Specialized Drug Court Participation

Across Offender Subtypes

by

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ABSTRACT

Over the last few decades, specialized courts have received an increasing amount of research attention. The existing literature mostly supports drug courts and demonstrates their effectiveness in reducing recidivism and substance abuse, more generally (Belenko, 1998; Bouffard & Richardson, 2007; Gottfredson, Najaka, & Kearley, 2003). Whether the drug court model "works" across offender subgroups remains an open empirical question. The current study uses data originally collected by Rossman and colleagues (2003-2009) for the Multi-Site Adult Drug Court Evaluation (MADCE) to examine the effect of drug court participation on recidivism among unique offender subgroups. First, a context-specific risk score is used to examine recidivism outcomes. Second, offender subgroups are statistically created using latent class analysis (LCA). Recidivism outcomes are then assessed by subgroup, with these results compared to the initial measure of risk. Both analyses are performed using the full sample of drug court participants and the comparison groups. Finally, the third model uses a split sample analysis by court participation to explore the full effects of drug court. The findings of the present study contribute to the theoretical literature and help inform future policy regarding risk assessment and the treatment of offenders in drug courts.

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INTRODUCTION

Drug courts have received an increasing amount of research attention since their inception in 1989 in Dade County (Miami), Florida. Many have viewed the expansion of drug courts, and specialized courts more generally, as a way to reduce incarceration and promote rehabilitation efforts. As a result, overall drug court recidivism rates have been reduced and drug court participants have access to more treatment options which targets the root cause of their criminality – addiction (Fielding, 2002; Koetzle et al., 2015; Gray, & Saum, 2005; Gottfredson, Najaka, & Kearley, 2003; Marlowe et al., 2006; Mitchell et al., 2012; Myer & Buchholz, 2016; Spohn et al., 2001; Thanner & Taxman, 2003; Turner et al., 2002; Wilson, Mitchell, & Mackenzie, 2006).

There is a general consensus within the literature that drug courts work by reducing subsequent drug use and recidivism (Belenko, 1998; Gottfredson, Najaka, & Kearley, 2003; Mitchell et al., 2012; Spohn et al., 2001; Wilson, Mitchell, & Mackenzie, 2006). However, many of the studies in the drug court literature suffer from methodological shortcomings. Some have very weak designs and limited statistical capabilities (Wilson, Mitchell, & Mackenzie, 2006). Additionally, few studies have looked at individual characteristics such as risk factors. Even fewer studies have looked at subgrouping offenders within drug courts (Larsen, Nylund-Gibson, Cosden, 2014).

The primary critique of drug courts, in general, has been that they fail to consider individual characteristics and too often they look at program effectiveness based on program characteristics. The current study uses Rossman, Roman, Zweig, Rempel, and Lindquist’s Multisite Adult Drug Court Evaluation (MADCE) to fill in the gap in the literature by constructing statistically meaningful subgroups within adult drug court participants that account for individual differences and risk factors. Our goal is to determine if there are pathways that offenders take which cluster together and whether such clusters differ in terms of predicting recidivism as an outcome. In other words, is it possible to identify subgroups of adult drug court participants by risk factors, apart from traditional recidivism predictors, and do these formulated subgroups differ in the likelihood of recidivism? Addressing this question will contribute to the general literature on drug court effectiveness and will also help inform classification and treatment strategies.

REVIEW OF THE LITERATURE

Risk – Need – Responsivity Model

Risk assessment is a tool that is widely used within the criminal justice system. In fact, it is used at nearly every decision point from pretrial detention through parole. Over the past few decades, research has confirmed its applicability to programming and expanded on the validity of instruments used to measure risk across different populations (Andrews, Bonta, & Wormith, 2006; Bonta, 2002; Desmarais & Singh, 2013; Gendreau, Little, & Goggin, 1996; James, 2015; Myer & Buchholz 2016; Pusch & Holtfreter, 2018; Taxman & Marlowe, 2006; Thanner & Taxman, 2003). Actuarial risk assessments rely on a series of items to measure the likelihood of a person reoffending after taking different individualized factors into consideration. Offenders (or inmates, in the correctional setting) are often classified as high, moderate, or low risk. In the risk-needs-responsivity model, there are two different types of risk factors –static and dynamic. Static factors are the factors that cannot be changed (e.g., age at first arrest, prior record, etc.) while dynamic factors are those that do change (e.g., substance abuse, mental health issues, attitude, etc.) either on their own or through an intervention. Often times, dynamic factors are also referred to as “criminogenic needs” (Latessa & Lovins, 2010). Risk is also used to determine level of supervision imposed on an offender in the correctional setting, ultimately helping correctional agencies manage scarce resources.

Research on risk assessment indicates that the most effective instruments take into account static and dynamic risk and needs (Bonta, 2002; Latessa & Lovins, 2010). For example, Clarke, Peterson-Badali, & Skilling (2017) examined the effect of the inclusion of dynamic risk scores among youth offenders and found that including dynamic risk scores in the assessment improves the prediction of recidivism. Research has often involved the use of actuarial risk assessment instruments (rather than clinical assessments) such as the Level of Supervision Inventory-Revised (LSI-R). The validity and reliability of the LSI-R to predict recidivism is well-documented within the literature (Bonta, 2002; Gendreau, Little, & Goggin, 1996; Guastaferro, 2012; Simourd, 2004). However, some have found that the LSI-R does not predict recidivism equally across sex (Holtfreter & Cupp, 2007; Holtfreter & Morash, 2003; Holtfreter et al., 2004; Reisig, Holtfreter, & Morash, 2006). More specifically, the LSI-R, which claims to be gender neutral, does not accurately predict risk for female recidivism because it does not acknowledge the gendered nature of offending (Holtfreter & Morash, 2003; Holtfreter et al. 2004;). In the sections that follow, each principle of the risk-needs-responsivity model are described.

The *risk* principle refers to the relationship between treatment services and offender risk. Put differently, "the *risk* principle dictates that treatment and intervention should be proportionate to each offender's recidivism *risk*" (Desmarais & Singh, 2013:3). Andrews, Bonta, & Hoge (1990) suggest that high levels of treatment services (in a correctional setting) should be reserved for high risk cases. It has been widely accepted within scholars and practitioners that the most intensive treatment should be provided to the highest risk offenders (Andrews, Bonta, & Wormith, 2006; James, 2015; Koetzle, 2015; Latessa & Lovins, 2010; Lowenkamp & Latessa, 2004; Lowenkamp, Holsinger, & Latessa, 2005; Marlowe et al., 2006; Myer & Buchholz, 2016; Taxman & Marlowe, 2006; Thanner & Taxman, 2003). Risk is viewed as the probability of recidivism – not necessarily risk for violent offenses. As James (2015: 1) notes, "…the crime someone is committed of is not always the best proxy for the risk that person might pose to the community." Additionally, there is empirical evidence suggesting that if an offender is classified as low risk but is placed in a high intensity treatment (targeted at high risk offenders), their probability to recidivate increases (Andrews, Bonta, & Hoge 1990; Latessa & Lovins, 2010). In other words, there may be alternative interventions that would benefit low risk offenders more than high intensity treatment services (e.g., community service). Feminist criminologists also point out that this over-classification results in unnecessary social control. This underscores the importance of classifying offenders by risk using valid and reliable measures.

The *needs* principle is a way for researchers and practitioners to target changes in an offender. In other words, effective treatment should focus on identifying and addressing needs that are related to criminal behavior (or the risk to reoffend). More specifically, Andrews, Bonta, & Wormith (2006) identified the “Central Eight” major risk factors associated with criminal conduct that should be reliable predictors of future behavior:

1. History of antisocial behavior
2. Antisocial personality pattern
3. Antisocial cognition
4. Antisocial associates
5. Family and/or marital problems
6. School and/or work problems
7. Leisure and/or recreation problems
8. Substance abuse

All of these factors are considered to be influential and indicative of risk level, but the first four (often termed the “Big Four”) are considered to be the strongest risk factors amongst the eight. Additionally, the “Central Eight” factors include both static and dynamic factors. Including dynamic and static factors in the measurement allows for a more holistic understanding of the individual. It is important to note that most offenders who are considered “high risk” possess multiple factors mentioned above.

The *responsivity* principle takes into account personal characteristics of the offender that may influence their treatment plan (e.g., mental health, readiness to change, etc.). Latessa & Lovins (2010: 210) outline an example where, “an offender might be moderate risk to offend, but due to a low level of cognitive functioning they would not be successful in a program that required normal functioning.” A central feature of the responsivity principle is that programming should be tailored to the ability and learning style of the offender (Andrews, Bonta, & Hoge 1990; Desmarais & Singh, 2013; James, 2015).

As demonstrated above, risk assessment can be used to tailor treatment plans for individual offenders needs. Adhering to the risk-needs-responsivity model incorporates empirically justified assessments while simultaneously predicting recidivism outcomes. The importance of accurately classifying offenders suggests that the classification has serious implications. An offender may be placed in a high-risk program when he or she is actually considered low risk and vice versa. In Latessa & Lovins's (2010) policy maker guide, they indicate that misclassifying offenders and placing low risk offenders in high intensity correctional interventions can lead to three consequences: 1) exposure to high risk offenders transmits antisocial behaviors and values; 2) disruption of prosocial networks – as low risk individuals are fairly prosocial by definition; and 3) low functioning and low risk offenders may be manipulated by high risk offenders. The use of unnecessary social control that accompanies over-classification is also a concern noted by feminist criminologists (Holtfreter & Morash, 2003). One must carefully consider the methods and assumptions when using risk assessment to label and group offenders as this can have serious consequences – intended or unintended.

General Theory

Risk assessment is largely driven by social learning theory. It has been argued that when treatment programs adhere to the principles of social learning theory, they are more likely to reduce recidivism (Bonta, 2002). Broadly speaking, social learning theory posits that learning is a cognitive process taking place in social contexts which occur through observations. It emphasizes the balance of these influences by capitalizing on past behavior, current behavior, and predictive behavior. There are four fundamental learning mechanisms within the social learning framework: differential association, definitions, differential reinforcement, and imitation.

Differential association refers to the direct learning process by exposure to behaviors, norms, values, and attitudes. The interactions and identity that is formed with association to different groups provide the social environments where non-conforming behavior takes place. Definitions, according to Akers & Jensen (2009: 39) are, "one's own orientations, rationalizations, justifications, excuses, and other attitudes that define the commission of an act as relatively more right or wrong, good or bad, desirable or undesirable, justified or unjustified, and appropriate or inappropriate." Differential reinforcement is described as the intended or actual consequences that follow a particular behavior. Most learning in criminal behavior is the direct result of social interactions. "Whether individuals will refrain from or initiate, continue committing or desist from criminal and deviant acts depends on the relative frequency, amount, and probability of past, present, and anticipated rewards and punishments perceived to be attached to the behavior" (Tittle, Antonaccio, & Botchkovar, 2012: 864). Imitation of others' deviant behaviors can occur in the same way in which law abiding behaviors are modeled.

In theory, each of the social learning mechanisms may operate individually; however, the empirical reality is that multiple sources of influence, motivations, and controls likely operate simultaneously to guide human behavior (Andrews & Dowden, 2007). Bonta (2002: 363) briefly summarized the relevance of social learning theory in regard to offender risk assessment:

> Criminal behavior is learned through complex interactions between cognitive, emotional, personality, and biological factors and environmental reward-cost contingencies. Within the model, there are a number of factors or paths that lead to criminal conduct and some factors are more important than others. Andrews and Bonta (1998a) described what they call "the Big Four" – criminal history, antisocial personality, antisocial attitudes, and social support for crime. Other, less important but nonetheless relevant variables in the model are indicators of prosocial convention (e.g., employment and education), family relationships, and facilitators and inhibitors of antisocial and conventional behavior (e.g., substance abuse).

With regard to risk factors, the social learning perspective assumes that the same risk factors apply equally across all groupings of offenders. In other words, the same risk assessment instrument should work equally well for across all groups of offenders and all different types of settings. However, feminist criminologists argue that social learning theory does not take into account the context of female offending (Holtfreter & Morash, 2003; Holtfreter et al., 2004; Morash, 1999; Reisig, Holtfreter, & Morash, 2006; Sampson, 1999).

Gender-Specific Approach

Perhaps the most influential feminist theory of lawbreaking has been Daly's (1992) gendered pathways to crime. The fundamental assumption here is that women commit crime for different reasons and often possess different risk factors than men. There has been considerable empirical support confirming the gendered pathways to crime (Belknap & Holsinger, 2006; Holtfreter & Morash, 2003; Reisig, Holtfreter, &

Morash, 2006). Therefore, the traditional risk/needs assessment may be appropriate for some women whose constellations of risk, needs, and offending histories closely resemble their male counterparts; however, it may be inappropriate for women following gendered pathways to crime.

Brennan et al. (2012) introduce gender responsive and gender neutral measures to examine pathways to crime. Gender responsive factors are risk/needs that have been previously identified in samples of women offenders (abuse, victimization, etc.) and gender neutral factors are considered the traditional risk/needs factors that are not gender specific. There is evidence of some research examining the role of gender on drug court's effectiveness (Andrew Fulkerson, 2012; Brown, 2011; Gray & Saum, 2005; Listwan et al., 2003; Peters & Murrin, 2000; Myer & Buchholz, 2016; Shannon et al., 2014; Spohn et al., 2001), however, the majority of this research fails to consider gendered pathways to crime. In sum, the pathways-informed research suggests that not all offenders possess the same sets of risks and needs. With regard to developing programs and services (e.g., drug treatment), approaches to subgrouping offenders in addition to traditional risk measures should also be considered.

Measuring Risk Using the Addiction Severity Index (ASI)

It has been established within the drug court literature that the risk principle is necessary to consider when it comes to evaluating the effectiveness of drug court. In fact, Lowenkamp, Holsinger, & Latessa's (2005) meta-analysis not only found that risk level was a significant predictor of drug court effectiveness, but they actually showed that the average treatment effect was twice as high for courts that dealt with higher risk participants. Since it has been established that risk is an essential component of any study on drug courts, the next logical question then becomes how to measure risk. As mentioned previously, the LSI-R is frequently used along with the Wisconsin Risk Needs Scale, COMPAS, YLS/CMI, and ASI (Andrews, Bonta, & Wormith, 2006; Bonta, 2002; Clarke, Peterson-Badali, & Skilling, 2016; Desmarais & Singh, 2013; Gendreau, Little, & Goggin, 1996; Guastaferro, 2012; Koetzle et al., 2015; Myer & Buchholz, 2016; Pusch & Holtfreter, 2018; Simourd, 2004; Thanner & Taxman, 2003). All of the assessment tools mentioned above have been associated with accuracy of risk prediction (Bonta, 2002; Desmarais & Singh, 2013; Gendreau, Little, & Goggin, 1996; Guastaferro, 2012; Luborsky, Woody, & O'Brien, 1980; Simourd, 2004), but no one instrument has been empirically documented as superior (James, 2015).

The present study uses the ASI scale as the measure for risk. The ASI is a context specific actuarial measure of risk assessment used to score offenders on several measurable domains. These domains include substance abuse, medical, employment/support, family/social, legal, and psychological (Luborsky, Woody, & O'Brien, 1980). Based on the scores of each domain, the results are then summed to develop a scale of clinical addiction severity. One of the primary strengths of using the ASI is that it provides a description of the offender's risk/needs and is necessary to assist within developing individual treatment plans. It is worth noting that the ASI scale used in the present study does not include items measuring the psychological domain.

Drug Court Context

Drug courts in the United States were formed nearly thirty years ago in response to the proclaimed "war on drugs" and steadily increasing incarceration rates. Still today, drug-related crime is a substantial problem in the United States and represents a large portion of jail and prison populations (Federal Bureau of Prisons, 2018). Because such a large portion of the incarcerated population has some involvement with substance use and/or abuse, the drug court model represents an alternative to incarceration. The central idea behind the drug court model is that drug courts will work with various criminal justice and treatment agencies to help facilitate treatment plans which reduce drug addiction and drug-related crime, in turn, reducing jail and prison populations. However, drug court models and their characteristics vary by jurisdiction. Longshore et. al's (2001) conceptual framework outlines the drug court structure and processes. This framework includes five dimensions: leverage, population severity, program intensity, predictability, and rehabilitation emphasis.

Leverage is described as the seriousness of the consequences imposed on an offender through the drug court program. Longshore et al. (2001) note that leverage primarily depends on the court's entry point – pre-plea, post-plea, or probation. In pre-plea courts, the offender enters the program before entering a plea and then once the offender completes the program, the charge would be reduced or completely dropped. In post-plea courts, the offender enters the program after they have plead guilty. If the offender fails the program, the case is directly referred to sentencing where they would face possible incarceration. In probation drug courts, the offender already has a conviction and is entering the drug court program in lieu of a court ordered sanction (e.g., incarceration). The amount of leverage varies by type of court. In other words, the stakes are high (so the leverage would be strong) in a post-plea drug court, because if they fail the program they know they will be sent directly to sentencing which would likely result in their original sentence being imposed.

Population severity refers to the measurement of the severity of drug use and the severity of criminal involvement. Population severity varies based on the eligibility requirements of a particular drug court program. Most programs aim resources at serious drug offenders, but some programs target resources toward first-time or minor offenders. Longshore et al. (2001) provide ways to operationalize the two dimensions of population severity. The severity of drug use can be measured by using clinical assessments or self-reported measures of drug use. They suggest that the severity of criminal involvement can be measured by creating a ratio of felonies to misdemeanors from the offender's criminal records (Longshore et al., 2001).

Program intensity refers to the program requirements the offender must complete in order to successfully graduate from the drug court program. Some of these requirements include urine testing, status court hearings, drug abuse treatment, and fines or restitution. Program intensity often varies throughout the drug court program as a typical drug court program is divided into phases (e.g., Phase I, Phase II, Phase III, Phase IV). Therefore, the participant typically must complete the requirements of Phase I before proceeding to Phase II. Gradually, the phases become less intensive as the participant moves toward the end of the program.

Predictability refers to the perceived certainty of the courts response to compliance or noncompliance through incentives and sanctions. In other words, it is argued that the participant should know what incentives they will receive if they have been compliant and they should also know what the sanction will be if they have been noncompliant (e.g., missed a urine test or missed a counseling session). The court should be distributing incentives and sanctions on a consistent basis and the distribution of sanctions and incentives should be transparent.

Rehabilitation emphasis refers to the amount of emphasis that the drug court program places on rehabilitation. Rehabilitation emphasis is indicated by many factors including: involvement of all court actors in handling cases, the focus on participant's individualized needs, degree to which the court actors take a therapeutic approach in their roles, number of positive drug tests tolerated before sanctions are imposed or the participant is discharged from the program, and re-entry criteria. In sum, Longshore et al.'s (2001) conceptual framework provides a substantial amount of insight into the drug court structure and processes, but fails to consider individual constellations of risks/needs. For this reason, subgrouping offenders should be considered in order to gain a more wholesome understanding of the population being served.

CURRENT FOCUS

Although it is has been consistently demonstrated in the literature that drug courts are effective, less is known about whether drug court participation exerts similar effects across all groups of offenders. Risk assessment is a common practice and is used widely among criminal justice practitioners (e.g., from probation to correctional institutions).

Accordingly, it is important to first examine the relationship between risk, as measured by a reduced version of the ASI, and recidivism. The effect of drug court participation on recidivism is also considered. Given the potential limitations associated with risk assessment, this study also uses Latent Class Analysis (LCA) to determine whether offenders can be “grouped” according to risks and needs that are not considered within the ASI (e.g., prior victimization). A subsequent logistic regression analysis will then examine the relationship between group membership and recidivism. More specifically the following directional hypotheses are tested:

H1: Risk will be a significant, positive predictor of recidivism.

H2: Drug court participation will be a significant negative predictor of recidivism.

Additionally, these non-directional hypotheses will be tested:

H3: Latent class membership will be a significant predictor of recidivism.

H3a: The relationship between risk and recidivism will no longer be significant once latent class membership is considered.

H3b: The relationship between drug court participation and recidivism will no longer be significant once latent class membership is considered.

H4: Latent class membership will have different effects on recidivism in the context of drug court participation and comparison court participation (potential interaction).

RESEARCH DESIGN AND METHODOLOGY

Research Design and Data Source

This thesis uses data originally collected for the Multi-Site Adult Drug Court Evaluation (MADCE), funded by the National Institute of Justice (NIJ), from 2003 to 2009, consisting of 23 geographically diverse drug courts and 6 comparison courts (Rossman et al., 2011). The original study included three separate phases: 1) process evaluation, 2) impact evaluation, and 3) cost-benefit analysis. However, the current study uses information only from the impact evaluation phase, as it included relevant outcome measures and many individual-level variables (such as demographics, mental health indicators, and criminal history variables). The MADCE investigators included many different data sources for their analyses, such as field visits, self-report surveys, oral fluids drug tests, and administrative (official) records. The self-reported surveys (the data source used for the impact evaluation) were administered at baseline, 6 months after baseline, and 18 months after baseline and were conducted through a Computer Assisted Personal Interview system. The total sample for the original study consisted of 1,781 offenders, of which 1,149 were drug court participants and 632 were participants from the comparison sites. Due to missing data on primary variables of interest, the current study excludes 249 offenders, permitting a final analytic sample of 1,532 offenders (1,012 drug court participants and 520 comparison court participants). The original investigators used super-weighting strategies (propensity score modeling and retention score modeling) to eliminate selection biases and attrition biases on variables of interest. These super-weighted variables were used in the current study to maintain consistency throughout. Separate super weights were computed at each wave of the data including baseline, 6 months, and 18 months, and one super weight was used for the administrative data; in essence, the super weights assign higher weights to participants that have been deemed as under-represented in the sample (Rossman et al., 2011).

Dependent Variable

The dependent variable used in the study is *recidivism*. Reisig, Holtfreter, & Morash (2006) note that the best way to operationalize recidivism is debatable and they propose using multiple indicators, as opposed to relying on a single source. The MADCE dataset contained several sources of recidivism data, which included: self-report measures, official arrest records, and oral swab drug tests. An offender was deemed a recidivist if they reported yes to *any* of the three measures noted above. The original data collectors received training for the collection of the oral swab drug tests and a six-panel oral fluid screen was used which tested for amphetamines, cannabinoids, cocaine, methamphetamines, opiates, and phencyclidine (Rossman et al., 2011). Each of the above measures were individually coded into dichotomous measures where 1=yes and 0=no to capture whether or not they recidivated. Following Reisig, Holtfreter, & Morash's (2006) approach, each individual measure was combined into one binary variable measuring *any* form of recidivism within 24 months of their conviction. About 73% of the total analytic sample reported some type of recidivism within 24 months ($\bar{x}$ = .73, *SD* = .44) which is slightly higher than both the individual self-report and official rearrest measures (self-report: $\bar{x}$ = .48, *SD* = .50; official rearrest: $\bar{x}$ = .54, *SD* = .50).

Independent Variables

The primary independent variable in this study is risk which is measured using the ASI scale. As noted previously, the ASI spans domains which include: substance abuse, family/social, support, medical, and psychological. However, the ASI is an offense-specific measure focusing heavily on addiction severity and substance abuse. The ASI is a summary scale consisting of the answers to twenty questions: 1) In the past six months, have you used drugs other than those required for medical reasons? 2) In the past six months have you abused prescription drugs? 3) In the past six months did you abuse more than one drug at a time? 4) In the past six months did you get through the week without using drugs or alcohol? 5) In the past six months, were you always able to stop using drugs or alcohol when you wanted to? 6) In the past six months, have you had 'blackouts' or 'flashbacks' as a result of drug or alcohol use? 7) In the past six months, did you ever feel bad or guilty about drug or alcohol use? 8) In the past six months, did your partner or other family members ever complain about your involvement with drugs or alcohol? 9) In the past six months, has drug or alcohol abuse created problems between you and your partner or your other family members? 10) In the past six months, have you lost friends because of use of drugs or alcohol? 11) In the past six months, have you neglected your family because of use of drugs or alcohol? 12) In the past six months, have you been in trouble at work because of use of drugs or alcohol? 13) In the past six months, have you lost a job because of drug or alcohol abuse? 14) In the past six months, have you gotten into fights when under the influence of drugs or alcohol? 15) In the past six months, have you engaged in illegal activities in order to obtain drugs or alcohol? 16) In the past six months, have you been arrested for possession of illegal drugs? 17) In the past six months, have you experienced withdrawal symptoms, such as feeling sick, when you stopped taking drugs or drinking alcohol? 18) In the past six months, have you had medical problems, such as memory loss, convulsions, bleeding, hepatitis, or any other medical problems, as a result of drug or alcohol use? 19) In the past six months, have you gone to anyone for help for a drug or alcohol problem? 20) In the past six months, have you been involved in a treatment program especially related to drug or alcohol use? It is important to note that two of the questions were only asked if the respondent had been employed at some point in the past six months and since a majority of the sample was unemployed, the original authors omitted those two questions (12 and 13) in the ASI variable and reported a Cronbach's α of 0.74 for the 18-point scale (Rossman et al., 2011). The 18-point scale variable is used in this analysis.

Other independent variables used in the current study include drug court participation, history of drug or alcohol treatment, and mental health indicators such as depression, narcissism, and anti-social personality disorder. Drug court participation was coded as a binary measure where 0=individual not in drug court (meaning they are in the matched comparison group) and 1=individual in drug court. Recent alcohol or drug treatment was combined into one dichotomous measure indicating whether the respondent has had any alcohol, drug, or outpatient treatment in the last six months (0=no treatment, 1=some type of treatment). Three separate mental health indicators were included (depression, narcissism, and Anti-Social Personality Disorder), following previous research on substance abusing populations and risk (Somers & Holtfreter, 2018). The depression variable was measured using a 10-item depression scale based on the Center for Epidemiologic Studies-Depression scale (CES-D). The depression scale consisted of ten questions with scores ranging from 0-3; as a result of the scoring style, the depression scale ranged from 0-30. The depression variable used in the present study is a binary measure indicating whether or not the respondent scored over 10 on the depression scale which equates to a clinical diagnosis of depression (0=did not score 10+, 1=scored above 10+). Narcissism was coded dichotomously where 0=not narcissist, 1=narcissist and was measured using a two-item scale based on the DSM-IV-TR. Anti-social personality disorder (ASPD) was coded as 0=no ASPD and 1=ASPD, but participants who were classified as having anti-social personality disorder must exhibit both a conduct disorder and a pervasive pattern of disregard for the rights of others. Adequate levels of reliability have been reported for the CES-D and antisocial personality disorder in other studies using instruments derived from these sources as well (e.g., α=0.79 and 0.83, respectively) (Boey, 1999; Edens, Marcus, & Vaughn, 2011).

Latent Class Analysis Variables

The indicator variables used in the LCA model and subsequent regression models include: substance abuse, mental health, recent prior victimization, employment problems, and housing instability. These variables are not captured in the ASI instrument and have been empirically identified as variables which contribute to pathways of offending (Daly, 1992; Reisig et al., 2006). Substance abuse is measured using a “cumulative frequency of drug use in the past 6 months” variable where 1=heavy user, 2=moderate user, 3=light user, and 4=did not use drugs in past 6 mos. This was recoded into 4 separate dummy variables indicating: heavy drug use (1=heavy drug use and 2=not heavy drug use), moderate drug use (1=moderate drug use and 2=not moderate drug use), light drug use (1=light drug use and 2=not light drug use), and no drug use (1=no drug use and 2=some drug use).[1] The same mental health indicators were used from above (depression, narcissism, and ASPD), but they were recoded for this portion of the analysis as follows: depression (1=depressed, 2=not depressed), narcissism (1=narcissist, 2=not narcissist), and ASPD (1=ASPD, 2=no ASPD). Recent victimization was measured using three separate binary measures. First, recent prior physical abuse was originally measured from responses to the following questions: 1) During the past year, how often did someone push, slap, or grab; you; twist your arm, pull your hair; restrain or shove you; or throw something at you that could hurt you? 2) During the past year, how often did someone punch or hit you with something that could hurt, kick you, slam you against a hard surface, beat you up, choke, strangle, burn or scald you on purpose, or use a knife or gun on you? The original authors created a binary variable where 0=no and 1=yes, but for purposes of the present study, it was recoded to 1=yes and 2=no. Second, recent prior sexual abuse was originally measured from the responses to the following questions: 1) During the past year, how often did someone verbally insist that you have sex, including oral, anal, or vaginal sex when you didn‘t want to, or insist that you have sex without a condom? and 2) During the past year, how often did someone physically force you—by

[1] The Latent Class Analysis STATA plugin prohibits the use of coding 0’s for the purposes of the analysis. Consequently, all of the latent class analysis variables are coded as (1,2) instead of (0,1).

hitting, holding you down, or using a weapon—to have oral sex, anal sex, or vaginal sex? The original authors condensed this into a dichotomous variable where 0=no and 1=yes, and it was recoded for the present study to 1=yes and 2=no. Finally, a measure was included for recent prior abuse using the question, "During the past year, how often did someone make harassing phone calls to you, keep you from spending time or talking with your friends, stop you from going some place you wanted to go, insult you, swear at you, humiliate you, put you down, or make you feel worthless?" Again, the original authors created a dichotomous variable indicating any recent prior abuse where 0=no and 1=yes, and it was recoded for the present study where 1=yes and 2=no. Employment/school problems was measured using the question, "In the past 5 years have you been unemployed for 6 months or more when you were expected to work and work was available or have you been out of school for 6 months or more when you were expected to be attending an academic program?" Their response dichotomously coded where 1=yes and 2=no. Housing instability was constructed from the question, "At any point during past six months, did you ever live in these places? (On the street; In your own house or apartment, meaning your name is on the title, mortgage, or lease; In someone else's house or apartment; In a transitional housing building or halfway house; In a motel/hotel or rooming house; In a shelter; In an abandoned building or vacant unit; In some other place)." Respondents who answered "yes" to the following options were coded as 1 which indicated housing instability: On the street, Transitional housing/Halfway house, Motel/hotel, In a shelter, In an abandoned building or vacant unit. Respondents who answered "yes" to any of the other options (e.g., in your own house or apartment) were coded as 2 which indicates they did not have issues with housing instability.

Control Variables

Several demographic variables are included to control for spuriousness. Age is a continuous variable ranging from 18.01 to 67.73 years. Race is coded using three separate binary measures including: White (0=not white; 1=white), Black/African American (0=not black; 1=black), and other (0=not other; 1=other). White is the omitted reference category for all subsequent models. Ethnicity is coded as a dummy variable where 0=not Hispanic, 1=Hispanic. Sex is measured using the respondent's self-reported gender where 0=female, 1=male. Female is the omitted reference category for all subsequent models. Marital status was collapsed and coded as a binary measure indicating whether the respondent was married or not (0=not married, 1=married). Education is coded as a categorical variable where 1=Less than HS degree/GED, 2=HS degree/GED, and 3=Some college or higher. Less than HS degree/GED was the omitted reference category for all subsequent models. Employment is coded as 0=no job for pay, 1=job for pay. Prior criminal convictions was collapsed into a dichotomous variable using 9 separate measures of convictions (prior conviction(s) for: violent crimes, crimes against people, weapon, drug possession, drug sales, other drug, DUI/DWI, property, and prostitution, public order, or vagrancy). If the respondent answered yes to any of the convictions noted above, they were coded as 1 and if the respondent answered no to the above measures, they were coded as 0.[2] Prior incarceration was originally a continuous variable measured by the number of times the participant had previously been incarcerated. This measure was collapsed into a dichotomous variable where 0=no prior incarceration and 1=at least 1 prior incarceration. Prior arrests is used as a continuous measure, ranging from 0 arrests to 67 arrests. Table 1 provides summary statistics for the variables of interest for the full analytic sample as well as drug court and comparison court subsamples.

Most of the sample consisted of white, non-Hispanic, men in their thirties who would be classified as "medium risk" because their average ASI scores were about 9.32 (*SD* = 3.53). Nearly 75% of the sample reported some type of recidivism. Most of the sample did not have a job for pay and they were not married. Additionally, they have at least 1 prior criminal conviction, at least 1 prior incarceration, and an average of 10.42 prior arrests (*SD* = 11.85). About 56% of the full sample reports a history of some drug/alcohol treatment. Additionally, about 40% of the entire sample was diagnosed as having both clinical depression and ASPD, while about 50% were considered narcissistic.

[2] Nine convictions were incorporated into the convictions measure. These nine were chosen because they were the only measures present in the dataset.

Table 1: Descriptive Statistics

	Full Sample		Drug Court		Comparison Court	
Variable	Percentage	(*n*)	Percentage	(*n*)	Percentage	(*n*)
Recidivism (1=yes)	73.17	(1,121)	70.75	(716)	77.88	(405)
Addiction Severity Index (M;*SD*)	9.32	(3.53)	9.64	(3.43)	8.70	(3.65)
Age: In Years (M;*SD*)	34.07	(10.50)	33.17	(10.46)	35.80	(10.36)
Race/Ethnicity						
White	55.03	(843)	57.31	(580)	50.58	(263)
Black	32.57	(499)	28.06	(284)	41.35	(215)
Other	6.33	(97)	7.41	(75)	4.23	(22)
Hispanic	6.07	(93)	7.21	(73)	3.85	(20)
Sex						
Male	69.52	(1,065)	68.18	(690)	72.12	(375)
Female	30.48	(467)	31.82	(322)	27.88	(145)
Drug Court Participation						
Drug Court	66.06	(1,012)	66.06	(1,012)	—	—
Comparison Court	33.94	(520)	—	—	33.94	(520)
Marital Status						
Not married	89.23	(1,367)	89.33	(904)	89.04	(463)
Married	10.77	(165)	10.67	(108)	10.96	(57)
Education						
Less than HS degree/GED	41.71	(639)	39.33	(398)	46.35	(241)
HS degree/GED	34.40	(527)	35.28	(357)	32.69	(170)
Some college or Higher	23.89	(366)	25.40	(257)	20.96	(109)
Employment (1=yes)	34.07	(522)	37.25	(377)	27.88	(145)
Alcohol/Drug Treatment (past 6 months) (1=yes)	56.92	(872)	67.69	(685)	35.96	(187)
Prior Criminal Convictions (1=yes)	72.78	(1,115)	67.69	(700)	79.81	(415)
Prior Incarceration (1=yes)	72.26	(1,107)	67.69	(685)	81.15	(422)
Prior Arrests (M;*SD*)	10.42	(11.85)	9.02	(10.47)	13.13	(13.77)
Mental Health						
Depression (1=yes)	37.99	(582)	38.74	(392)	36.54	(190)
Narcissist (1=yes)	50.91	(780)	49.80	(504)	53.08	(276)
Anti-Social Personality Disorder (1=yes)	44.58	(683)	44.96	(455)	43.85	(228)
n		*(1,532)*		*(1,012)*		*(520)*

ANALYTICAL STRATEGY

This analysis proceeds in five steps. First, bivariate relationships were examined using a correlation matrix which tests the associations between all variables of interest including recidivism, risk, and all controls (see Appendix A). Test statistics indicate that there are no issues with multicollinearity (the mean VIF = 1.23). Second, LCA was used to identify potential subgroups of offenders using the indicator variables discussed previously. Third, a logistic regression model (referred to as Model 1) was estimated which estimated the effects of risk and drug court participation on recidivism, net of a number of control variables (Hypotheses 1 and 2). Fourth, to test Hypotheses 3, 3a, and 3b, a logistic regression model (Model 2) was estimated (which again tested the effects of risk and drug court participation on recidivism), but the latent classes were included in this model as independent variables and four control variables are excluded due to inclusion in the LCA indicator variables (job for pay and all three mental health indicators – depression, narcissism, ASPD).[3] Finally, to test the interactive hypothesis (H4), the sample was split between drug court and comparison court participants and a subsequent logistic regression was estimated to examine the effects of risk and the latent classes on recidivism. All analyses were completed using STATA 14 and the latent class analysis models were estimated using the latent class analysis plugin (doLCA) version 1.2 in STATA 14 (Lanza, Dziak, Huang, Wagner, & Collins, 2015). Latent class

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[3] Logistic regression analysis automatically omits missing cases and about 12% (*n* = 249) of the cases were dropped due to missing data, permitting a final analytic sample size of *1,532*. Accordingly, a sample variable was generated and chi-square tests were run to ensure that no significant differences exist between the analytic sample and missing cases. Results of these tests confirm that there is nothing inherently different between the analytic sample and the cases that were dropped due to missing data.

analysis, the model selection process, and the characteristics of each group are described in detail prior to the discussion of the results of the logistic regression models.

Latent Class Analysis

LCA is used to develop typologies and clusters across individuals. There must be an unobserved categorical variable that separates the population into subgroups. Membership in these latent classes is defined by the patterns of responses to the set of indicator variables. "Latent class analysis enables the researcher to identify a set of mutually exclusive latent classes that account for the distribution of cases that occur within a crosstabulation of observed discrete variables" (McCutcheon, 1987: 8).

When selecting the model that best fits the data, there are important parameters and goodness-of-fit statistics to consider: latent class probabilities, conditional probabilities, average posterior probabilities (or AvePPs), Bayesian Information Criterion (BIC), and the class-average ratio (CAR; Yan, *in press*). The latent class probabilities indicate the size of each class with which one can tell if all of the classes are evenly distributed or if individuals are concentrated in certain classes. Conditional probabilities indicate the probability of observing each category in each of the indicator variables, conditional on a given class. Put simply, these probabilities indicate the characteristics of each class. The posterior probability is the probability (at the individual level) that one belongs to each class. By definition, the posterior probability for each class must sum to 1. The average posterior probability is the average of each individual's class membership. Tahamont et al. (2015: 440) suggest, "the rule of thumb is that for a model to be considered adequate, the AvePPs in *all groups* should be higher than 0.70." The BIC statistic is used as a method in determining the model's goodness of fit. . In general, the lower the BIC, the better the fit of the model; although realistically the lowest BIC may not be the best fit for the data (Nagin, 2005). CAR values indicates the relative rather than the absolute prevalence of class membership, unique to each LCA variable. For example, if one has a CAR value of 2 for the "heavy drug use" variable, this indicates that they are 2 times more likely than the average person in the sample to use heavy drugs (Yan, *in press*). All of these criterion should be considered together in order to determine the model that best fits the data.

Table 2: Model Selection Statistics for the Four- to Eight-Group Models

	Total Number of Groups				
Model	4	5	6	7	8
BIC	2193.11	1817.37	1572.42	1497.17	1473.03
Adjusted BIC	2031.09	1614.05	1327.80	1211.25	1145.81
AvePP					
Group 1	0.99	0.97	0.99	0.93	0.88
Group 2	0.95	0.85	0.88	0.82	0.86
Group 3	0.99	0.99	0.83	0.86	0.85
Group 4	0.97	0.95	0.86	0.83	0.83
Group 5	–	0.85	0.94	0.85	0.87
Group 6	–	–	0.80	0.88	0.86
Group 7	–	–	–	0.87	0.88
Group 8	–	–	–	–	0.79

Table 2 provides a description of the relevant model selection statistics for the four- to eight-group models. Taken together, the 6-group model seemed to fit the data the best. Although it does not have the lowest BIC, the AvePP's do meet the requirement suggested by Tahamont et al. (2015) of values greater than 0.70, and after further examination of the individual group characteristics, the 6-group model provides the most consistent and most meaningful description of the data. The 6-group model will be used for further analyses, but first, the individual groups will be described.

RESULTS

Table 3 provides the descriptive statistics for each latent class group as it relates to each variable. Table 4 reports the conditional probabilities *and* the CARs for each group with respect to each LCA indicator variable.[4] These two tables, taken together, provide insight into the qualitative differences between the groups.

Group 1

Group 1 is, for the purposes of this study, considered to be the least serious in terms of drug use, prior victimization, and mental health indicators. Individuals belonging to this group report that they do not use drugs and they are not victims of recent abuse. Accordingly, this group has the lowest recidivism within the study recent (64.96%) and the lowest average ASI score ($\bar{x}$ = 6.27). They are also, on average, the oldest ($\bar{x}$ = 36 years). They have the highest percentage of females among all other groups (34.62%). They also have the highest percentage of individuals in the comparison court. This group serves as the omitted reference category in the subsequent multivariate regressions.

[4] Following Yan's (*in press)* method for selecting "cutoff values", any conditional probability that is greater than 0.90 or less than 0.10 is marked, while any CAR value greater than 2 or lower than 0.5 is marked. A conditional probability greater than 0.90 indicates that 90% (or more) of the individuals classified in the respective group reported "yes" to the indicator variable; a conditional probability less than 0.10 indicates that 10% (or less) of the individuals classified in the respective group reported "no" to the indicator variable. A CAR value greater than 2 indicates that the individual is twice as likely (or more) to answer "yes" to the indicator variable in comparison to the prevalence of the sample; whereas a CAR value less than 0.5 indicates that the individual is less likely to answer "yes" to the indicator variable in comparison to the prevalence of the sample.

Table 3: Descriptive Statistics of the Latent Classes

	Group 1		Group 2		Group 3		Group 4		Group 5		Group 6	
Variable	Percentage	(*n*)	Percentage	(*n*)	Percentage	(*n*)	Percentage	(*n*)	Percentage	(*n*)	Percentage	(*n*)
Recidivism (1=yes)	64.96	(152)	68.13	(124)	70.83	(187)	76.97	(117)	73.37	(303)	82.93	(238)
Addiction Severity Index (M;SD)	6.27	(3.13)	7.83	(3.18)	9.89	(3.05)	11.34	(2.91)	9.61	(3.17)	10.76	(3.36)
Age: In Years (M;SD)	36.00	(10.57)	34.21	(10.69)	35.59	(10.11)	32.70	(10.19)	34.60	(10.84)	30.95	(9.62)
Race/Ethnicity												
White	44.87	(105)	63.19	(115)	49.62	(131)	55.92	(85)	54.72	(226)	63.07	(181)
Black	43.59	(102)	21.43	(39)	35.61	(94)	29.61	(45)	34.14	(141)	27.18	(78)
Other	5.98	(14)	4.95	(9)	7.20	(19)	7.89	(12)	6.30	(26)	5.92	(17)
Hispanic	5.56	(13)	10.44	(19)	7.58	(20)	6.58	(10)	4.84	(20)	3.83	(11)
Sex												
Male	65.38	(153)	70.88	(129)	65.53	(173)	67.11	(102)	73.61	(304)	71.08	(204)
Female	34.62	(81)	29.12	(53)	34.47	(91)	32.89	(50)	26.39	(109)	28.92	(83)
Drug Court Participation												
Drug Court	53.42	(125)	67.03	(122)	67.8	(179)	63.82	(97)	74.82	(309)	62.72	(180)
Comparison Court	46.58	(109)	32.97	(60)	32.20	(85)	36.18	(55)	25.18	(104)	37.28	(107)
Marital Status												
Not married	85.90	(201)	84.07	(153)	86.36	(228)	96.71	(147)	90.07	(372)	92.68	(266)
Married	14.10	(33)	15.93	(29)	13.64	(36)	3.29	(5)	9.93	(41)	7.32	(21)
Education												
Less than HS degree/GED	47.44	(111)	27.47	(50)	42.05	(111)	46.05	(70)	39.71	(164)	46.34	(133)
HS degree/GED	35.04	(82)	36.81	(67)	33.33	(88)	28.29	(43)	36.56	(151)	33.45	(96)
Some college or Higher	17.52	(41)	35.71	(65)	24.62	(65)	25.66	(39)	23.73	(98)	20.21	(58)
Alcohol/Drug Treatment (past 6 months) (1=yes)	56.84	(133)	65.38	(119)	56.44	(149)	57.24	(87)	54.72	(226)	55.05	(158)
Prior Criminal Convictions (1=yes)	76.07	(178)	63.19	(115)	75.76	(200)	78.95	(120)	69.25	(286)	75.76	(216)
Prior Incarceration (1=yes)	74.36	(174)	60.44	(110)	71.59	(189)	83.55	(127)	69.01	(285)	77.35	(222)
Prior Arrests (M;SD)	13.82	(14.45)	8.08	(11.45)	12.66	(12.50)	14.01	(13.93)	8.03	(9.59)	8.58	(9.19)
n		*234*		*182*		*264*		*152*		*413*		*287*

Table 4: Conditional probabilites (CPs) and Class-average ratios (CARs) of the LCA Model

	Group 1		Group 2		Group 3		Group 4		Group 5		Group 6	
Variable	CPs	CARs	CPs	CARs	CPs	CARs	CPs	CARs	CPs	CARs	CPs	CARs
Heavy drug use	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	2.32	1.00	2.32
Moderate drug use	0.00	0.00	0.00	0.00	1.00	3.56	1.00	3.56	0.00	0.00	0.00	0.00
Light drug use	0.00	0.00	1.00	7.99	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
No drug use	1.00	6.13	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Depression	0.27	0.72	0.29	0.77	0.31	0.82	0.48	1.27	0.36	0.96	0.56	1.46
Narcissism	0.42	0.85	0.38	0.78	0.41	0.83	0.58	1.19	0.48	0.98	0.66	1.35
ASPD	0.31	0.72	0.35	0.81	0.33	0.78	0.59	1.38	0.40	0.94	0.61	1.43
Physical abuse	0.21	0.69	0.24	0.79	0.00	0.00	0.79	2.58	0.00	0.00	0.81	2.64
Sexual abuse	0.07	0.77	0.05	0.54	0.00	0.00	0.29	3.20	0.00	0.00	0.22	2.42
Any prior abuse	0.31	0.75	0.37	0.87	0.01	0.04	1.00	2.39	0.08	0.18	1.00	2.39
Employment problems	0.52	0.98	0.72	1.37	0.54	1.03	0.37	0.70	0.57	1.08	0.43	0.82
Housing instability	0.12	0.81	0.06	0.38	0.16	1.05	0.28	1.90	0.14	0.95	0.16	1.07
Pr(Class)		*15.27%*		*11.88%*		*17.23%*		*9.92%*		*26.96%*		*18.73%*

Group 2

Group 2 reported light drug use and no recent sexual abuse. They are also less likely than the average person in the sample to have housing instability issues. Individuals in this group have a low average ASI score ($\bar{x}$ = 7.84) and the average age is 34.21. This group has the largest proportion of Whites, the lowest proportion of Blacks, and most are male (70.88%). This group has the highest percentage of individuals with some level of college education or higher (35.71). They also have the highest percentage of individuals who have completed some type of drug/alcohol treatment (65.38%). They have the lowest level of prior criminal convictions, incarceration, and one of the lowest average number of prior arrests ($\bar{x}$ = 8.08).

Group 3

Individuals in group 3 report moderate drug use, but no recent victimization. They closely resemble the entire sample in terms of percentage who recidivated (70.83%), average ASI score ($\bar{x}$ = 9.89), average age ($\bar{x}$ = 35.59), racial/ethnic composition, sex (65.53% male), drug court participation (67.80% in drug court, 32.20% in comparison court), marital status (86.36% not married), education level (most have less than a HS degree/GED – 42.05%), history of treatment (56.44% had some treatment), prior criminal convictions (75.76% had at least 1 prior criminal conviction), prior incarceration (71.59% had at least 1 prior incarceration), and average number of prior arrests ($\bar{x}$ = 12.66).

Group 4

Individuals in group 4 report moderate drug use, 100% reported some type of recent abuse, and nearly 80% reported recent physical abuse. Group 4 members are over 2.5 times more likely to report recent physical abuse than the average person in the sample, over 3 times more likely to report recent sexual abuse than the average person in the sample, and over 2 times more likely to report any recent abuse than the average person in the sample. In terms of mental health indicators, this group has the second highest percentages of individuals suffering from depression (48%), narcissism (58%), and ASPD (59%). This group also has the second highest percentage of recidivists (76.97%) and is one of the youngest groups ($\bar{x}$ = 32.7). Individuals in this group have the highest average ASI score ($\bar{x}$ = 11.34). Individuals comprising this group have the highest percentage of prior criminal convictions (78.95%), the highest percentage of prior incarcerations (83.55%), and the highest average number of prior arrests ($\bar{x}$ = 14). In sum, Group 4 members share characteristics that tend to predict recidivism in general offending populations (e.g., more extensive criminal history) but simultaneously also exhibit many characteristics commonly prevalent in the literature on pathways to offending (e.g., victimization; Reisig et al., 2006).

Group 5

The biggest proportion of the sample belongs to this group (26.96%) who reports heavy drug use but no recent victimization. Nearly 75% of individuals in this group recidivated and the average ASI score is 9.61 (considered “moderate risk” on the actual ASI assessment). Over half of the sample in this group is White (54.72%). This group has the highest proportion of males and drug court participation (73.61% and 74.82%, respectively). Over 90% are not married and most of them have less than a HS degree/GED, suggesting that education may be a potential criminogenic need for them. A little over half of them have had some type of drug/alcohol treatment (54.72%) and almost 70% of them have had at least 1 prior criminal conviction and prior incarceration (69.25% and 69.01%, respectively). Interestingly enough, this group had the lowest average number of prior arrests ($\bar{x}$ = 8.03).

Group 6

Individuals in group 6, which is considered the most serious in terms of drug use, prior victimization, and mental health indicators, report heavy drug use (100%), over 80% report recent physical abuse, and 100% report some type of recent abuse. Group 6 individuals are over 2.5 times more likely than the average person in the sample to report recent physical abuse, over 2.4 times more likely than the average person in the sample to report recent sexual abuse, and over 2.3 times more likely than the average person in the sample to report any recent abuse. This group has the highest percentage of members with mental health problems as over half of individuals in this group suffer from depression (56%), narcissism (66%), and ASPD (61%). This group is characterized by the highest percentage of recidivism (nearly 83% of them did recidivate), but their average ASI score was not the highest ($\bar{x}$ = 10.76). It is worth noting that this group is considered the highest risk in the LCA model, but their average ASI score of 10.76 would classify them as “moderate risk” on the actual ASI assessment. This finding suggests the potential for underclassification on the ASI. In other words, the moderate risk suggested by ASI score also would not necessarily warrant extensive correctional programming, but the LCA results point to the importance of programming that could be used to target criminogenic needs. Additionally, individuals in this group have the youngest average age ($\bar{x}$ = 30.95). Demographically speaking, they are mostly white, males, in the drug court program with at least one prior criminal conviction and least one prior incarceration.

Model 1

Model 1 examines the effects of risk on recidivism using the ASI scale, net of all other control variables. The results of the logistic regression analyses (both Models 1 and 2) are presented in table 5. This analysis, in particular, tests the effects of drug court participation on recidivism and the results of this model offer evidence confirming both Hypotheses 1 and 2. As expected (and confirming hypothesis 1), risk is a significant, positive predictor of recidivism. More specifically, for every one unit increase on the ASI scale, the odds of recidivating increase by 5%. Age, race, and sex were all significant predictors of recidivism. Age was negatively associated with recidivism, meaning that as age increases, the odds of recidivating decrease; this finding is consistent with decades of research in life-course criminology. Being male (compared to female) increases one's odds of recidivating by 45% and being Black (compared to White) increases one's odds of recidivating by nearly 75%. It is possible that these results are a reflection of disparate treatment at other points of the criminal justice system (e.g., the decision to arrest or the decision to prosecute). Additionally, drug court participation was approaching significance ($p<0.10$) and in the expected direction (offering partial support for Hypothesis 2), meaning that offenders in the drug court program were less likely to recidivate than offenders in the comparison court, but this results was not significant at the stringent level of $p<0.05$. Prior arrests was a significant predictor of recidivism ($p<0.01$). The only significant mental health indicator was depression; for every one-unit increase in depression, the odds of the likelihood of recidivism increase by about 35%.

Table 5: Logistic Regression Models Estimating the Effects of Risk and Drug Court Participation on Recidivism

	Model 1			Model 2		
Variable	Coefficient	Odds Ratio	(SE)	Coefficient	Odds Ratio	(SE)
Addiction Severity Index Scale	0.04**	1.05**	(0.02)	0.02	1.02	(0.02)
Age	- 0.05***	0.95***	(0.01)	- 0.04***	0.96***	(0.01)
Race/Ethnicity						
Black	0.55***	1.74***	(0.15)	0.55***	1.74***	(0.15)
Other	0.33	1.39	(0.27)	0.35	1.42	(0.27)
Hispanic (1=yes)	- 0.05	0.95	(0.25)	- 0.01	0.99	(0.25)
Male (1=yes)	0.37***	1.45***	(0.14)	0.31**	1.36**	(0.13)
Drug Court Participation (1=yes)	- 0.24†	0.79†	(0.14)	- 0.24	0.79	(0.15)
Married (1=yes)	- 0.10	0.91	(0.19)	- 0.06	0.94	(0.19)
Education						
HS degree/GED	0.23	1.25	(0.15)	0.22	1.24	(0.15)
Some college or Higher	- 0.04	0.97	(0.16)	- 0.04	0.96	(0.16)
Employment (1=yes)	0.16	1.17	(0.14)	—	—	—
Alcohol/Drug Treatment (past 6 months) (1=yes)	- 0.24	0.79	(0.14)	- 0.20	0.82	(0.14)
Prior Criminal Convictions (1=yes)	0.18	1.19	(0.16)	0.21	1.23	(0.16)
Prior Incarceration (1=yes)	0.12	1.13	(0.16)	0.09	1.09	(0.16)
Prior Arrests (1=yes)	0.05***	1.05***	(0.01)	0.05***	1.06***	(0.01)
Group 2	—	—	—	0.55**	1.74**	(0.23)
Group 3	—	—	—	0.36	1.43	(0.22)
Group 4	—	—	—	0.52	1.68	(0.28)
Group 5	—	—	—	0.67***	1.96***	(0.21)
Group 6	—	—	—	1.04***	2.84***	(0.24)
Mental Health						
Depression (1=yes)	0.29**	1.34**	(0.14)	—	—	—
Narcissism (1=yes)	0.14	1.15	(0.13)	—	—	—
Anti-Social Personality Disorder (1=yes)	- 0.01	0.91	(0.14)	—	—	—
Constant	1.16***	3.18***	(0.32)	0.99***	2.68***	(0.33)
Psuedo R^2			0.0966			0.1043
n			*1,532*			*1,532*

Note: Reference categories are as follows: White, less than HS/GED, Group 1
*** p<0.01, ** p<0.05, † p<0.10

Model 2

Model 2 estimates the same logistic regression model, but adds the latent classes in addition to the ASI scale, drug court participation, and all other relevant control variables. Confirming Hypothesis 3, latent class membership is a significant predictor of recidivism. More specifically, individuals in groups 2, 5, and 6 all have significantly greater odds of recidivism than members of group 1.[5]

Supplementary Analyses

Given that the previous findings suggest that neither risk nor drug court participation are significant predictors of recidivism once group membership is accounted for, it is necessary to examine whether the groups have differential effects in drug courts and comparison courts, respectively (Hypothesis 4). This is akin to determining whether drug court participation interacts with group membership. Toward this end, table 6 reports the findings from a set of logistic regressions estimating the effects of LCA group membership (relative to group 1) on recidivism among drug court participants and comparison court participants. Initially, a reduced model (not shown) testing the effects of risk (using the ASI) on recidivism in each of these court contexts was also estimated. This analysis revealed that risk was a significant predictor of recidivism in the drug court sample ($p<0.05$) and was approaching significance in the

[5] Given that the dependent variable combines three separate measures of recidivism (official re-arrest, self-report, and results from oral swab tests), it is necessary to split the dependent variable up to estimate the effects of key independent variables on all individual dependent variables. Model 1 was run (using each recidivism measure independently) and the ASI (primary independent variable) was only significant in the model using the self-reported recidivism measure as the dependent variable. Model 2 was run (using each recidivism measure independently) and the latent classes remained significant, while the ASI was significant in the model using the self-reported recidivism measure as the dependent variable.

comparison court sample ($p<0.10$). Additionally, Paternoster et al.'s (1998) equality of regression coefficients statistical test revealed that there are no significant differences between the latent class groups across either sample, although latent class membership is still considered a significant predictor of recidivism across both samples.

Turning to the main question of interest regarding Hypothesis 4, the results, at first glance, show that latent class membership is a significant predictor of recidivism, but the effects of group membership (relative to the omitted group 1) *do not* depend on court status. Consequently, no support is found for Hypothesis 4. Across both court settings, the likelihood of recidivism continues to decrease significantly with age, consistent with life-course criminology, and number of prior arrests also has a positive and significant effect on recidivism; both of these effects were also found in the full sample analyses, suggesting neither interacts with court context. Note, however, that the effects of being black and being male that were reported in the full sample analyses are restricted only to the drug court setting. This speaks to the importance of subsample analyses or other means of examining interactive effects that may not otherwise be easily observable. In the section that follows, the implications of the findings for theory, future research, and policy are discussed.

Table 6: Logistic Regression Model Estimating the Effects of Risk on Recidivism by Drug Court Participation

	Model 3						
	Drug Court Sample			Comparison Court Sample			
Variable	Coefficient	Odds Ratio	(SE)	Coefficient	Odds Ratio	(SE)	*z* test
Group 2	0.41	1.51	(0.29)	0.89**	2.44**	(0.43)	0.93
Group 3	0.46	1.59	(0.29)	- 0.02	0.98	(0.38)	1.00
Group 4	0.79**	2.20**	(0.36)	- 0.09	0.92	(0.45)	1.53
Group 5	0.68**	1.98**	(0.27)	0.56	1.75	(0.36)	0.27
Group 6	0.90***	2.46***	(0.32)	1.24***	3.46***	(0.42)	- 0.64
Addiction Severity Index Scale	0.01	1.01	(0.03)	0.05	1.05	(0.04)	–
Age	- 0.04***	0.96***	(0.01)	- 0.05***	0.95***	(0.01)	–
Race/Ethnicity							
Black	0.64***	1.89***	(0.19)	0.39	1.48	(0.27)	–
Other	0.52	1.69	(0.31)	- 0.32	0.73	(0.57)	–
Hispanic (1=yes)	0.03	1.03	(0.28)	- 0.06	0.94	(0.61)	–
Male (1=yes)	0.34**	1.40**	(0.16)	0.34	1.41	(0.25)	–
Married (1=yes)	0.13	1.13	(0.24)	- 0.44	0.64	(0.33)	–
Education							
HS degree/GED	0.12	1.13	(0.18)	0.48	1.61	(0.27)	–
Some college or higher	- 0.10	0.90	(0.19)	0.12	1.12	(0.30)	–
Alcohol/Drug Treatment (past 6 months) (1=yes)	- 0.27	0.77	(0.17)	0.01	1.01	(0.26)	–
Prior Criminal Convictions (1=yes)	0.19	1.21	(0.19)	0.14	1.15	(0.31)	–
Prior Incarceration (1=yes)	0.11	1.12	(0.19)	0.07	1.07	(0.33)	–
Prior Arrests (1=yes)	0.07***	1.07***	(0.01)	0.04***	1.05***	(0.01)	–
Constant	0.72	2.05	(0.40)	1.05	2.86	(0.56)	
Psuedo R^2			0.1112			0.1107	
n			*1,012*			*520*	

Note: Reference categories are as follows: Group 1, White, less than HS/GED.

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

DISCUSSION

Drug courts are known to be effective in reducing recidivism and subsequent drug use, but less is known about whether drug court participation exerts similar effects across all groups of offenders. This study used a context-specific risk assessment instrument (the ASI) to examine the relationship between risk—conceptualized as a host of substance abuse problems—and the effect of drug court participation on recidivism, statistically created subgroups of offenders according to risks and needs not captured by the ASI, and examined the effect of group membership on recidivism. Findings for age and criminal history are consistent with prior research with age being a significant negative predictor of recidivism and criminal history being a significant positive predictor of recidivism. Risk assessment, in the initial model, has intended effects; however, risk becomes non-significant when theoretically relevant clusters of risk and need (as measured by latent class membership) are considered. Implications for theory, future research, and policy are discussed below.

The results of the current study suggest that there are clearly some issues with relying on risk alone to predict recidivism and also to assign offenders to programming and services. Generally speaking, risk predicts recidivism, but once the LCA groups were introduced in to the models, group membership becomes more important than risk or drug court participation. The fact that drug court participation initially reduces recidivism (approaching significance at $p<0.10$) suggests that it works, at least initially, as intended. Although it should be noted that we do not have any direct measures of the five dimensions included in Longshore et al.'s (2001) conceptual framework; as such, any claims about the effectiveness of drug court participation would be crude at best.

From the results, though, it is apparent that there are some other factors – potentially reflecting criminogenic needs – that are not being picked up by the ASI; these point to important subgroup differences that should be considered. Actuarial risk assessment instruments, many of which are driven by social learning theory, need to better measure risk factors and criminogenic needs known to influence offending. Additionally, the findings of the present study lend some support to strain theory (Agnew, 1992, 2006). The prevalence of the mental health variables was the highest for the two groups who reported high substance use and high recent victimization. These groups, more specifically, were exposed to a strain (victimization) which produces negative emotions like depression, and pressure for coercive action, which is clearly taking the place of maladaptive coping in the form of drug use, and criminal coping in the form of persistent offending. This finding is consistent with prior literature suggesting that strain is an important theory to consider, more generally, but especially when dealing with substance-abusing populations and when attempting to identify treatment strategies (Golladay & Holtfreter, 2017; Holtfreter, Reisig, & O'Neal, 2015; Reisig, Holtfreter, & Turanovic, 2018).

There are a few limitations worth noting as well as suggestions for future research to consider. This study relied on secondary data from a study that was not designed to test the questions of interest examined here. While the results are generally consistent with prior research, it is possible that the potential unmeasured variables not included by the original researchers (e.g., peer effects) might also influence recidivism; future research on this topic should consider a broader set of theoretical perspectives and/or variables. Also, we cannot say whether results generalize beyond substance abusing populations. The research on pathways to crime identifies a diverse set of trajectories that offenders take to court; a study in a more general offending context might similarly reveal more variation in classes. The secondary data used here relied on the ASI to measure risk; it may be worth considering using the present analytical strategy on datasets with information on other actuarial risk assessment instruments (LSI-R, COMPAS, YLS/CMI, etc.). There is a substantial amount of literature attesting to the validity and reliability of actuarial risk assessment instruments (Andrews, Bonta, & Wormith, 2006; Bonta, 2002; Clarke, Peterson-Badali, & Skilling, 2016; Desmarais & Singh, 2013; Gendreau, Little, & Goggin, 1996; Guastaferro, 2012; Koetzle et al., 2015; Myer & Buchholz, 2016; Pusch & Holtfreter, 2018; Simourd, 2004; Thanner & Taxman, 2003), but the unique analytical approach taken here could reveal different findings. Finally, future research should consider the gendered-context of offending. Feminist criminologists have confirmed that there are gender-specific pathways to crime (Belknap & Holsinger, 2006; Brennan et al., 2012; Holtfreter & Morash, 2003; Reisig, Holtfreter, & Morash, 2006); considering these gendered differences may aid in developing programs and services tailored to an individual's specific set of risks and needs (Holtfreter & Wattanaporn, 2014; Wattanaporn & Holtfreter, 2014).

Drug courts should not abandon the use of the ASI (and actuarial risk assessment instruments, more generally), but the results indicate that it should be supplemented in a way that accounts for other offender risks and needs that are not being captured by this measure of risk. For example, taking a comprehensive history of offenders' victimization and experiences and mental illness can help the courts identify untreated needs that could be addressed through programming, such as counseling, in addition to the drug court itself. The effect of race should be carefully considered. Race was a significant, positive predictor of recidivism in all models, with the exception of the comparison court subsample. Close attention should be paid to how court officers treat all offenders—especially those who historically have been mistreated and/or overrepresented in the criminal justice system—to determine whether biases are present and unnecessary social control is being used on different types of offenders.

CONCLUSION

In the end, the current study represents a preliminary attempt to move beyond actuarial risk assessment in understanding the complex sets of offender risks and needs that contribute to recidivism. As drug courts continue to expand and receive an increasing amount of research attention, it is imperative that the issues presented here are considered and, quite frankly, addressed. Many have viewed the expansion of drug courts, and specialized courts more generally, as a way to reduce incarceration and promote rehabilitation efforts and much of the literature offers support for the use of drug courts (Belenko, 1998; Gottfredson, Najaka, & Kearley, 2003; Mitchell et al., 2012; Spohn et al., 2001; Wilson, Mitchell, & Mackenzie, 2006). However, improving the classification of offenders is essential as many drug courts reserve their resources for "high risk, high need" offenders. It has been demonstrated that considering an offender's recent victimization experiences and mental illness can add to risk assessment and help address the offender's needs through tailored programming, in turn, lending greater support for the use of drug court programs.

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APPENDIX A

CORRELATION MATRIX

Figure 1: Correlation Matrix

Variable	Y1	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13
Y1 Recidivism	1													
X1 ASI	0.01***	1												
X2 Age	-0.12***	-0.01	1											
X3 White	-0.10***	0.09***	-0.10***	1										
X4 Black	0.11***	-0.08***	0.14***	-0.77***	1									
X5 Other	0.20	0.01	0.01	-0.28***	-0.18*	1								
X6 Hispanic	-0.04	-0.05**	-0.07***	-0.28***	-0.18***	-0.07***	1							
X7 Sex	0.10*	-0.09***	-0.03	-0.04	0.07***	-0.05**	0.00	1						
X8 Drug Court Participation	-0.07***	0.15***	-0.10***	0.07***	-0.13***	0.05**	0.05**	-0.04	1					
X9 Marital	-0.07***	-0.05	0.15***	0.04	-0.06**	0.04	0.056**	0.01	0.00	1				
X10 Education	-0.07***	0.00	0.14***	0.12***	-0.13***	0.05**	-0.04	0.04	0.07***	0.05	1			
X11 Employment	-0.05**	-0.17***	-0.09***	0.20***	-0.24***	-0.01	0.08***	0.16***	0.06***	0.04	0.13***	1		
X12 Alcohol/Drug Treatment	-0.08***	0.15***	-0.03	0.13***	-0.17***	0.04	0.03	-0.14***	0.29***	0.06***	0.09***	0.07***	1	
X13 Prior Conviction	0.11***	0.16***	0.19***	-0.04	0.08***	0.04	-0.12***	0.07***	-0.09***	-0.03	-0.07***	-0.10*	-0.03	1
X14 Prior Incarceration	0.15***	0.20***	0.16***	-0.10***	0.13***	0.03	-0.08***	0.06***	-0.11***	-0.07***	-0.09***	-0.19***	-0.06***	0.54***
X15 Prior Arrests	0.18***	0.13***	0.34***	-0.19***	0.18***	0.08***	-0.05	0.05	-0.17***	-0.04	-0.04	-0.20***	-0.05**	0.31***
X16 Depression	0.05	0.22***	0.00	0.06***	-0.08***	0.04	-0.01	-0.09***	0.02	-0.02	-0.04	-0.11***	-0.01	0.03
X17 Narcissism	0.10***	0.23***	-0.07***	-0.08***	0.12***	-0.02	-0.04	0.01	-0.02	-0.06**	-0.07***	-0.10***	-0.04	0.08***
X18 ASPD	0.09***	0.26***	-0.18***	0.00	-0.02	0.04	0.01	0.11***	0.01	-0.06**	-0.11***	-0.05**	-0.03	0.14***
X19 Heavy Drug Use	-0.09***	-0.24***	0.11***	-0.08***	0.06**	0.01	0.06**	-0.05**	-0.07***	0.06**	0.02	-0.09***	0.04*	0.06**
X20 Moderate Drug Use	0.01	-0.18***	-0.03	0.06**	-0.04	-0.03	-0.01	0.05**	-0.02	0.02	0.01	0.14***	0.00	-0.8***
X21 Light Drug Use	0.05**	0.15***	-0.02	-0.07***	0.09***	0.01	-0.06**	-0.1	0.00	-0.05**	-0.12***	-0.11***	-0.06**	0.05*
X22 No Drug Use	0.07***	0.40***	-0.09***	0.10***	-0.11***	0.02	-0.01	0.02	0.12***	-0.05**	0.06**	0.04**	0.00	-0.03
X23 Group 1	-0.08***	-0.37***	0.08***	-0.09***	0.10***	-0.01	-0.01	-0.04	-0.11***	0.05*	-0.07**	-0.04*	0.00	0.03
X24 Group 2	-0.04	-0.15***	0.00	0.06**	-0.09***	-0.02	0.07	0.01	0.01	0.06**	0.12***	0.10***	0.06**	-0.08***
X25 Group 3	-0.02	0.07***	0.07***	-0.05*	0.03	0.02	0.03	-0.4	0.02	0.04	0.00	-0.11***	0.00	0.03
X26 Group 4	0.03	0.19***	-0.04*	0.01	-0.02	0.02	0.01	-0.02	-0.02	-0.08***	-0.01	-0.06**	0.00	0.05
X27 Group 5	0.00	0.05*	0.03	0.00	0.02	0.00	-0.03	0.05**	0.11***	-0.02	0.01	0.10***	-0.03	-0.05
X28 Group 6	0.11***	0.20***	-0.14***	0.08***	-0.06**	-0.01	-0.05	0.02	-0.03	-0.05**	-0.05**	-0.01	-0.02	0.03

Variable	X14	X15	X16	X17	X18	X19	X20	X21	X22	X23	X24	X25	X26	X27	X28
Y1 Recidivism															
X1 ASI															
X2 Age															
X3 White															
X4 Black															
X5 Other															
X6 Hispanic															
X7 Sex															
X8 Drug Court Participation															
X9 Marital															
X10 Education															
X11 Employment															
X12 Alcohol/Drug Treatment															
X13 Prior Conviction															
X14 Prior Incarceration	1														
X15 Prior Arrests	0.37***	1													
X16 Depression	0.06**	0.04	1												
X17 Narcissism	0.09***	0.05	0.21***	1											
X18 ASPD	0.16***	0.07***	0.17***	0.24***	1										
X19 Heavy Drug Use	0.02	0.18***	-0.12***	-0.12***	-0.12***	1									
X20 Moderate Drug Use	-0.06**	-0.15***	0.00	0.02	-0.01	-0.54***	1								
X21 Light Drug Use	0.09***	0.07***	0.07***	0.08***	0.06**	-0.33***	-0.24***	1							
X22 No Drug Use	-0.04	-0.12***	0.09***	0.06**	0.11***	-0.38***	-0.28***	-0.17***	1						
X23 Group 1	0.02	0.12***	-0.09***	-0.04***	-0.09***	0.38***	0.28***	0.17***	-1	1					
X24 Group 2	-0.04*	-0.12***	-0.06**	-0.08***	-0.08***	-0.67***	0.36***	-1.00	0.17***	-0.16***	1				
X25 Group 3	-0.01	0.09***	-0.09***	-0.07***	-0.18***	0.41***	-0.75***	0.18***	0.21***	-0.19***	-0.17***	1			
X26 Group 4	0.08***	0.10***	0.08***	0.06**	0.16***	0.29***	-0.54***	0.13***	0.15***	-0.14***	-0.12***	-0.15***	1		
X27 Group 5	-0.10***	-0.07***	-0.08***	-0.08***	-0.06**	0.33***	0.24***	0.22***	0.26***	-0.26***	-0.23***	-0.27***	-0.20***	1	
X28 Group 6	0.05**	-0.07***	0.24***	0.22***	0.22***	-0.54***	0.29***	0.18***	0.21***	-0.20***	-0.18***	-0.22***	-0.15***	-0.29***	1

***p<0.01, **p<0.05, *p<0.10