBR model-implied counts of $outDrgTotPos_{i6}$, **MS2F**, $n = 194$.

Table 32

Lower (LCLM) and upper (UCLM) bias-corrected 95% confidence limits, **MS2F**, $n = 194$.

	LCLM	UCLM
$psiSubHeEU$	3.21	4.99
$arrPro.d$	-.0791	.0418
$psiCrmAdlCnv$	-.0756	.163

The single most important characteristic influencing the rate of positive screens for opiates is having ever used opiates $psiSubHeEU_i$. The rate of positive screens among those having never used opiates is .00179. Having used opiates increases the expected rate of positives by 0.11—a factor of 60.

MS2G. The criterion for model **MS2G** is the number times the i th probationer tested positive for phencyclidine $outDrgTotPos_{i7}$; interest centers on the expected rate of this criterion in the population $\widehat{\mu}_i$. Screens for phencyclidine occurred roughly 5 times monthly, on average, through-

out the supervision period, $M = 4.59$, $SD = 7$. $190/199 = 0.95$ of the sample was screened at least once for phencyclidine; one or more of these were positive for $33/190 = 0.17$ of these probationers. The 95%CI around mean $\frac{n_{positives}}{n_{screens}}$ is shown in Table 26.

Potential predictors were included in a general model which was then recursively partitioned⁶⁸ into the binary tree shown in Figure 14a using Poisson-splitting methods (see, Breiman et al., 1984; Therneau & Atkinson, 1997).⁶⁹ This classification tree, since it was likely too complex to validate, was trimmed back to that shown in Figure 14b.⁷⁰

Predictors having the largest effect on the rate of positive phencyclidine screens $outDrgTotPos_{i7}$ included (a) whether the probationer ever used phencyclidine $psiSubPcEU_i$, (b) the number of substances ever used $psiSubEU1_i$, and (c) the highest grade attempted $psiEduGrdAt_i$; remaining predictors did not appear in the model.

The resultant model separated sampled probationers into 4 groups. The groups (and predicted values) included probationers (a) never having used phencyclidine (0.26); (b) having previously used phencyclidine, used more than 2 substances, and whose highest grade attempted was at least grade 11 (0.64); (c) having previously used phencyclidine, used more than 2 substances, whose highest grade attempted was 10th or less (4.5) (d) having used phencyclidine and used 2 or fewer substances (13);

An initial model

$$\widehat{\Pr}(outDrgTotPos_{i7} | \mathbf{x}_i) = \frac{\exp(-\mu_i)\mu_i^{outDrgTotPos_{i7}}}{outDrgTotPos_{i7}!}$$

⁶⁸Using the R library RPART (Therneau & Atkinson, 1997).

⁶⁹The Gini rule was used for splitting, prior probabilities were set proportional to observed frequencies, and altered priors were used for the loss function.

⁷⁰Cost-complexity pruning was based on the $1 - SE$ rule among cross-validated data.

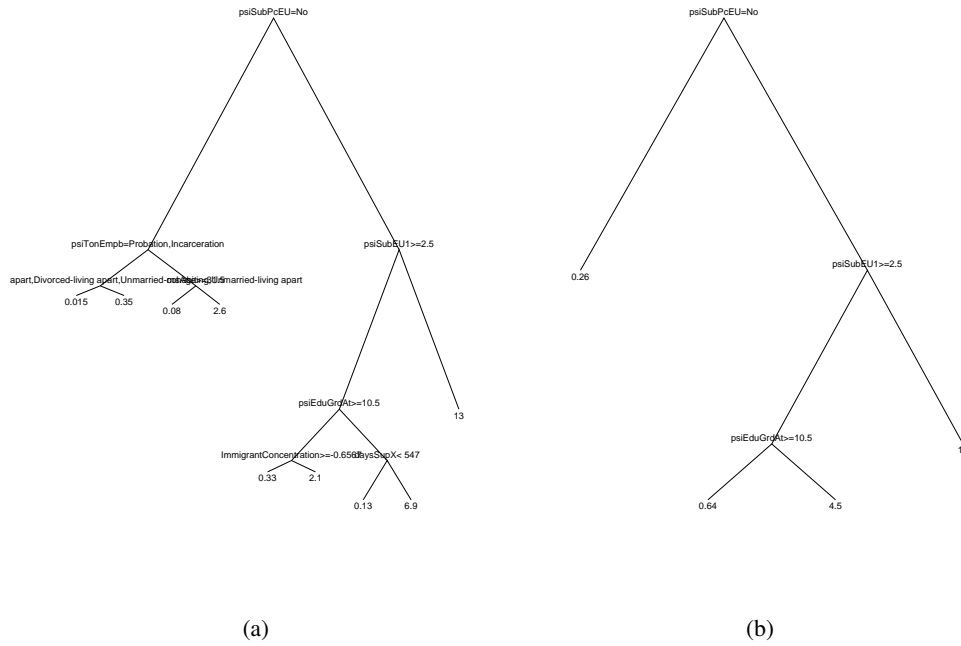


Figure 14. Initial (a) and pruned (b) classification trees predicting $outDrgTotPos_{i7}$, **MS2G**, $n = 190$.

where $\mu_i = \exp(\mathbf{x}_i\boldsymbol{\beta})$ and $x_{i1} = psiSubPcEU_i$, $x_{i2} = psiSubEU1_i$, and $x_{i3} = psiEduGrdAt_i$, was fitted to the sample data with the pruned-tree predictors in their original form; parameter estimates are shown in the first column of Table 33.⁷¹

After this initial model was fit there was significant evidence that the observations were overdispersed with respect to the Poisson model, $G^2 = 612.486, p = 0.000$. Thus, **MS2G** was respecified to include a multiplicative disturbance term v_i to capture unobserved heterogeneity. The model

$$\widehat{\Pr}(outDrgTotPos_{i7} | \mathbf{x}_i) = \frac{\exp(-\widetilde{\mu}_i)\widetilde{\mu}_i^{outDrgTotPos_{i7}}}{outDrgTotPos_{i7}!}$$

⁷¹A robust estimator of variance was used in place of the standard estimator to adjust for $k = 122$ block-group clusters (Huber, 1967; Rogers, 1993; H. White, 1980). Also, to account for varying times-at-risk, the logged number of drug screens $\log(outDrgTotScr_{i7})$ was included and constrained to a coefficient of 1.

Table 33

Parameter estimates, Poisson and negative binomial regressions of $outDrgTotPos_{i7}$, **MS2G**, $n = 190$.

	b/z	b/z	b/z
$psiSubPCEU$	3.596*** (4.42)	2.731*** (4.33)	2.721*** (4.03)
$psiSubEU1$	-0.615* (-2.15)	-0.297 (-1.62)	
$psiEduGrdAt$	-0.071 (-0.82)	-0.249 (-1.69)	
$psiSubEU1^*$			-0.422 (-1.61)
$psiEduGrdAt^*$			-0.428* (-1.98)
α	-3.590*** (-3.98)	-1.979 (-1.10)	0.298 (0.11)
Overdispersion α		2.183*** (8.63)	2.149*** (7.86)
Model χ^2	47.091***	24.899***	23.693***

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

where $\tilde{\mu}_i = \exp(\mathbf{x}_i\boldsymbol{\beta} + v_i)$ and $x_{i1} = psiSubPcEU_i$, $x_{i2} = psiSubEU1_i$, and $x_{i3} = psiEduGrdAt_i$, was then fitted to the sample data. Parameter estimates from this regression are shown in the second column of Table 33.⁷²

The model had $D=356.69$, $AIC=1.930$, and $BIC=-614.014$.

By comparison, the PR shown in the first column of Table 33 performed at its worse in predictions of zero where it overpredicted counts. The NBR shown in the second column of Table 33 performed at its worse in predictions of counts of 8 where it underpredicted counts.

⁷²A robust estimator of variance was used in place of the standard estimator to adjust for $k = 122$ block-group clusters (Huber, 1967; Rogers, 1993; H. White, 1980). Also, to account for varying times-at-risk, the logged number of drug screens $\log(outDrgTotScr_{i7})$ was included and constrained to a coefficient of 1.

Overall, the NBR, with mean absolute difference between predicted and observed values $|\Delta_{\widehat{\pi}_o - \widehat{\pi}_p}| = 0.007$, outperformed the PR, with $|\Delta_{\widehat{\pi}_o - \widehat{\pi}_p}| = 0.061$.

I then turned to assessing scale. To account for sparse representation in its upper levels, the last three levels of $psiSubEU1_i$ were collapsed as $psiSubEU1_i^*$. As for $psiEduGrdAt_i$, only $13/199 = 0.065$ of the probationers had values of $psiEduGrdAt_i$ less than 9; the same proportion of probationers had values above 13. To accommodate this, grades 0–9 and grades 13–16 were collapsed to represent highest grade attempted as 9th or below and 13th and higher, respectfully, as $psiEduGrdAt_i^*$.

The model

$$\widehat{\Pr}(outDrgTotPos_{i7} | \mathbf{x}_i) = \frac{\exp(-\widetilde{\mu}_i) \widetilde{\mu}_i^{outDrgTotPos_{i7}}}{outDrgTotPos_{i7}!}$$

where $\widetilde{\mu}_i = \exp(\mathbf{x}_i \boldsymbol{\beta} + v_i)$ and $x_{i1} = psiSubPcEU_i$, $x_{i2} = psiSubEU1_i^*$, and $x_{i3} = psiEduGrdAt_i^*$, was then refitted to the sample data. Parameter estimates from this regression are shown in the third column of Table 33.⁷³

The model had $D=355.44$, $AIC=1.923$, and $BIC=-615.255$.

The Wald test⁷⁴ of the hypothesis that all coefficients except the intercept were zero $H_0: \beta_1 = \beta_2 = \beta_3 = 0$ was rejected, $\chi_W^2 = 23.69$, $df = 3$, $p = 0.00$. The test of $H_0: \beta_1 = 0$ was rejected ($\chi_W^2 = 16.23$, $df = 1$, $p = 0.00$), the test of $H_0: \beta_2 = 0$ was not rejected ($\chi_W^2 = 2.61$, $df = 1$, $p = 0.11$), and the test of $H_0: \beta_3 = 0$ was rejected, $\chi_W^2 = 3.91$, $df = 1$, $p = 0.05$.

A visual indication of model calibration is given in the plot in Figure 15. This plot shows the observed and predicted probabilities of counts zero through 9. As indicated, the model-implied

⁷³A robust estimator of variance was used in place of the standard estimator to adjust for $k = 122$ block-group clusters (Huber, 1967; Rogers, 1993; H. White, 1980). Also, to account for varying times-at-risk, the logged number of drug screens $\log(outDrgTotScr_{i7})$ was included and constrained to a coefficient of 1.

⁷⁴The χ_L^2 test is likely invalid given the robust estimator of variance used to adjust for $k = 122$ block-group clusters.

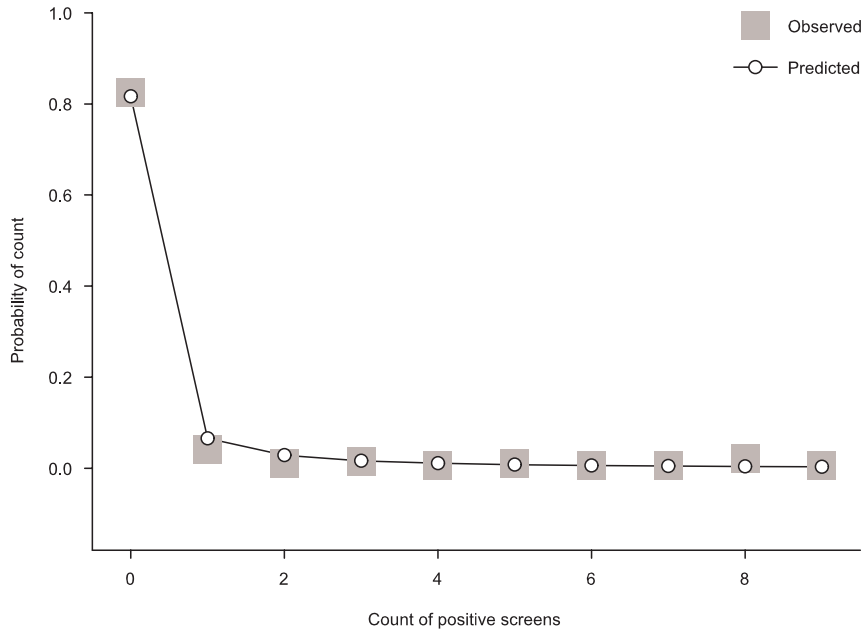


Figure 15. Observed and NBR model-implied counts of $outDrgTotPos_{i7}$, **MS2G**, $n = 190$.

Table 34

Lower (LCLM) and upper (UCLM) bias-corrected 95% confidence limits, **MS2G**, $n = 190$.

	LCLM	UCLM
$psiSubPCEU$.366	5.08
$psiSubEU1^*$	-1.02	.181
$psiEduGrdAt^*$	-.96	.103

and observed probabilities track closely throughout the distribution, with the poorest fit in counts of 1.

The NBR of $S2G$ on $x_{i1} = psiSubPcEU_i$, $x_{i2} = psiSubEU1_i^*$, and $x_{i3} = psiEduGrdAt_i^*$, shown in the third column of Table 33 was validated by bootstrapping. Bias-corrected confidence intervals around the estimated parameters are shown in Table 34. As indicated, the effects of $psiSubEU1^*$ and $psiEduGrdAt^*$ are not likely to replicate in the population.

The most important characteristic influencing rates of testing positive for phencyclidine is having ever used phencyclidine. Holding ψ_{SubEU1}^* and $\psi_{EduGrdAt}^*$ at their modal values, having ever used phencyclidine increases the expected rate by a factor of 15, from .0022 to .034.

Arrest-convictions

Models **MC1** and **MC2** estimate the probabilities that probationers in the population will be convicted for new crimes given an arrest. Model **MC1** focuses on convictions during the supervision period; Model **MC2**, the post-supervision period.

MC1. The criterion for **MC1** is whether the i th probationer is arrested and subsequently convicted on new charges during the supervision period $outC1_i$. If so, $outC1_i = 1$. Roughly one-fourth ($51/199 = 0.26$) of the sampled probationers were indeed arrested and subsequently convicted of new crimes during the supervision period. Interest centers on the predicted probability of the criterion, $\widehat{\Pr}(outC1_i = 1)$.

Potential predictors of this process were included in a general model which was then recursively partitioned⁷⁵ into the binary tree shown in Figure 16a.⁷⁶ This classification tree, since it was likely too complex to validate, was trimmed back to that shown in Figure 16b.⁷⁷

Predictors having the largest influence on whether probationers are arrested and subsequently convicted on new charges during the supervision period included (a) the Salient Factor Score (SFS)-98 $\psi_{CrmAdlSFS1_i}$, (b) the recommended sentence ψ_{SR_i} , and (c) the number of adult convictions involving weapons $\psi_{CrmAdlCnvWea_i}$; remaining predictors did not appear in the model.

⁷⁵Using the R library RPART (Therneau & Atkinson, 1997).

⁷⁶The Gini rule was used for splitting, prior probabilities were set proportional to observed frequencies, and altered priors were used for the loss function.

⁷⁷Cost-complexity pruning was based on the $1 - SE$ rule among cross-validated data.

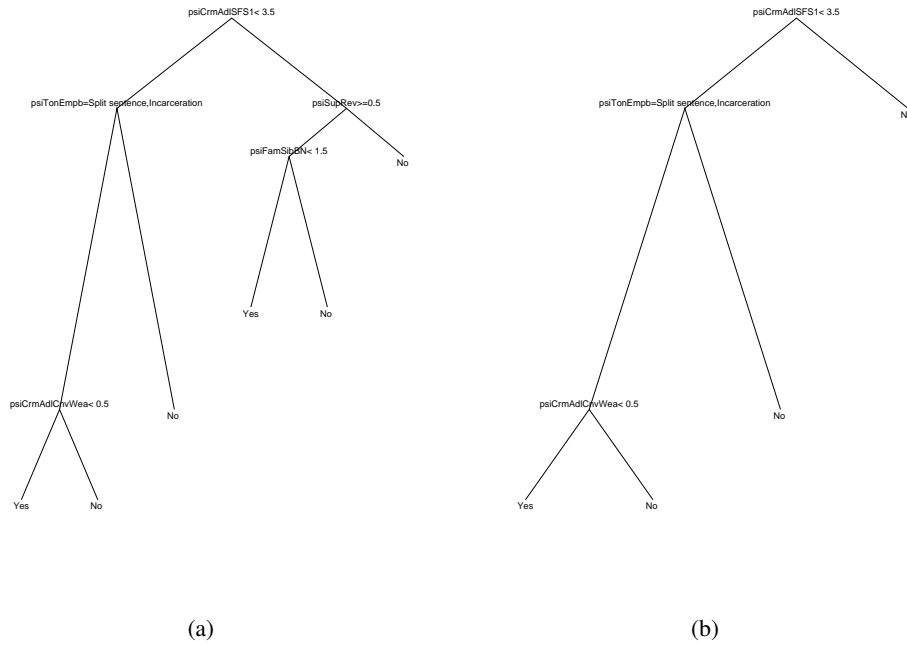


Figure 16. Initial (a) and pruned (b) classification trees predicting $outC1_i$, **MC1**, $n = 199$.

The resultant model separated sampled probationers into 4 groups. These groups (and predicted values) included probationers having (a) an SFS-98 score lower than 4, a recommended sentence of either split sentence or incarceration, and fewer than 1 adult convictions involving weapons (Yes); (b) an SFS-98 score lower than 4, a recommended sentence of either split sentence or incarceration, and 1 or more adult convictions involving weapons (No); (c) an SFS-98 score lower than 4 and a recommended sentence of probation, (No); and (d) an SFS-98 score equal to or greater than 4, (No).

Indicators $recSInc$ and $recSSpl$ representing, respectfully, recommended sentences of incarceration and split sentence were created and an initial model

$$\begin{aligned} \widehat{\Pr}(outC1_i = 1 | \mathbf{x}_i) &= \frac{1}{1 + \exp[-(\mathbf{x}_i \boldsymbol{\beta})]} \\ &= \frac{1}{1 + \exp[-(\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \beta_4 x_{i4})]}, \end{aligned}$$

Table 35

Parameter estimates, **MC1**, logistic regression of $outC1_i$, $n = 199$.

	b/z	b/z	b/z	b/z
<i>psiCrmAdIS FS 1</i>	-0.201** (-2.82)	-0.190** (-2.66)	-0.215** (-3.12)	-0.468*** (-3.43)
<i>recS Inc</i>	1.615*** (3.67)	1.555*** (3.57)		
<i>recS S pl</i>	0.460 (0.96)	0.483 (1.01)		
<i>psiCrmAdlCnvWea</i>	-0.617* (-2.20)			
<i>CnvWeaHi</i>		-0.673 (-1.36)	-0.606 (-1.29)	-0.754 (-1.37)
<i>probation</i>			-1.145** (-3.03)	-3.354*** (-3.63)
<i>psiCrmAdIS FS 1 × probation</i>				0.431** (2.65)
α	-0.487 (-1.04)	-0.555 (-1.16)	0.727 (1.79)	1.852** (2.88)
Model χ^2	31.237***	28.496***	20.221***	32.811***

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

where $x_{i1} = psiCrmAdIS FS 1_i$, $x_{i2} = recS Inc_i$, $x_{i3} = recS S pl_i$, and $x_{i4} = psiCrmAdlCnvWea_i$, was fitted to the sample data; parameter estimates are shown in the first column of Table 35.⁷⁸

The Wald test⁷⁹ of $H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$ was rejected, $\chi_W^2 = 31.24$, $df = 4$, $p = 0.00$. The test of $H_0: \beta_1 = 0$ was rejected ($\chi_W^2 = 7.97$, $df = 1$, $p = 0.00$); the test of $H_0: \beta_2 = \beta_3 = 0$ was rejected ($\chi_W^2 = 14.01$, $df = 2$, $p = 0.00$); and the test of $H_0: \beta_4 = 0$ was rejected ($\chi_W^2 = 4.83$, $df = 1$, $p = 0.03$).

⁷⁸A robust estimator of variance was used in place of the standard estimator to adjust for $k = 122$ block-group clusters (Huber, 1967; Rogers, 1993; H. White, 1980).

⁷⁹The χ_L^2 test is likely invalid given the robust estimator of variance used to adjust for $k = 122$ block-group clusters.

The model correctly classified 0.79 of the sample; the AUC suggested it demonstrated acceptable discrimination, $AUC = 0.76$. The model had $D=189.45$, $AIC=1.002$, and $BIC=-837.448$; the \hat{c} suggested it was empirically consistent, $\chi_{HL}^2 = 8.34$, $df = 8$, $p = 0.40$.

Focus turned to refining this preliminary model in terms of parametric relationships and scale beginning with the relationship between $outC1_i$ and $psiCrmAdlSFS1_i$. A plot of the lowess smoothed logit against linear $psiCrmAdlSFS1_i$ suggested a linear relationship and there was no evidence that an interval representation introduced loss of information. The predictor $psiCrmAdlSFS1_i$ was thus left as linear and continuous in the regression of $outC1_i$.

I next turned to $psiCrmAdlCnvWea_i$. The tree in Figure 16b unexpectedly indicates having fewer than 1 weapons-related convictions is associated with increased probabilities of being arrested and subsequently convicted on new charges during the supervision period, but that having more than 1 weapons-related convictions is associated with decreased probabilities.

Some of this unanticipated relationship reflected severe non-normality in the predictor. A plot of the lowess smoothed logit against linear $psiCrmAdlCnvWea$ indicated there was a sharp spike in the logit between 0 and 1 previous weapons convictions, a flat relationship from 1 to 3, then a slow, negative effect thereafter.

While originally scaled as continuous, ranging within $[0, +\infty)$, the distribution of $psiCrmAdlCnvWea_i$ in the sample showed strong positive skew. The majority ($162/199 = 0.81$) of probationers did not have any previous weapons-related convictions, $30/199 = 0.15$ had 1, $4/199 = 0.02$ had 2, and $3/199 = 0.015$ had 3 or more. The predictor was recoded as a binary indicator $CnvWeaHi_i = psiCrmAdlCnvWea_i \geq 1$.

A refined model was fitted to the sample data replacing $psiCrmAdlCnvWea_i$ with its binary representation; parameter estimates from the model

$$\begin{aligned}\widehat{\Pr}(outC1_i = 1 | \mathbf{x}_i) &= \frac{1}{1 + \exp[-(\mathbf{x}_i\boldsymbol{\beta})]} \\ &= \frac{1}{1 + \exp[-(\beta_0 + \beta_1x_{i1} + \beta_2x_{i2} + \beta_3x_{i3} + \beta_4x_{i4})]},\end{aligned}$$

where $x_{i1} = psiCrmAdlSFS1_i$, $x_{i2} = recSInc_i$, $x_{i3} = recSSpl_i$, and $x_{i4} = CnvWeaHi_i$, are shown in the second column of Table 35.⁸⁰

The Wald test⁸¹ of $H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$ was rejected, $\chi^2_W = 28.50$, $df = 4$, $p = 0.00$. The test of $H_0: \beta_1 = 0$ was rejected ($\chi^2_W = 7.09$, $df = 1$, $p = 0.01$); the test of $H_0: \beta_2 = \beta_3 = 0$ was rejected ($\chi^2_W = 13.08$, $df = 2$, $p = 0.00$); the test of $H_0: \beta_4 = 0$ was not rejected ($\chi^2_W = 1.85$, $df = 1$, $p = 0.17$).

The model correctly classified 0.79 of the sample and the AUC suggested it demonstrated acceptable discrimination, $AUC = 0.75$. The model had $D=192.49$, $AIC=1.018$, and $BIC=-834.411$; the \widehat{c} suggested it was empirically consistent, $\chi^2_{HL} = 8.80$, $df = 8$, $p = 0.36$.

The tree in Figure 16b suggests the effect of $recSent_i$ is likely isolated to the comparison of probation versus both incarceration and split sentence. To capture this, an indicator of probation recommendations versus the remaining categories $probation_i = (recSent_i == \text{'Probation'})$ was created.

Using it in place of $recSent_i$, the model

$$\begin{aligned}\widehat{\Pr}(outC1_i = 1 | \mathbf{x}_i) &= \frac{1}{1 + \exp[-(\mathbf{x}_i\boldsymbol{\beta})]} \\ &= \frac{1}{1 + \exp[-(\beta_0 + \beta_1x_{i1} + \beta_2x_{i2} + \beta_3x_{i3})]},\end{aligned}$$

⁸⁰A robust estimator of variance was used in place of the standard estimator to adjust for $k = 122$ block-group clusters (Huber, 1967; Rogers, 1993; H. White, 1980).

⁸¹The χ^2_L test is likely invalid given the robust estimator of variance used to adjust for $k = 122$ block-group clusters.

where $x_{i1} = \text{psiCrmAdlsFS } 1_i$, $x_{i2} = \text{probation}_i$, and $x_{i3} = \text{CnvWeaHi}_i$, was fitted; parameter estimates are shown in the third column of Table 35.⁸²

The Wald test⁸³ of $H_0: \beta_1 = \beta_2 = \beta_3 = 0$ was rejected, $\chi^2_W = 20.22$, $df = 3$, $p = 0.00$. The test of $H_0: \beta_1 = 0$ was rejected ($\chi^2_W = 9.18$, $df = 1$, $p = 0.00$); the test of $H_0: \beta_3 = 0$ was not rejected ($\chi^2_W = 1.67$, $df = 1$, $p = 0.20$).

The model correctly classified 0.82 of the sample and the the AUC indicated acceptable discrimination, $AUC = 0.74$. The model had $D=197.33$, $AIC=1.032$, and $BIC=-834.870$; the \widehat{c} suggested the model was empirically consistent, $\chi^2_{HL} = 15.97$, $df = 8$, $p = 0.04$.

There is also an indication that the effect of *psiCrmAdlsFS 1* depends on the recommended sentence. These two predictors overlap slightly: the SFS-98 captures elements of criminal history (see, Appendix B for details) and, quite rightly, PSI authors base much of their sentence recommendation on these same criteria.

I created the product term $\text{psiCrmAdlsFS } 1_i \times \text{probation}_i$ to capture this potential interaction. The model was refitted as

$$\begin{aligned} \widehat{\Pr}(\text{outC}1_i = 1 \mid \mathbf{x}_i) &= \frac{1}{1 + \exp[-(\mathbf{x}_i\boldsymbol{\beta})]} \\ &= \frac{1}{1 + \exp[-(\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \beta_4 x_{i1} x_{i2})]}, \end{aligned}$$

where $x_{i1} = \text{psiCrmAdlsFS } 1_i$, $x_{i2} = \text{probation}_i$, and $x_{i3} = \text{CnvWeaHi}_i$; parameter estimates are shown in the fourth column of Table 35.⁸⁴

The model had $D=188.51$, $AIC=0.998$, and $BIC=-838.391$; the \widehat{c} suggested the model was empirically consistent, $\chi^2_{HL} = 12.48$, $df = 8$, $p = 0.13$.

⁸²A robust estimator of variance was used in place of the standard estimator to adjust for $k = 122$ block-group clusters (Huber, 1967; Rogers, 1993; H. White, 1980).

⁸³The χ^2_L test is likely invalid given the robust estimator of variance used to adjust for $k = 122$ block-group clusters.

⁸⁴A robust estimator of variance was used in place of the standard estimator to adjust for $k = 122$ block-group clusters (Huber, 1967; Rogers, 1993; H. White, 1980).

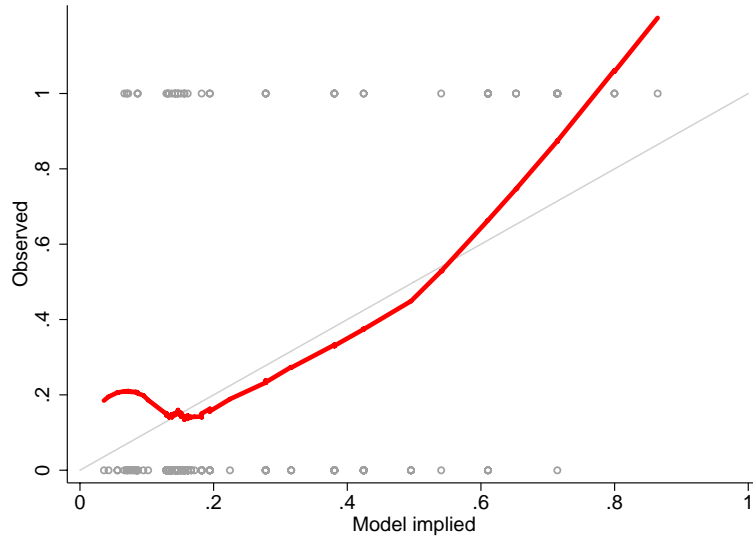


Figure 17. Comparison between model-implied probabilities of experiencing $outC1_i$ and a moving average of the proportion of probationers arrested and convicted on new charges during the supervision period, $n = 199$.

The Wald test⁸⁵ of the interaction $H_0 : \beta_4 = 0$ was rejected ($\chi^2_W = 7.03$, $df = 1$, $p = 0.01$). Aside from the significant interaction term, there was evidence that this change led to an improvement in model calibration.

The model correctly classified 0.83 of the sample and the the AUC indicated acceptable discrimination, $AUC = 0.73$.

A visual indication of model calibration is given in the plot in Figure 17. The thick line represents the fraction of probationers arrested and subsequently convicted of a new crime within the supervision period at each level of predicted probabilities, and, here, suggests the model may lack calibration throughout this range. However, compared to calibration curves⁸⁶ for the models shown in Columns 1–3 of Table 35, the model in Column 4 demonstrates visible improvement.

⁸⁵The χ^2_L test is likely invalid given the robust estimator of variance used to adjust for $k = 122$ block-group clusters.

⁸⁶Not presented.

Table 36

Lower (LCLM) and upper (UCLM) bias-corrected 95% confidence limits, **MC1**, $n = 199$.

	LCLM	UCLM
<i>psiCrmAdls FS 1</i>	-.765	-.17
<i>probation</i>	-5.31	-1.39
<i>CnvWeaHi</i>	-1.96	.45
<i>psiCrmAdls FS 1 × probation</i>	.0808	.781

The regression of $outC1_i$ on $psiCrmAdls FS 1_i$, $probation_i$, $CnvWeaHi_i$, and $psiCrmAdls FS 1_i \times probation_i$ shown in the fourth column of Table 35 was validated by bootstrapping. Bias-corrected confidence intervals around the estimated parameters are shown in Table 36. As indicated in the table, the effects of $psiCrmAdls FS 1_i$, $probation$, and their interaction were likely to validate in the population. On the other hand, the effect of $CnvWeaHi$ was not. Interpretations of the model are based on the effects of $psiCrmAdls FS 1_i$, $probation$, and $psiCrmAdls FS 1_i \times probation$ while holding $CnvWeaHi$ at its modal value of no previous weapons-related convictions.

Predicted values $\hat{\pi}$ ranged within the interval [0.036, 0.864], with mean $\hat{\pi} = 0.256$ ($SD = 0.20$). The two most important characteristics influencing $\widehat{\Pr}(outC1_i = 1)$ are $psiCrmAdls FS 1_i$ and $probation$.

The plot in Figure 18 shows predicted probabilities an offender will be arrested and subsequently convicted on new charges during the supervision period by $psiCrmAdls FS 1_i$ and recommended sentence. Lower SFS-98 scores are associated with increased chances an offender will be arrested and subsequently convicted on new charges during the supervision period. As indicated, this is especially true among those whose recommended sentence was either incarceration or split-sentence. For these offenders, the predicted probability of being arrested and subsequently convicted increases exponentially as SFS-98 decreases. For those whose recommended sentence

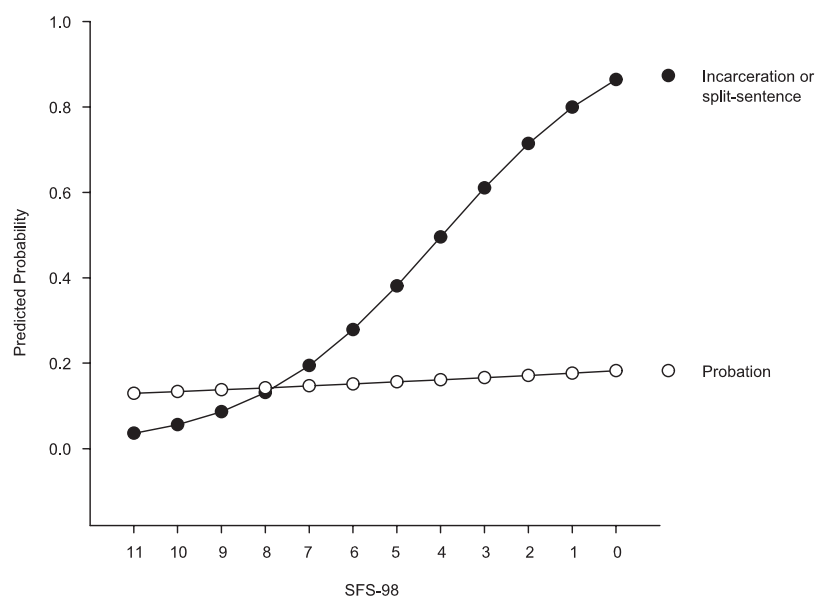


Figure 18. Predicted probabilities an offender in the population will be convicted of a new crime during the supervision period, by SFS-98 score and recommended sentence, **MC1**, $n = 199$.

was probation, however, changes in the SFS-98 scores have little impact: predicted probabilities are essentially flat. This is expected given the potential overlap between the two measures.

MC2. The criterion for **MC2** is whether the i th probationer is arrested and subsequently convicted on new charges during the post-supervision period. If so, $outC2_i = 1$. Indeed, roughly one-fourth ($49/199 = 0.25$) of the sampled probationers were arrested and subsequently convicted of new crimes during this period. Interest centers on the predicted probability of the criterion, $\widehat{\Pr}(outC2_i = 1)$.

Potential predictors of $outC2_i$ were included in a general model which was then recursively partitioned⁸⁷ into the binary tree shown in Figure 19a.⁸⁸ This classification tree, since it was likely too complex to validate, was trimmed back to that shown in Figure 19b.⁸⁹

⁸⁷Using the R library RPART (Therneau & Atkinson, 1997).

⁸⁸The Gini rule was used for splitting, prior probabilities were set proportional to observed frequencies, and altered priors were used for the loss function.

⁸⁹Cost-complexity pruning was based on the $1 - SE$ rule among crossvalidated data.

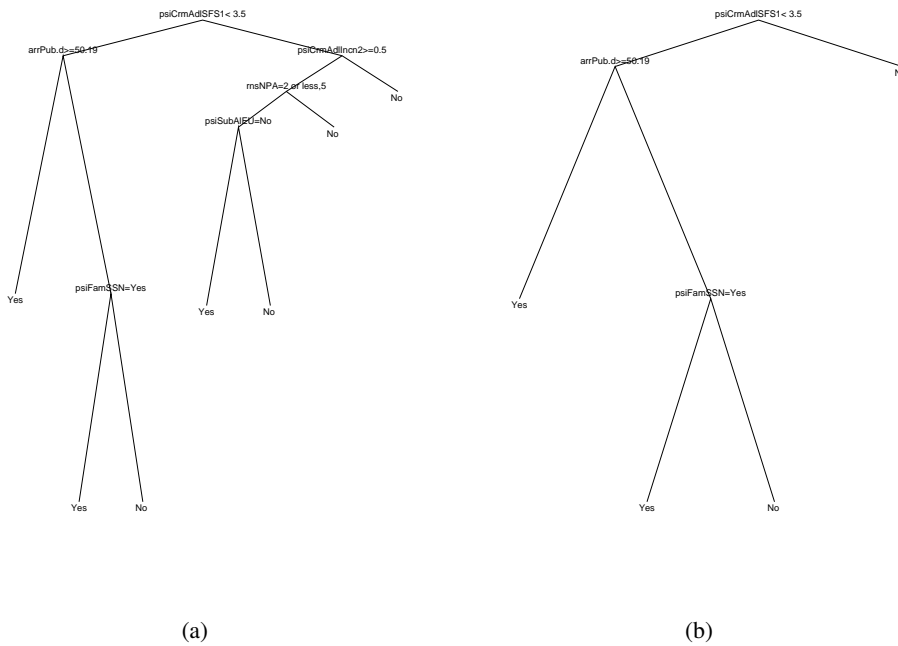


Figure 19. Initial (a) and pruned (b) classification trees predicting $outC2_i$, **MC2**, $n = 199$.

Predictors having the largest influence on whether probationers are arrested and subsequently convicted on new charges during the post-supervision period included (a) the SFS-98 $psiCrmAdlSFS1$, (b) the rate of public order related arrests within the BG $arrPub.d$, and (c) whether the PSI author found a supportive social network $psiFamSSN$; remaining predictors did not appear in the model.

The resultant model separated sampled probationers into 4 groups. These groups (and associated predicted values) were (a) an SFS-98 score lower than 4 and a rate of public order related arrests greater than or equal to 50.19 (Yes); (b) an SFS-98 score lower than 4, a rate of public order related arrests less than 50.19, and supportive social network (Yes); (c) an SFS-98 score lower than 4, a rate of public order related arrests less than 50.19, and an absence of a supportive social network (No); and (d) an SFS-98 score equal to or greater than than 4, (No).

Table 37

Parameter estimates, **MC2**, logistic regression of $outC2_i$, $n = 199$.

	b/z	b/z	b/z
$psiCrmAdlSFS1$	-0.268*** (-4.32)	-0.267*** (-4.33)	-0.268*** (-4.28)
$arrPub.d$	0.005 (1.41)		
$psiFamSSN$	-0.021 (-0.05)	-0.043 (-0.11)	0.030 (0.08)
$arrPub.d^*$		0.093 (0.43)	
$arrPub.dHi$			0.916** (3.22)
α	0.195 (0.31)	0.158 (0.19)	0.109 (0.17)
Model χ^2	19.294***	18.822***	24.515***

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

An initial model

$$\begin{aligned}\widehat{\Pr}(outC2_i = 1 | \mathbf{x}_i) &= \frac{1}{1 + \exp[-(\mathbf{x}_i\boldsymbol{\beta})]} \\ &= \frac{1}{1 + \exp[-(\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3})]},\end{aligned}$$

where $x_{i1} = psiCrmAdlSFS1_i$, $x_{i2} = arrPub.d_i$, and $x_{i3} = psiFamSSN_i$, was fitted to the sample data; parameter estimates are shown in the first column of Table 37.⁹⁰

The Wald test⁹¹ of $H_0: \beta_1 = \beta_2 = \beta_3 = 0$ was rejected, $\chi_W^2 = 20.13$, $df = 3$, $p = 0.00$. The test of $H_0: \beta_1 = 0$ was rejected ($\chi_W^2 = 18.46$, $df = 1$, $p = 0.00$), but neither test of $H_0: \beta_2 = 0$ or $H_0: \beta_3 = 0$ were rejected, $\chi_W^2 = 3.66$, $df = 1$, $p = 0.06$ and $\chi_W^2 = 0.00$, $df = 1$, $p = 0.97$, respectively.

⁹⁰A robust estimator of variance was used in place of the standard estimator to adjust for $k = 122$ block-group clusters (Huber, 1967; Rogers, 1993; H. White, 1980).

⁹¹The χ_L^2 test is likely invalid given the robust estimator of variance used to adjust for $k = 122$ block-group clusters.

The model correctly classified 0.76 of the sample. and the AUC suggested it demonstrated acceptable discrimination, $AUC = 0.71$. The model had $D=200.37$, $AIC=1.047$, and $BIC=-831.823$; the \hat{c} suggested the model was empirically consistent, $\chi_{HL}^2 = 9.70$, $df = 8$, $p = 0.29$.

Focus then turned to refining this preliminary model in terms of parametric relationships and scale beginning with the relationship between $outC2_i$ and $psiCrmAdlSFS1_i$. A plot of the lowess smoothed logit against linear $psiCrmAdlSFS1$ indicated the predictor was well-modeled as linear and continuous. I next turned to $arrPub.d_i$. A plot of the lowess smoothed logit against linear $arrPub.d$ suggested a fairly complex non-linearity: there was an initial spike in the logit increasing near linearly from roughly $arrPub.d = 20$ peaking at roughly $arrPub.d = 100$. It cupped at roughly $arrPub.d = 150$ then flattened thereafter. There was likely very little to make of the apparent nonlinearities in the right half of the distribution. The predictor was poorly behaving in the upper tail. In fact, mean $arrPub.d$ was roughly equal to the $0.68Q$, $M = 25.40$, $SD = 30.90$. A normal quantile-comparison plot of $arrPub.d_i$ indicated non-normality, especially in the upper region, which was corrected using the unconditional Box-Cox method. The ML normalizing transformation parameter λ in x^λ was estimated as $\hat{\lambda} = 0.278$; the predictor was normalized by applying the transformation $arrPub.d_i^* = (arrPub.d_i + 0.5)^{0.278}$.

The model

$$\begin{aligned}\widehat{\Pr}(outC2_i = 1 | \mathbf{x}_i) &= \frac{1}{1 + \exp[-(\mathbf{x}_i\boldsymbol{\beta})]} \\ &= \frac{1}{1 + \exp[-(\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3})]}\end{aligned}$$

where $x_{i1} = psiCrmAdlSFS1_i$, $x_{i2} = arrPub.d_i^*$, and $x_{i3} = psiFamSSNi_i$, was refitted to the sample data; parameter estimates are shown in the second column of Table 37.⁹²

⁹²A robust estimator of variance was used in place of the standard estimator to adjust for $k = 122$ block-group clusters (Huber, 1967; Rogers, 1993; H. White, 1980).

The predictor $arrPub.d_i^*$ was split at 50.19 and the model

$$\begin{aligned}\widehat{\Pr}(outC2_i = 1 | \mathbf{x}_i) &= \frac{1}{1 + \exp[-(\mathbf{x}_i\boldsymbol{\beta})]} \\ &= \frac{1}{1 + \exp[-(\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3})]},\end{aligned}$$

where $x_{i1} = psiCrmAdlSFS1_i$, $x_{i2} = arrPub.d.hi_i$, and $x_{i3} = psiFamSSN_i$, was refitted to the sample data; parameter estimates are shown in the third column of Table 37.⁹³

The Wald test⁹⁴ of $H_0: \beta_1 = \beta_2 = \beta_3 = 0$ was rejected, $\chi_W^2 = 24.52$, $df = 3$, $p = 0.00$. The test of $H_0: \beta_1 = 0$ was rejected ($\chi_W^2 = 18.33$, $df = 1$, $p = 0.00$) and the test of $H_0: \beta_2 = 0$ was rejected ($\chi_W^2 = 10.36$, $df = 1$, $p = 0.00$); the test of $H_0: \beta_3 = 0$ was not rejected ($\chi_W^2 = 0.01$, $df = 1$, $p = 0.94$).

The model correctly classified 0.78 of the sample and the AUC suggested it demonstrated acceptable discrimination, $AUC = 0.71$. The model had $D=198.34$, $AIC=1.037$, and $BIC=-833.851$; the \widehat{c} suggested it was empirically consistent, $\chi_{HL}^2 = 10.08$, $df = 8$, $p = 0.26$.

A visual indication of model calibration is given in the plot in Figure 20 which compares predicted probabilities from the regression of $outC2$ with a moving average of the proportion of probationers arrested and convicted on new charges during the supervision period. The thick line represents the fraction of probationers arrested and subsequently convicted of a new crime during the post-supervision period at each level of predicted probabilities. Here, that the thick line tracks closely with the diagonal indicates the model is well-calibrated.

The regression of $outC2_i$ on $psiCrmAdlSFS1_i$, $arrPub.d_i^*$, and $psiFamSSN_i$, shown in the third column of Table 37 was validated by bootstrapping. Bias-corrected confidence intervals around the estimated parameters are shown in Table 38. As indicated in the table, the

⁹³A robust estimator of variance was used in place of the standard estimator to adjust for $k = 122$ block-group clusters (Huber, 1967; Rogers, 1993; H. White, 1980).

⁹⁴The χ_L^2 test is likely invalid given the robust estimator of variance used to adjust for $k = 122$ block-group clusters.

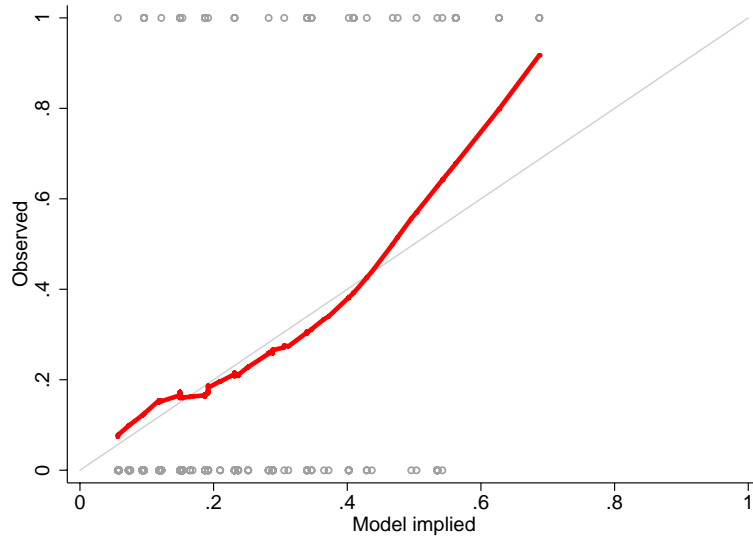


Figure 20. Comparison between model-implied probabilities of experiencing $outC2_i$ and a moving average of the proportion of probationers arrested and convicted on new charges after the supervision period, $n = 199$.

Table 38

Lower (LCLM) and upper (UCLM) bias-corrected 95% confidence limits, **MC2**, $n = 199$.

	LCLM	UCLM
$psiCrmAdlSFS1_i$	-.4	-.136
$arrPub.d_i^*$.294	1.54
$psiFamSSN_i$	-.771	.832

effects of $psiCrmAdlSFS1_i$ and $arrPub.d_i^*$ were likely to validate in the population. The effect of $psiFamSSN$, however, was not. Interpretations of the model are based on the effects of $psiCrmAdlSFS1_i$ and $arrPub.d_i^*$ while holding $psiFamSSN$ at its modal value of “No”.

Predicted values $\widehat{\pi}$ ranged within the interval $[.0568, .687]$, with mean $\widehat{\pi} = 0.246$ ($SD = 0.15$). The two most important characteristics influencing $\widehat{\Pr}(outC2_i = 1)$ are $psiCrmAdlSFS1_i$ and $arrPub.d_i^*$.

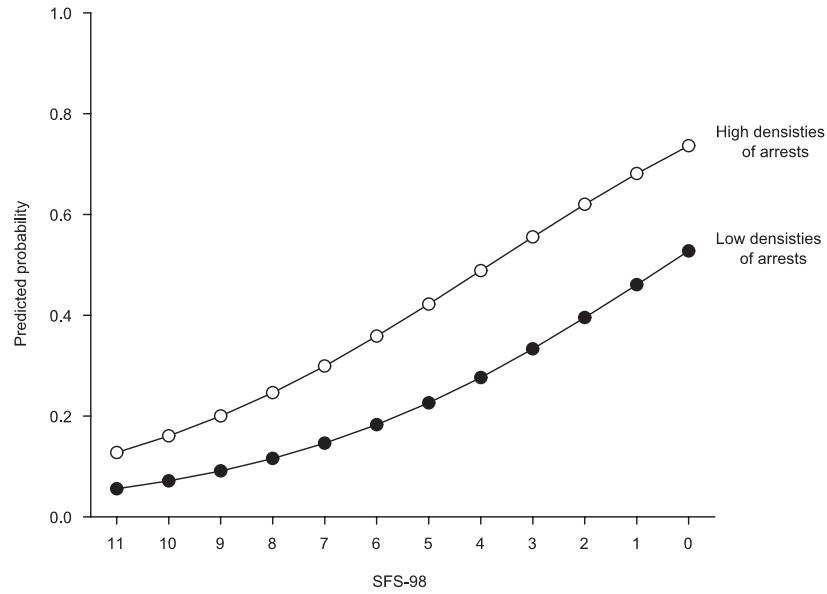


Figure 21. Predicted probabilities an offender in the population will be convicted of a new crime during the post-supervision period, by SFS-98 score and densities of public order arrests within the block group of residence, **MC2**, $n = 199$.

Holding $psiCrmAdlSFS1_i$ at its mean and $psiFamSSN_i$ at its modal value, varying $arrPub.d_i^*$ from its minimum of zero to its maximum of 1 increases the predicted probability of $outC2$ by 0.1784, from 0.1876 to 0.3659.

The plot in Figure 21 shows changes in the predicted probability an offender will be arrested and subsequently convicted on new charges during the post-supervision period by $psiCrmAdlSFS1_i$ and $arrPub.d_i^*$. Predicted probabilities increase linearly as SFS-98 decreases. The rate of change is nearly identical between offenders living in BGs with high and low rates of public order related arrests. However, predicted probabilities among those living in areas with higher rates of public order related arrests are consistently higher than those among their counterparts living in areas with lower rates of public order related arrests.

Table 39

Frequencies of violations, by violation type, $n = 199$.

Variable	Description	0	1	2	[3, 5)	[5, 7)	[7, 23]
<i>outV1</i>	Supervision-specific	79	49	35	22	8	6
<i>outV2</i>	Drug-related	87	28	25	25	13	21

Violations

Model **MV1** estimates factors associated with population rates of supervision-related condition violations. Model **MV2** similarly estimates factors associated with rates of drug-related condition violations. I describe these models next.

The criteria *outV1* and *outV2* are described in Table 39. $79/199 = 0.40$ offenders terminated sentences without violating supervision-related conditions. $185/199 = 0.93$ had fewer than 5. One offender had 23. Only 2 others had more than 10. Half of the sample $87/199 = 0.44$ terminated without violating any drug-related conditions. Its maximum reached 21, but, here again, few offenders ($10/199 = 0.05$) accumulated more than 10 drug-related violations.

MV1. The criterion for **MV1** is the number of supervision-related violations, *outV1*_{*i*}. $120/199 = 0.6$ of the sample had at least one supervision-related violation and offenders accumulated, on average, roughly 2 throughout the supervision period, $M = 1.53$, $SD = 2.47$. The highest number of supervision-related violations was 23. Interest centers on the predicted rate of the criterion, $\widehat{\mu}_i$.

Potential predictors were included in a general model which was then recursively partitioned⁹⁵ into the binary tree shown in Figure 22a using Poisson-splitting methods (see, Breiman et

⁹⁵Using the R library RPART (Therneau & Atkinson, 1997).

al., 1984; Therneau & Atkinson, 1997).⁹⁶ This classification tree, since it was likely too complex to validate, was trimmed back to that shown in Figure 22b.⁹⁷

Predictors having the largest influence on the rate of supervision-related violations included (a) the impression of risk on the CSO $rnsImp_i$, (b) the SFS-98 score $psiCrmAdlsFS1_i$, and (c) the supervision level $supLvl_i$; remaining predictors did not appear in the model.

The resultant model separated sampled probationers into 4 groups. The groups (and predicted values) included those for whom (a) the impression on the interviewing officer was either low or medium and SFS-98 score greater than 8 (0.48); (b) the impression on the interviewing officer was either low or medium and SFS-98 score less than or equal to 8 (1.3); (c) the impression on the interviewing officer was high and supervised at either minimum, medium, or maximum levels (1.8); and (d) the impression on the interviewing officer was high and supervised at the intensive level (4.6).

The indicators $imprHig_i$, $imprMed_i$, $imprLow_i$ were created to represent $rnsImp_i$ and the indicators min_i , med_i , max_i , and int_i were created to represent $supLvl_i$.⁹⁸ An initial model

$$\Pr(outV1_i | \mathbf{x}_i) = \frac{\exp(-\mu_i)\mu_i^{outV1_i}}{outV1_i!}$$

where $\mu_i = \exp(\mathbf{x}_i\boldsymbol{\beta})$ and $x_{i1} = psiCrmAdlsFS1_i$, $x_{i2} = imprHig_i$, $x_{i3} = imprLow_i$, $x_{i4} = min_i$, $x_{i5} = med_i$, and $x_{i6} = int_i$, was then fitted to the sample data; parameter estimates are shown in the first column of Table 40.⁹⁹

After this initial model was fit there was significant evidence that the observations were overdispersed with respect to the Poisson model, $G^2 = 186.817$, $p = 0.000$. Thus, **MV1** was

⁹⁶The Gini rule was used for splitting, prior probabilities were set proportional to observed frequencies, and altered priors were used for the loss function.

⁹⁷Cost-complexity pruning was based on the $1 - SE$ rule among cross-validated data.

⁹⁸Indicators representing modal categories were omitted as references.

⁹⁹A robust estimator of variance was used in place of the standard estimator to adjust for $k = 122$ block-group clusters (Huber, 1967; Rogers, 1993; H. White, 1980). Also, to account for varying times-at-risk, the logged number of days supervised $\log(daysSupAct_i)$ was included and constrained to a coefficient of 1 (not reported in estimates tables).

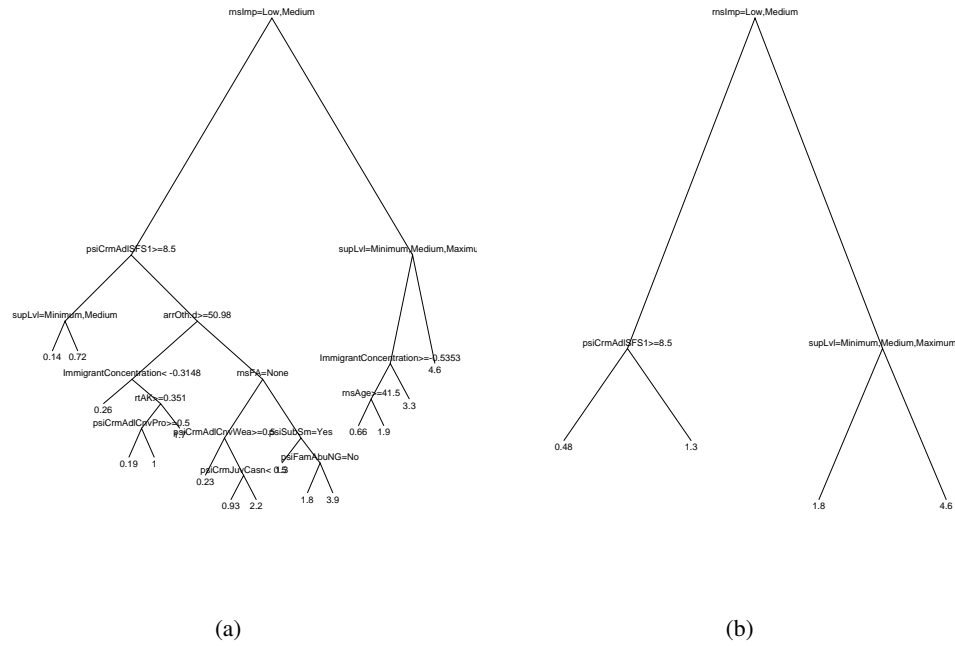


Figure 22. Initial (a) and pruned (b) classification trees predicting $outV1_i$, $\mathbf{MV1}$, $n = 199$.

respecified to include a multiplicative disturbance term v_i to capture unobserved heterogeneity.

The model

$$\Pr(outV1_i | \mathbf{x}_i) = \frac{\exp(-\tilde{\mu}_i)\tilde{\mu}_i^{outV1_i}}{outV1_i!}$$

where $\tilde{\mu}_i = \exp(\mathbf{x}_i\boldsymbol{\beta} + v_i)$ and $x_{i1} = psiCrmAdlSFS1_i$, $x_{i2} = imprHig_i$, $x_{i3} = imprLow_i$, $x_{i4} = min_i$, $x_{i5} = med_i$, and $x_{i6} = int_i$, was then fitted to the sample data. Parameter estimates from this regression are shown in the second column of Table 40.¹⁰⁰

By comparison, the PR shown in the first column of Table 40 performed at its worse in predictions of 0 where it greatly underpredicted counts. The NBR shown in the second column of Table 40 performed at its worse in predictions of counts of 2 where it, too, underpredicted. Predictions from both models converge near counts of 4; both appear equally capable of predictions

¹⁰⁰A robust estimator of variance was used in place of the standard estimator to adjust for $k = 122$ block-group clusters (Huber, 1967; Rogers, 1993; H. White, 1980). Also, to account for varying times-at-risk, the logged number of days supervised $\log(daysSupAct_i)$ was included and constrained to a coefficient of 1 (not reported in estimates tables).

Table 40

Parameter estimates, Poisson and negative binomial regressions of $outV1_i$, **MV1**, $n = 199$.

	b/z	b/z
<i>psiCrmAdIS FS 1</i>	-0.065 (-1.92)	-0.108** (-2.90)
<i>imprHig</i>	0.813** (3.00)	0.721* (2.37)
<i>imprLow</i>	0.153 (0.67)	-0.089 (-0.32)
<i>min</i>	-0.581 (-1.27)	-0.830* (-2.23)
<i>med</i>	-0.337 (-1.16)	-0.424 (-1.13)
<i>int</i>	0.481 (1.83)	0.393 (1.35)
α	-5.917*** (-23.32)	-5.239*** (-21.16)
Overdispersion α		0.235 (1.31)
Model χ^2	20.904**	45.384***

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

of counts ≥ 5 . Overall, the NBR, with mean absolute difference between predicted and observed values $|\Delta_{\widehat{\pi}_o - \widehat{\pi}_p}| = 0.009$, outperformed the PR, with $|\Delta_{\widehat{\pi}_o - \widehat{\pi}_p}| = 0.022$.

The Wald test¹⁰¹ of the hypothesis that all coefficients in the regression shown in the second column of Table 40 except the intercept were zero $H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = 0$ was rejected, $\chi^2_W = 45.38$, $df = 6$, $p = 0.02$. The test of $H_0: \beta_1 = 0$ was rejected, $\chi^2_W = 8.40$, $df = 1$, $p = 0.00$. The test of $H_0: \beta_2 = \beta_3 = 0$ was rejected, $\chi^2_W = 7.39$, $df = 2$, $p = 0.02$. The test of $H_0: \beta_4 = \beta_5 = \beta_6 = 0$ was not rejected, $\chi^2_W = 7.73$, $df = 3$, $p = 0.05$.

The model had D=684.95, AIC=3.522, and BIC=-326.071.

¹⁰¹The χ^2_L test is likely invalid given the robust estimator of variance used to adjust for $k = 122$ block-group clusters.

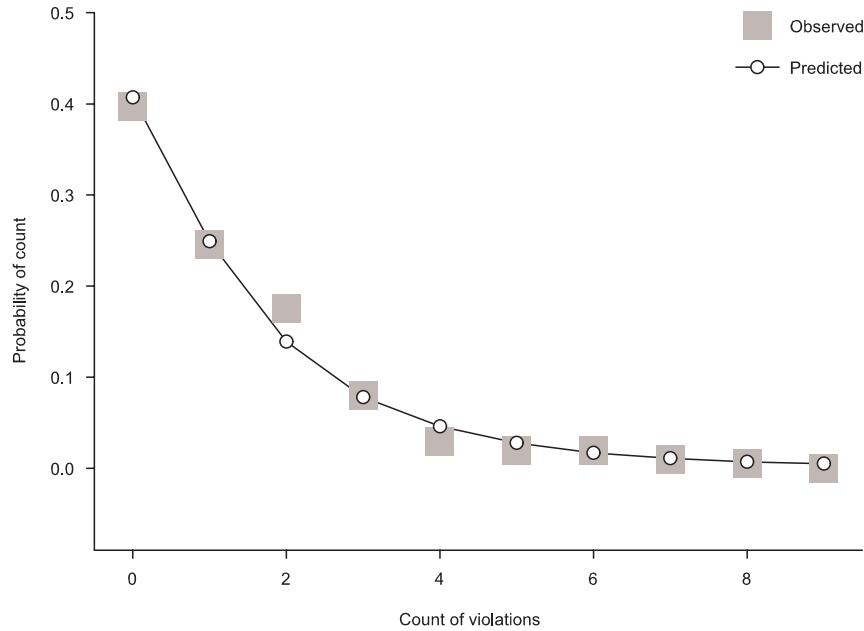


Figure 23. Observed and NBR model-implied counts of $outV1_i$, **MV1**, $n = 199$.

A visual indication of model calibration is given in the plot in Figure 23. This plot shows the observed and predicted probabilities of counts zero through 9. As indicated, the model-implied and observed probabilities track closely throughout the distribution, with the poorest fit in counts of 2.

Focus then turned to the parametric relationship between $outV1_i$ and $psiCrmAdlSFS1_i$. Checking the scale of the predictor revealed no substantial non-linearity and thus $psiCrmAdlSFS1_i$ was parameterized as linear and continuous.

The NBR of $outV1$ on $psiCrmAdlSFS1_i$, $imprHig_i$, $imprLow_i$, min_i , med_i , and int_i , shown in the second column of Table 40 was validated by bootstrapping. Bias-corrected confidence intervals around the estimated parameters are shown in Table 41. As indicated, the effects of $psiCrmAdlSFS1_i$ and $imprHig$ were likely to replicate in the population; interpretations are based on these effects.

Table 41

Lower (LCLM) and upper (UCLM) bias-corrected 95% confidence limits, **MV1**, $n = 198$.

	LCLM	UCLM
<i>psiCrmAdIS FS 1</i>	-.19	-.0264
<i>imprHig</i>	.107	1.34
<i>imprLow</i>	-.668	.49
<i>min</i>	-4.37	1.93
<i>med</i>	-1.71	.0741
<i>int</i>	-.972	.187

The most important characteristics influencing the rate of supervision-related violations included the SFS-98 score *psiCrmAdIS FS 1_i* and whether interviewing officers believed the offender represented a high supervision risk *imprHig*.

Each additional point on the SFS-98 decreases the expected number of violations by a factor of 0.8974 (10.3%) holding all other predictors constant. Having a high impression versus a medium impression increases the expected number of violations by a factor of 2.0566 (105.7%). Being supervised at the minimum level versus maximum level decreases the expected number of violations by a factor of 0.2945 (70.6%).

MV2. The criterion for **MV2** is the number of drug-related violations, *outV2_i*. Among the sample, $112/199 = 0.56$ had at least one drug-related violation; they accumulated, on average, roughly 2 during the supervision period, $M = 2.4$, $SD = 3.81$. The maximum observed number of drug-related violations was 21. Interest centers on the predicted rate of the criterion, $\widehat{\mu}_i$.

Potential predictors were included in a general model which was then recursively partitioned¹⁰² into the binary tree shown in Figure 24a using Poisson-splitting methods (see, Breiman

¹⁰²Using the R library RPART (Therneau & Atkinson, 1997).

et al., 1984; Therneau & Atkinson, 1997).¹⁰³ This classification tree, since it was likely too complex to validate, was trimmed back to that shown in Figure 24b.¹⁰⁴

Predictors having the largest effect on the rate of drug-related violations included (a) supervision level $supLvl_i$, (b) the number of previous weapons-related convictions $psiCrmAdlCnvWea_i$, and (c) the rates of arrests for drug-related crimes within the block-group $arrDrg.d_i$; remaining predictors did not appear in the model.

The resultant model separated sampled probationers into 4 groups. The groups (and predicted values) included those (a) supervised at either minimum, medium, or maximum levels (1.9); (b) supervised at intensive level and having one or more previous adult weapons-related convictions (0.42); (c) supervised at intensive level, having no previous adult weapons-related convictions, and living within a block-group having rates of drug-related arrests greater than or equal to 9.95 (3.3); and (d) supervised at intensive level, having no previous adult weapons-related convictions, and living within a block-group having rates of drug-related arrests less than to 9.95 (9.5).

Indicators min_i , med_i , max_i , and int_i were created to represent $supLvl_i$ and indicators $cnvWea0_i$, $cnvWea1_i$, and $cnvWea2_i$ were created to represent the levels of $psiCrmAdlCnvWea_i$.¹⁰⁵ An initial model

$$\Pr(outV2_i | \mathbf{x}_i) = \frac{\exp(-\mu_i)\mu_i^{outV2_i}}{outV2_i!}$$

¹⁰³The Gini rule was used for splitting, prior probabilities were set proportional to observed frequencies, and altered priors were used for the loss function.

¹⁰⁴Cost-complexity pruning was based on the 1 – SE rule among cross-validated data.

¹⁰⁵Indicators representing modal categories were omitted as references.

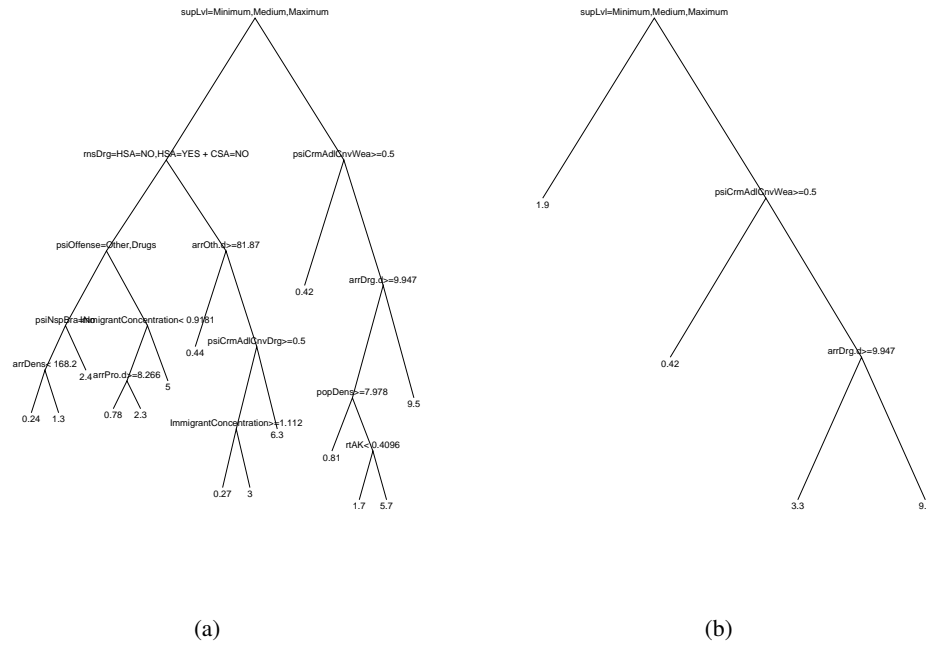


Figure 24. Initial (a) and pruned (b) classification trees predicting $outV2_i$, **MV2**, $n = 199$.

where $\mu_i = \exp(\mathbf{x}_i\boldsymbol{\beta})$ and $x_{i1} = min_i$, $x_{i2} = med_i$, $x_{i3} = int_i$, $x_{i4} = cnvWea1_i$, $x_{i5} = cnvWea2_i$, and $x_{i6} = arrDrgD_i$ was then fitted to the sample data; parameter estimates are shown in the first column of Table 42.¹⁰⁶

There was significant evidence that the observations were overdispersed with respect to the Poisson model, $G^2 = 477.904$, $p = 0.000$. **MV2** was thus respecified to include a multiplicative disturbance term v_i to capture unobserved heterogeneity. The NBR model

$$\Pr(outV2_i | \mathbf{x}_i) = \frac{\exp(-\tilde{\mu}_i)\tilde{\mu}_i^{outV2_i}}{outV2_i!}$$

¹⁰⁶A robust estimator of variance was used in place of the standard estimator to adjust for $k = 122$ block-group clusters (Huber, 1967; Rogers, 1993; H. White, 1980). Also, to account for varying times-at-risk, the logged number of days supervised $\log(daysSupAct_i)$ was included and constrained to a coefficient of 1 (not reported in estimates tables).

Table 42

Parameter estimates, Poisson and negative binomial regressions of $outV2_i$, **MV2**, $n = 199$.

	b/z	b/z	b/z
<i>min</i>	-1.900** (-2.90)	-1.955* (-2.31)	-2.046* (-2.28)
<i>med</i>	-0.224 (-0.65)	-0.323 (-0.83)	-0.294 (-0.77)
<i>intensive</i>	0.616** (2.65)	0.341 (1.16)	0.356 (1.22)
<i>cnvWea1</i>	-1.423*** (-3.87)	-1.309** (-2.90)	-1.171** (-2.64)
<i>cnvWea2</i>	0.006 (0.02)	-0.457 (-1.05)	-0.433 (-0.99)
<i>arrDrgD</i>	-0.004 (-0.73)	-0.001* (-1.97)	-0.012** (-3.10)
α	-5.248*** (-22.88)	-4.915*** (-25.06)	-4.697*** (-21.49)
Overdispersion α		0.773*** (4.73)	0.757*** (4.51)
Model χ^2	29.670***	20.610**	26.237***

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

where $\tilde{\mu}_i = \exp(\mathbf{x}_i\boldsymbol{\beta} + v_i)$ and $x_{i1} = min_i$, $x_{i2} = med_i$, $x_{i3} = int_i$, $x_{i4} = cnvWea1_i$, $x_{i5} = cnvWea2_i$, and $x_{i6} = arrDrgD_i$ was then fitted to the sample data. Parameter estimates from this regression are shown in the second column of Table 42.¹⁰⁷

The Wald test¹⁰⁸ of the hypothesis that all coefficients except the intercept were zero $H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = 0$ was rejected, $\chi^2_W = 20.61$, $df = 6$, $p = 0.02$. The test of $H_0 : \beta_1 = \beta_2 = \beta_3 = 0$ was rejected, $\chi^2_W = 9.21$, $df = 3$, $p = 0.03$. The test of

¹⁰⁷A robust estimator of variance was used in place of the standard estimator to adjust for $k = 122$ block-group clusters (Huber, 1967; Rogers, 1993; H. White, 1980). Also, to account for varying times-at-risk, the logged number of days supervised $\log(daysSupAct_i)$ was included and constrained to a coefficient of 1 (not reported in estimates tables).

¹⁰⁸The χ^2_L test is likely invalid given the robust estimator of variance used to adjust for $k = 122$ block-group clusters.

$H_0: \beta_4 = \beta_5 = 0$ was rejected, $\chi^2_W = 8.78$, $df = 2$, $p = 0.01$. The test of $H_0: \beta_6 = 0$ was rejected, $\chi^2_W = 3.87$, $df = 1$, $p = 0.05$.

The model had $D=791.17$, $AIC=4.056$, and $BIC=-219.853$.

By comparison, the PR shown in the first column of Table 42 performed at its worse in predictions of 0 where it greatly underpredicted counts. The NBR shown in the second column of Table 42 performed at its worse in predictions of 1 where it overpredicted counts. The PR continued to perform poorly through counts [1,5] where it consistently overpredicted counts. Model predictions from the two models do not converge until near counts of 7. Overall, the NBR, with mean absolute difference between predicted and observed values $|\Delta_{\hat{\pi}_o - \hat{\pi}_p}|$ of 0.009, outperformed the PR, with $|\Delta_{\hat{\pi}_o - \hat{\pi}_p}| = 0.059$.

Focus then turned to refining the model shown in the second column of Table 42 in terms of the scale of $arrDrg.d_i$. A normal quantile-comparison plot of $arrDrg.d_i$ indicated, aside from one extreme value, the distribution of $arrDrg.d_i$ approximated the normal. With this outlying case removed, the relationship was approximately normal.

The probationer representing this single outlying value was removed from the analysis and the model

$$\Pr(outV2_i | \mathbf{x}_i) = \frac{\exp(-\mu_i)\mu_i^{outV2_i}}{outV2_i!}$$

where $\mu_i = \exp(\mathbf{x}_i\boldsymbol{\beta})$ and $x_{i1} = min_i$, $x_{i2} = med_i$, $x_{i3} = int_i$, $x_{i4} = cnvWea1_i$, $x_{i5} = cnvWea2_i$, and $x_{i6} = arrDrgD_i$ was refitted to the sample data with the outlying probationer excluded; parameter estimates are shown in the third column of Table 42.¹⁰⁹

¹⁰⁹A robust estimator of variance was used in place of the standard estimator to adjust for $k = 122$ block-group clusters (Huber, 1967; Rogers, 1993; H. White, 1980). Also, to account for varying times-at-risk, the logged number of days supervised $\log(daysSupAct_i)$ was included and constrained to a coefficient of 1 (not reported in estimates tables).

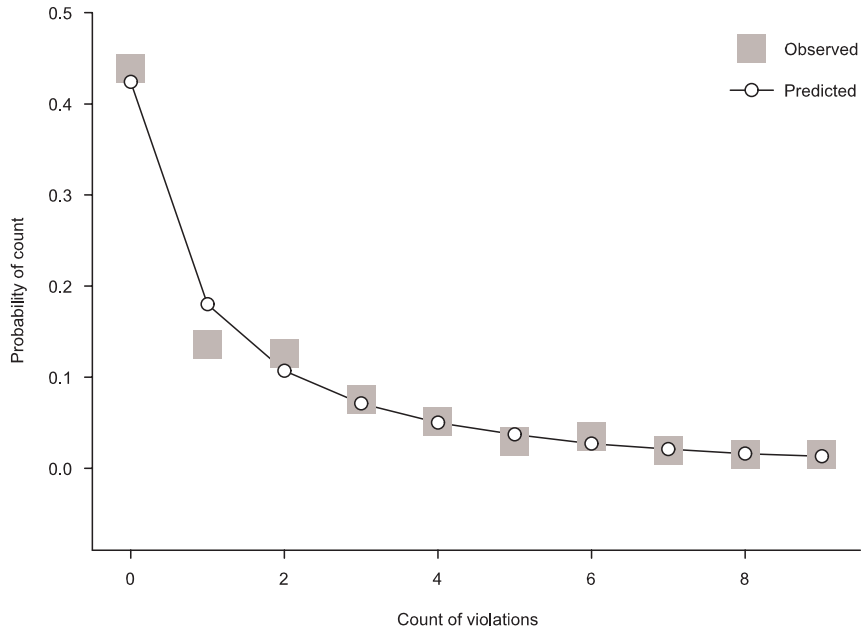


Figure 25. Observed and NBR model-implied counts of $outV2_i$, **MV2**, $n = 198$.

The Wald test¹¹⁰ of the hypothesis that all coefficients except the intercept were zero $H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = 0$ was rejected, $\chi^2_W = 26.24$, $df = 6$, $p = 0.00$. The test of $H_0: \beta_1 = \beta_2 = \beta_3 = 0$ was rejected, $\chi^2_W = 9.07$, $df = 3$, $p = 0.03$. The test of $H_0: \beta_4 = \beta_5 = 0$ was rejected, $\chi^2_W = 7.39$, $df = 2$, $p = 0.02$. The test of $H_0: \beta_6 = 0$ was rejected, $\chi^2_W = 9.59$, $df = 1$, $p = 0.00$.

The model had $D=784.46$, $AIC=4.043$, and $BIC=-220.313$.

A visual indication of model calibration is given in the plot of observed and predicted probabilities of counts 0 through 9 shown in Figure 25. As indicated, the model-implied and observed probabilities track closely throughout the distribution, with the poorest fit in counts of 1 and 2.

The NBR of $outV2$ on min_i , med_i , int_i , $cnvWea1_i$, $cnvWea2_i$, and $arrDrgD_i$ shown in the third column of Table 42 was validated by bootstrapping. Bias-corrected confidence intervals

¹¹⁰The χ^2_L test is likely invalid given the robust estimator of variance used to adjust for $k = 122$ block-group clusters.

Table 43

Lower (LCLM) and upper (UCLM) bias-corrected 95% confidence limits, **MV2**, $n = 198$.

	LCLM	UCLM
min_i	-9.1	5.007
med_i	-1.07	.482
$intensive_i$	-.236	.947
$cnvWea1_i$	-2.08	-.261
$cnvWea2_i$	-8.94	8.07
$arrDrgD_i$	-.0212	-.00275

around the estimated parameters are shown in Table 43. As indicated in the table, the effects of $cnvWea1_i$ and $arrDrgD_i$ were likely to replicate in the population; the others were not.

The most important characteristics influencing the rate of violations included $cnvWea1_i$ and $arrDrgD_i$. Being supervised at the minimum level versus maximum level decreases the expected number of drug-related violations by a factor of 0.1293 (-87.1%) holding all other predictors constant. Having 1 previous weapons-related convictions versus none decreases the expected number of drug-related violations by a factor of 0.6565 (-34.4%) holding all other predictors constant. For a standard deviation increase in the rate of arrests for drug-related crimes ($M = 24.89, SD = 23.36$), the expected number of drug-related violations decreases by a factor of 0.7560 (-24.4%).

Modes of termination

Model **MT1** estimates likelihoods probationers in the population will terminate sentences unsuccessfully and Model **MT2** estimates how soon such failures are likely to occur.

The criteria $outT1_i$ and $outT2_i$ are described in Table 44. The two commonest modes of termination were revocation and successful; the two rarest, absconsion and death. Roughly 0.5 of the sample terminated within 412 days; 0.75 by 730 days; and 0.9 by 951 days. By type, median

Table 44

Median days until termination, by mode of termination, $n = 199$.

	Not Successful				
	Absconson	Death	Unsuccessful	Revoked	Successful
n	2	2	24	89	82
Days	48	329	463	341	546

days until termination ranged (0.25 and 0.75 quantiles) within [37.5, 58.5] days until absconson, [237, 420] days until death, [231, 584] days until revoked, [365, 738] days until successful, and [240, 681] days until unsuccessful termination modes.

MT1. The criterion for **MT1** is whether probationers terminated their sentence unsuccessfully $outT1_i$. If so, $outT1_i = 1$. Roughly three-fifths ($115/199 = 0.58$) of the sampled probationers did indeed terminate unsuccessfully. Interest centers on the predicted probability of the criterion, $\widehat{\Pr}(outT1_i = 1)$.

Potential predictors of this criterion were included in a general model which was then recursively partitioned¹¹¹ into the binary tree shown in Figure 16a.¹¹² This classification tree, since it was likely too complex to validate, was trimmed back to that shown in Figure 26b.¹¹³

Predictors with the largest influence on the criteria were (a) recommended sentence $psiSR_i$, (b) proportion of positive drug screens for cocaine $piPos4$, (c) supervision level $supLvl$, and (d) age at first arrest $rnsAF_i$; remaining predictors did not appear in the model.

The resultant model separated sampled probationers into 5 groups. These groups (and predicted values) included those (a) recommended to probation, having less than 0.028 of screens positive for cocaine, and supervised at either minimum or medium levels (Success). There were

¹¹¹Using the R library RPART (Therneau & Atkinson, 1997).

¹¹²The Gini rule was used for splitting, prior probabilities were set proportional to observed frequencies, and altered priors were used for the loss function.

¹¹³Cost-complexity pruning was based on the $1 - SE$ rule among crossvalidated data.

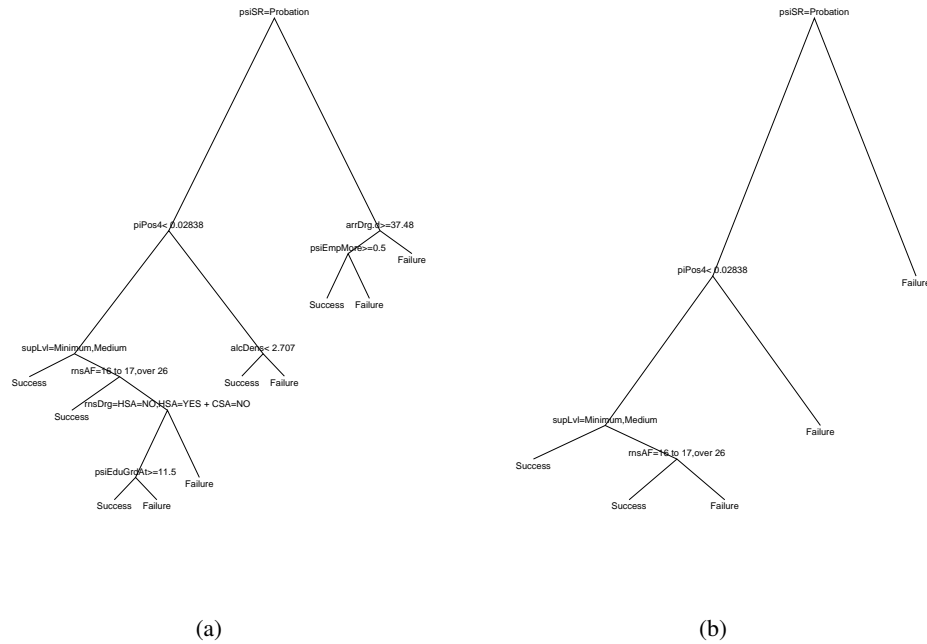


Figure 26. Initial (a) and pruned (b) classification trees predicting $outT1_i$, **MT1**, $n = 199$.

$1/25 = 0.04$ unsuccessful terminations among this group; (b) recommended to probation, having less than 0.028 of screens positive for cocaine, supervised at either maximum or intensive levels, and first arrested at ages 16 to 17 or over age 26 (Success). $0/10 = 0.00$ of these offenders terminated unsuccessfully; (c) recommended to probation, having less than 0.028 of screens positive for cocaine, supervised at either maximum or intensive levels, and first arrested at age 15 and younger or ages 18 to 25 (Failure). $22/41 = 0.54$ of these offenders terminated unsuccessfully; (d) recommended to probation and 0.028 or more of screens positive for cocaine (Failure). $22/33 = 0.67$ of these offenders terminated unsuccessfully; and (e) recommended to either split-sentence or incarceration (Failure). $70/90 = 0.78$ of these probationers terminated unsuccessfully.

The most influential predictor was whether the PSI author recommended a sentence of probation versus either incarceration or split-sentence. The indicator $probation_i$ was created to capture this. In addition, the indicators Min_i , Med_i , Max_i , and Int_i were created to represent

the levels of supervision level $supLvl_i$. Finally, the indicators $AF1_i$, $AF2_i$, $AF3_i$, and $AF4_i$ were created to represent the levels of age at first arrest $rnsAF_i$.

An initial model

$$\widehat{\Pr}(outT1_i = 1 | \mathbf{x}_i) = \frac{1}{1 + \exp[-(\mathbf{x}_i\boldsymbol{\beta})]}$$

$$= \frac{1}{1 + \exp[-(\beta_0 + \beta_1x_{i1} + \beta_2x_{i2} + \beta_3x_{i3} + \beta_4x_{i4} + \beta_5x_{i5} + \beta_6x_{i6} + \beta_7x_{i7} + \beta_8x_{i8})]},$$

where $x_{i1} = probation_i$, $x_{i2} = piPos4_i$, $x_{i3} = Min_i$, $x_{i4} = Med_i$, $x_{i5} = Int_i$, $x_{i6} = AF1_i$, $x_{i7} = AF2_i$, and $x_{i8} = AF4_i$, was then fitted to the sample data; parameter estimates are shown in the first column of Table 45.¹¹⁴

The Wald test¹¹⁵ of $H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = \beta_8 = 0$ was rejected, $\chi_W^2 = 49.08$, $df = 8$, $p < 0.00$. The test of $H_0: \beta_1 = 0$ was rejected ($\chi_W^2 = 16.85$, $df = 1$, $p = 0.00$); the test of $H_0: \beta_2 = 0$ was rejected ($\chi_W^2 = 13.62$, $df = 1$, $p = 0.00$); the test of $H_0: \beta_3 = \beta_4 = \beta_5 = 0$ was rejected ($\chi_W^2 = 11.62$, $df = 3$, $p = 0.01$); the test of $H_0: \beta_6 = \beta_7 = \beta_8 = 0$ was not rejected ($\chi_W^2 = 6.63$, $df = 3$, $p = 0.08$).

The model correctly classified 0.74 of the sample and the AUC suggested the it demonstrated acceptable discrimination, $AUC = 0.80$. The model had $D=208.98$, $AIC=1.141$, and $BIC=-796.746$; the \widehat{c} suggested the model was empirically consistent, $\chi_{HL}^2 = 9.29$, $df = 8$, $p = 0.32$.

Focus then turned to refining this preliminary model in terms of parametric relationships and scale beginning with the relationship between $outT1_i$ and $piPos4_i$. The tree in Figure 26b suggested a split in $piPos4$ in the low end of the distribution. It ranged within $[0.0, 0.69]$ with $M = 0.07$ and $SD = 0.14$ and near evenly split the sample: just under half $^{93/199} = 0.47$ had $piPos_i > 0$. As this predictor represents a proportion which, in general, do not respond well

¹¹⁴A robust estimator of variance was used in place of the standard estimator to adjust for $k = 122$ block-group clusters (Huber, 1967; Rogers, 1993; H. White, 1980).

¹¹⁵The χ_L^2 test is likely invalid given the robust estimator of variance used to adjust for $k = 122$ block-group clusters.

Table 45

Parameter estimates, **MT1**, logistic regression of $outT1_i$, $n = 199$.

	b/z	b/z
<i>probation</i>	-1.584*** (-4.10)	-1.565*** (-4.06)
<i>piPos4</i>	6.438*** (3.69)	
<i>Min</i>	-2.402* (-2.38)	-2.376* (-2.37)
<i>Med</i>	-0.638 (-1.68)	-0.622 (-1.69)
<i>Int</i>	0.520 (1.24)	0.550 (1.32)
<i>AF1</i>	-0.199 (-0.34)	-0.118 (-0.21)
<i>AF2</i>	-0.782 (-1.84)	-0.710 (-1.72)
<i>AF4</i>	-1.168* (-2.15)	-0.912 (-1.81)
<i>piPos4*</i>		1.029** (2.75)
α	1.282*** (3.36)	1.240** (3.26)
Model χ^2	49.079***	40.081***

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

when values approach the boundaries, power transformations were ineffective. As was an arcsine transformation. On the other hand, a binary split at zero implied a zero-tolerance policy on drug use. In practice, however, positive screens for cocaine may be met initially with sanctions aimed at curtailing the behavior and thus some probationers with non-zero proportions of positive screens for cocaine may indeed terminate successfully. To account for this $piPos_i$ was replaced with the indicator $piPos_i^* = piPos_i > 0.02$, just under the 0.25 Q of the distribution of non-zero values.

The model

$$\widehat{\Pr}(outT1_i = 1 | \mathbf{x}_i) = \frac{1}{1 + \exp[-(\mathbf{x}_i\boldsymbol{\beta})]} = \frac{1}{1 + \exp[-(\beta_0 + \beta_1x_{i1} + \beta_2x_{i2} + \beta_3x_{i3} + \beta_4x_{i4} + \beta_5x_{i5} + \beta_6x_{i6} + \beta_7x_{i7} + \beta_8x_{i8})]}$$

where $x_{i1} = probation_i$, $x_{i2} = piPos4_i^*$, $x_{i3} = Min_i$, $x_{i4} = Med_i$, $x_{i5} = Int_i$, $x_{i6} = AF1_i$, $x_{i7} = AF2_i$, and $x_{i8} = AF4_i$, was refitted to the sample data; parameter estimates are shown in the second column of Table 45.¹¹⁶

The Wald test¹¹⁷ of $H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \beta_7 = \beta_8 = 0$ was rejected, $\chi_W^2 = 40.08$, $df = 8$, $p < 0.00$. The test of $H_0: \beta_1 = 0$ was rejected ($\chi_W^2 = 16.45$, $df = 1$, $p = 0.00$); the test of $H_0: \beta_2 = 0$ was rejected ($\chi_W^2 = 7.54$, $df = 1$, $p = 0.01$); the test of $H_0: \beta_3 = \beta_4 = \beta_5 = 0$ was rejected ($\chi_W^2 = 12.22$, $df = 3$, $p = 0.01$); the test of $H_0: \beta_6 = \beta_7 = \beta_8 = 0$ was not rejected ($\chi_W^2 = 5.01$, $df = 3$, $p = 0.17$).

The model correctly classified 0.74 of the sample. The AUC suggested the model demonstrated acceptable discrimination, $AUC = 0.78$. The model had $D=216.21$, $AIC=1.177$, and $BIC=-789.522$; the \widehat{c} suggested the model was empirically consistent, $\chi_{HL}^2 = 11.32$, $df = 8$, $p = 0.18$.

¹¹⁶A robust estimator of variance was used in place of the standard estimator to adjust for $k = 122$ block-group clusters (Huber, 1967; Rogers, 1993; H. White, 1980).

¹¹⁷The χ_L^2 test is likely invalid given the robust estimator of variance used to adjust for $k = 122$ block-group clusters.

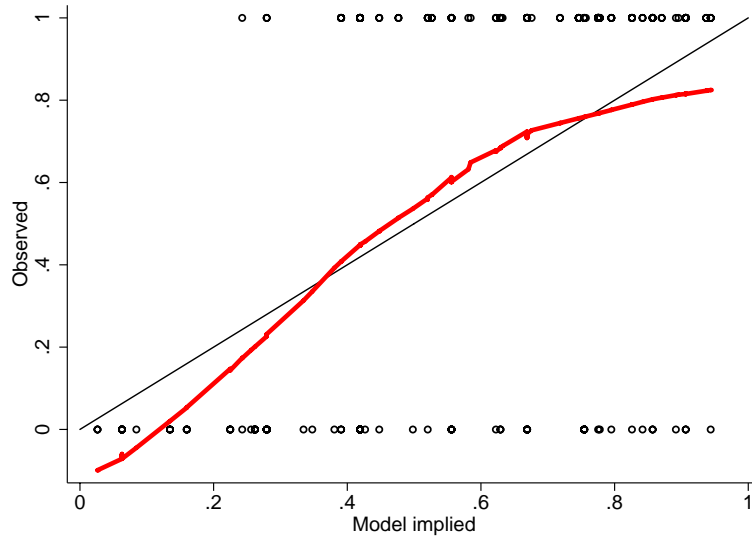


Figure 27. Comparison between model-implied probabilities of experiencing $outT1_i$ and a moving average of the proportion of probationers terminating unsuccessfully, $n = 199$.

A visual indication of model calibration is given in the plot in Figure 27 which compares predicted probabilities from the regression of $outT1$ with a moving average of the proportion of probationers terminating unsuccessfully.

The regression of $outT1_i$ on $probation_i$, $piPos4_i^*$, Min_i , Med_i , Int_i , $AF1_i$, $AF2_i$, and $AF4_i$ shown in the second column of Table 45 was validated by bootstrapping. Bias-corrected confidence intervals around the estimated parameters are shown in Table 46.

As indicated in Table 46, the effects of both $probation_i$ and $piPos4_i^*$ on $outT1_i$ are likely to validate in the population. Also, the Wald test¹¹⁸ of $H_0 : \beta_3 = \beta_4 = \beta_5 = 0$ was rejected ($\chi^2_W = 22.00$, $df = 3$, $p = 0.00$). On the other hand, the test of $H_0 : \beta_6 = \beta_7 = \beta_8 = 0$ was not rejected ($\chi^2_W = 4.16$, $df = 3$, $p = 0.25$). Interpretations of the regression of $outT1_i$ focus on the effects likely to replicate in the population, which are, namely whether the PSI author recommended probation versus either incarceration or split sentence, whether the proportion of positive screens for cocaine exceeded 0.02, and supervision level.

¹¹⁸The χ^2_L test is likely invalid given the robust estimator of variance used to adjust for $k = 122$ block-group clusters.

Table 46

Lower (LCLM) and upper (UCLM) bias-corrected 95% confidence limits, **MT1**, $n = 199$.

	LCLM	UCLM
<i>probation</i>	-2.4	-.727
<i>piPos*</i>	.23	1.83
<i>Min</i>	-3.55	-1.21
<i>Med</i>	-1.4	.155
<i>Int</i>	-.332	1.43
<i>AF1</i>	-1.41	1.18
<i>AF2</i>	-1.59	.169
<i>AF4</i>	-2.01	.183

Predicted values $\widehat{\pi}$ ranged within the interval [.026, 0.944], with mean $\widehat{\pi} = .578$ and $SD = .248$. The most important characteristics influencing $\widehat{\Pr}(outT1_i = 1)$ include the recommended sentence, the proportion of positive screens for cocaine, and supervision level.

The expected odds of terminating unsuccessfully are roughly 4.8 times larger among those whose recommended sentence is either incarceration or split-sentence compared to those whose recommended sentence is probation and roughly 2.8 times larger among those having failed more than 0.02 of cocaine screens compared to their counterparts, holding all else constant. Compared to those supervised at the maximum level, the expected odds of terminating unsuccessfully are roughly 90% smaller among those supervised at the minimum level and roughly 46% smaller among those supervised at the medium level. The odds of terminating unsuccessfully are roughly 73% larger among those supervised at the intensive level.

The plot in Figure 28 shows predicted probabilities of terminating sentences unsuccessfully by recommended sentence, supervision level, and whether proportions of positive screens for cocaine exceed 0.02. As indicated, the predicted probabilities of terminating unsuccessfully increase with each supervision level and probabilities are consistently higher among those recommended

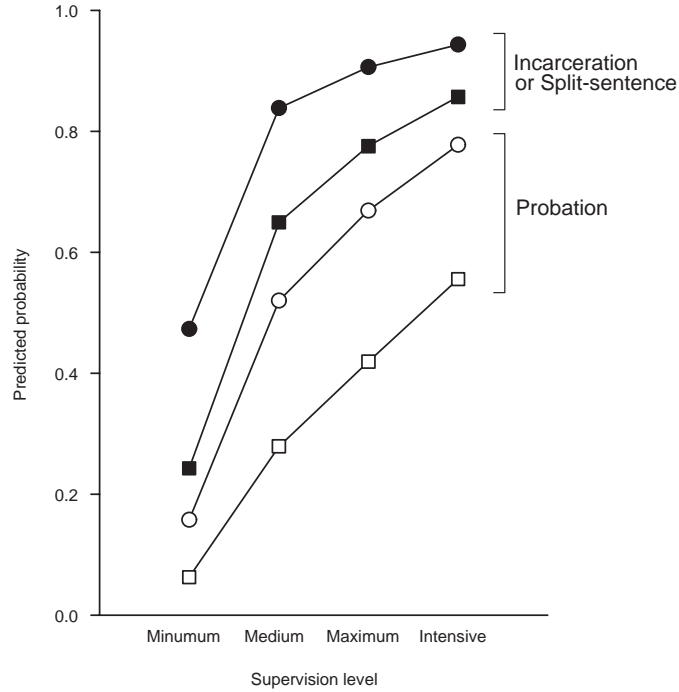


Figure 28. Predicted probabilities of terminating sentences unsuccessfully, circles represent probationers having failed more than 0.02 of screens for cocaine and squares represent their counterparts, hollow symbols represent those whose recommended sentence is probation and solid symbols represent those whose recommended sentence is either incarceration or split sentence, **MT1**, $n = 199$.

to either incarceration or split sentence and among those whose proportions of positive screens for cocaine exceed 0.02.

MT2. The criterion for **MT2** is the time until unsuccessful termination $outT2_i$. Roughly three-fifths ($115/199 = 0.58$) of the sampled probationers did indeed terminate unsuccessfully. The average followup time ranged within the interval [16, 2219]; the 95%CI around median survival time spanned the interval [516, 734].

Potential predictors of time until failure were included in a general model which was then recursively partitioned¹¹⁹ into the binary tree shown in Figure 29a.¹²⁰ This classification tree, since it was likely too complex to validate, was trimmed back to that shown in Figure 29b.¹²¹

Predictors with the largest influence on the criterion were (a) the number of previous drug-related convictions $psiCrmAdlCnvDrg_i$, (b) the proportion of positive screens for marijuana $piPos5_i$, and (c) the expected number of days of supervision $daysSupExp_i$; remaining predictors did not appear in the model.

The resultant model separated sampled probationers into 4 groups. These groups (and predicted values) included those having (a) fewer than 5 previous drug convictions, less than 0.3909 of positive screens for marijuana, and expected to be supervised for more than 487 days (0.67); (b) fewer than 5 previous drug convictions, less than 0.3909 of positive screens for marijuana, and expecting to be supervised for less than 487 days (1.3); (c) fewer than 5 previous drug convictions and 0.3909 or more of positive screens for marijuana (2.6); and (d) 5 or more previous drug convictions (3);

The indicators $cnvDrg0_i$, $cnvDrg1_i$, and $cnvDrg2_i$ were created to represent the levels None, One, and Two or more of $psiCrmAdlCnvDrg_i$ and an initial Cox regression model

$$\begin{aligned} h(t|\mathbf{x}_i) &= h_0(t) \exp(\mathbf{x}_i\boldsymbol{\beta}) \\ &= h_0(t) \exp(\beta_1 x_{i1} + \beta_2 x_{i2} + \beta_3 x_{i3} + \beta_4 x_{i4}) \end{aligned}$$

where $x_{i1} = cnvDrg1_i$, $x_{i2} = cnvDrg2_i$, $x_{i3} = piPos5_i$, and $x_{i4} = daysSupExp_i$, was then fitted to the sample data; parameter estimates are shown in the first column of Table 47.¹²²

¹¹⁹Using the R library RPART (Therneau & Atkinson, 1997).

¹²⁰The Gini rule was used for splitting, prior probabilities were set proportional to observed frequencies, and altered priors were used for the loss function.

¹²¹Cost-complexity pruning was based on the 1 – SE rule among cross-validated data.

¹²²A robust estimator of variance was used in place of the standard estimator to adjust for $k = 122$ block-group clusters (Huber, 1967; Rogers, 1993; H. White, 1980).

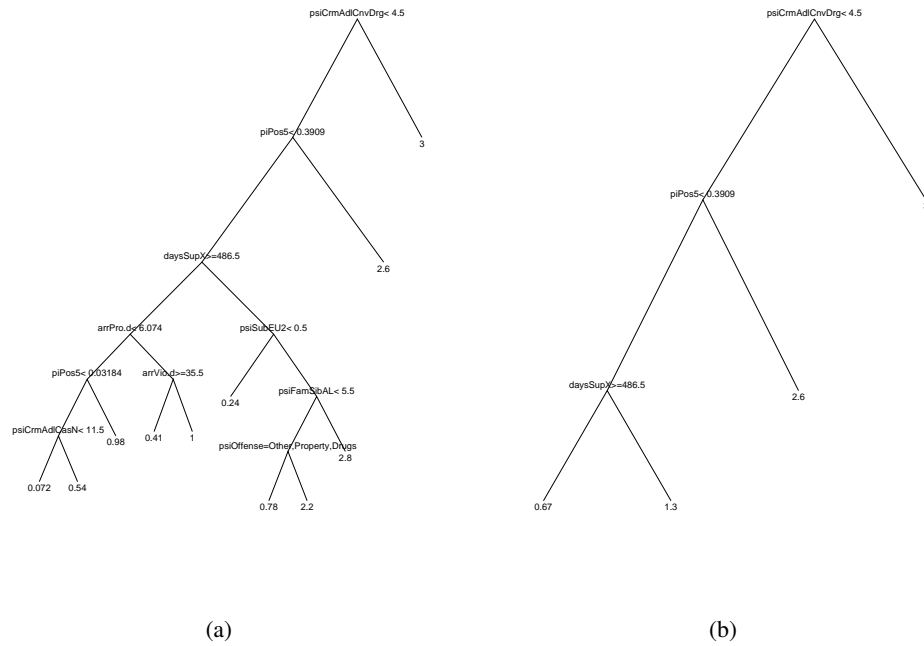


Figure 29. Initial (a) and pruned (b) classification trees predicting $outT2_i$, **MT2**, $n = 199$.

Table 47

Parameter estimates, **MT2**, Cox regression of $outT2_i$, $n = 199$.

	b/z
$cnvDrg1$	0.387 (1.41)
$cnvDrg2$	0.583* (2.50)
$piPos5$	2.215*** (4.10)
$daysSupExp$	-0.001*** (-3.38)
Model χ^2	37.511***

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

The Wald test¹²³ of $H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$ was rejected, $\chi_W^2 = 37.56$, $df = 4$, $p < 0.00$. The test of $H_0: \beta_1 = \beta_2 = 0$ was rejected ($\chi_W^2 = 6.39$, $df = 2$, $p = 0.04$), the test of $H_0: \beta_3 = 0$ was rejected ($\chi_W^2 = 16.82$, $df = 1$, $p = 0.00$), and the test of $H_0: \beta_4 = 0$ was rejected ($\chi_W^2 = 11.39$, $df = 1$, $p = 0.00$).

The model had $\log L = -493.982$, $AIC = 995.964$, and $BIC = 1,009.137$.

An analogue to the \widehat{c} for BLR models has been proposed by May and Hosmer (1998) that involves partitioning the covariate space in a manner similar to that proposed by Hosmer and Lemeshow (1980). Rather than partitioning subjects into groups based on the percentiles of the predicted probabilities from the fitted logistic regression model, subjects are partitioned into groups based on their predicted hazard rates from the Cox model (also see, DeMaris, 2004; Parzen & Lipsitz, 1999). There was no evidence here to suggest the model lacked empirical consistency, $\chi_{MH}^2 = 10.89$, $df = 9$, $p = 0.28$.

A visual indication of model calibration is given in the plot in Figure 30 which compares the Nelson-Aalen cumulative hazard function with the Cox-Snell residuals. If a Cox regression fits the data well then the Cox-Snell residuals should follow a standard exponential distribution with a hazard function of 1 and the cumulative hazard of these residuals should lie on a straight 45° line (see, Cleves, Gould, & Gutierrez, 2002). Here, that the thick line tracks closely with the diagonal¹²⁴ indicates the model is well-calibrated.

Focus then turned to assessing whether the two continuous predictors were linear in the log hazard and, if not, which transformation would linearize them. I began with the relationship between $outT2_i$ and $piPos5_i$ by replacing $piPos5_i$ with design variables formed from the Q25, Q50, and Q75 of the non-zero values. These were, respectfully, 0.0656, 0.188, and 0.346. I refitted

¹²³The χ_L^2 test is likely invalid given the robust estimator of variance used to adjust for $k = 122$ block-group clusters.

¹²⁴Cleves et al. (2002) point out that due to the reduced effective sample caused by failures and censoring, there will be some variability around the 45° line especially in the upper region.

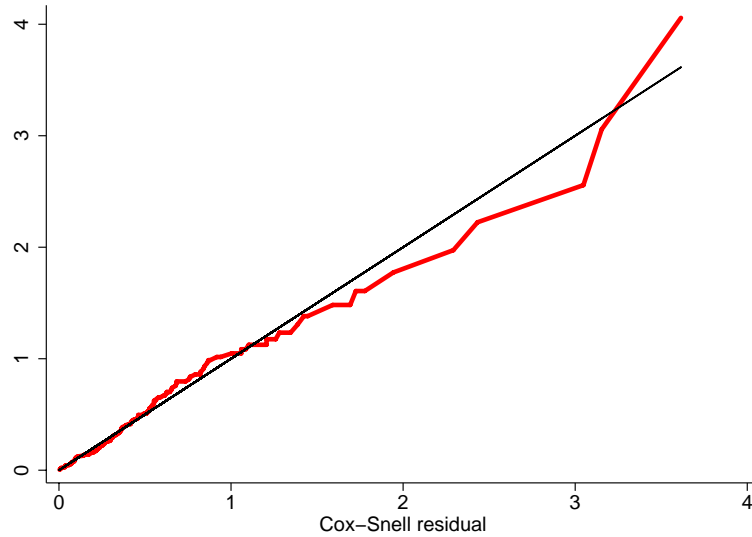


Figure 30. Comparison between the Nelson-Aalen cumulative hazard function and the Cox-Snell residuals, **MT2**, $n = 199$.

the model with the design variables then plotted the estimated coefficients against group midpoints. The overall trend indicated a positive effect without substantial departure from linearity. The assumption of linearity in the log hazard was thus supported.

I then turned to checking the scale of $daysSupExp_i$. Here again design variables were used. I began by replacing $daysSupExp_i$ with design variables formed from Q25, Q50, and Q75. These were, respectfully, 365, 548, and 730 days. I refitted the model with the design variables then plotted the estimated coefficients against group midpoints. The overall trend indicated a negative effect without substantial departure from linearity which, again, supported the assumption of linearity in the log hazard.

Given evidence supporting the assumption of linearity in the log hazard, the Cox regression shown in the first column of Table 47 was evaluated for proportional hazards. All the predictors were examined for proportionality by fitting a model that included the interaction of each variable with mean-centered log-time $\log(t) - \overline{\log(t)}$. The nonsignificant Wald tests¹²⁵ of $H_0: \beta_1 cnvDrg1 \times$

¹²⁵The χ^2_L test is likely invalid given the robust estimator of variance used to adjust for $k = 122$ block-group clusters.

Table 48

Lower (LCLM) and upper (UCLM) bias-corrected 95% confidence limits, **MT2**, $n = 199$.

	LCLM	UCLM
<i>cnvDrg1</i>	-.169	.943
<i>cnvDrg2</i>	.105	1.06
<i>piPos5</i>	1.04	3.39
<i>daysSupExp</i>	-.00182	-.00042

$[\log(t) - \overline{\log(t)}] = \beta_2 \text{cnvDrg2} \times [\log(t) - \overline{\log(t)}] = 0$ ($\chi_W^2 = 4.50$, $df = 2$, $p < 0.11$), $H_0 : \beta_3 \text{piPos5} \times [\log(t) - \overline{\log(t)}] = 0$ ($\chi_W^2 = 0.27$, $df = 1$, $p = 0.60$), and $H_0 : \beta_4 \text{daysSupExp} \times [\log(t) - \overline{\log(t)}] = 0$ ($\chi_W^2 = 0.09$, $df = 1$, $p = 0.77$) suggested that the hazard function may be proportional in each of the predictors.

The Cox regression shown in the first column of Table 47 was validated by bootstrapping. Bias-corrected confidence intervals around the estimated parameters are shown in Table 48. As indicated in the table, except for the effect of *cnvDrg1_i*, all effects are likely to replicate in the population.

Controlling the other predictors in the model, the hazard rate is expected to increase by roughly 25% for each 0.10 increase in the proportion of positive screens for marijuana. On the other hand, the expected hazard decreases by roughly 18% for each 180 day increase in the expected length of supervision.

Survival experience does not appear to differ between those with no previous drug-related convictions and those with one. It does differ between those with two or more and those with none. Compared to those with no previous drug related convictions, those with two or more are expected to fail at a rate that is roughly 79% higher. It also differs between those with two or more and those with one. Compared to those with only one previous drug-related conviction, those with two or more are expected to fail at a rate that is roughly 22% higher.

DISCUSSION

This chapter describes the findings that were reported in the previous chapter, and the majority of the discussion is devoted to a summary of the key findings and integrating these findings with extant theory and research. A discussion of the limitations of the study and suggestions for future work follows, and I conclude with a few summary statements regarding the project as a whole.

The findings from this study are largely in accordance with available research convincingly suggesting a sizeable fraction of offenders enters probation yet fails to comply with conditions of release (see, BJS, 2000, 2002, 2003; Bonczar, 1997; Bork, 1995; Clear et al., 1992; Glaze & Bonczar, 2006; Glaze & Palla, 2004; Gray et al., 2001; Langan & Cunniff, 1992; Mayzer et al., 2004; Petersilia et al., 1985; Petersilia, 1985a, 1985b, 1998). For instance, about 4 out of every 5 probationers in the sample tested positive, provided a bogus specimen, or failed to appear for a drug testing event at least once while supervised. One or more screens were positive for about 1 in every 2 probationers screened for marijuana and cocaine and about 1 in every 5 or 6 probationers screened for opiates and phencyclidine. As for convictions, roughly one-fourth of the sampled probationers was arrested and subsequently convicted of new crimes during the supervision period; a roughly equal fraction was arrested and subsequently convicted of new crimes during the post-supervision period. Roughly 5 out of every 8 probationers violated one or more supervision-related conditions and 4 out of every 8 violated one or more drug-related conditions. Ultimately, about 3 out of every 5 probationers terminated their sentences unsuccessfully. These levels of negative supervision performance (NSP) steepen the challenges of offender management and reintegration facing the Court Services and Offender Supervision Agency for the District of Columbia (CSOSA).

Choices facing supervision agencies often necessitate judgments about the future behaviors of those under their charge. Such behaviors include whether supervised offenders will abstain from illegal substances, discontinue criminal involvement, comply with release conditions, and, ultimately, successfully complete their sentences and reintegrate with their communities. A small but growing body of research has begun to identify characteristics associated with these aspects of supervision performance (see, Albonetti & Hepburn, 1997; Benedict & Huff-Corzine, 1997; R. L. Cohen, 1995; Gray et al., 2001; Harer, 1994; M. Jones, 1995; Kronick et al., 1998; Langan & Levin, 2002; MacKenzie et al., 1998; MacKenzie & Li, 2002; MacKenzie et al., 1992; MacKenzie & Souryal, 1994; MacKenzie, 1991; Mayzer et al., 2004; Minor et al., 2003; Morgan, 1993; Schwaner, 1997; Silver & Chow-Martin, 2002; Sims & Jones, 1997; F. P. Williams III et al., 2000). This study has drawn heavily on and adds to this body of research by refining this set of characteristics with respect to probationers supervised in the the District of Columbia (DC) by the CSOSA.

The results presented in the previous chapter identified from well over 200 theoretically plausible predictors a very small set that provide the agency with advance notice of the most challenging groups of offenders. This set of characteristics, tabulated in Table 49 with relevant models and domains, includes (a) the age at the time of assessment, (b) the expected length of supervision, (c) the number of substances ever used, (d) whether the probationer had ever used opiates or phencyclidine, (e) the number of weapons-related convictions, (f) the SFS-98 score, (g) the recommended sentence, (h) the impression of recidivism risk on the supervising CSO, and (i) local rates of arrests for drug-related and public order crimes. It is important to point out that each of these characteristics are knowable prior to the commencement of supervision; most are derivable from the PSIs and thus all lend themselves to immediate, risk-anticipated security and treatment decisions.

Table 49

Characteristics associated with increased levels of negative supervision performance among Black males supervised in the DC.

Model	Criterion	Description
S1	Probabilities of ever testing positive, providing a bogus specimen, or failing to appear for a drug-testing event while supervised	<ol style="list-style-type: none"> 1. Probationers expecting longer periods of supervision are more likely to fail 2. Probationers having used a greater number of substances are more likely to fail
S2D	Expected rates of positive screens for cocaine	<ol style="list-style-type: none"> 1. Expected rates of positive screens increase with number of substances ever used 2. Expected rates of positive screens increase with age
S2E	Expected rates of positive screens for marijuana	<ol style="list-style-type: none"> 1. Expected rates of positive screens decrease with age
S2F	Expected rates of positive screens for opiates	<ol style="list-style-type: none"> 1. Expected rates of positive screens higher among those having ever used heroin
S2G	Expected rates of positive screens for PCP	<ol style="list-style-type: none"> 1. Expected rates of positive screens higher among those having ever used PCP
C1	Probabilities of being arrested and subsequently convicted on new charges during the supervision period	<ol style="list-style-type: none"> 1. Lower SFS-98 scores are associated with increased chances 2. Those recommended to incarceration or split-sentence have higher chances
C2	Probabilities of being arrested and subsequently convicted on new charges during the post-supervision period	<ol style="list-style-type: none"> 1. Lower SFS-98 scores are associated with increased chances 2. Offenders living in areas with higher public order arrests have higher chances
V1	Expected rates of supervision-related violations	<ol style="list-style-type: none"> 1. Lower SFS-98 scores are associated with increased rates 2. Having a high impression of risk increases the expected rate
V2	Expected rates of drug-related violations	<ol style="list-style-type: none"> 1. Offenders living in areas with lower drug-related arrests have higher expected rates 2. Having fewer weapons-related convictions is associated with higher expected rates
T1	Probabilities of terminating unsuccessfully	<ol style="list-style-type: none"> 1. Those supervised at more intense levels have higher chances 2. Those failing 0.02 of cocaine tests have higher chances 3. Those recommended to incarceration or split-sentence have higher chances
T2	Expected rates of unsuccessful termination	<ol style="list-style-type: none"> 1. Expected hazard increases as proportion of positive marijuana screens increases 2. Expected hazard decreases as length of supervision increases

As indicated by the predictors shown in Table 49, those having the strongest influence on NSP are largely those bearing on criminal histories and substance use. As such, there are some obvious theoretical linkages that remain unsupported among the data examined here with respect to substance use, rearrests resulting in convictions, condition violations, and termination modes.

For instance, while research suggests certain educational characteristics will predict NSP, they were not influential among these data (cf., Gray et al., 2001; Harer, 1994; Irish, 1989; Landis et al., 1969; Mayzer et al., 2004; Morgan, 1993; Rhodes, 1986; Roundtree et al., 1984; Silver & Chow-Martin, 2002; Sims & Jones, 1997). Nor were either residential or employment stabilities (cf., J. Austin & Litsky, 1982; Gray et al., 2001; Harer, 1994; Irish, 1989; M. Jones, 1995; Landis et al., 1969; MacKenzie & Li, 2002; Mayzer et al., 2004; Morgan, 1993; Silver & Chow-Martin, 2002; Sims & Jones, 1997; F. P. Williams III et al., 2000). Childhood and family factors are also expected to influence NSP, but none of the characteristics observed among these data were influential (cf., Clarke et al., 1988; Harer, 1994; Landis et al., 1969; MacKenzie & Li, 2002; Morgan, 1993; Petersilia, 1985a; Sims & Jones, 1997). Nor were any of the health-related characteristics (cf., Bland et al., 1998; Estroff et al., 1985; Farrington, 1995; Johnston & O'Malley, 1986; Lin et al., 1996; Link, Andrews, & Cullen, 1992; Link, Cullen, & Wozniak, 1992; Monahan, 1992; Shepherd et al., 2002; Teplin et al., 1996; Teplin, 1990). Research also suggests certain contextual characteristics will influence NSP, however, none of the sociodemographic predictors, either singly or in combination, were important among these data (cf., Harer, 1994; Silver & Chow-Martin, 2002; Sims & Jones, 1997). Nor were either local commercialization levels or concentrations of alcohol-related businesses (cf., Cochran et al., 1998; Costanza et al., 2001; D. M. Gorman et al., 2001; D. Gorman, Speer, Labouvie, & Subaiya, 1998; Gyimah-Brempong, 2001; R. Lipton & Gruenewald, 2002; Scribner et al., 1999, 1995; Sherman et al., 1989; Speer et al., 1998; Stitt & Giacomassi, 1992). And, except for arrest rates for public order and drug-related

offenses, objective crime levels within the block-group had little influence on the production of NSP in these data (cf., Boggs, 1965; Carter & Hill, 1978; Gould, 1969; Kelling & Coles, 1996; Reppeto, 1974; D. A. Smith, 1986; Stark, 1987; Taylor, 1999; Wilson & Kelling, 1982).

The absence of these seemingly fitting predictors of NSP could reflect a genuine lack of relationship or at least a substantially smaller and different than expected relationship among Black male probationers supervised in the DC. At the same time, their absence could be a consequence of a few specific methodological limitations. I discuss these limitations later in the chapter. Ultimately, if causal relationships were chief among methodological interests—which here they are not—separate, targeted analyses of specific linkages would be an interesting digression.

I turn for now to an examination of those characteristics that are associated with heightened risks for NSP and that are likely to replicate in the population beginning with characteristics related to substance use.

This research examined two sets of criteria bearing on substance use. The first examined whether offenders in the population will ever test positive, provide a bogus specimen, or fail to appear for a drug-testing event while supervised. The second examined how often they will test positive for 7 different illegal substances.

The two most important characteristics influencing whether probationers will ever test positive, provide a bogus specimen, or fail to appear for a drug testing event while supervised are the number of substances ever used and the expected length of supervision. The likelihood of ever failing a drug testing event is higher among nonabstainers than their counterparts. It is important to point out, though, that most of the sample reported having used at least one substance; only $12/199 = 0.06$ reported having used none. Hence, while having never used illegal substances in the past is a good predictor of abstinence while supervised, it is a fairly uncommon characteristic

and thus of dubious importance when making immediate, risk-anticipated security and treatment decisions.

Versatility in the number of different substances ever used, on the other hand, was diverse. For instance, about 2 in every 16 ($30/199 = 0.15$) sampled probationers had previously used one illegal substance, 4 in every 16 ($53/199 = 0.27$) had used two, 5 in every 16 ($59/199 = 0.30$) had used three, 2 in every 16 ($27/199 = 0.14$) had used four, and 1 in every 16 ($18/199 = 0.09$) had used five or more. The findings reported here suggest the likelihood of failing a drug testing event while supervised increases with versatility in the number of different substances ever used.

That the criteria was itself a measure of drug use highlights the importance of behavioral stability. In addition, as was pointed out in the review, research strongly links illegal substances with contemporaneous offending (Anglin & Speckart, 1988; Bland et al., 1998; M. R. Chaiken & Chaiken, 1987; Clayton & Tuchfeld, 1982; Dembo et al., 1995; Dembo, Williams, Getreu, et al., 1991; Dobinson & Ward, 1986; Elliott et al., 1989; L. Gardner & Shoemaker, 1989; S. D. Gottfredson & Gottfredson, 1979; Greenfield & Weisner, 1995; Guze et al., 1968; Inciardi, 1980; D. C. McBride & McCoy, 1981; McGlothlin, 1979; Newcomb & Bentler, 1986; Nurco, 1979; J. Palmer & Carlson, 1976; Speckart & Anglin, 1985; Stacy & Newcomb, 1995; Stice et al., 1998; Swanson et al., 1990; Wish & Johnson, 1986). Thus, probationers with the highest chances of failing drug testing events are likely also to be those that will continue to be criminally active while serving their sentences in the community (J. Austin & Litsky, 1982; Baird et al., 1984; Benedict & Huff-Corzine, 1997; Gray et al., 2001; Harer, 1994; MacKenzie et al., 1998; MacKenzie & Li, 2002; Schmidt & Witte, 1988; Silver & Chow-Martin, 2002). The agency should thus carefully examine past substance use when making immediate, risk-anticipated security and treatment decisions bearing on future use.

Probationers serving longer sentences are also more likely to fail drug testing events than their counterparts. The review highlighted evidence that length of supervision has been consistently linked with supervision performance (Benedict & Huff-Corzine, 1997; Kronick et al., 1998; MacKenzie et al., 1992; MacKenzie, 1991; Mayzer et al., 2004; Morgan, 1993; Rhodes, 1986; Roundtree et al., 1984; Sims & Jones, 1997). Those serving longer sentences tend to fair worse. While the review focused mainly on the linkage between sentence length and either contemporaneous offending or failure while supervised, the implication here is that sentence length is also related to abstinence while supervised: offenders with longer sentences are less likely to abstain. Whether this reflects anticipation or artifact is unclear.

With lengthening sentences, nonabstainers may believe their chances of staying drug-free and sober become too slim to pressure abstention. As they have little expectation of complying with conditions of community release, some offenders may buy time in the community fully anticipating eventual revocation and incarceration. This could suggest either that the conditions of community release, particularly the policies on drug abstinence, are not fully understood or that there is a shared belief that drug testing methods are fallible. On the other hand, those unlikely to abstain while supervised may be more likely to receive longer sentences in the first place as a result of sentencing patterns targeting chronic drug offenders. Thus, for perfectly understandable and predictable reasons, those with longer sentences will probably fail drug testing events and would probably do so even if their sentences were shorter. What is clear, nevertheless, is that supervision agencies should consider the influence of sentence length when making risk-anticipated decisions bearing on substance use because those serving relatively longer sentences are likely to continue using substances and, by extension, to be criminally active while serving their sentence in the community.

In addition to assessing whether they will fail drug testing events, this study also estimated how often probationers in the population will test positive for 7 different substances. Unfortunately, sample screening rates were relatively low for alcohol, methadone, and amphetamines. It was suspected that this infrequency reflected a non-random selection process. As such, these 3 substances were excluded. On the other hand, screens for cocaine, marijuana, opiates, and phencyclidine were common across the sample. The findings from the models predicting rates of positive screens for these substances are discussed next beginning with cocaine and marijuana.

Age is an important predictor of how often probationers will test positive for both cocaine and marijuana. It is, in fact, the single most important characteristic influencing marijuana positives: younger offenders test positive at higher rates than their older counterparts. Age is important in predicting rates of cocaine positives as well—as is the number of substances ever used—but the relationship is inverted: older offenders and those having used a greater number of substances test positive for cocaine at higher rates than their counterparts.

The bulk of the evidence suggests that offending and NSP is concentrated among the youth (Clarke et al., 1988; Cloninger & Guze, 1973; Dembo et al., 1995; Dembo, Williams, Schmeidler, et al., 1991; Farrington, 1986; Gendreau, Little, & Goggin, 1996; M. R. Gottfredson & Hirschi, 1986; Harer, 1994; Harrison & Gfroerer, 1992; Hoffman & Beck, 1984; Irish, 1989; Matza, 1964; Morgan, 1993; Osgood et al., 1989; Rhodes, 1986; Sampson & Laub, 1993; Sims & Jones, 1997; Whitehead, 1991; Wolfgang et al., 1987). We expect drug use, by extension, to have a similar distribution. The evidence presented here with respect to marijuana is largely consistent with such a pattern. The evidence with respect to cocaine, however, is not.

This raises the question of whether older offenders are more likely to use cocaine and thus more likely to test positive more often than younger offenders or rather that older cocaine users are more likely than younger users to continue using cocaine while supervised. The lack of association

Table 50

Frequencies, ever used cocaine and marijuana, by age, $n = 199$.

Age	<i>n</i>	Cocaine		Marijuana	
		No	Yes	No	Yes
[19, 26)	72	52	20	7	65
[26, 39)	61	30	31	10	51
[39, 62]	66	11	55	23	43
Total	199	93	106	40	159

between past cocaine use and rates of testing positive suggests not all users of cocaine continue to use the substance while supervised. This inconsistency might then reflect the drug popularity trends within age groups that Golub and Johnson (1999) discuss. They argue older offenders are more likely to favor cocaine whereas younger offenders are more likely to favor marijuana (and see, H. R. White & Gorman, 2000). The findings presented here are consistent with this.

Frequencies of probationers having ever used cocaine and marijuana are tabulated in Table 50 by age tertiles. As indicated, previous use of cocaine was less common across the sample than was previous use of marijuana: just over half ($106/199 = 0.53$) of the sample had previously used cocaine whereas about four-fifths ($159/199 = 0.80$) had previously used marijuana. By age, older offenders were more likely to have used cocaine than their younger counterparts: $20/72 = 0.28$ of those ages 19 to 26 as compared to $55/66 = 0.83$ of those ages 39 to 62 had used cocaine in the past. On the other hand, younger offenders were more likely to have used marijuana than their older counterparts. In fact, nearly all ($65/72 = 0.9$) of those ages 19 to 26 had used marijuana as compared to $43/66 = 0.65$ of those ages 39 to 62.

The implication is that even though research largely suggests younger offenders will be the most crime involved and the most likely to perform poorest while supervised, older offenders do not necessarily pose less of a supervision challenge. Here, older offenders—especially those with

more extensive drug use histories—have higher chances of continued cocaine use while supervised. This is particularly important given research suggesting, compared to marijuana, cocaine is a less manageable substance and one that is more likely to be implicated in predatory crime (see, D. McBride, 1981; Wright & Klee, 2001; H. R. White & Gorman, 2000). This caution is relevant when considering the two other substances examined in this research as well.

Positive screens for opiates and phencyclidine were less common than those for cocaine and marijuana, and, for these substances, the single most important characteristic influencing population rates is having ever used either. Having done so is associated with large increases in the expected rates of positive screens: expected rates of positive opiate screens, for instance, are about 60 times higher; those of phencyclidine are about 15 times higher.

This is a clear example of behavioral stability with at least one rather obvious treatment implication: if programs designed specifically for opiate or phencyclidine users exist, selecting participants from among those having ever used either substance is an obvious tool because, unlike the case for cocaine and marijuana, there is a considerable amount of persistence in the use of both. Aside from the obvious importance of abstinence in determining success while supervised, these findings also raise a public safety concern. Phencyclidine, like cocaine, is less manageable, tends largely to evoke erratic behaviors, and is associated with a host of physiological problems in comparison to other substances (see, D. McBride, 1981; Wright & Klee, 2001; H. R. White & Gorman, 2000). And while opiates are similar to marijuana in that neither tend to evoke uncontrollable behaviors and neither are associated with long term physiological problems, unlike marijuana, available research suggests opiate users are more criminally active than users of other types of drugs.

Thus, when making risk-anticipated security and treatment decisions bearing on substance use, the agency should consider sentence length, age, the number of substances ever used, and

whether the offender has ever used either opiates or phencyclidine. These characteristics are associated with subsequent use while supervised; moreover, there is reason to believe those offenders that fail to abstain will also continue to be criminally active throughout supervision.

Two additional legal criteria examined here included arrests and subsequent convictions during and shortly after the supervision period. The SFS-98 is an important predictor of convictions during both periods, with lower values linked with increased likelihoods.¹²⁶ Additionally, the recommended sentence well-predicts convictions during the supervision period, where those recommended to either incarceration or split-sentence as opposed to probation stand a greater chance of being convicted. The importance of the recommended sentence shrinks in comparison to the influence of the rate of public-order related arrests within the BG of residence once the supervision period terminates.

The sole purpose of the SFS-98 is to assess the probability that a federal inmate will reoffend once released. As described in Appendix B, this measure is based on a wide range of attributes including the number of past adjudications and convictions, the number of past commitments, age at the time of the instant offense, the time between this and the most recent commitment, and criminal justice status at the time of arrest. It has been extensively validated and demonstrates reasonable predictive accuracy (Hoffman, 1994; Hoffman & Beck, 1974, 1976, 1984), and, not surprisingly, proves important in predicting these two legal criteria.

Sentence recommendations are made by PSI authors after having researched the background of offenders. Recommendations are ultimately based on the DC sentencing guidelines with qualifications stemming from the extensive information in the PSI. Unlike the SFS-98, the guidelines emphasize only a limited set of attributes: the severity of the offense on conviction,¹²⁷

¹²⁶The SFS-98 is scored such that lower values are associated with higher recidivism risk.

¹²⁷The severity of the offense on conviction is based on a hierarchical scale developed by the DC Sentencing and Criminal Code Revision Commission.

Table 51

Component comparisons of the SFS-98 and the recommended sentence.

SFS-98	Recommended sentence
1 Number of past juvenile adjudications and criminal convictions	Number and severity of past adjudications and convictions
2 Time between this and the most recent commitment	Time between this and the most recent sentence
3 NA	Severity of the offense on conviction
4 Criminal justice status at the time of arrest	NA
5 Number of previous commitments exceeding 30 days	NA
6 Age at the time of the instant offense	NA

the number and severity of prior convictions and adjudications, and the length of time between the imposition or the expiration of the last sentence and the commission of the instant offense. Those with lengthier criminal histories, those with more serious convictable offenses, and those with shorter durations between this and the most recent sentence are typically recommended to incarceration or split-sentence.

The components of the two measures are shown in Table 51 with comparable items tabulated together and incomparable items indicated with NAs. As indicated, while there is some overlap in that both address past adjudications and convictions and the time between this and the most recent sentence or commitment, there are some important differences between them. For example, while the SFS-98 examines the number of past adjudications and convictions, the recommended sentence examines their severity as well. The recommended sentence also emphasizes the nature of the convictable offense. And, unlike the recommended sentence, the SFS-98 examines the criminal justice status at the time of the arrest, the number of previous commitments, and age at the time of the instant offense.

While the SFS-98 is a good predictor of behaviors during both periods, the recommended sentence is important in predicting behaviors only during the supervision period. The severity of the offense on conviction is the central contribution of the recommended sentence over and above what is represented in the SFS-98. Thus, this key aspect of criminal history should be considered along with the number of past adjudications and convictions, the number of past commitments, age at the time of the instant offense, the time between this and the most recent commitment, and criminal justice status at the time of arrest when making immediate, risk-anticipated security and treatment decisions especially as they turn on assessing offenders for risk of continued offending while supervised.

Once supervision periods terminate, the added information stemming from the recommended sentence is no longer important. Instead, rates of public order arrests become more predictive: offenders living in areas with higher rates of public order related arrests have increased chances of being arrested and subsequently convicted shortly after their sentences are complete.

This might be an indication that offenders supervised in these communities are the main contributors of the high arrest rates. However, as rates of arrests were measured prior to most of the supervision activity this explanation is not convincing. At least not with these data. A more convincing explanation points to the likely direct and indirect influences of neighborhood crime on the residents. Akers (1998), for instance, suggests the level of crime in an area might influence subsequent NSP directly by providing learning contexts conducive to criminal behaviors. High crime rates may alternatively stigmatize communities, degrade the moral standing of its residents, and potentially undermine strong social ties (Stark, 1987). Why this characteristics is important only after sentences are complete is unclear. There may be some level of protection against these forces while sentences are active that decays upon completion. Nevertheless, when making risk-anticipated security and treatment decisions, especially as they pertain to risk of post-sentence

recidivism, agencies should consider the impact of local, particularly public-order related arrests, along with the number of past adjudications and convictions, the number of past commitments, age at the time of the instant offense, the time between this and the most recent commitment, and criminal justice status at the time of arrest, as these characteristics influence the chances of sustained law-abiding behavior upon release.

This study also examined characteristics associated with higher expected rates of both supervision and drug-related violations. There are some redundancies among these two criteria and those that have been discussed so far. For instance, one of the most common types of supervision-related violations was failing to obey all laws, which is also captured in the first arrest-conviction criterion albeit at a lower burden of proof. Other common supervision-related violations include failing to report as directed and failing to carry out CSO instructions, and thus supervision-related violations is a more sensitive one in that it captures not only law obedience but additional non-compliance as well. Also, along with the use of illegal substances, drug-related violations capture failing to comply with drug or alcohol treatment or surveillance programs or procedures; visiting places where illegal substances are bought, sold, or consumed; and purchasing, possessing, or selling illegal substances. So, while there is some overlap among this criteria and those bearing on substance use, this one captures a broader range of drug-related behaviors.

The most important characteristics influencing how often offenders will violate supervision-related conditions are the impression of risk on the supervising CSO and the SFS-98 score. One is a subjective measure, the other is objective; neither alone is sufficient in predicting which offenders will violate supervision-related conditions at higher rates. As both assess recidivism risk, it is no surprise—given the nature of these types of violations—to find either to be important.

When conducting the initial screening assessment the supervising CSO makes a judgment about the level of risk the given offender represents vis-à-vis the other offenders in the CSO's

caseload. Those for whom the CSO has a high impression of recidivism risk are expected to violate supervision related conditions at a rate roughly twice as high as those for whom the CSO has a lower impression. This may be an indication of the power of professional judgment: CSOs are in a perfect position to gauge which of their offenders will likely fail to comply with release conditions. However, because assessments are made by the supervising CSO one has to wonder whether this indeed represents accurate prediction or, instead, self-fulfillment. It is possible, for example, that CSOs make inaccurate predictions, but, because they expect certain offenders to violate conditions more often, they increase monitoring levels for these offenders and this heightened exposure alone increases the chances of finding violations and of subsequently making good on their predictions.

This self-fulfilling argument, however, is less compelling given the additional importance of the number of past adjudications and convictions, the number of past commitments, age at the time of the instant offense, the time between this and the most recent commitment, and criminal justice status at the time of arrest as captured in the SFS-98. Here, each additional point on the SFS-98 is associated with a roughly 10% decrease in the expected number of supervision-related violations. Thus, when making immediate, risk-anticipated security and treatment decisions—especially as they bear on risks of supervision-related violations, the agency should carefully examine the components of the SFS-98 and the impression of risk on the supervising CSO, as both are associated with changes in expected supervision-related violation rates.

The most important characteristics influencing the rate of drug-related violations are the number of previous weapons-related convictions and the rates of arrests for drug-related crimes within the block-group. The findings from this study suggest the number of weapons-related convictions is inversely related to rates of drug-related violations. This relationship is unexpected, as the weight of the evidence suggests instead that having more convictions will be associated with higher likelihoods of NSP (J. Austin & Litsky, 1982; J. Austin et al., 1989; M. Jones, 1995;

Mayzer et al., 2004; Petersilia, 1985a; Quinsey et al., 1998; Schwaner, 1997; Silver & Chow-Martin, 2002; Whitehead, 1991). Most of the empirical studies, however, have focused on either technical and criminal behaviors or ultimate failure while supervised; little has been written about this specific, drug-related aspect of supervision performance.

Contrary to expectations, having more weapons-related convictions is associated with lowered expected rates of drug-related violations. Compared to those without any previous weapons-related convictions, for example, the expected number of drug-related violations will be about 34% lower among those with at least one. This could indicate either that those with more extensive weapons-related criminal histories are less involved in drug-related behaviors or that while supervised in the community this group of offenders eschews non-complying behaviors—especially those related to illegal substances—as much as possible. While it seems obvious that those with lengthy weapons related convictions will pose a risk to the public, here, at least as it concerns this specific, drug-related aspect of NSP, there is a lower associated risk of NSP. Also, that weapons-related convictions were unrelated to other aspects of NSP, including the substance use criteria, suggests that this characteristic is related more so to the broader range of drug-related behaviors captured by this criterion than simply contemporary use.

The relationship between local rates of drug-related arrests and the rate of drug-related violations is also inconsistent with expectations. The findings presented here suggest as local rates of arrests for drug-related crimes increase, the expected number of drug-related violations decreases. This finding is not theoretically supported.

Both Akers (1998) and Stark (1987), for instance, provide plausible explanations for why rates of drug-related arrests might increase the rate of drug-related violations. Indeed, here we find just the opposite effect. Its absence when considering the use of substances as captured by the previously discussed substance use criteria suggests the effect of local drug-related crime op-

erates primarily on the additional characteristics captured in this criterion (viz., failing to comply with drug or alcohol treatment or surveillance programs or procedures; visiting places where illegal substances are bought, sold, or consumed; and purchasing, possessing, or selling illegal substances). The inverse effect found here suggests offenders living within high drug-crime neighborhoods might be more aware of the systemic, drug-related problems within their neighborhoods and thus more likely to comply with drug-related conditions while supervised. This is speculative and demands further study.

To the extent choices facing the agency depend on expected rates of drug-related violations, the agency will benefit from carefully examining past weapons-related convictions and local rates of drug-related arrests, as both are associated with subsequent rates of violations. However, given that neither of these predictors behave in a way that is consistent with existing theory and research, these conclusions should be approached cautiously until they can be examined in greater detail.

This study also examined characteristics associated with whether and, if so, how soon offenders will terminate their sentences unsuccessfully. The most important characteristics influencing whether probationers will terminate their sentence unsuccessfully include the recommended sentence, the proportion of positive screens for cocaine, and the level of supervision. The most important characteristics influencing how fast they will do so include the proportion of positive screens for marijuana, having a history of drug-related convictions, and the expected length of supervision.

Probationers most likely to terminate sentences unsuccessfully are those whom the PSI author recommended a sentence of either incarceration or split-sentence, those having a proportion of positive screens for cocaine of 0.02 or more, and those supervised at higher levels of intensity.

Sentence recommendations are made by PSI authors after having researched the background of offenders. Recommendations are ultimately based on the DC sentencing guidelines

with qualifications stemming from the extensive information in the PSI. Unlike the SFS-98, the guidelines emphasize only a limited set of attributes: the severity of the offense on conviction,¹²⁸ the number and severity of prior convictions and adjudications, and the length of time between the imposition or the expiration of the last sentence and the commission of the instant offense. Those with lengthier criminal histories, those with more serious convictable offenses, and those with shorter durations between this and the most recent sentence are typically recommended to incarceration or split-sentence. These data suggest offenders recommended to incarceration or split sentence are likely to perform more poorly than those recommended to probation; their odds of terminating unsuccessfully are roughly 4.8 times larger.

The proportion of positive screens for cocaine is also associated with whether offenders ultimately terminate sentences unsuccessfully. The expected odds of failure are roughly 2.8 times larger among those having failed more than 0.02 of their cocaine screens. This suggests that even though a small proportion of positives are tolerated, continued use of cocaine is clear reason for supervision failure. From an earlier model we know offenders having the highest expected rates of cocaine positives are older particularly drug-involved offenders. This group thus poses higher chances of terminating unsuccessfully.

Supervision level essentially captures intensity: those supervised at higher levels are seen more often by supervising CSOs and face stricter penalties in response to noncomplying behaviors. Here, those supervised at higher levels are more likely to fail while supervised. Compared to those supervised at the maximum level, for instance, the expected odds of terminating unsuccessfully are roughly 90% smaller among those supervised at the minimum level, 46% smaller among those supervised at the medium level, and roughly 73% larger among those supervised at the intensive level.

¹²⁸The severity of the offense on conviction is based on a hierarchical scale developed by the DC Sentencing and Criminal Code Revision Commission.

Although the CSO can increase or decrease supervision level based on professional judgment, it is primarily determined by a linear combination of the RNS items (see, Appendix A). On one hand this suggests, even though the individual RNS items are themselves irrelevant, the algorithm determining supervision level successfully identifies offenders posing the highest risk of NSP—at least, that is, with respect to ultimately terminating unsuccessfully. On the other, it could suggest either that closely monitoring offenders has a detrimental effect on performance or simply that monitoring offenders more closely increases the chances that CSOs will find grounds for termination. These data do not give any insight into which of these plausible explanations is driving the variations. They do, however, suggest a linear combination of the RNS items is a good predictor of whether probationers in the population will ultimately fail or succeed while supervised.

From this model we know which characteristics influence whether probationers will fail while supervised. These are, namely, the recommended sentence, the proportion of positive screens for cocaine, and the level of supervision. The next model examined characteristics influencing how fast they will do so and, in the end, the most important characteristics include the proportion of positive screens for marijuana, having a history of drug-related convictions, and the expected length of supervision.

Failure rates will be highest among persistent marijuana users and those having a higher number of previous drug-related convictions. These two findings are anticipated by the research. That lower hazards are expected among those with shorter supervision sentences is simply too closely tied with supervision time to be meaningful. I therefore exclude this finding in the discussion that follows.

The hazard rate increases by roughly 25% for each 0.10 increase in the proportion of positive screens for marijuana. This suggests drug abstinence is key in successfully completing sen-

tences. Misconduct—especially persistent use of marijuana—is grounds for terminating supervision, but these data also suggest a modicum of leniency. CSOs may, for instance, initially respond to continued use by increasing sanctions or introducing directed, drug-related interventions. When these efforts fail they are nevertheless forced to terminate sentences earlier than anticipated.

It is important to note that these data tell us only about the status at the end of the sentence and not the details on how this status came about. A sentence may be revoked or terminated unsuccessfully due to specific, unmeasured processes like contemporaneous offending or, more generally, lack of adjustment to supervision requirements. It is likely that early failures result not only from continued marijuana use but also from behaviors related to continued use. For instance, MacKenzie and her colleagues found that offending is highest during months when probationers were actively using illegal substances (MacKenzie et al., 1998; MacKenzie & Li, 2002). Similarly, J. Austin and Litsky (1982) found those probationers with higher levels of drug use were more likely to eventually abscond.

Findings from a previous model suggest those most likely to use marijuana while supervised are younger offenders. Age was, in fact, the most important predictor of this criterion. Thus, those at highest risk of early failure while supervised are most likely to be younger offenders. The other influential predictor of the rate of failure also suggests a linkage between illegal substances and NSP, but here focus shifts from contemporaneous to past use. Probationers with two or more drug-related convictions are expected to fail at a rate that is roughly 22% higher than those with only one and 79% higher than those with none.

As noted throughout the review, past behaviors are among the strongest predictors of future behaviors: both a lengthy history of convictions and patterned criminality is related to subsequent NSP (J. Austin & Litsky, 1982; J. Austin et al., 1989; Bartell & Thomas, 1977; Cunniff, 1986; Irish, 1989; M. Jones, 1995; Mayzer et al., 2004; McGaha et al., 1987; Petersilia et al., 1985;

Petersilia, 1985a; Quinsey et al., 1998; Schwaner, 1997; Silver & Chow-Martin, 2002; Sims & Jones, 1997; Vito, 1987; Whitehead, 1991). Also, because the number of convictions for drug-related offenses is more important than, say, the total number of convictions for all types of offenses or offenses of a different nature, illegal substances are obviously implicated in the rate failure. Research linking a history of substance use (e.g., Benedict & Huff-Corzine, 1997; Silver & Chow-Martin, 2002; D. A. Smith & Polsenberg, 1992) and an underlying pattern of abuse (Baird et al., 1984; Gray et al., 2001; Harer, 1994; Schmidt & Witte, 1988) with later offending and NSP anticipates this.

Ultimately, we have a fairly strong indication that both contemporaneous and past drug use has a particularly negative impact on failure rates. This could be because drug use is a particular form of misconduct that directly triggers early termination, but how closely the use of drugs and the ultimate termination are tied is unclear. It could also mean that drug use is an indication of a larger process including contemporaneous offending or, more generally, a lack of adjustment to supervision requirements, and it is these characteristics that speed offenders into early termination.

Out of well over 200 potential predictors included in this study, only a fraction were both related to NSP and likely to replicate in the population. These characteristics are tabulated in Table 49; a summary of the findings follows.

The most important characteristics of offenders likely to continue using illegal substances while supervised are past substance use, age, and length of supervision. Those having used a greater number of illegal substances and those expecting to serve longer community sentences are more likely than their counterparts to fail drug testing events. And while younger offenders are at greater risk of using marijuana while supervised, older offenders—especially those with more extensive substance use histories—are at greater risk of using cocaine. Also, those offenders

having ever used either opiates or phencyclidine are much more likely than their counterparts to use these substances while supervised.

The most important characteristics of offenders likely to be criminally active while supervised include the SFS-98 score, the recommended sentence, and the rate of public-order related arrests within the BG of residence. Those with lower SFS-98 values are more likely to be arrested and subsequently convicted. During the supervision period, those offenders that were recommended to either incarceration or split-sentence as opposed to probation are more likely to be convicted and, afterward, those living in BGs with higher rates of public-order related arrests are more likely to be convicted.

The most important characteristics of offenders unlikely to comply with release conditions include the impression of risk on the supervising CSO, the SFS-98 score, the number of previous weapons-related convictions, and the rates of arrests for drug-related crimes within the BG. Those offenders for whom CSOs have high impressions of recidivism risk and those having lower SFS-98 scores are expected to violate supervision related conditions at a higher rate than their counterparts. Those offenders having fewer previous weapons-related convictions and those living in BGs with lower rates of drug-related arrests are expected to violate drug-related conditions at higher rates than their counterparts.

The most important characteristics of whether and, if so, how soon probationers will terminate sentences unsuccessfully include the recommended sentence, the expected length of supervision, the level of supervision, the proportion of positive screens for both cocaine and marijuana, and the number of previous drug-related convictions. Those offenders recommended to either incarceration or split-sentence, those failing 0.02 or more of their screens for cocaine, and those supervised at higher levels of intensity are more likely to fail while supervised; those continuing

to use marijuana and those having a higher number of previous drug-related convictions will fail at the fastest rates.

There is reason for caution when considering the findings from this study. I discuss a few of these next.

This study examined characteristics increasing the risk that supervised offenders will engage in NSP, which was defined here by two domains of criteria: legal and supervision-specific. Legal criteria included substance use and continued offending and supervision-specific criteria included condition violations and termination modes. These criteria were chosen from common criteria in criminological risk-assessments, but perhaps a better approach would have been to first survey the supervision staff regarding their focal supervision concerns and then to construct criteria based on their responses. It is thus possible the criteria studied here do not fully represent their concerns.

Despite having a wide collection of potential predictors there are many that have been omitted. Those characteristics that have not been included, and there are many, were omitted primarily because of their unrealistic availability for supervision line staff when making immediate, risk-anticipated decisions. This includes immediate situational, physiological, or cognitive factors, as well as unforeseen sociological, psychological, and contextual characteristics. Also, among those measures that were included, there is reason to expect any lack of association with NSP is a consequence of how they were measured and scaled and not of a genuine lack of relationship. I discuss some of these possibilities next.

Available research suggests educational performance, commitment to educational goals, and educational attainment are inversely associated with criminal justice involvement (Agnew & White, 1992; Agnew, 1985, 1989, 1992; Beck et al., 1993; Brezina, 1996; Farnworth & Leiber, 1989; Farrington, 1997; S. D. Gottfredson & Gottfredson, 1979; Harrison & Gfroerer, 1992;

Hindelang, 1973; Hirschi, 1969; Horney et al., 1995; Jarjoura, 1996; Kruttschnitt et al., 1986; Quinsey et al., 1998; Sampson & Laub, 1993; Thornberry et al., 1985a, 1985b; Ward & Tittle, 1994; L. Zhang & Messner, 1996). These characteristics are decisive predictors of NSP (Gray et al., 2001; Harer, 1994; Irish, 1989; Landis et al., 1969; Mayzer et al., 2004; Morgan, 1993; Rhodes, 1986; Roundtree et al., 1984; Silver & Chow-Martin, 2002; Sims & Jones, 1997). However, none of the measures used here (viz., the highest grade attempted and completed and whether the offender earned a GED) were associated with the production of NSP. While this suggests these characteristics are unimportant, it could also mean they do not adequately operationalize the concept. In particular, the measures used here capture attainment exclusively. It is likely, then, that if measures capturing how well offenders performed while in they were in school and how strongly they agreed with educational goals were included they would appear important in predicting NSP.

Residential instability is also related to offending (Kasarda & Janowitz, 1974; Sampson, 1988) and NSP (J. Austin & Litsky, 1982; Mayzer et al., 2004; F. P. Williams III et al., 2000). None of the measures used here, however, namely the number of residential changes within the previous year and whether the offender resides with relatives, were important.¹²⁹ The lack of relationship among these measures and NSP could suggest residential stability is unrelated to supervision performance. On the other hand, it might indicate that these measures do not fully capture the most important aspects. One of these aspects is likely to be the embeddedness of the offender within the community (i.e., Sampson, 1988). Had measures tapping both interpersonal ties with neighbors and willingness to participate in community activities and organizations been included, it is likely they would be important predictors of the production of NSP in the population.

Unemployment and job instability are both linked with elevated offending (Farrington, 1986, 1997; Thornberry & Christenson, 1984; Thornberry & Farnworth, 1982), recidivism (S. D. Got-

¹²⁹Other measures were intended, including the type of living quarters and whether the offender rents or owns, but were excluded due to high levels of missingness.

tfredson & Gottfredson, 1979; D. M. Gottfredson et al., 1978; Uggen, 2000), and NSP (J. Austin & Litsky, 1982; Gray et al., 2001; Harer, 1994; Irish, 1989; M. Jones, 1995; Landis et al., 1969; MacKenzie & Li, 2002; Mayzer et al., 2004; Morgan, 1993; Silver & Chow-Martin, 2002; Sims & Jones, 1997; F. P. Williams III et al., 2000); however, none of the employment characteristics included here were important predictors of NSP. While this suggests these characteristics may be unimportant in the production of NSP, it could also mean that they fail to fully operationalize the concept.

For instance, the measures used here capture the number of employment changes within the past year, whether there are any jobs within the past year lasting less than 30 days, the number of months at the current job, and employment status at time of instant offense. These characteristics may not be observed for long enough periods to fully represent stability patterns. Thus, had all employment behaviors since, say, age 18, rather than only within the past year or month, been included it is likely these characteristics would prove important predictors of NSP. In addition, Sampson and Laub (1993) argue that employment stability is only partially important and that the quality of employment is also important. It is likely then that had measures of wages, job quality, and job satisfaction been included, they too would lead to different findings.

Early childhood experiences are expected to influence NSP (Cloward & Ohlin, 1960; Farrington, 2000, 1997; M. R. Gottfredson & Hirschi, 1990; Gove et al., 1979; Hirschi, 1983, 1994; Kolvin et al., 1988; McCord, 1979; Merton, 1957; Robins, 1978; Sampson & Laub, 1993; Stark, 1987; Thornberry et al., 1999; Wells & Rankin, 1991; Wilson & Hernnstein, 1985); however, none of the measures included here (viz., parent marital status at birth, whether parents were involved in their upbringing, whether they have sustained contact with their parents, and whether they experienced neglect or abuse as a child) were important predictors. While this could mean

such early experiences do not have a genuine relationship with later NSP, it might also suggest these measures do not adequately capture the most important processes.

For instance, while the literature highlights lifelong consequences of lowered economic conditions and the structure of illegitimate opportunities, neither of these characteristics were available. It is likely, had they been included, they would have been important predictors. Similarly, while parent and sibling criminality are also linked with later offending, these characteristics were excluded due to high levels of missingness. Had they been included, it is likely they too would have been important and the findings would be different.

Immediate family characteristics, such as marital quality and family involvement, are also associated with offending and NSP (Clarke et al., 1988; Farrington, 1989; M. R. Gottfredson & Hirschi, 1990; Harer, 1994; Horney et al., 1995; Landis et al., 1969; Laub et al., 1998; MacKenzie & Li, 2002; Morgan, 1993; Petersilia, 1985a; Sampson & Laub, 1990, 1993; Sampson et al., 1997; Sims & Jones, 1997; Warr, 1993, 1998; West, 1982; Wilson & Hernnstein, 1985). However, none of the characteristics included here were important predictors of NSP. This is likely due to an incomplete operational definition.

In particular, though marital status was included, evidence suggests it is not merely being married but also the quality of the relationship that matters (Laub et al., 1998; Sampson & Laub, 1993). The absence of this aspect of marriage may explain why it was unrelated to NSP here and why it has appeared unimportant in other studies (Gray et al., 2001; Mayzer et al., 2004; Roundtree et al., 1984). The same holds for family involvement. While the number of children and the number of children under age 18 the offender lives with were included, these measures likely fail in capturing the quality of the relationships. Had measures been included that captured, for example, having an agreeable marital climate or the extent of parent-child involvement, it is likely they would have been important in predicting NSP and would have led to different findings.

Research also suggests the less healthy and more injury prone are involved more so criminally than their counterparts (Farrington, 1995; National Commission on Correctional Health Care, 2002; Shepherd et al., 2002). However, none of the measures capturing physical health were important here. These were, namely, the number of disabilities, injuries, gunshot wounds, and stabbing wounds. While this suggests these aspects of physical health are unrelated to the production of NSP, it does not suggest these attributes are unrelated to NSP. In particular, other aspects, such as chronic illness, may be important.¹³⁰

Research also suggests a linkage between mental health and offending (see, Bland et al., 1998; Ditton, 1999; Estroff et al., 1985; Johnston & O'Malley, 1986; Lin et al., 1996; Link, Andrews, & Cullen, 1992; Link, Cullen, & Wozniak, 1992; MacKenzie et al., 1998; Monahan, 1992; Teplin et al., 1996; Teplin, 1990) and thus it was expected that mental health characteristics would be implicated in the production of NSP. However, none of the measures included here (viz., whether the offender had a current or history of mental disorder, whether the offender was diagnosed with mental illness, whether the offender is currently prescribed or taking psychotropic medications, the number of previous mental health hospitalizations, and whether the offender ever attempted suicide) were associated with the production of NSP in the population. This does not, however, suggest mental health is unrelated. Instead, it might reflect inadequate or incomplete measurement.

Had broader and more refined measures of, for instance, psychological distress, stress, depression, problems with emotions and items capturing defined classes of mental illness, such as depression, bipolar disorder, schizophrenia, or obsessive-compulsive disorder, it is likely these characteristics would indeed demonstrate a relationship with NSP resulting in different findings.

¹³⁰Note, several additional health-related characteristics were included as part of the PSI instrument. Due to extreme missingness, however, they were excluded from the analysis.

Despite research linking environmental conditions with individual behaviors (e.g., Garofalo, 1987; Greenberg & Schneider, 1994; Morenoff, Sampson, & Raudenbush, 2001; Sampson & Lauritsen, 1994; W. R. Smith, Frazee, & Davison, 2000; Stark, 1987), except for arrest rates for public order and drug-related offenses, none of the contextual characteristics were important predictors of NSP.

This included sociodemographic and economic predictors drawn from the 2000 Census, such as the proportion of the block-group that was non-white, foreign born, Hispanic or Latino, living in a different house in 1995, having less than a high school diploma or equivalency, income below the poverty line, and unemployed, as well as the proportion of female-headed households and households receiving public assistance, the proportion of renter occupied housing units, the ratio of children to adults, and the population per square meter of block-group land area. None of these items were associated with NSP. These items were also reduced to a 3-factor solution representing concentrated disadvantage, immigrant concentration, and residential stability; however, these items were also unimportant in the production of NSP in the population. While this might suggest such sociodemographic characteristics are unimportant in the production of NSP, this lack of relationship could instead reflect that the block-group is a poor neighborhood-level proxy. It was chosen for this study as it is the closest approximation to the neighborhood for which Census data are publicly available. Had measures been constructed for areas that more closely align with neighborhood boundaries, it is possible the findings reported here would differ.

Research also suggests there are intrinsic, crime generating characteristics in areas wherein residential units are coexistent with or adjacent to commercial areas (see, Kelling & Coles, 1996; Reiss, 1986; Sampson & Raudenbush, 2001; Skogan, 1992; Stark, 1987; Taylor, 1999; Wilson & Kelling, 1982). However, the item constructed here representing commercialization—the density

of all licensees¹³¹ per 1,000 residential housing units within U.S. Census Bureau (Census) block-group (BG)—was not an important predictor of NSP. This suggests local commercialization levels are unimportant in the production of NSP. On the other hand, this lack of relationship could be a consequence of the aggregational measure. There may very well be multiple dimensions of commercialization each with differing effects on the production of NSP. Aggregating these dimensions into a single measure may thus mask any differential effects. Had disaggregated measures of various types of commercialization been included, it is possible they would change the findings.

There is also evidence suggesting the concentration of alcohol-related businesses is associated with criminal offending (see, Cochran et al., 1998; Costanza et al., 2001; D. M. Gorman et al., 2001; Gyimah-Brempong, 2001; R. Lipton & Gruenewald, 2002; Scribner et al., 1999, 1995; Sherman et al., 1989; Speer et al., 1998; Stitt & Giacomassi, 1992). The measures included here captured densities of retailers licensed for the on- and off-premises sale of beer, wine, and spirits and of beer and wine only. None, however, were associated with NSP. While this suggests concentrations of alcohol-related businesses are unimportant in the production of NSP, it could suggest that the appropriate processes are not fully captured.

For instance, while these measures capture the densities of alcohol-related businesses, they tell nothing about the situational and sociocultural environments in which they are located (see, Bushman, 1997; Fagan, 1990; Gustafson, 1994; Linsky et al., 1986; MacAndrew & Edgerton, 1969; Parker & Auerhahn, 1998; Parker & Rebhun, 1995; Reiss & Roth, 1993; Roncek & Maier, 1991; Skog, 1985; Wiseman, 1991). Had measures of, for instance, perceptions with respect to acceptable alcohol-related behaviors or the levels of uncharacteristic behaviors in and around these retailers been included, it is possible the findings would differ.

¹³¹Excluding retail alcohol outlets.

Ample research indicates criminal activities cluster in place and time (e.g., Boggs, 1965; Bursik & Grasmick, 1993; Carter & Hill, 1978; Gould, 1969; Reiss, 1986; Reppeto, 1974; Sherman et al., 1989; Wilson & Hernnstein, 1985) and there is reason to expect such levels will influence the production of NSP. Much of this relates to direct influences expected from exposure to criminal activities as well as indirect influences expected through stigmatization, increased crime tolerances, and weakened formal and informal controls (Akers, 1998; Kelling & Coles, 1996; D. A. Smith, 1986; Stark, 1987; Taylor, 1999; Wilson & Kelling, 1982). The measures used here included rates of violent, property, drug- and alcohol-related, public-order, and otherwise unclassified arrests within the block-group, yet, only arrest rates for public order and drug-related offenses were related to NSP. Further, the relationship between drug-related offenses and NSP was unanticipated. While this suggests local crime may be unimportant or misunderstood in the production of NSP, it might also be that the measures included here do not fully capture the important processes.

As Akers (1998) points out, one of the key processes likely involves the sociocultural traditions and control systems. Objective crime measures may not fully account for this, as areas with high levels of crime may not necessarily provide learning environments conducive to crime. Likewise, Stark (1987) points to the stigmatizing effect of high crime on communities and how this degrades the moral standing of its residents and potentially undermines strong social ties. While local crime levels are obviously implicated, areas with high levels of crime may not be characterized necessarily by weakened social ties.

Thus, despite the lack of support for some obvious theoretical linkages there is reason for caution when interpreting the findings from this study, as much of it could be a consequence of the measures chosen and how they were constructed and not a reflection of a genuine lack of relationship. There are two additional considerations when interpreting these findings. Both bear

on the generalizability of these findings to broader supervision populations. The first relates to the sample size; the second, the sampling frame. I discuss both next.

There were only 200 offenders in the present sample and, due to extreme missingness, one was removed. This left a sample comparatively smaller than some suggestions (e.g., P. R. Jones, 1996). The reason for the small sample was to accommodate data extracted from the PSIs. Much of the analytic work here relied on these rich data, but, as I described previously, they did not readily lend themselves to analysis. It is possible had a larger sample been developed the findings would differ. However, incorporating more than a handful of PSIs was unapproachable for this study.

Another reason for caution bears on the generalizability of these findings to broader supervision populations. Because they represented a large proportion of the CSOSA caseload, only Black male probationers were included. Thus, characteristics found here to associate with heightened risks of NSP may not be universal across other dimensions such as non-Blacks, females, and those sentenced to parole supervision. It made sense to concentrate on the bulk of the agency caseload for this study. Expanding it to include these smaller caseloads is an obvious direction for future research. I highlight some additional suggestions next.

The present study should be seen as part, in fact, the beginnings, of a comprehensive risk assessment strategy. An instrument characterizing offenders at high risk of NSP was developed. The next step is putting the instrument into practice and assessing how well it performs.

The implications of the study are clear. Past behaviors were once future behaviors and so it makes good sense to draw our lessons therein. And we need not look too closely: with just a handful of characteristics bearing on past criminality and substance use we know where to focus immediate attention when making risk-anticipated security and treatment decisions. The highest and lowest risks can be identified with this small set of characteristics, and this speeds appropriate

control and therapeutic responses and, ultimately, increases agency accountability, public safety, and offender reintegration.

The findings presented here, however, were based largely on data either not currently available or in a format not lending itself to analytics. Presentence Investigation reports (PSIs) are prime examples. They provide an unmatched picture of personal and social aspects and the most comprehensive description available of both the triggering event and the criminal and supervision histories, they provide insight into the production of NSP in the population, but are, for the most part, unreachable.

An instrument was developed specifically for this study for extracting the most common PSI features that have also been shown to vary with NSP. The findings from the analysis suggest that among these data information required to calculate the SFS-98 and information bearing on substance use and criminal histories are particularly important in predicting NSP. So, to put this instrument into practice an obvious, necessary first step involves automating the recovery of at least those data from the PSIs required to calculate the SFS-98 and those bearing on substance use and criminal histories. Ideally, more formality would be imposed on the content and structure of the PSIs themselves thus leading to greater consistency across reports. Also, future reports would be collected and stored in a format conformable to warehousing and this to future researches.

When considering the findings presented here it is important to heed the lessons learned over the years with respect to the superiority of statistical assessments vis-à-vis clinical assessments. Statistical assessments like this one are characterized by objectivity, formality, and empirical rigor, and, compared to clinical assessments—such as line officer risk assessments—when validated and implemented properly they are more accurate and the instruments on which they are based demonstrate higher reliabilities (Brennan, 1987; Cocozza & Steadman, 1976; D. M. Gottfredson, 1987; Grove & Meehl, 1996; Grove et al., 2000; P. R. Jones, 1996; Lidz et al., 1993; Meehl, 1954;

Menzies et al., 1994; Monahan & Steadman, 1994; Monahan et al., 2001; Monahan, 1981; Morris & Miller, 1985; Mossman, 1994; Quinsey et al., 1998; Quinsey & Maguire, 1986; Rice & Harris, 1995; Sawyer, 1966; van Voorhis & Brown, 1997).

Line officer risk assessments are likely ripe with misjudgment. Although there is much to say in favor of such assessments—especially in light of well-developed professional judgement and creative insight—without clairvoyant knowledge they are doomed to fail. Historically, for instance, such assessments are accurate no more than one-third of the time (Monahan, 1981). It is unfair to expect otherwise.

Line officers may lack an appreciation of basic statistical properties, such as regression effects, and basic risk assessment concepts, such as true and false positives and negatives, base rates, and selection ratios. An understanding of both is critical in making precise judgments. More importantly, because human capacity to deal with a large number of potentially highly intercorrelated variables is limited, they may be unable to apprehend the complexities giving rise the variations in the data. Even with a handful of predictors with which to wrestle, often they are inappropriately weighted. This stems often from excessive, ungrounded emphases on illusory correlates or putative causes of criminality and results in assessments that magnify less important factors and fail to emphasize more important ones. And because they focus exclusively on individualized assessments, they largely overlook competing influences such as those stemming from social or environmental forces.

Objectivity and formality are chief among strengths setting statistical assessments apart from their less powerful counterparts. It is thus imperative statistical assessments remain free from the spoils undermining clinical assessments. These include, for instance, complete replacement of model-implied decisions as well as downward or upward departures from model implications.

In his “disturbing little book,” Meehl (1954) asserts risk-based decisions can be made in either a clinical or statistical fashion—there being no hybrids—and that decision-makers should use that method which results in the most accurate predictions. The weight of the evidence from over 80 years of study clearly identifies statistical approaches as the best tools. Further, the view here is that these assessments should be seen as tools to supplant rather than merely support line officer assessments. Such a view is mildly shared among some (e.g., Monahan et al., 2001) and vigorously defended by others (Quinsey et al., 1998; Webster, Harris, Rice, Cormier, & Quinsey, 1994). In the end, statistical risk assessments should be viewed not as mere guidance, but rather *gospel*.

Appendix A

Risk-needs Screener

The Risk-needs Screener (RNS) is an instrument designed by the Community Supervision Services (CSS) and Community Justice Programs (CJP) offices of the Court Services and Offender Supervision Agency for the District of Columbia (CSOSA) to partition caseloads into supervision level groups (viz., minimum, medium, maximum, or intensive) as a function primarily of NSP risk. In 20 items it captures and weights demographic and social characteristics; criminal and supervision histories; dependencies, disorders, and disabilities; and Community Supervision Officer (CSO) perceptions of risk posed by the screened offender. These items, their levels, and the associated item-level weights are described in this Appendix as is the construction of $rnsTotalScore_i$, a recommended supervision level classifier based on these weights.

Demographic and social characteristics include (a) age as of the day of the screening $rnsAge_i$, where values are categorized into

$$rnsAge_i = \begin{cases} \text{Age} \geq 35, & 0; \\ 30 < \text{Age} \leq 34, & 2; \\ 25 < \text{Age} \leq 29, & 3; \\ 21 < \text{Age} \leq 24, & 4; \text{ and} \\ \text{Age} \leq 20, & 5; \end{cases}$$

based on the age of the i th offender at the time of the assessment; (b) the highest education level completed $rnsEdu_i$, recorded as either 10th grade or below, 11th grade, high school diploma or

equivalency, or some college. Values are mapped as

$$rnsEdu_i = \begin{cases} \text{Some College,} & 0; \\ \text{HS/GED,} & 1; \\ \text{11th,} & 3; \text{ and} \\ \text{10th or below,} & 5; \end{cases}$$

(c) residential changes within the past year $rnsRes_i$, which is recorded as either currently incarcerated in either an institution or Community Correctional Center (CCC), has been released in the past 6 months or resides at a shelter, 2 or fewer moves or residing in a residential treatment program, or 3 or more moves. Values reflect

$$rnsRes_i = \begin{cases} \text{2 or fewer moves in past year,} & 0; \\ \text{Currently/Recently incarcerated/shelter,} & 3; \text{ and} \\ \text{3 or more moves in past year,} & 5; \end{cases}$$

(d) employment changes within the past year $rnsEmp_i$, which is recorded as either incarcerated or shelter if the offender has been released from incarceration and is currently residing in a CCC, has been released from incarceration in the past 6 months or is currently incarcerated, 2 or fewer employment changes, or 3 or more changes. Responses encode

$$rnsEmp_i = \begin{cases} \text{2 or fewer jobs,} & 0; \\ \text{Currently/Recently incarcerated/shelter,} & 3; \text{ and} \\ \text{3 or more jobs in past year or unemployed,} & 5; \end{cases}$$

(e) the number and quality of close, supportive, prosocial relationships $rnsSSN_i$. This is recorded as either None, Relationships with 1 person, or Relationships with 2 or more and

$$rnsSSN_i = \begin{cases} \text{Relationships with 2 or more,} & 0; \\ \text{Relationship with 1 person,} & 3; \text{ and} \\ \text{No Relationships,} & 5; \end{cases}$$

and (f) whether the offender experienced the loss of a significant relationship $rnsRL_i$ through, for instance, divorce, death, or separation within the past 6 months. If so, $rnsRL_i = 5$; Otherwise, 0.

Information regarding criminal and supervision histories includes (a) the age at first arrest $rnsAF_i$ recorded as either 15 or younger, 16–17, 18–25, or over 26. Levels are assigned to $rnsAF_i$ as

$$rnsAF_i = \begin{cases} \text{Age at first arrest} \geq 26, & 0; \\ 18 < \text{Age at first arrest} \leq 25, & 1; \\ 16 < \text{Age at first arrest} \leq 17, & 3; \text{ and} \\ \text{Age at first arrest} \leq 15, & 5; \end{cases}$$

(b) the frequency of arrests in the past year $rnsFA_i$, which is recorded as either none, 1, 2–4, or 5 or more. These values are scored such that

$$rnsFA_i = \begin{cases} \text{None,} & 0; \\ 1, & 2; \\ 2 \leq \text{Arrests} \leq 4, & 3; \text{ and} \\ \text{Arrests} \geq 5, & 5; \end{cases}$$

(c) the number of prior convictions $rnsPC_i$, which is recorded as either none, 1–5, or 6 or more.

The number of prior convictions are mapped to $rnsPC_i$ as

$$rnsPC_i = \begin{cases} \text{None,} & 0; \\ 1 \leq \text{Convictions} \leq 5, & 3; \text{ and} \\ \text{Convictions} \geq 5, & 5 \end{cases}$$

(d) the number of previous violent convictions $rnsPV_i$, which is recorded as either none, 1, or 2 or more. Values are mapped such that

$$rnsPV_i = \begin{cases} \text{None,} & 0; \\ 1, & 3; \text{ and} \\ \text{Offenses} \geq 2, & 5; \end{cases}$$

(e) the initiating offense $rnsOO_i$, which is either violent, drug-related, or non-violent and mapped as

$$rnsOO_i = \begin{cases} \text{Non-violent,} & 0; \\ \text{Drug-related,} & 3; \text{ and} \\ \text{Violent,} & 5; \end{cases}$$

(f) the number of prior adult arrests $rnsNPA_i$, which is recorded as either 2 or less, 3–4, 5, or 6 or more. Values of $rnsNPA_i$ are recorded as

$$rnsNPA_i = \begin{cases} \text{Arrests} \leq 2, & 0; \\ 3 \leq \text{Arrests} \leq 4, & 3; \text{ and} \\ \text{Arrests} \geq 5, & 5; \end{cases}$$

(g) the number of prior supervision failures $rnsPSF_i$, which is recorded as either none, 1–2, or 3 or more with values mapped such that

$$rnsPSF_i = \begin{cases} \text{none,} & 0; \\ 1 \leq \text{Failures} \leq 2, & 3; \text{ and} \\ \text{Failures} \geq 3, & 5; \end{cases}$$

Items bearing on dependencies, disorders, and disabilities include (a) whether there is evidence of current substance abuse $rnsCSA_i$ such as positive drug tests within the past 60 days or admission of current substance abuse. If so, $rnsCSA_i = 5$; Otherwise, 0; (b) a history of substance abuse $rnsHSA_i$ as indicated by previous positive drug tests, admissions of substance abuse, or sentences to treatment. If so, $rnsHSA_i = 5$; Otherwise, 0; (c) a current mental disorder $rnsCMD_i$, which is indicated by the use of psychotropic medications, admissions of psychological problems, current treatment for mental disorders, or admissions of homicidal or suicidal thoughts. If so, $rnsCMD_i = 5$; Otherwise, 0; (d) a history of mental disorder $rnsHMD_i$ as indicated by previous prescriptions for psychotropic medications, previous care by a mental health professional for a period exceeding three months, previous hospitalizations for mental illness, or previous diagnoses for mental disorders. If so, $rnsHMD_i = 5$; Otherwise, 0; and (e) physical disabilities or illnesses potentially disruptive for the current sentence $rnsPD_i$, including hyperglycemia, HIV, migraine headaches, or chronic pain. If so, $rnsPD_i = 5$; Otherwise, 0.

And, finally, CSO perceptions include (a) the level of cooperation at the time of the interview $rnsLOC_i$. This refers to an offender’s willingness to cooperate with the CSO and the conditions of supervision. If an offender appears willing and is able to comply (e.g., is on time for appointments, appears for drug testing, or participates in treatment) the CSO scores the response as fully cooperative. If an offender is willing and able to comply with some but not all conditions of supervision the CSO scores the response as noncooperative. On the other hand if an offender is

unwilling or unable to comply with these conditions, the CSO scores the response as restrained.

Values reflect

$$rnsLOC_i = \begin{cases} \text{Fully Cooperative,} & 0; \\ \text{Restrained,} & 3; \text{ and} \\ \text{Non-cooperative,} & 5; \end{cases}$$

and (b) the CSOs impression of risk $rnsImp_i$. This is a subjective measure of risk the offender represents to the CSO with respect to recidivism. The CSO scores this response as either low, medium, or high based on an evaluation of other offenders currently supervised.

$$rnsImp_i = \begin{cases} \text{Low,} & 0; \\ \text{Medium,} & 3; \text{ and} \\ \text{High,} & 5. \end{cases}$$

Item-level weight summations return y_i^* which is then discretized as y_i using the cutpoints

$\tau_0 = 25$, $\tau_1 = 50$, and $\tau_2 = 75$ as

$$rnsTotalScore_i = \begin{cases} 0 \leq y_i^* \leq \tau_0, & \text{Minimum;} \\ \tau_0 < y_i^* \leq \tau_1, & \text{Medium;} \\ \tau_1 < y_i^* \leq \tau_2, & \text{Maximum; and} \\ \tau_2 < y_i^* \leq 100, & \text{Intensive.} \end{cases}$$

Appendix B

SFS-98

The derivation formula for the Salient Factor Score (SFS) 98 as outlined by the United States Parole Commission (USPC) and the steps taken to construct this measure from the PSIs is described in this Appendix. The SFS 98 is an additive scale comprising 6 items (see, USPC, 2003), which are

Item A. Prior convictions/adjudications (adult/juvenile). Scores reflect None = 3; One = 2;

Two or three = 1; and Four or more = 0.

Item B. Prior commitment(s) of more than 30 days (adult/juvenile). Scores reflect None = 2;

One or two = 1; and Three or more = 0.

Item C. Age at current offense/prior commitments. Scores reflect, for those ages 26 and older at

the time of their current offense,

$$\text{Item C} = \begin{cases} 3, & \text{Three or fewer prior commitments;} \\ 2, & \text{Four prior commitments; and} \\ 1, & \text{Five or more prior commitments.} \end{cases}$$

For those ages 22 to 25,

$$\text{Item C} = \begin{cases} 2, & \text{Three or fewer prior commitments;} \\ 1, & \text{Four prior commitments; and} \\ 0, & \text{Five or more prior commitments.} \end{cases}$$

For those ages 20 to 21,

$$\text{Item C} = \begin{cases} 1, & \text{Three or fewer prior commitments; and} \\ 0, & \text{Four prior commitments.} \end{cases}$$

And, for those ages 19 and younger, Item C = 0 for any number of prior commitments.

Item D. Recent commitment free period (three years). Scores reflect there was no prior commitment of more than 30 days (adult or juvenile) or released to the community from last such commitment in at least 3 years prior to the commencement of the current offense. If so, Item D = 1; Otherwise, 0.

Item E. Probation/parole/confinement/escape status violator this time. Scores reflect neither on probation, parole, confinement, or escape status at the time of the current offense; nor committed as a probation, parole, confinement, or escape status violator at this time. If so, Item E = 1; Otherwise, 0.

Item F. Older offenders. Scores reflect the offender was ages 41 or older at the commencement of the current offense and also that the total score from Items A–E is 9 or less. If so, Item F = 1; Otherwise, 0.

The value of the SFS 98 is the sum of Items A–F and spans the interval [0, 11]. Lower scores reflect higher recidivism risks.

The SFS 98 was proxied among each $i = 1, 2, \dots, N$ probationers from items found in the PSIs. Specifically, SFS_{1i} is calculated as

$$SFS_{1i} = 3 \times (0 \leq ic_i < 1) + 2 \times (1 \leq ic_i < 2) \\ + 1 \times (2 \leq ic_i < 4) + 0 \times (4 \leq ic_i < +\infty)$$

with ic_i representing the sum of adult convictions $psiCrmAdlCnvAll_i$ and juvenile adjudications $psiCrmJuvAdjAll_i$ as an Item A proxy.

To proxy Item B, SFS_{2i} is calculated as

$$SFS_{2i} = 3 \times (0 \leq c_i < 1) + 2 \times (1 \leq c_i < 3) \\ + 1 \times (3 \leq c_i < \infty),$$

with c_i representing the sum of the number of juvenile $psiCrmJuvCon_i$ and adult $psiCrmAdlInc_i$ commitments lasting longer than 30 days.

SFS_{3i} is a proxy for Item C as the r th row and c th column of \mathbf{M} , where age at current offense r_i is encoded into one of four categories as

$$r_i = \begin{cases} 1, & \text{Ages 26 and older;} \\ 2, & \text{ages 22–25;} \\ 3, & \text{Ages 20–21; and} \\ 4, & \text{Ages 19 and under;} \end{cases}$$

the number of commitments c_i is encoded into one of three categories as

$$c_i = \begin{cases} 1, & \text{Three or fewer;} \\ 2, & \text{Four; and} \\ 3, & \text{Five or more;} \end{cases}$$

$$\text{and } \mathbf{M} = \begin{matrix} & \begin{matrix} 3 & 2 & 1 \end{matrix} \\ \begin{matrix} 4 \times 3 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{matrix} & \end{matrix}$$

SFS_{4i} proxies Item D as

$$SFS_{4i} = 1 - [(ic_i \geq 1) \times (b_i - rc_i \geq 1095.75 \text{ days})]$$

where ic_i represents the sum of the number of juvenile $psiCrmJuvCon_i$ and adult $psiCrmAdlInc_i$ commitments of 30 days or more; b_i represents the supervision begin date; and rc_i represents the date of release from the most recent commitment $psiCrmAdlLstIC_i$.

To proxy Item E, SFS_{5i} is calculated as

$$SFS_{5i} = (psiSupSta_i = 5)$$

where criminal justice status at the time of arrest $psiSupSta_i$ is coded as 0 = fugitive, 1 = probation, 2 = parole, 3 = supervised release, 4 = incarcerated, 5 = not under criminal justice sentence.

SFS_{6i} is calculated as

$$SFS_{6i} = (x_i \geq 41) \times \left(\sum_{j=1}^5 SFS_{ji} \leq 9 \right)$$

to proxy Item F, where x_i represents the age on the date supervision began $psiAge_i$.

Finally, $psiSFS_i$ is calculated as

$$psiSFS_i = \sum_{j=1}^6 SFS_{ji} \quad , \text{ for } i = 1, 2, \dots, N$$

and, like the scale it proxies, takes on values within [0, 11].

Appendix C

Crime categories

Crime taxonomies can be futile and, at times, especially when blindly adopted, veritably useless. Multifarious itself, the meaning of crime hinges largely on theoretical, empirical, and organizational perspectives, goals, and requirements. Any taxonomy is germane only in how it answers particular questions at hand, and as this study aims at developing an instrument for guiding risk-anticipated security and treatment decisions among the most common offenders supervised by the CSOSA, its significance here is deeply connected to antecedents and consequences of NSP. As such, crime is cast along those broad dimensions appearing regularly in the researches and literatures that were discussed in Chapter 2, which were, namely (a) violent, (b) property, (c) drug- and alcohol-related, and (d) public order.

Enumerating ad nauseam specific offenses subsumed within these 4 broad dimensions is excessive, so, instead, representative offenses from each are provided as examples.¹³² Characteristic crimes of violence include (a) homicide, (b) rape, (c) robbery, (d) assault, and (e) weapons offenses. Among property crimes are (a) burglary, (b) theft, (c) arson, and (d) fraud. Those characterizing drug- and alcohol-related crimes include (a) selling or possessing illegal substances and (b) alcohol-related offenses. And, finally, offenses typical of public order crimes include (a) disorderly conduct, (b) vagrancy, and (c) prostitution.

¹³²A complete listing of specific offenses, the mapping between these and the more comprehensive categories, and the C code to both extract and classify specific crimes is available upon request.

Appendix D
Conditions of supervision

All probationers are subject to the general conditions shown in Table D1; certain probationers are subject to the special conditions shown in Table D2. In both cases, conditions are imposed by the sentencing body and the CSOSA is charged with ensuring they are obeyed.

Table D1

General probation conditions.

Code	Description
GC1	Obey all laws, ordinances and regulations
GC2	Keep all appointments with CSO
GC3	Notify CSO of any change of address within 48 hours and obtain the permission of Probation Officer if planning to leave the Washington Metropolitan Area for more than two weeks
GC4	Abstain from the use of hallucinatory or other illegal drugs
GC5	Obtain a job as soon as possible or continue present employment

Table D2

Special probation conditions.

Code	Description
SC01	Victims of Violent Crime Compensation
SC02	Drug/Alcohol Treatment
SC03	Other Condition
SC04	Drug Testing
SC05	Employment
SC06	Education
SC07	Community Service
SC08	Mental Health
SC09	Restitution
SC10	Stay Away Order
SC11	Anger Management
SC12	Sex Offender Conditions
SC13	Fine
SC14	Halfway House
SC15	Electronic Monitoring/Curfew
SC16	Domestic Violence/Family Violence
SC17	VOTEE

Appendix E

Modes of termination

Termination modes take on 1 of 5 categories and are captured in $outTrmMod_i$ as

$$outTrmMod_i = \begin{cases} 1, & \text{death;} \\ 2, & \text{successful;} \\ 3, & \text{unsuccessful and terminated;} \\ 4, & \text{revoked; and} \\ 5, & \text{absconsion.} \end{cases}$$

Aside from absconsion, $outTrmMod_i$ is derived directly from SMART entries. Entries describe whether probationers (a) died while supervised, (b) complete their sentences and fulfill imposed conditions, (c) complete their sentences and fail to fulfill imposed conditions, or (d) fail to complete their sentences and instead have it revoked either outright or followed by incarceration.

Determinations of absconsion, in contrast, rely on several entries in Supervision and Management Automated Record Tracking (SMART). For clarity, absconders are those offenders that essentially evade the agency's scope between the beginning of supervision and the full term date. Once CSOs become aware of this, through, for example, failure to establish initial contacts, a series of missed appointments, or reports from personal or employer contacts, they notify both the sentencing authority and the Metropolitan Police Department for the District of Columbia (MPDC). A warrant is issued in most cases. In some of these, the warrant is executed within the relatively short time it takes to determine the probationer had died, been hospitalized, been arrested, or had forgotten about scheduled contact appointments. In others, months or years could pass before the warrant is executed—if it is at all.

Absconders are defined here as those probationers having violated General Condition 2 (see, Table D1), a warrant issued subsequent this violation, and a warrant remaining open for at

least 30 days. If so, the triggering event is excluded from the set of violations accumulated to date, the date of the triggering violation replaces the date of supervision termination $outTrmMod_i$, and $outTrmMod_i$ is set to $outTrmMod_i = 4$ to indicate absconsion.

Probationers having violated General Condition 2 and either not having a warrant issued or having a warrant issued and expired within 30 days are not considered absconders. These events are, instead, considered acts of noncompliance.

Appendix F

Technical details

Technical details with respect to validation by bootstrapping and recursive partitioning are included in this appendix. Technical details about bootstrapping are provided in the first section and those for recursive partitioning are provided in second.

Bootstrapping

Two of the more common validation techniques include cross-validation and resampling. Traditionally, replications using new data are compared to original estimates (Farrington & Tarrington, 1985b; S. D. Gottfredson & Gottfredson, 1986; Monahan et al., 2001). Recently, though, more are turning to resampling procedures, like bootstrapping, to estimate validity. Often, instruments are developed using one sample, the construction sample, and prospectively validated using a different sample, the validation sample (P. R. Jones, 1996). Factors associated with events and outcomes of interest are identified in the construction sample, the persistence of which is examined in the validation sample (P. R. Jones, 1996). One approach includes dividing samples into two or more subsamples. The population processes are modeled using the construction sample then applied to the validation sample(s). The difference in how well the model performed in the construction versus the validation samples is considered a measure of shrinkage. This sample fractionation method is typical (S. D. Gottfredson & Gottfredson, 1986), but, while appealing, might be ill-considered. Fractionation methods are the least desirable (S. D. Gottfredson & Gottfredson, 1986). Central drawbacks include their waste of potentially useful information (W. Gardner, Lidz, Mulvey, & Shaw, 1996) and the consequent reduction in effective sample size. The observations held out for later validation could better contribute to the modeling. Because the stability of model estimates depends largely on the number of cases used in estimation, limiting sample size leaves fewer cases for model construction, reducing stability, and, in turn, constraining reliability

(S. D. Gottfredson & Gottfredson, 1986; P. R. Jones, 1996; Monahan et al., 2001). Thus, while giving an indication of cross-sample performance, this technique will not necessarily reflect the expected variability when the model is applied to the population (Farrington & Tarling, 1985b).

A more recent alternative involves estimating the expected variability from multiple, unbiased samples (S. D. Gottfredson & Gottfredson, 1986; Monahan et al., 2001). Bootstrapping is only one of many methods under the rubric of resampling methods. It is, however, the only method discussed here. This exclusiveness is reflective only of relevance. With advances in computational power, similar approaches, such as the jackknife or the delta method, are inferior. Essentially bootstrapped population parameters are estimated by first repetitively sampling observed data, with replacement, estimating the parameter on each subsample, then calculating confidence intervals around the statistic by pooling and averaging all of the subsample estimates. Monahan et al. (2001) recently used this approach when examining $n = 939$ patients from the MacArthur Risk Assessment Study. Their criterion was serious violence in the community within 20 weeks of discharge. So as not to limit the data available for analyses, they bootstrapped parameter estimates. Essentially this entailed constructing 1,000 subsamples from their original data, applying their model to each subsample, then summarizing the central tendency of these estimates.

To gauge how well they will perform when put into practice, models developed in this study were validated by bootstrapping using, specifically, random- x , or case, resampling (see, Fox, 2002). Given the regression of y_i on $x_{i1}, x_{i2}, \dots, x_{ik}$, R resamples are drawn randomly with replacement from

$$\mathbf{z} = \{y_i, x_{i1}, x_{i2}, \dots, x_{ik}\}$$

for $i = 1, 2, \dots, N$ of size N . The regression of y_i on $x_{i1}, x_{i2}, \dots, x_{ik}$ is fitted to each R bootstrap sample. These are then used to estimate what the confidence intervals around coefficients $\hat{\beta}_1, \hat{\beta}_2, \dots, \hat{\beta}_k$.

Recursive partitioning

Initial, general models to predict each criterion using predictors identified in the review as likely influences were reduced to binary trees using recursive partitioning analysis (RPA) (Breiman et al., 1984; Clark & Pregibon, 1992; Therneau & Atkinson, 1997)¹³³ and then pruned back to account for replacement optimism using an AIC-like pruning scheme (see, Venables & Ripley, 2002; Ciampi et al., 1995).

RPA algorithms typically proceed in two stages. The first involves finding the single most important predictor with respect to its ability to divide the sample into levels of the criterion. This process repeats, separately, on the resulting halves of the sample and continues recursively until subsequent improvements are minimal. Second, a constant model is imposed on resulting partitions (Hothorn, Hornik, & Zeileis, 2006; Venables & Ripley, 2002). Historically, such models have been limited to either classification or regression problems, but recent extensions include the prediction of both rates and survival probabilities (Ciampi et al., 1995; Therneau & Atkinson, 1997). Splits were chosen based on the Gini index (see, Breiman et al., 1984). This strategy is attractive for risk assessments. Venables and Ripley (2002) point out RPA can be seen as a form of variable selection, and this is particularly useful when facing large numbers of predictors—something RPA algorithms handle well. Because they lack parametric assumptions, RPA algorithms can identify potential interactions and monotonic transformations without concerns over linearity, independence and normality of the errors, or homoscedasticity.

This does not come cheap, however. RPA algorithms are notorious for overfitting and capitalizing on selection bias. Initial trees can and often do over-adapt to data and must be adjusted for this optimism. This is the so-called cost-complexity pruning Breiman et al. (1984) introduced

¹³³Using the R library RPART (Therneau & Atkinson, 1997).

(and see, Ripley, 1996). Here, trees were pruned back to account for replacement optimism based on an AIC-like pruning scheme (see, Venables & Ripley, 2002; Ciampi et al., 1995).

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