Published in final edited form as:

J Subst Abuse Treat. 2014 February ; 46(2): . doi:10.1016/j.jsat.2013.07.006.

Short-term Trajectories of Substance Use in a sample of Drug-involved Probationers

Michael S. Caudy, Ph.D.,
Department of Criminology, Law & Society, George Mason University, 10519 Braddock Road, Suite 1900, MS 6D3, Fairfax, VA 22030, United States of America, Office: 703-993-4859, Fax: 703-993-6020

Liansheng Tang, Ph.D.,
Department of Statistics, George Mason University

Alese Wooditch, M.A., and
Department of Criminology, Law & Society, George Mason University

Faye S. Taxman, Ph.D.
Department of Criminology, Law & Society, George Mason University

Michael S. Caudy: mcaudy@gmu.edu

Abstract

The current study estimates trajectories of illegal substance use in a sample of 251 drug-involved probationers to identify risk profiles that predict group membership and explores the impact of treatment participation across these trajectories. Trajectory analyses reveal five patterns of drug use during probation supervision. Age and the use of hard drugs are identified as the strongest predictors of involvement in illicit drug use while on probation. The effect of participation in substance use treatment varies across treatment settings and trajectory groups. Prior research has tended to treat drug abusers as a homogeneous population, but the current study findings suggest considerable heterogeneity amongst drug users involved in the criminal justice system. Identifying trajectories of drug use during supervision can help identify individuals who may be more likely to persist in drug use, can inform practice by identifying individuals in need of more intensive treatment services, and can assist in developing new drug treatment strategies.

Keywords

probation; substance use; trajectories; treatment participation; heterogeneity; risk factors

Introduction

A substantial proportion of justice-involved individuals in the United States are currently under some form of community supervision, such as probation (Carey, 2011; Taxman, Perdoni & Harrision, 2007). National data compiled by the Bureau of Justice Statistics (BJS) indicate that over 4.2 million individuals were on probation during 2009 (Glaze, Bonczar, & Zhang, 2010), approximately 60 to 70 percent suffer from substance use disorders (SUDs)

(Lurigio et al., 2003; Mumola & Bonczar, 1998; Staton-Tindall, Havens, Oser, & Burnett, 2011; Taxman, Perdoni, & Harrison 2007). Yet, few studies have examined different profiles of offenders on probation or explored whether illicit drug use patterns and criminal justice risk factors vary for different types of probationers. The degree to which offenders change their behavior while under supervision and the mechanisms through which supervision impacts substance use behaviors is largely unknown (MacKenzie, Browning, Skroban, & Smith, 1999).

Few criminological studies have examined the impact of probation on the illegal substance use among offenders (De Li, Priu, & MacKenzie, 2000; MacKenzie et al., 1999; MacKenzie & De Li, 2002). The current study augments this limited body of literature by exploring heterogeneity in patterns of self-reported substance use in a sample of drug-involved probationers over a 12 month period using a group-based trajectory (GBT) modeling approach. The study identifies offender characteristics that predict continued involvement in illegal substance use and explores the relationship between treatment participation and drug use patterns among probationers with a focus on the impact of different treatment modalities. GBT modeling allows for the identification of probationers who continue to use illegal substances while under supervision. Identifying risk factors for continued involvement in illicit substance use during probation has direct policy and treatment implications.

Review of Relevant Literature

Substance Use Treatment Need among Probationers

While research has indicated that substance abuse treatment is related to improved outcomes among probationers (Huebner & Cobbina, 2007; Krebs, Strom, Koetse & Lattimore, 2009; Lattimore, Krebs, Koetse, Lindquist & Cowell, 2005), estimates of the extent to which drug-involved probationers receive treatment services suggest that a majority of community-supervised offenders who are in need of treatment do not receive it. Only 17% of surveyed adult probationers reported receiving any drug treatment while on probation, according to a national survey conducted by the Bureau of Justice Statistics in 1995; this number increased to 40% when alcohol treatment was included (Mumola & Bonczar, 1998). Nearly a decade later, Taxman and colleagues (2007) found that less than 10% of substance-involved individuals on community supervision could receive treatment on any given day with the allocated treatment slots. Most probationers who are in need of substance abuse treatment are not linked to the proper type and intensity of services needed to improve their likelihood of successful completion of probation.

Over the past two decades, special conditions, such as mandatory drug testing, mandated drug or mental health treatment, community service, and payment of restitution have become a central component of community supervision. Due to these stipulations, drug-involved probationers face unique challenges and barriers to successful navigation through the probation process. Abstinence from drug use and participation in treatment are required for many probationers, yet these requirements are difficult to comply with given the availability of treatment services. Empirical studies suggest that special conditions or programs that increase the level of control and monitoring over community-supervised offenders often increase the likelihood of failure (Chanhatasilpa, MacKenzie & Hickman, 2000; Petersilia & Turner, 1990; 1993). Treating probationers with SUDs is essential if these individuals are expected to conform to the special conditions stipulated as part of their probation sentence.

Understanding short-term trajectories of substance use is important, especially for justice-involved individuals. The criminal justice system expects drug-involved offenders to attend treatment and stop using illegal substances when they are placed on supervision, but this is often an unrealistic goal. Before reaching a period of sustained recovery, most individuals with SUDs cycle through several periods of treatment, recovery, and relapse (Scott, Dennis, & Foss, 2005; Scott, Foss, & Dennis, 2003; 2005). Individuals who continue to use illegal substances while on supervision are at an increased risk for technical violations, rearrests, revocations, and incarceration (Krebs et al., 2009; Lattimore et al., 2005; MacKenzie, et al., 1999).

The Effectiveness of Drug Treatment on Probationer Outcomes

An existing body of empirical research is devoted to examining the effectiveness of drug treatment within different justice-involved populations. While there is variability in the results regarding which types or modalities of treatment are most effective, there appears to be a consensus that well-designed, properly-implemented, and sustained drug treatment has a positive effect on both drug use and recidivism outcomes (Anglin & Hser, 1990; MacKenzie, 2000; 2006; MacKenzie, Mitchell, & Wilson, 2011; Pendergast, Anglin, & Wellish, 1995). The findings from studies examining the relationship between drug treatment and recidivism among probationers are mixed (Chanhatasilpa et al., 2000; Huebner & Cobbina, 2007; Krebs et al., 2009; Lattimore et al., 2005; Thanner & Taxman, 2003; Taxman & Thanner, 2006), owing to the variability in treatment components and differing levels of substance use disorders.

Treatment effectiveness among probationers has been found to vary across treatment modalities and populations. Studies by Lattimore et al. (2005) and Kerbs et al. (2009) examined the impact of nonresidential and residential drug treatment on recidivism among a sample of nearly 134,000 drug-involved[1] probationers from the state of Florida who began community supervision between 1995 and 2000. Their studies included a comparison between 51,979 individuals who participated in some form of substance abuse treatment and 81,797 drug-involved offenders who were not treated. Lattimore and colleagues (2005) found that nonresidential treatment was related to a reduction in recidivism (rearrests), with an 18.7% reduction in the number of probationers arrested within a 12-month period and a 21.4% reduction in total number of arrests relative to what was expected if these individuals received no treatment. In a further analysis of the Florida data, Krebs and colleagues (2009) compared the effectiveness of residential, nonresidential, and no treatment on time to failure on probation. Using propensity score matching to establish equivalent comparison groups, their analyses revealed that nonresidential treatment was related to an increased time to failure on probation for drug-involved probationers, but time to failure did not differ significantly between probationers receiving residential treatment and those receiving no treatment. The combined findings of these studies support the effectiveness of nonresidential substance abuse treatment for reducing negative outcomes among probationers, but raise questions about the effectiveness of residential treatment for this population.

Empirical support for the effectiveness of community-based drug treatment for offenders is not universal. Based on a review of 15 studies examining the effectiveness of community-based treatment for chemically dependent offenders conducted during the 1990s, Chanhatasilpa and colleagues (2000) concluded that outpatient treatment was not effective at reducing recidivism; they attributed much of the lack of effectiveness of outpatient programs to the increased supervision, monitoring and control associated with community-based treatment programs, and community supervision sentences. Taken with the research reviewed above, these findings suggest that while community-based treatments can reduce

[1]Drug involvement was defined as anyone who was ever arrested for a drug-related offense, ever participated in a drug court program, ever enrolled in drug offender probation, ever tested positive on a CJ-administered drug test, or was ever referred to substance abuse treatment by the criminal justice system (Lattimore et al., 2005).

recidivism and improve drug use outcomes, the increased surveillance associated with community supervision may have unintended consequences that contribute to increased likelihood of failure.

The Effects of Probation on Substance Using Behaviors

A study by MacKenzie and colleagues (1999) provides perhaps the most rigorous test of the effect of probation on substance use behaviors to date. Early evaluations of intensive probation programs generally found that probation had little effect on recidivism or drug use (Langan & Cunnif, 1992; Petersilia & Turner, 1990; 1993). These studies found that as many as two-thirds of all probationers were rearrested within three years (Minor, Wells, & Sims, 2003). These studies relied heavily on official measures of recidivism which are influenced considerably by the degree of surveillance associated with intensive probation (MacKenzie & De Li, 2002). MacKenzie and colleagues (1999) overcame this limitation by examining both self-report and official measures of offending and substance use in the year prior to arrest and during the first year of probation. They found that probation was related to a decline in illegal drug use; the percentage of probationers who self-reported drug use decreased from 69% to 27% during the first year of probation. They also observed that illegal drug use was related to continued involvement in offending. This work was pioneering in that it found that probation had a suppression effect by reducing both recidivism and substance use behaviors for many, but not all, offenders.

Predicting Probation Failure

Factors related to probation failure that have received empirical support include age, gender, race, criminal history/risk, substance use/abuse, offense type, and social bonds. While the relative importance of these factors for predicting probation outcomes varies across studies, there is considerable empirical support for these as some of the strongest predictors of probation outcomes available (Albonetti & Hepburn, 1997; Gray, Fields, & Maxwell, 2001; Hepburn & Griffin, 2004; Huebner & Cobbina, 2007; Jones, 1995; MacKenzie & Brame, 2001; MacKenzie et al., 1999; Mackenzie & De Li, 2002; Minor et al., 2003; Morgan, 1994; Olson & Lurigio, 2000; Sims & Jones, 1997). Rates of probation failure vary across jurisdiction, sample composition, length of follow-up, and definitions of failure. Probationers are more likely to be revoked for technical violations (e.g., for failed drug tests or failure to attend mandated drug treatment) than for the commission of new criminal offenses (Gray et al., 2001; Jones, 1995; Sims & Jones, 1997).

Failure on probation is most likely to occur early in the supervision period while revocation for technical violations is the most common reason for early failure (Gray et al., 2001). Gray and colleagues (2001) found that 30% of all probation failures occurred within the first 100 days of probation; failure to report was the most prevalent reason for probation failure followed by failed drug tests. While long-term follow-up studies are valuable for understanding sustained changes in behavior as the result of probation, it is clear that understanding the behavior of probationers during the first few months of their time under supervision is also important (Byrne, Gelb, & Horowitz, 2009). Identifying probationers who persist in illegal substance use and are subsequently at an increased risk for early failure is an area in need of further empirical investigation. The question of whether predictors of failure on supervision have general effects for all probationers or whether some risk factors have differential salience for different types of probationers has not previously been explored.

In conclusion, the literature has shown that continued substance use during probation is one of the most common reasons for probation failure. Providing substance abuse treatment during probation is related to improved justice and substance use outcomes. No studies thus far have examined the heterogeneity of substance abusers and their outcomes on supervision. This is relevant because there is a tendency within the justice system to consider the substance abusing population as homogenous when there are different types of SUDs and distinct trajectories of use that require different treatment responses. These key issues are addressed in this study that examines patterns of substance use behaviors within a sample of drug-involved probationers. The current study overcomes the limitation of extant research that treats all substance users as a homogeneous population by examining group-based trajectories of drug use over a 12-month period during probation.

The Current Study

The primary goal of this study is to assess potential patterns of continued substance use for drug-involved probationers. The study addresses three primary research questions: 1) is there heterogeneity in patterns of drug use for probationers during supervision; 2) can demographic, criminal justice, and/or substance use risk factors distinguish probationer drug use trajectories; and 3) does the impact of treatment participation on drug use affect trajectories of use?

Study Hypotheses

The current study predicts that heterogeneity will be found in patterns of illegal substance use over the course of the study period. More specifically, it is hypothesized that at least three trajectories of illegal drug use will be identified; one that shows little or no drug use during probation, one that shows declining frequency of drug use as a function of time on probation (suppression effect) and another that maintains a stable rate of drug use despite involvement in probation. This prediction is grounded in extant research that finds that probation has a suppressing impact on substance use for many, but not all, probationers (De Li et al., 2000; MacKenzie et al., 1999).

It is also hypothesized that probationers with more extensive criminal histories and more severe drug use disorders will be more likely to follow trajectories characterized by persistent involvement in drug use. Probationers with less severe addictions are predicted to be more likely to be classified in trajectories characterized by abstinence or declining use. Finally, it is expected that participation in substance abuse treatment will distinguish probationers who continue to engage in illegal substance use from those who show signs of declining involvement or abstinence. Consistent with prior research (Krebs et al., 2009; Lattimore et al., 2005), the current study hypothesizes that outpatient treatment participation will be more strongly related to improved substance use outcomes than inpatient or self-help treatment.

Materials and Methods

Sample

The current study used data originally collected as part of a randomized clinical trial (RCT) conducted with probationers from three parole and probation offices located in two Maryland jurisdictions. The RCT tested the effectiveness of a seamless model for probationer drug treatment. Study participants were randomly assigned to the seamless condition where drug treatment was part of their probation supervision or the traditional model where they were referred to treatment within the community. The RCT employed a randomized block design to ensure that there was an equal distribution of high and moderate recidivism risk offenders[2]. Participants with mandated conditions for treatment were recruited at the study sites starting in March of 2007 through referrals by probation officers. All participants signed informed consent forms approved by the George Mason University Human Subjects Review Board (HSRB). Eligibility criteria required that study participants had to be on probation with substance abuse treatment as a stipulation of their sentence. Participants were excluded if they were on parole, were part of a specialized caseload, or had less than six months left on their sentence.

The demographics for the study sample are provided in Table 1 (n=251). The average age of the participants was 37 (SD=11.5) and they reported an average of 11 years of formal education. The majority of the subjects were male (75%), employed at the time of the baseline interview (58%), single (89%), and African-American (67%). On average, the probationers had 11 prior arrests and 5 prior incarcerations. The study sample was characterized by high drug addiction severity, as measured by the Texas Christian University (TCU) Drug Screen (Knight, Garner, Simpson, Morey, & Flynn, 2006), and 45% were classified as high risk for recidivism using salient factors (Austin, 2006). A large portion of the sample reported attending some type of drug treatment during their lifetime, with outpatient treatment being the most commonly attended (75%), followed by inpatient treatment (24%) and self-help groups (20%). Most probationers (72%) reported using some type of illicit substance in the 90 days prior to their baseline interview including heroin (35%), cocaine (18%), and marijuana (19%). During the same time period, probationers reported on average 3.5 (SD=15.6) days of criminal involvement (excluding drug use crimes and technical violations) and 28.1 days of drug use (SD=20.3).

Measures

Subjects completed several instruments to gather demographics, personal history information, and psychological indicators, discussed below. All subjects were assessed at baseline, and re-assessed at 3 months, 6 months, and 12 months post-randomization. Each subject contributed data at four time intervals, for a total of 1,004 observations[3]. The battery of data collection instruments included the Addiction Severity Index (ASI), the TCU Criminal Thinking Scales (CTS), the Client Evaluation of Self and Treatment (TCU CEST), the Texas Christian University Drug Screen II (TCUDS-II), and the Community Assessment Inventory (CAI).

Dependent Variable

Frequency of Drug Use: Probationers completed life history event calendars to collect data on social bonds, drug use, criminal offending, treatment experiences, and periods of incarceration. During data collection, an interviewer asked each participant to retrospectively identify on a calendar days when each activity occurred over the prior 90 days (Sobell and Sobell 1992). The life event calendar approach has been shown to be more reliable for measuring self-reported data on drug use and criminal offending than alternative methods (Horney and Marshall 1991). The present study used this technique to obtain the number of days of drug use at each observation point. A drug use day was considered any day the client self-reported illicit substance use (e.g., benzodiazepines, cocaine, marijuana, heroin or other opiates)[4]. Marijuana use was included as an illicit substance based on state laws; continued use of marijuana can result in failed drug tests and subsequent probation failures. The number of days the client reported engaging in drug use was adjusted for time spent incarcerated, hospitalized, or in residential drug treatment and standardized due to varied reporting times so the maximum possible days of drug use and criminal offending for

[2]Risk in this case refers to criminal justice risk and was determined based on a static risk measure of criminal history information (see Austin, 2006).

[3]While the experiment had high retention rates (Time 2 = 97 percent; Time 3 = 95 percent; Time 4 = 90 percent), a mean imputation was used to impute missing values by wave, which allowed us to retain the baseline sample size through all time points analyzed. No study attrition was due to death.

[4]Clients were asked not to self-report legal use of prescribed medications (such as methadone, buprenorphine, or opioid painkillers) unless the medication was used to get high.

each wave was 90 days. The following equation was used to calculate the number of self-reported drug use days for each wave: number of days of drug use/(number of days the client is reporting on − number of days incarcerated or hospitalized) * 90. A client asked to self-report on activity over a 100 day period, of which 35 days were spent using illicit drugs and 15 days incarcerated, would have a frequency of drug use calculated as follows:

$$\begin{aligned}\text{Drug use days} &= (35/100-15)*90\\ &= (.41)*90\\ &= 37\end{aligned}$$

The process of adjusting self-reported use days allowed the present study to obtain estimates of drug use that were unaffected by time spent incarcerated or hospitalized. Accordingly, the dependent variable represents the mean number of illicit drug use days over the prior 90 days while the participant was at-risk in the community. The total number of drug use days was calculated for each participant, across all four waves. The number of illegal drug use days served as the outcome measure for the trajectory estimations in the current study.

Independent Variables

Study Condition: The current study controls for the experimental category to which the individual was assigned. Those probationers who were randomized into the seamless system group received on-site assessment of treatment needs, intensive cognitive-behavioral therapy, goals group treatment sessions administered by their probation officer and treatment counselor, weekly drug testing, and interaction with their probation officers. The control group received on-site treatment assessment and traditional supervision including a referral to treatment services in the community. A total of 128 clients were randomized into the control group and 123 clients into the seamless system group, respectfully coded as 0 and 1.

Addiction Severity: The severity of drug addiction was assessed by the TCU Drug Screen, an instrument that measures drug use dependence for correctional-based populations (Knight et al., 2006). Each participant was asked nine binary questions concerning drug dependency with “yes” responses tallied to determine the TCU Drug Score, where a score of 3 or greater meets diagnostic criteria (Peters et al., 2000) for drug dependence given in the *Diagnostic and Statistics Manual of Mental Disorders* (DSM-IV) (American Psychiatric Association, 2000).

Hard Drug Use: Items from the Addiction Severity Index (ASI) were used to dichotomize clients into those who self-reported hard drug use (coded as 1) in the 30 days leading up to the baseline interview and those who did not (coded as 0). For these analyses, hard drug use was defined as the use of any illegal drug, with the exception of marijuana, for the purpose of getting high within the last 30 days. This variable included all drugs except marijuana and alcohol (e.g., barbiturates, amphetamines, and methadone). Most of the individuals in the study sample who were flagged for hard drug use (132 of 135; 97.8%) reported using heroin or cocaine, either in isolation or in combination with other drugs. In instances where respondents reported abusing multiple drugs, the most severe drug was used to determine the category.

Risk Score: We used criminal history factors identified by Austin (2006) to measure static risk. The questions were as follows: (1) how many times have you been arrested before this current offense (worth up to 2 points); (2) how many times have you been convicted as an adult (worth up to 3 points); (3) do you have three or more present offenses (worth up to 1 point); (4) were you ever arrested before you turned 16 (worth up to 1 point); (5) were you ever incarcerated upon conviction (worth up to 1 point); and (6) have you ever escaped from a correctional facility (worth up to 1 point). Individuals could score a total of 9 points.

Drug Treatment Participation: The life event calendar, discussed above, was also used to calculate the number of days involved in drug treatment for each wave by treatment setting: self-help (e.g. alcoholics and narcotics anonymous meetings), outpatient (e.g. individual or group therapy), or in-patient (e.g. detox and residential treatment). For each participant at each wave, these variables represent the number of days on which the participant reported attending treatment in each setting over the last 90 days. These variables are continuous with a possible range of 0 – 90 days. In some analyses, these variables are dichotomized into indicators of treatment participation in each setting at any point during the prior 90 days.

Treatment motivation: The Client Evaluation of Self and Treatment intake version (TCU CEST-Intake) was administered during treatment initiation to assess psychological functioning, social functioning, and treatment motivation (Joe, Broome, Rowan-Szal, & Simpson, 2002). The response options on the instrument range from disagree strongly (1) to agree strongly (5). Scores of scales were calculated by summing responses after reverse coding some measures, dividing the sum by the number of items, and multiplying by 10 to rescale the final scores to range from 10 to 50. We included three treatment motivation scales from the CEST; desire for help, problem recognition, and treatment readiness. The cronbach's α for each subscale was calculated to ensure acceptable scale reliabilities: desire for help (.798), problem recognition (.889), and treatment readiness (.794).

Demographics: The present study included gender and age as potential predictors of trajectory group membership. Demographic data was obtained during the baseline interview. Gender and age were also included as control variables in some models.

Analytic Strategy

After conducting basic descriptive analyses, the first step in the analytic strategy involved the identification of developmental trajectories of drug use days using semiparametric group-based mixture modeling (Nagin, 2005). Models were estimated with the TRAJ procedure available as a macro for SAS statistical software (Jones, Nagin, & Roeder, 2001). Group-based trajectory (GBT) models allow for the identification of developmental trajectories within longitudinal datasets. A primary strength of these models is that they are not based on the assumption that an outcome is distributed continuously throughout a population, rather they are based on the assumption that there are unique clusters of developmental patterns within a population that may or may not be the product of different underlying causal processes (Nagin, 2005). This methodology allowed the current study to test the hypothesis that there is heterogeneity in patterns of drug use that probationers follow during their time on supervision.[5] GBT model selection was guided by the Bayesian Information Criterion (BIC) and the mean posterior probabilities of group membership (Nagin, 2005). The zero-inflated Poisson (ZIP) model developed by Nagin and Land (1993) was used to estimate the trajectories. This distribution is used in PROC TRAJ when the dependent variable is count data.[6]

[5]Interested readers can contact the first author for more information regarding the underlying mathematical models used in the trajectory analyses. Further reading on this is available through Nagin, 2005.

[6]An earlier review of this manuscript questioned the appropriateness of if the ZIP model as opposed to a zero-inflated negative binomial (ZINB) model. According to Lambert (1992), the ZINB model is computationally more difficult to fit than the ZIP model, and thus the resulting estimators from the ZINB model may not achieve reasonable accuracy for relatively small sample sizes. Accordingly, the ZINB model was not fit to our data given the relatively small sample. In addition, ZINB is not currently available in PROC TRAJ.

The current analyses used Nagin's GBT modeling approach to identify clusters of probationers who followed approximately the same pattern of illicit substance use during probation and to explore potential risk and protective factors for involvement in divergent trajectories Consistent with the study hypotheses regarding between-group heterogeneity rather than between-subject variation within the same group, the GBT method is appropriate. The data-driven nature of the GBT approach is also preferable because there is a lack of established a priori theoretical justification for hypothesizing a specific number of short-term substance use trajectories.[7]

After identifying trajectories of drug use, the second step in the analyses involved examining distributions and mean differences in risk and protective factors across the trajectories that emerged from the GBT model. More specifically, this step involved a series of cross tabulations and one-way ANOVAs assessing the prevalence and mean levels of the risk factors across the trajectory groups identified in step one. This procedure allowed the current study to gain a better understanding of the risk profiles that were associated with the different trajectories and helped provide justification for the inclusion of risk factors as predictors of trajectory group membership in multivariate models.

The next stage of the analyses employed multinomial logistic regression to assess the strength of the relationship between risk factors and trajectory group membership. Including covariates in these models allowed the present research to examine the ability of risk factors to distinguish trajectories characterized by divergent patterns of drug use while controlling for other relevant factors. Within step three, we examined four separate multinomial logistic models. In the first three models, controlling for study condition, we regressed trajectory group membership onto time stable covariates that have been found to be predictors of probation failure and substance use. These factors included age, gender, risk score, hard drug use, addiction severity, and a control for study condition. In each of the first three multinomial logistic regression models we specified a different trajectory group as the reference category against which the remaining four groups were contrasted. In the fourth model, we re-estimated the trajectories to assess the time-varying impact of substance abuse treatment participation in each of the three treatment settings on mean drug use days across the trajectories, while controlling for the time stable covariates described above. This time-varying model assessed whether or not changes in treatment participation were related to changes in drug use outcomes and whether this impact differed across trajectories.

Finally, repeated measures analysis of variance (ANOVA) tests were conducted to compare longitudinal changes in treatment attendance between trajectory groups. These tests examined how mean days of self-reported treatment attendance varied between assigned trajectory groups (a between-subjects factor) across time. Three separate repeated measures ANOVAs were conducted to explore self-help, inpatient, and outpatient treatment attendance between trajectory groups.[8]

[7]There are methods other than the GBT approach for modeling developmental trajectories. An alternative approach, generalized growth mixture modeling (GGMM), developed by Muthen and Shedden (1999), has also been employed to estimate trajectories. The primary distinction between the two techniques is that GGMM includes random effects in each group's trajectory model. The inclusion of random effects within each trajectory potentially improves overall model fit and allows for better understanding of within group variation around the trajectory mean (Nagin, 2010; Nagin & Odgers, 2010; Petras & Masyn, 2010; Saunders, 2010). However, the inclusion of random effects in the GGMM approach may also limit their practical interpretability because of the amount of within group heterogeneity that is included in the model (Nagin, 2010; Nagin & Odgers, 2010).

[8]While treatment days are count data, the sample mean of treatment days in each trajectory group approximately follows a normal distribution because a group size of more than 30 is reasonably large for the central limit theorem to take effect (Casella and Berger, 1990). Thus, all three ANOVA analyses comparing means of treatment days among groups are valid.

Results

Trajectories of Self-Reported Drug Use Days

As shown in Table 2, the mean posterior probabilities for the five groups were all well above the 0.7 cutoff value suggested by Nagin (2005)[9]. Using the model fit indices available in PROC TRAJ, and a model selection approach that favored parsimony over complexity, it was determined that a five-group solution fit the data well (Table 2). Although the BIC continued to improve with more groups added to the model, adding additional groups beyond the five-group solution did not clarify the model. The additional group that emerged in the six-group solution mirrored a rapidly declining trajectory that emerged in the five-group model, but had a slightly lower level of baseline drug use. In addition to this substantive justification, the mean posterior probabilities in the six-group model were slightly worse than in the five-group model indicating possible ambiguity in trajectory group assignment. Table 3 displays the mean posterior probabilities for each trajectory in the five group model, as well as the frequency and proportion of the sample that fall within each group.

Findings from the trajectory estimations with drug use days as an outcome suggest that, within this sample of drug-involved probationers, there is a considerable amount of variability in patterns of illicit drug use. Figure 1 displays the trajectories of self-reported drug use days over the 12 month study period. Probationers classified in Group 1 (14.0%) were unlikely to use drugs throughout the study observation period. Individuals in this group averaged less than two drug use days per 90 days during the study. Because of the low rate of use within this group, we labeled individuals who followed this trajectory as *abstainers*. Group 2 (21.5%) displayed a relatively low, but stable trajectory of drug use days across the four study waves. This group showed little change in number of drug use days during the course of the study averaging 10.5 days of use per 90 days; we labeled this group as *low-rate stable users*. A third trajectory (19.1%) emerged which displayed the highest initial rate of drug use (43 of 90 days), but evinced a steep drop in frequency of use between baseline and the three-month follow-up interview and remained low across the subsequent waves. This group was labeled as *rapidly declining users*. A fourth group (19.1%) was identified which evinced an initially high rate of drug use (39 of 90 days) that increased between baseline and three months before gradually declining over the final two waves of the study period. At 12 months, this group displayed the second lowest rate of use (5.5 of 90 days) of any of the five groups. Because this group displayed an initially high rate of drug use that declined over time, we labeled this group as *gradually declining users*. A fifth group (26.3%) was identified which displayed a pattern of stable drug use throughout the observation period. This group began with a high rate of drug use at the baseline assessment (35 of 90 days) that peaked at the three-month follow-up (53 of 90 days), and declined only slightly over the subsequent measurement waves. We labeled this group as *high-rate stable users* because of their elevated levels of use across the four waves of observation. The high-rate stable trajectory averaged 42 days of illicit drug use per 90 across the four study waves.

Descriptive Profiles of Drug Use Trajectories

The next step in the analysis examined mean and prevalence differences in risk and protective factors across the five trajectory groups. The results of these analyses are displayed in Table 4. The findings point to several significant differences in risk and protective factors across the various trajectories of drug use days.[10] Interestingly,

[9]No two posterior probabilities of group assignment for any individuals were identified that were exactly the same. In the case of a tie, the group assignment recommended by PROC TRAJ would have been observed.

[10]Tukey's b post-hoc analyses were conducted in SPSS to establish significant mean differences between trajectory groups.

probationers classified in the low-rate stable use trajectory scored lowest on both the addiction severity and risk score variables. Risk score significantly distinguished probationers in the low-rate stable group from all other groups (F=6.89, p<.001), while addiction severity significantly distinguished low-rate stable users from high-rate stable users only (F=3.59, p<.01).

Probationers in the rapidly declining trajectory were the most likely to have ever attended inpatient substance abuse treatment (35.4%) and scored significantly higher on the CEST treatment readiness subscale than individuals in the abstainer trajectory (F=2.00, p<.10). Probationers who were classified in the abstainer trajectory reported attending significantly more inpatient (F=3.13, p<.05) and outpatient treatment sessions (F=4.07, p<.01) during the 90 days prior to enrollment in the study than any of the other trajectory groups. Study participants who were classified in the rapidly declining, gradually declining, and high-rate stable drug use trajectories were more likely to be hard drug users than the abstainers or low-rate stable users and scored significantly higher than abstainers on the CEST problem recognition subscale (F=3.77, p<.01). This suggests that probationers who were classified into more serious drug use trajectories were more likely to be users of hard drugs and self-reported having more serious drug problems. Probationers in these three trajectories also scored highest on the addiction severity measure although significant differences were only observed between the high-rate stable users and the low-rate stable users. These analyses indicate that several factors distinguish between drug use trajectories at the bivariate level. In order to better understand the relationship between these factors and drug use trajectory group membership, we included several of the significant risk factors from the bivariate analyses in our multivariate models predicting trajectory group membership.

Predicting Trajectory Group Membership

To further explore the profiles that emerged from the trajectory estimations and assess whether risk factors available to probation officers and treatment providers could be used to distinguish divergent drug use trajectories during probation, we conducted three multinomial logistic regressions using risk factors that were measured at the baseline interview to predict trajectory group membership. These factors included demographic characteristics (gender and age), addiction severity, criminal history risk score, hard drug use, and a control for study condition. SPSS statistical software was used to fit the first multinomial logistic regression model with covariates using the abstainer trajectory group (group 1) as the reference category (Table 5). The results presented in Table 5 depict the influence of each individual-level risk factor on the probability of membership in each trajectory group relative to the comparison group, while controlling for the influence of the other factors included in the model. Positive coefficients indicate that the risk factor increases the probability of membership in a given group relative to the comparison group, whereas a negative coefficient suggests that the risk factor decreases the likelihood of membership in a given trajectory relative to the comparison group.

Two risk factors emerged as significant predictors of group membership in three or more drug use trajectories relative to the abstainer trajectory. The results indicated that hard drug use was a significant and positive predictor of membership in all four of the drug use trajectories relative to the abstainer group. This finding indicates that probationers who have a recent history of hard drug (heroin, crack/cocaine) use are more likely to follow one of the drug use trajectories (low-rate stable, rapidly declining, gradually declining, or high-rate stable) and are less likely to abstain from drug use during probation. The beta coefficients presented in Table 5 indicate that hard drug use was most strongly related to membership in the high-rate stable use trajectory relative to the abstainer trajectory. Hard drug use was by far the strongest predictor of membership in one of the drug use trajectories relative to the abstainer trajectory.

Age also emerged as a significant predictor of group membership. The negative coefficient observed for age suggests that younger probationers had a higher probability of belonging to groups 3, 4, and 5 relative to group 1. This indicates that younger probationers were more likely to belong to one of the declining drug use trajectories or to the high-rate stable trajectory relative to the abstaining trajectory. This finding suggests that age is a risk factor for continued illicit drug use during probation.

Criminal history risk score emerged as a significant and negative predictor of membership in the low-rate stable use (group 2) trajectory only. This suggests that individuals in group 2 tended to have less severe criminal histories than individuals who abstained from drug use during the study observation period. Gender, addiction severity, and study condition were not significant predictors of membership in any of the drug use trajectories relative to the non-use trajectory.

Two additional multinomial logistic regression models were fitted to better understand the relationship between the included covariates and trajectory group membership. The results of the second multinomial logistic regression model (Table 6) contrast membership in any of the other trajectory groups against membership in the high-rate stable trajectory (group 5). This model explored which, if any, of the time-stable covariates predicted membership in the most problematic use trajectory relative to the other trajectories. These results indicated that age was positively related to membership in either the abstainer or low-rate stable use trajectory relative to the high-rate stable trajectory. Past month hard drug use at baseline was negatively related to membership in either of these two trajectories relative to the high-rate stable use group. Finally, criminal risk was negatively related to membership in the low-rate stable use trajectory relative to the high-rate stable use trajectory. Interestingly, none of the included covariates significantly distinguished either the rapidly declining or gradually declining trajectories from the high-rate stable trajectory.

In the final time-stable model, membership in the rapidly declining trajectory was contrasted with the other patterns of use to explore which baseline covariates significantly predicted membership in this group relative to the remaining trajectories. Age and past 30 day use of hard drugs again emerged as significant predictors of group membership (Table 7). Age was positively related to membership in either the abstainer or low-rate stable use trajectory relative to the rapidly declining trajectory while hard drug use was negatively related to membership in either of these trajectories relative to the rapidly declining group. This suggests that individuals assigned to the rapidly declining trajectory were younger and more likely to have used hard drugs in the past month at baseline relative to individuals in the abstainer or low-rate stable use groups. In addition to these covariates, male gender, addiction severity, and criminal risk score were significantly related ($p < .10$) to membership in the low-rate stable trajectory relative to the rapidly declining trajectory. This indicates that males were less likely than females to be classified in the low-rate stable use group relative to the rapidly declining use group and that individuals in the low-rate stable group also scored lower on the addiction severity and criminal risk scales than individuals classified in the rapidly declining use trajectory.

The Impact of Treatment Participation Days on Probationer Drug Use

Before assessing the impact of number of treatment days on drug use in multivariate models, we explored differences in treatment attendance (self-help, outpatient, and inpatient treatment) by drug use trajectory using a repeated-measures ANOVA analysis. Overall, the findings displayed in Table 8 indicate covariation between self-reported involvement in treatment and self-reported drug use during probation. The between-groups effects test examined whether there was a significant difference between the mean numbers of treatment sessions attended between trajectory groups. Probationers did not have statistically significant differences in mean self-help treatment days between trajectory groups, (F=1.17, p = n.s). There were significant differences in mean number of outpatient (F = 2.44, $p < 0.05$) and inpatient treatment (F =2.55, $p < 0.05$) sessions attended between trajectory groups over time. These analyses suggest that differences exist in the mean number of outpatient and inpatient treatment sessions attended between trajectory groups across time. Bonferroni multiple comparison tests were conducted for outpatient and inpatient treatment days to make pairwise comparisons between trajectory groups. The results suggest that the rapidly declining trajectory group had significantly more outpatient treatment days than the high-rate stable trajectory group on average across time ($p < 0.05$), but the rapidly declining trajectory group had significantly fewer inpatient treatment days than the gradually declining trajectory group ($p < 0.05$) on average across time.

In the final stage of the study analyses, we examined the time-varying impact of participation in three different treatment settings on probationer drug use days across the five trajectories, while controlling for baseline characteristics. The results reveal a differential impact of treatment participation on drug use across settings and across patterns of use (Table 9). For the probationers who followed the abstainer trajectory, participation in either outpatient or inpatient treatment was negatively associated with drug use days, although a stronger effect was observed for outpatient treatment. Participation in self-help groups (e.g., AA, NA) and other more informal treatment options was not significantly associated with drug use for the abstainer group. For probationers who followed the low-rate stable use trajectory, self-help treatment was negatively associated with drug use days and inpatient treatment was positively associated with drug use days. Outpatient treatment was not significantly related to drug use days for this group. For the rapidly declining trajectory, outpatient treatment was negatively associated with drug use days, whereas both self-help groups and inpatient treatment were positively associated with mean number of drug use days. For the gradually declining trajectory, both self-help and outpatient treatment were negatively associated with drug use days, while inpatient treatment was positively related to drug use days. Finally, for the high-rate stable use trajectory, participation in all three modalities of treatment was negatively associated with drug use days.

Discussion

This study set out with three primary goals. First, the study investigated whether or not there was observable heterogeneity in patterns of illegal drug use during probation within a sample of offenders who were sentenced to probation and classified as in need of substance abuse treatment. The second goal was to examine whether criminal justice and substance abuse risk factors could distinguish distinct patterns of drug use during probation. The final study goal was to explore the relationship between participation in three different settings of treatment and drug use for probationers who followed different drug use trajectories.

The study findings support the hypothesis that there is a considerable amount of heterogeneity in patterns of drug use during probation, even within a sample of offenders who were all classified as substance abusers. This suggests that not all offenders respond to probation and substance use treatment in the same way. The group-based trajectory analysis revealed five trajectories of drug use; one which was characterized by little or no use, two that were characterized by declining rates of use and two that were characterized by stable use throughout the 12 month observation period. The finding of abstinence and declining use during probation is consistent with prior research that has demonstrated that probation has a suppression effect on illegal substance use for some offenders (De Li et al., 2000; MacKenzie et al., 1999); however, 48% of the study sample demonstrated stable patterns of drug use during probation, suggesting that many drug users, especially younger users and users of hard drugs, may not change their using behaviors as a result of serving time on probation.

The stability of drug use that was observed for nearly half the study sample suggests that probation with drug treatment conditions and referrals to community treatment may not be an efficient means of responding to the varying types of substance-involved offenders. Although it was stipulated as a special condition of their probation, probationers in this sample attended relatively few sessions of treatment throughout the 12 month observation period. Probationers in the study sample reported an average of less than 10 days of outpatient treatment, less than 3 days of self-help treatment, and less than 2 days of inpatient substance abuse treatment per 90 days across the four study waves. The findings of low rates of treatment attendance and stable drug use for many of the study participants have policy relevance. These findings indicate that special conditions mandating participation in substance abuse treatment and referrals to community treatment are often ineffective means for facilitating individual-level change in substance use or motivation for treatment participation. As an alternative to these minimally effective procedures, correctional agencies should focus on providing evidence-based strategies aimed at increasing offender motivation to engage in treatment and linking offenders to available services that target their unique combination of SUDs and dynamic criminogenic needs.

Although divergent trajectories of substance use did emerge as expected, the criminal justice and substance use related risk factors did not distinguish the trajectories as clearly as was hypothesized. Hard drug use and age emerged as the most consistent predictors of membership in one of the four drug use trajectories relative to the abstainer trajectory suggesting that youthful probationers and those who abuse hard drugs should be prioritized for more intensive controls and treatments. Unexpectedly, addiction severity, gender, and criminal justice risk score were not consistently able to distinguish between offenders who followed divergent patterns of substance use during probation. These results illustrate that it is difficult to predict substance use trajectory group membership with a set of time-stable criminal justice and substance use risk factors other than age and recent hard drug use.

The failure of baseline covariates (e.g., gender and addiction severity) to significantly distinguish either of the declining use trajectories from the high-rate stable use trajectory provides a fruitful direction for future research. Distinguishing patterns of illegal substance use during probation may require consideration of more time-varying predictors (e.g., treatment motivation, treatment participation, or social bonds). With this in mind, future research should explore this issue in other data sources and also examine the influence of other risk and need factors which may be better able to distinguish between substance use trajectories and therefore more suited for making predictions about probationer drug use outcomes. Examining the utility of risk instruments and alternative measures of addiction severity for predicting substance use trajectory group membership is another valuable direction for future research.

Consistent with prior research that has indicated that outpatient treatment is more effective for probationers than residential treatment (Krebs et al., 2009; Lattimore et al., 2005), the present study found that participation in outpatient treatment was more consistently related to a decrease in drug use days across the different trajectories of substance use than either inpatient or self-help treatment. One possible explanation for this finding is that outpatient programming is likely to offer more clinical hours than residential treatment programming (see Taxman 1999 for a discussion of the clinical therapy offered in different settings). For four of the five trajectories, an increase in participation in outpatient treatment was significantly related to a decrease in number of drug use days; outpatient treatment was not significantly related to drug use days for the low-rate stable use trajectory. Attending inpatient treatment was negatively associated with drug use days for offenders in the abstainer trajectory and the high-rate stable trajectory but was positively related to drug use days in the other three trajectories. While any conclusions about the effectiveness of different types of treatment for probationers are limited by the fact that these data did not include measures of the treatment services offered in each program, the study findings do suggest that outpatient treatment is more consistently related to a decreased frequency of drug use by individuals supervised in the community than inpatient or self-help treatment. Future research should explore the relationship between treatment setting, content of services, dosage, and quality and substance use outcomes during probation in order to better understand the nuances of this relationship and inform practices for matching offenders to the treatments that will be most effective given their individual characteristics.

The heterogeneity that we observed within the study sample suggests that researchers who have previously examined the effectiveness of probation on substance use outcomes using aggregate samples of probationers may have overlooked potentially important differences in the suppression effect of probation for different types of offenders. This research suggests that probationers respond to criminal justice supervision and substance abuse treatment in qualitatively different ways. Responding to the dynamic needs of substance-involved offenders may require a more nuanced approach as opposed to a one-size-fits all system that treats all individuals in a general way. While treatment offered during probation may be an effective means of improving outcomes for some individuals, it is ineffective for others. The challenge for researchers and treatment providers alike is to identify the characteristics of individuals who will be most likely to respond well to treatment services.

Limitations

Like any research, this study must be considered in light of some limitations. First, the study relied on a self-reported measure of illegal substance use as an outcome for the trajectory analysis. While the life event calendar technique has been found to improve recall and potentially increase the validity of self-reports (Horney & Marshall, 1991; Horney et al., 1995; Roberts & Horney, 2010), the possibility of self-report bias is always a concern, especially with samples of individuals who are currently under correctional supervision. Future research should consider using both self-report and official measures of drug use to potentially replicate the current study findings. An additional limitation of the current analysis is that the outcome measure was drug use, and treated all drug use the same regardless of whether the individual had a change in drugs of choice. Future research should be conducted to explore drug-specific patterns of substance use and examine changes in type of drug being abused over time. These issues are critical areas for future inquiry.

The current study was also limited by the length of follow-up data that were available. This observation period allowed the current research to track short-term trajectories of substance use during only one year of probation. Different patterns of behavior may have emerged if the data followed the sample for a longer period of time. While prior research suggests that probation has a suppressing effect on offending and substance use (MacKenzie et al., 1999), research has also demonstrated that during the course of addiction careers, individuals with SUDs are likely to cycle through several transitions from recovery to active use (Scott et al., 2005a; 2005b).

A final limitation to note is that the study data is limited to drug-involved probationers with conditions for treatment based on the nature of the parent study. These data were collected from three sites in the state of Maryland. And, it might be that several unmeasured influences could have contributed to the type and composition of the drug use trajectories in the present study. This may limit the generalizability of the findings to other sites or populations of probationers. An area that needs further exploration is the geographical location of the individual and its influence on the observed trajectory; we noted in a paper using this study data that hard drug use in the current sample was more concentrated in the inner city than in the surrounding suburban areas and active drug markets affected drug use (Wooditch, Lawton, & Taxman, 2013). Future research should identify important exogenous factors contributing to membership in divergent substance use trajectories and explore heterogeneity in patterns of drug use by justice-involved individuals over longer follow-up periods and in other, perhaps more generalizable, samples.

Conclusions

Extending prior research that has examined the impact of probation on probationer substance use outcomes, this study illustrates the relationship between probation, treatment participation, and patterns of illegal substance use. Given the finding that there is heterogeneity in patterns of substance abuse during the period of supervision, this suggests a need for more research to explore the differential impact of probation among different types of offenders. Study findings also suggest the need for an increased focus on "what works for whom" with particular attention devoted to exploring how available treatments can best be matched to the substance abuse and other treatment needs of different individuals involved in the justice system. Probationers with a recent history of hard drug use (heroin and cocaine) are more likely to persist in substance use during probation than offenders who use marijuana or other drugs. Such a finding suggests the need to prioritize these offenders for treatment services instead of users of other drugs. The current study findings also suggest that increasing access to good quality programming can change the substance use trajectories of probationers with SUDs. This study begins to focus our attention on the differential patterns of engaging in drug use while under probation supervision, an important area for continued empirical investigation given that probation is currently the most frequently used sentence in the United States.

References

Albonetti CA, Hepburn JR. Probation revocation: A proportional hazards model of the conditioning effects of social disadvantage. Social Problems. 1997; 44(1):124–138.

American Psychological Association. Diagnostic and statistical manual of mental disorders. 4. Washington, DC: Author; 2000.

Anglin, MD.; Hser, Y. Treatment of drug abuse. In: Tonry, M.; Wilson, JQ., editors. Drugs and crime. Chicago: University of Chicago Press; 1990. p. 393-460.

Anglin MD, Hser Y, Grella CE. Drug addiction and treatment careers among clients in the drug abuse treatment outcome study (DATOS). Psychology of Addictive Behaviors. 1997; 11(4):308–323.

Austin J. How much risk can we take - the misuse of risk assessment in corrections. Federal Probation. 2006; 70:58–63.

Byrne, J.; Gelb, A.; Horowitz, J. Public Safety Policy Brief No. 9. Washington, DC: Pew Center on the States; 2009. Maximum impact: Targeting supervision on higher-risk people, places and times.

Carey, M. Probation. In: Leukefeld, C.; Gullota, TP.; Gregrich, J., editors. Handbook of evidence-based substance abuse treatment in criminal justice settings. New York: Springer Science + Business Media; 2011. p. 143-171.

Casella, G.; Berger, RL. Statistical inference. Belmont, CA: Duxbury Press; 1990.

Chanhatasilpa C, MacKenzie DL, Hickman LJ. The effectiveness of community-based programs for chemically dependent offenders: A review and assessment of the research. Journal of Substance Abuse Treatment. 2000; 19:383–393. [PubMed: 11166503]

De Li S, Priu HD, MacKenzie DL. Drug involvement, lifestyles, and criminal activities among probationers. Journal of Drug Issues. 2000; 30(3):593–620.

Glaze, LE.; Bonczar, TP.; Zhang, F. Probation and parole in the United States, 2009. Washington, DC: Bureau of Justice Statistics; 2010.

Gray MK, Fields M, Maxwell SR. Examining probation violations: Who, what, and when. Crime & Delinquency. 2001; 47:537–557.

Hepburn JR, Griffin ML. The effect of social bonds on successful adjustment to probation: An event history analysis. Criminal Justice Review. 2004; 29(1):46–75.

Horney J, Marshall IH. Measuring lambda through self-reports. Criminology. 1991; 29:102–121.

Horney J, Osgood DW, Marshall IH. Criminal careers in the short-term: Intra-individual variability in crime and its relation to local life circumstances. American Sociological Review. 1995; 60:655–673.

Huebner BM, Cobbina J. The effect of drug use, drug treatment participation, and treatment completion on probationer recidivism. Journal of Drug Issues. 2007; 22:619–642.

Joe GW, Broome KM, Rowan-Szal GA, Simpson DD. Measuring patient attributes and engagement in treatment. Journal of Substance Abuse Treatment. 2002; 22(4):183–196. [PubMed: 12072163]

Jones BL, Nagin DS, Roeder K. A SAS procedure based on mixture models for estimating developmental trajectories. Sociological Methods & Research. 2001; 29(3):374–393.

Jones M. Predictors of success and failure on intensive supervision. American Journal of Criminal Justice. 1995; 19(2):239–254.

Knight DK, Garner B, Simpson D, Morey J, Flynn P. An assessment for criminal thinking. Crime & Delinquency. 2006; 52(1):159– 177.

Krebs CP, Strom KJ, Koetse WH, Lattimore PK. The impact of residential and nonresidential drug treatment on recidivism among drug-involved probationers: A survival analysis. Crime & Delinquency. 2009; 55:442–471.

Lambert D. Zero-Inflated Poisson regression, with an application to defects in manufacturing. Technometrics. 1992; 34(1):1–14.

Langan, P.; Cunniff, MA. Recidivism of felons on probation, 1986–89. Washington DC: Bureau of Justice Statistics; 1992.

Lattimore PK, Krebs C, Koetse W, Lindquist C, Cowell AJ. Predicting the effect of substance abuse treatment on probationers. Journal or Experimental Criminology. 2005; 1:159–189.

Lurigio A, Cho Y, Swartz J, Graf I, Pickup L. Standardized assessment of substance-related, other psychiatric, and comorbid disorders among probationers. International Journal of Offender Therapy & Comparative Criminology. 2003; 47:630–652. [PubMed: 14661384]

MacKenzie DL. Evidence-based corrections: Identifying what works. Crime & Delinquency. 2000; 46:457–471.

MacKenzie, DL. What works in corrections. New York: Cambridge University Press; 2006.

MacKenzie DL, Brame R. Community supervision, prosocial activities, and recidivism. Justice Quarterly. 2001; 18(2):429–448.

MacKenzie DL, Browning K, Skroban SB, Smith DA. The impact of probation on the criminal activities of offenders. Journal of Research in Crime and Delinquency. 1999; 36:423–453.

MacKenzie DL, De Li S. The impact of formal and informal social controls on the criminal activities of probationers. Journal of Research in Crime and Delinquency. 2002; 39:243–276.

MacKenzie, DL.; Mitchell, O.; Wilson, DB. The impact of drug treatment provided in correctional facilities. In: Leukefeld, C.; Gullota, TP.; Gregrich, J., editors. Handbook of evidence-based substance abuse treatment in criminal justice settings. New York: Springer Science + Business Media; 2011. p. 183-203.

Minor KI, Wells JB, Sims C. Recidivism among federal probationers—Predicting sentence violations. Federal Probation. 2003; 67(1):31–36.

Morgan K. Factors associated with probation outcome. Journal of Criminal Justice. 1993; 22:341–353.

Mumola, CJ.; Bonczar, TP. Substance abuse and treatment of adults on probation, 1995. Washington, DC: Bureau of Justice Statistics; 1998.

Muthen B, Shedden K. Finite mixture modeling with mixture outcomes using the EM algorithm. Biometrics. 1999; 55:463–469. [PubMed: 11318201]

Nagin DS. Analyzing developmental trajectories: Semi-parametric group-based approach. Psychological Methods. 1999; 4:39–177.

Nagin, DS. Group-based modeling of development. Cambridge, MA: Harvard University Press; 2005.

Nagin, DS. Group-based trajectory modeling: An overview. In: Piquero, AR.; Weisburd, D., editors. Handbook of quantitative criminology. New York: Springer Science + Business Media; 2010. p. 53-67.

Nagin DS, Land KC. Age, criminal careers, and population heterogeneity: Specification and estimation of a nonparametric, mixed Poisson model. Criminology. 1993; 31:327–362.

Nagin DS, Odgers CL. Group-based trajectory modeling in clinical research. The Annual Review of Clinical Psychology. 2010; 6:109–138.

Olson DE, Lurigio A. Predicting probation outcomes: Factors associated with probation rearrest, revocations, and technical violations during supervision. Justice Research and Policy. 2000; 2(1): 73–86.

Petras, H.; Masyn, K. General growth mixture analysis with antecedents and consequences of change. In: Piquero, AR.; Weisburd, D., editors. Handbook of quantitative criminology. New York: Springer Science + Business Media; 2010. p. 69-99.

Peters RH, Greenbaum PE, Steinberg ML, Carter CR, Ortiz MM, Fry BC, Valle SK. Effectiveness of screening instruments in detecting substance use disorders among prisoners. Journal of Substance Abuse Treatment. 2000; 18:349–358. [PubMed: 10812308]

Petersilia JM, Turner S. Comparing intensive and regular supervision for high-risk probationers: Early results from an experiment in California. Crime & Delinquency. 1990; 36:87–111.

Petersilia, JM.; Turner, S. Evaluating intensive supervision probation/parole: Results of a Nationwide Experiment. Washington, DC: National Institute of Justice; 1993.

Prendergast ML, Anglin MD, Wellish J. Treatment for drug-abusing offenders under community supervision. Federal Probation. 1995; 59:66–75.

Roberts, J.; Horney, J. The life event calendar method in criminological research. In: Piquero, AR.; Weisburd, D., editors. Handbook of quantitative criminology. New York: Springer Science + Business Media; 2010. p. 289-312.

Roeder K, Lynch K, Nagin DS. Modeling uncertainty in latent class membership: A case study in criminology. Journal of the American Statistical Association. 1999; 94:766–776.

Saunders JM. Understanding random effects in group-based trajectory modeling: An application of Moffitt's developmental taxonomy. Journal of Drug Issues. 2010; 40(1):195–220. [PubMed: 21544268]

Sims B, Jones M. Predicting success or failure on probation: Factors associated with felony probation outcomes. Crime & Delinquency. 1997; 43:314–327.

Scott CK, Dennis ML, Foss MA. Utilizing recovery management checkups to shorten the cycle of relapse, treatment reentry, and recovery. Drug and Alcohol Dependence. 2005a; 78:325–338. [PubMed: 15893164]

Scott CK, Foss MA, Dennis ML. Pathways in the relapse, treatment, and recovery cycle over three years. Journal of Substance Abuse Treatment. 2005b; 28(2S):S63–S72. [PubMed: 15797640]

Sobell, LC.; Sobell, MB. Timeline follow-back: a technique for assessing self-reported alcohol consumption. In: Litten, RZ.; Allen, JP., editors. Measuring Alcohol Consumption: Psychological and Biochemical Methods. Totowa, NJ: Humana Press; 1992. p. 41-72.

Staton-Tindall, M.; Havens, JR.; Oser, CB.; Burnett, MC. Substance use prevalence in criminal justice settings. In: Leukefeld, C.; Gullota, TP.; Gregrich, J., editors. Handbook of evidence-based substance abuse treatment in criminal justice settings. New York: Springer Science + Business Media; 2011. p. 81-101.

Taxman FS. Unraveling "what works" for offenders in substance abuse treatment services. National Drug Court Institute Review. 1999; 2(2):93–134.

Taxman FS, Perdoni ML, Harrison LD. Drug treatment services for adult offenders: The state of the state. Journal of Substance Abuse Treatment. 2007; 32:239–254. [PubMed: 17383549]

Taxman FS, Thanner M. Risk, need, and responsivity (RNR): It all depends. Crime & Delinquency. 2006; 52(1):28–51. [PubMed: 18542715]

Thanner M, Taxman FS. Responsivity: The value of providing intensive services to high-risk offenders. Journal of Substance Abuse Treatment. 2003; 24:137–147. [PubMed: 12745031]

Wooditch A, Lawton B, Taxman FS. The geography of drug abuse epidemiology among probationers in Baltimore. Journal of Drug Issues. 2013; 43(2):231– 240.

NIH-PA Author Manuscript

NIH-PA Author Manuscript

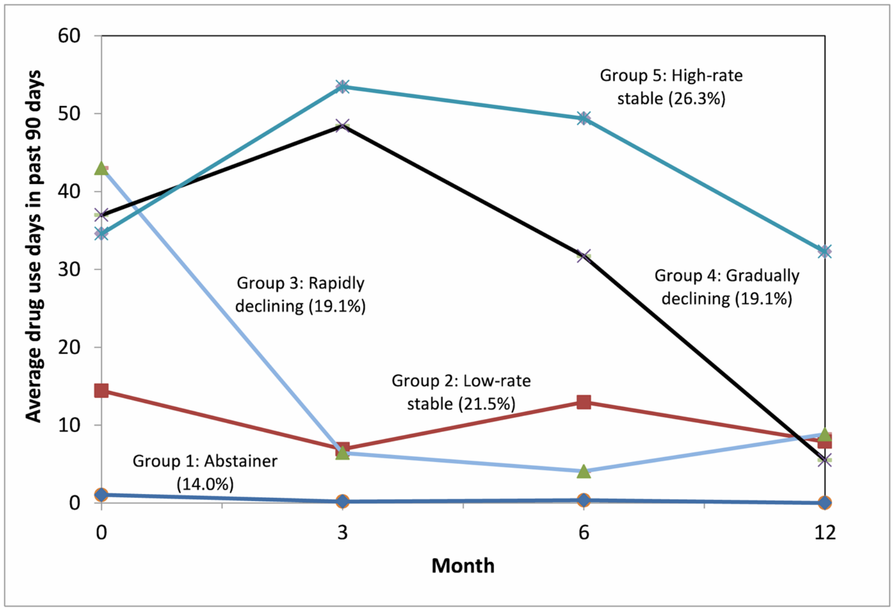

Figure 1.
Trajectories of Self-Reported Drug Use Days (n=251)

Table 1

Characteristics of the Study Sample (n=251)

Variable	Mean/%	(SD)
Demographics		
Age	36.8	(11.5)
% Male	74.9	
% Employed	58.2	
% Single	89.2	
% Non-white	68.9	
Years of Education Completed	11.3	(1.7)
Criminality		
Number of Prior Arrests	10.5	(11.1)
Number of Prior Incarcerations	4.9	(7.2)
Risk Score	5.1	(1.5)
Drug Use and Treatment		
Addiction Severity Score	6.0	(2.8)
Age at First Drug Use	15.8	(5.7)
% Hard Drug Users	53.8	
% Ever Injected Drugs	24.7	
% Ever Attended Self-Help Sessions before on probation	20.3	
% Ever Attended Inpatient Sessions before on probation	23.5	
% Ever Attended Outpatient Sessions before on probation	74.9	
Activity at Baseline (Past 90 days)		
Drug Use Days	28.1	(20.3)
Crime Days	3.5	(15.6)
Alcohol Use Days	10.7	(15.6)

Note: Hard drug use was defined as the use of any illegal drug, with the exception of marijuana, for the purpose of getting high within the prior 30 days.

Table 2

Model Fit Indices for Drug Use Trajectories – *Full Sample* (n=251)

	BIC	BIC	Mean Posterior Probabilities
# of Groups	**(n = 1004)**	**(n = 251)**	
2	−6566.60	−6559.67	.94, .99
3	−6031.37	−6021.66	.99, .96, .85
4	−5485.82	−5473.35	.96, .96, .95, .82
5	**−5337.72**	**−5322.47**	**.92, .96, .94, .93, .90**
6	−5131.05	−5113.03	.95, .93, .97, .93, .95, .87

Table 3

Mean Posterior Probabilities of Group Assignment for selected model (n=251)

Group Assignment	Prob. G1	Prob. G2	Prob. G3	Prob. G4	Prob. G5
Group 1 (n=35; 14.0%)	**.924**	.026	.016	.016	.019
Group 2 (n=54; 21.5%)	.003	**.965**	.009	.010	.013
Group 3 (n=48; 19.1%)	.000	.003	**.937**	.044	.016
Group 4 (n=48; 19.1%)	.000	.004	.029	**.933**	.033
Group 5 (n=66; 26.3%)	.000	.001	.021	.077	**.901**

Table 4

Risk and Protective Factors across Drug Use Trajectories (n=251)

Variable	Abstainer (n=35)	Low-rate stable (n=54)	Rapidly declining (n=48)	Gradually declining (n=48)	High-rate stable (n=66)
Demographics					
Age	38.4	36.5	36.0	37.3	36.4
% Male	80.0	64.8	79.2	77.1	75.8
Criminality					
Prior Arrests	10.5	7.7	10.1	12.8	11.3
Prior Incarcerations	5.4	3.9	5.3	5.3	4.9
Risk Score***	5.1	4.2	5.1	5.4	5.4
Drug Use and Treatment					
Addiction Severity Score**	5.4	5.0	6.3	6.5	6.6
Age at First Drug Use	16.7	17.3	14.6	15.4	15.3
% Hard Drug Users***	20.0	38.9	58.3	68.8	69.7
% Ever Attend Self-Help	74.3	68.5	62.5	70.8	59.1
% Ever Attend Outpatient	31.4	20.4	20.8	29.2	19.7
% Ever Attend Inpatient**	5.7	13.0	35.4	25.0	19.7
Activity at Baseline (Past 90 days)					
Drug Use Days***	1.0	14.5	44.1	37.9	34.8
Crime Days*	--	0.1	1.8	7.9	6.2
Self-Help Sessions	0.3	0.1	--	1.6	0.1
Outpatient Sessions**	11.6	4.2	0.7	1.9	1.5
Inpatient Sessions*	6.2	0.1	1.3	2.4	0.2
CEST Treatment Motivation Scales					
Desire for Help	35.9	37.5	38.4	39.7	38.4
Treatment Readiness †	34.2	36.1	38.0	36.8	36.6
Problem recognition**	29.6	31.9	35.3	36.2	34.4

† $p < .10$,

* $p < .05$,

** $p < .01$,

*** $p < .001$

Table 5

Predictors of group membership (abstainer trajectory is comparison group)

	Low-rate stable	Rapidly declining	Gradually declining	High-rate stable
Variable	***Beta***	***Beta***	***Beta***	***Beta***
Gender[1]	−.60	.24	.08	.06
Age	−.02	−.07**	−.07**	−.09***
Addiction severity	−.06	.09	.06	.08
Risk score	−.37*	−.01	.16	.16
Hard drug user[2]	1.46*	2.50***	2.92***	3.07***
Study condition[3]	−.09	−.55	−.34	−.40

* $p < .05$,

** $p < .01$,

*** $p < .001$

[1]Females are the comparison category

[2]Individuals who reported no hard drug use in the past 30 days are the comparison category

[3]The standard referral (control) group is the comparison category

Table 6

Predictors of group membership (high-rate stable trajectory is comparison group)

	Abstainer	Low-rate stable	Rapidly declining	Gradually declining
Variable	***Beta***	***Beta***	***Beta***	***Beta***
Gender[1]	−.06	−.66	.18	.03
Age	.09***	.07**	.01	.01
Addiction severity	−.08	−.14†	.01	−.02
Risk score	−.16	−.53***	−.17	−.00
Hard drug user[2]	−3.07***	−1.61**	−.56	−.15
Study condition[3]	.40	.31	−.15	.06

† $p < .10$

* $p < .05$,

** $p < .01$,

*** $p < .001$

[1] Females are the comparison category

[2] Individuals who reported no hard drug use in the past 30 days are the comparison category

[3] The standard referral (control) group is the comparison category

Table 7

Predictors of group membership (rapidly declining trajectory is comparison group)

	Abstainer	Low-rate stable	Gradually declining	High-rate stable
Variable	***Beta***	***Beta***	***Beta***	***Beta***
Gender[1]	−.24	−.84†	−.16	−.18
Age	.07**	.05*	.00	−.01
Addiction severity	−.09	−.15†	−.03	−.01
Risk score	.01	−.36*	.17	.17
Hard drug user[2]	−2.50***	−1.05†	.42	.56
Study condition[3]	.55	.46	.21	.15

$^{\dagger}p < .10$

$^{*}p < .05$,

$^{**}p < .01$,

$^{***}p < .001$

[1]Females are the comparison category

[2]Individuals who reported no hard drug use in the past 30 days are the comparison category

[3]The standard referral (control) group is the comparison category

Table 8

Repeated-Measures ANOVA Results on the Influence of Trajectory Group on Treatment Attendance

Dependent Variable	Trajectory Group	Mean Days by Wave (Past 90 Days)				Between-Groups Effects	Bonferroni Comparisons between Groups
		T1	T2	T3	T4		
Self-Help Days	Abstainer	.31	.00	2.17	2.74	*F*(4)=1.17	No Difference
	Low-rate stable	.02	3.11	2.94	3.96		
	Rapidly declining	.00	3.15	3.73	3.70		
	Gradually declining	1.60	1.63	2.15	7.73		
	High-rate stable	.09	.80	3.20	2.08		
	Overall sample	*.38*	*1.79*	*2.90*	*3.97*		
Outpatient Days	Abstainer	11.66	11.83	10.63	8.31	*F*(4)=2.44*	Rapidly declining > High-rate stable *
	Low-rate stable	4.22	13.57	15.50	10.56		
	Rapidly declining*	.71	20.06	19.10	13.15		
	Gradually declining	1.69	9.96	10.30	10.50		
	High-rate stable*	1.45	8.71	8.89	5.14		
	Overall sample	*3.37*	*12.60*	*12.79*	*9.30*		
Inpatient Days	Abstainer	6.20	.46	.00	.11	*F*(4)=2.55*	Rapidly declining < Gradually declining *
	Low-rate stable	.15	1.63	.69	3.80		
	Rapidly declining*	1.31	.73	.00	1.54		
	Gradually declining*	2.40	1.40	6.55	6.95		
	High-rate stable	.17	.85	1.76	3.29		
	Overall sample	*1.65*	*1.04*	*1.84*	*3.32*		

* $p < 0.05$

Table 9

Impact of Treatment Participation Days on Drug Use across Trajectories†

	Abstainer	Low-rate stable	Rapidly declining	Gradually declining	High-rate stable
Variable	***Beta***	***Beta***	***Beta***	***Beta***	***Beta***
Self-help days	−1.97	−.06***	.03***	−.06***	−.00***
Outpatient days	−.13***	.00	−.02***	−.02***	−.01***
Inpatient days	−.04*	.02***	.01***	.07***	−.02***

* $p < .05$,

** $p < .01$,

*** $p < .001$,

† Controlling for gender, age, addiction severity, risk score, hard drug use and study condition.