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DRIVING UNDER THE INFLUENCE AND RECIDIVISM RISK: A CROSS-COUNTRY DEVELOPMENT AND COMPARISON OF DUI RISK ASSESSMENT INSTRUMENTS

A Dissertation in

Criminology

by

Lauren Kay Knoth

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The dissertation of Lauren Kay Knoth was reviewed and approved* by the following:

Barry Ruback
Professor of Criminology and Sociology
Dissertation Adviser
Chair of Committee

Eric Baumer
Head of the Department of Criminology and Sociology
Professor of Criminology and Sociology

Jeremy Staff
Director of the Graduate Program in Criminology
Professor of Criminology and Sociology

Jennifer Maggs
Professor, Human Development and Family Studies

*Signatures are on file in the Graduate School.

Abstract

Driving under the influence (DUI) of drugs or alcohol is a global problem. In the United States, arrests for DUI constitute the most common type of arrest. Internationally, impaired-drivers account for a significant portion of all motor vehicle traffic fatalities. Despite the prevalence and severity of this crime, DUI offenders are largely excluded from criminological research, which focuses on property and violent criminal behavior. The current dissertation shifts the focus of DUI research from analyzing DUI offenders as addicts to analyzing DUI offenders as criminals. By conducting studies in Pennsylvania and Finland, the current dissertation moves toward a global understanding of DUI offending and recidivism.

This dissertation expands our knowledge of DUI offenders by asking three overarching questions. First, how do DUI offenders differ from the general offending population (i.e., property and violent offenders)? Second, what factors influence the commission of DUI offenses, and are those factors different from those that influence general and DUI-specific recidivism? Third, how do these factors vary across different structural and cultural contexts?

Recent developments in recidivism research and criminal justice policies have increased the use of actuarial risk assessment instruments. However, the advancements in risk assessment instruments are largely limited to populations of offenders in the United States. Furthermore, DUI offenders are consistently excluded from the development of actuarial recidivism risk assessment instruments. This dissertation expands our understanding of risk assessments by studying a new population of offenders (DUI offenders), developing risk assessments in a new criminal justice context (Finland), and directly comparing DUI risk assessment instruments developed on similar populations in two different jurisdictions.

Much of what we know about DUI offenders comes from studies analyzing data from Departments of Motor Vehicles or on data from convenience samples in drug and alcohol treatment programs. In addition, most prior research analyzing DUI recidivism focuses solely on repeat DUI offenses. The studies in this dissertation expand upon prior research by using data from multiple criminal justice agencies to create two of the most comprehensive criminal databases of DUI offenders in the world. Using these criminal datasets, the studies in this dissertation analyze both general and DUI-specific recidivism.

The first study uses a comprehensive statewide criminal dataset of DUI offenders in Pennsylvania to analyze the general profiles of DUI offenders. This study challenges prior notions that DUI offenders can be characterized based on their use of drugs and alcohol. The results from Study 1 indicate that there are three types of DUI offenders: (1) non-criminal, one-time DUI offenders, (2) repeat DUI offenders who may have an underlying alcohol use disorder, and (3) general offenders who engage in DUI as well as other crimes.

The first study also uses existing methods to test whether risk assessment instruments based on offender, offense, and criminal history characteristics can predict the likelihood of recidivism for DUI offenders. The findings indicate that Burgess models can be used to predict the likelihood of general recidivism within an acceptable range of accuracy. However, traditional methods are less effective for developing risk assessments predicting the likelihood of DUI-specific recidivism. Due to low base rates of DUI recidivism, DUI-specific risk assessments had high rates of false positives and struggled to reach an accuracy level above 50% overall.

Given that DUI offenders already undergo assessments focused on detecting substance use disorders and identifying populations who are likely to recidivate with a repeat DUI, I propose and test alternative risk models that predict non-DUI recidivism. The findings suggest that new approaches are needed to model crime-specific recidivism for DUI offenders. The study finds that models predicting non-DUI recidivism were generally more accurate than models predicting DUI recidivism.

The second study builds upon the findings in the first study by analyzing a nationwide sample of offenders in Finland. The dataset in the second study included DUI and non-DUI offenders, allowing for a direct comparison of the characteristics of DUI and non-DUI offending populations. The findings for this study indicate that, while the general correlates of offending were similar for DUI and non-DUI offenders, there were statistically significant differences in the specific trends for nearly all categories of offender, offense, criminal history, and recidivism characteristics. For example, younger offenders were always more likely than older offenders to commit crimes. However, DUI offending declined more slowly than non-DUI offending as age increased.

The findings from the second study provided additional support for the typology proposed in the first study. However, the distribution of offenders across the three groups varied. In Finland, there were more DUI offenders with extensive criminal histories who recidivated with non-DUI offenses. In addition, there were far fewer DUI offenders with no criminal history. Finally, recidivists in Finland were less likely than recidivists in Pennsylvania to recidivate with a subsequent DUI offense.

Using Burgess methods, I constructed actuarial risk assessment instruments for DUI offenders in Finland predicting the likelihood of general and DUI-specific recidivism. Similar to the findings in the first study, the second study developed general recidivism risk assessment instruments that met a minimum threshold of overall accuracy. However, low base rates for DUI-specific recidivism made it difficult to accurately model DUI-specific recidivism.

Rather than developing an alternative scale in Finland that predicts non-DUI recidivism, the findings from the second study indicated that Finland would likely benefit from models identifying individuals who are low-risk for general recidivism and who are low-risk for DUI specific recidivism. Given these findings, I propose that Finland develop and use risk assessment instruments for DUI offenders as a method of reducing the sanctions for DUI offending.

The final study tests the generalizability of risk assessment instruments. By applying the Finnish risk assessment instrument to DUI offenders in Pennsylvania, I test whether locally developed instruments are more accurate at predicting the likelihood of recidivism. The findings indicate that risk assessments developed on non-local populations may be able to predict recidivism with an acceptable level of accuracy. However, models that are developed on local populations perform significantly better. This study supports the notion that jurisdictions should invest in the local development of custom risk assessment instruments rather than relying on general instruments developed on non-local populations.

The final study compares the general findings from the study in Pennsylvania and the study in Finland. This study reviews important structural and cultural differences as potential explanations for the convergence and divergence of findings in Pennsylvania and Finland. This comparison further explores how criminological theories could explain the behaviors of DUI offenders and emphasizes the need for replicating criminological research in diverse contexts. In addition, this study highlights how similar methods could be used to develop risk assessment instruments that achieve varying policy goals.

This dissertation lays the foundation for future research applying criminological theories to explain DUI offending and recidivism. This dissertation challenges prior approaches to studying DUI offenders as addicts by instead focusing on the criminal characteristics of DUI populations. It is not sufficient to study DUI offenders without considering their broader involvement in criminal offending. Future research should synthesize the approach of this dissertation with prior literature by simultaneously analyzing the criminal characteristics and substance use characteristics of DUI offenders.

This dissertation also challenges the norms for developing and using actuarial risk assessment instruments to predict recidivism. While traditional methods are effective for predicting general recidivism among DUI offenders, new methods may be needed to predict DUI-specific recidivism. Future research should continue to explore new methods for improving the accuracy of recidivism predictions and should consider alternative uses of specialized risk assessment instruments at sentencing. For example, in punitive jurisdictions, specialized risk assessments may be useful for identifying populations for diversionary sanctions. In contrast, in more lenient jurisdictions, specialized risk assessments may be useful for identifying high-risk populations who would benefit from greater supervision or from specialized treatment programs. Most importantly, policy makers should support additional comprehensive research of DUI offenders that could help inform policies that more effectively target criminal justice resources to reduce the prevalence of impaired driving and crime more broadly.

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Introduction

Almost all of the research on the punishment and treatment of offenders examines normal crimes and typical offenders, the sorts of stereotypical property and violent crimes that are the focus of the media and entertainment industries. Even when the research is focused on understanding the underlying relationships between mental illness, substance use disorders, and crime, crime-specific research tends to concentrate on violent offenders or drug offenders. The mismatch with reality comes from the fact that driving under the influence (DUI) [1] of drugs or alcohol accounts for more than 30 percent of all arrests in the United States.

DUI is different from these other crimes in five ways. First, DUI offenders are always intoxicated at the time of their offending. In general, substance use may be a motivator for criminal behavior or it may expose individuals to subcultures where criminal behaviors are reinforced through social interactions. Consequently, research on substance use disorder treatment and desistance from crime has produced mixed findings. In contrast, for DUI offenders, substance use disorders may have a more direct causal relationship with offending.

Second, the characteristics of DUI offenders differ from those of offenders who commit other types of crimes. DUI offenders tend to be older, to have more prosocial bonds (e.g., employment, marriage), and to have fewer arrests than offenders who commit non-DUI offenses. DUI offenders are less likely than violent or property offenders to be committed to criminal

[1] The terms driving under the influence (DUI) and driving while intoxicated (DWI) are both used to characterize driving while under the influence of alcohol or drugs. In this dissertation, DUI will primarily be used to refer to all of these terms. However, I use DWI in Chapters 3, 4, and 5 when referring to studies analyzing Finnish populations. There are varying statutory definitions of DUI offending. This dissertation refers to research in different jurisdictions which may have different definitions of DUI offending classifications. In general, these terms refer to driving when impaired by alcohol, specifically when the individual's blood alcohol content exceeds a prescribed threshold (e.g., .05% or .08%), or driving when impaired by illegal drugs.

lifestyles. Consequently, these offenders may be more amenable to punishment and treatment that facilitates desistance from crime.

Third, DUI offenders recidivate less than other offenders. In general, DUI offenders have shorter "criminal careers" than non-DUI offenders. Many DUI offenders have no prior record and do not recidivate after their first offense. Those who do recidivate are more likely to have prior involvement in other types of crime, suggesting that there are two populations of DUI offenders: general offenders for whom DUI is just one of many crimes they have committed, and individuals who commit only DUI offenses and do not engage in other criminal behaviors.

Fourth, the majority of DUI offenders are alcohol offenders, not drug offenders. Following the war on drugs and mass incarceration of drug offenders in the United States, research on substance use disorders and crime has greatly increased. However, this research has focused on drug offenders and may not be generalizable to DUI offenders. The consumption of alcohol is legal in most places and is common in social gatherings. Access to alcohol is ubiquitous and, compared to drug use, drinking alcohol is more socially acceptable. Drinking is not confined to disorganized neighborhoods or impoverished communities. Rather, alcohol use spans all demographic groups and geographic locations.

Finally, when DUI offenders are discussed in academic journals or in policy research, the emphasis is often on fatal DUI accidents. However, fatal DUI accidents account for a very small portion of all DUI offenses. In addition, research finds that most fatal DUI accidents involve first-time DUI offenders, not repeat offenders. Still, discussions of DUI offenders tend to be centered on threats to public safety and the need to increase the severity of punishment.

Driving under the influence is a serious criminal and public health issue in nearly all countries. The World Health Organization (2007) estimates that around 20% of all drivers fatally injured in traffic accidents in high-income countries have a blood alcohol concentration beyond the legal limit. In low- and middle-income countries as many as 69% of drivers fatally injured in traffic accidents have a blood alcohol concentration beyond the legal limit. Even if a fatal accident does not occur, there is still a risk of serious injury or property damage from non-fatal accidents.

Arrests for DUI constitute the most common type of arrest in the United States (Snyder, 2012). Alcohol-impaired-driving crashes account for nearly 31% of all motor vehicle traffic fatalities annually (NHTSA, 2013). In some states, up to 14% of licensed drivers have a DUI conviction (Ross, 1992). Despite the prevalence and severity of this crime, DUI offenders are largely excluded from research that develops or tests criminological theories. Instead, most studies on DUI offenders focus on addiction, biological identifiers of impairment, and the effectiveness of treatment programs, and they are published in medical and psychological journals (see DeJong and Hingson, 1998; Nochajski and Stasiewicz 2006; Maenhout et al, 2014). This absence of research on DUI by criminologists means that we know very little about the correlates of DUI offending and how criminal justice systems ought to respond to these offenders.

The need for understanding DUI offenses spans policy concerns across society. Criminal justice organizations have an inherent interest in promoting road safety and effectively using resources to enforce the law. Medical professionals, community organizations, and rehabilitation organizations benefit from using research on DUI offenders to inform the development of effective treatment and education programs. Businesses involved in the sale of alcohol have an economic and social incentive to understand the risks of driving under the influence in order to avoid risky drinking behaviors that may result in regulations of alcohol sales. Insurance companies have a financial incentive to promote programs that can reduce the likelihood of accidents. Despite the importance of these policy issues, however, current research offers little explanation of DUI offending and the appropriate societal response.

Moreover, there is limited understanding of recidivism patterns for DUI offenders, which differ from the general offending population. Nationally, only one-third of DUI offenders recidivate (Fell, 1995) whereas two-thirds of the general offending population recidivate (Langan and Levin, 2002). Despite fears that repeat DUI offenders pose a larger threat to public safety, only 8% of alcohol related fatal accidents in the United States involve drivers with a prior DUI record (Jones and Lacey, 2000). The National Highway Traffic Safety Administration (NHTSA) called for research capable of identifying offenders who have a high risk of being a repeat DUI offender (Jones and Lacey, 2000). Such risk assessments are one tool that can help achieve the goals outlined by NHTSA and help courts target high-risk offenders without unnecessarily increasing sanctions for all DUI offenders.

This dissertation is concerned with analyzing DUI offenders to better understand this unique population. Determining whether or not current literature applies to DUI offenders necessitates an understanding of how characteristics of DUI offenders differ from non-DUI offenders, how courts process DUI offenders compared to non-DUI offenders, and how patterns of offending among DUI offenders differ from non-DUI offenders.

This dissertation expands our knowledge of DUI offenders by asking three important questions. First, how do DUI offenders differ from the general offending population (i.e., property and violent offenders)? Second, what factors influence the commission of DUI offenses, and are those factors different from those that influence general and DUI-specific recidivism? Third, how do these factors vary across different geographic and cultural contexts?

This dissertation also expands our knowledge of risk assessments by studying a new population of offenders, developing risk assessments in a new criminal justice context, and comparing risk assessments for similar populations in two different national contexts. Answering the call for an increase in comparative criminology, this dissertation greatly contributes to our theoretical and methodological understanding of sentencing risk assessment instruments while contributing to the development of ethically responsible public policies.

This dissertation includes two separate studies that are synthesized in a final chapter to provide a cross-national comparison of sentencing risk assessments for DUI offenders. Chapter 1 reviews the current literature on DUI offending, recidivism, and risk assessments generally. Most of this research focuses on populations of DUI offenders in the United States. Chapter 2 uses a statewide dataset of offenders in Pennsylvania to develop a sentencing risk assessment instrument for DUI offenders. Chapter 2 also examines the current methods for predicting general and specific types of recidivism while proposing alternative approaches for DUI offenders. Chapter 3 discusses the benefits of international criminology and reviews the current literature on DUI offending and recidivism in Finland. Chapter 4 uses a nationwide register-based dataset to develop a sentencing risk assessment instrument for DUI offenders in Finland. The fourth chapter also provides a comparison between DUI and non-DUI offenders to identify similarities and differences in offender- and offense-based characteristics of these two populations. Chapter 5 applies the Finnish risk scale to the sample of DUI offenders in Pennsylvania in order to assess the need for locally-developed risk assessment instruments. Chapter 5 also discusses the similarities and differences between the DUI offenders and recidivism in Finland and Pennsylvania.

Each study in this dissertation was conducted independently and restrictions on data limited my ability to directly compare samples in multivariate analyses. IRB approval was obtained through the Pennsylvania State University for each study, and additional approvals were obtained through the University of Helsinki for research conducted using Finnish data and the Pennsylvania Commission on Sentencing for research conducted in Pennsylvania.

Chapter 1 : DUI Offending, Recidivism, and Risk Assessments, A Review of the Literature

This introduction provides a general review of the current literature on drinking norms and the associations between alcohol and crime and explains the need for the research conducted in this dissertation. In addition, this introduction reviews the relevant literature on the correlates of DUI offending and recidivism among DUI offenders in the United States. Finally, this introduction reviews current literature concerning the development and validation of sentencing risk assessments and the need for DUI specific risk assessment instruments.

Drinking Norms

Theories explaining drinking behaviors across different populations can be helpful for understanding factors related to DUI rates and recidivism. Higher rates of alcohol consumption may create increased opportunities for DUI offenses to occur. Additionally, identifying motivations to consume alcohol are necessary for understanding the behavior that necessarily precedes DUI offenses. Finally, understanding how societies view the consumption of alcohol may also inform how societies view alcohol-related problem behaviors.

Attitudes and behaviors are often influenced by broad social norms, the formal and informal rules and social expectations that govern behavior (see Gibbs, 1965). For example, laws (e.g., it is illegal to drink under the age of 21) are one type of norm that informs general expectations of behavior. Alternatively, mores (see Sumner, 1940/1906) constitute informal social structures that shape expectations of behavior of members of a community (e.g., one should not drink in excess). Typically, mores are broad claims of morality or of right and wrong and are not necessarily associated with formal punishment.

Even though it is legal to drink once an individual is past a societally-established threshold age, there are still formal and informal norms that structure expectations of alcohol consumption and the subsequent behaviors of individuals who do drink. Laws restrict particular drinking behaviors such as drinking and driving, public intoxication, and sales of alcohol without a proper license. Although not illegal, communities or groups of individuals often develop their own norms regarding the use of alcohol. These norms range from strict prohibition to nearly unconditional acceptance. Research on alcohol use and alcoholism has focused on how these norms guide the behaviors of individuals and result in different patterns of drinking behaviors between and within communities.

For example, Bales (1946) developed a general aggregate level theory of alcoholism as a response to stress. This stress hypothesis, based on studies in Ireland, posits that rates of alcoholism are directly related to the degree to which individuals are exposed to significant societal stress and tension. A study of drinkers in the United States found support for the stress hypothesis and operationalized socially derived stress as a combination of stressful life events that require adaptation, such as divorce, the death of a child, unemployment, or moving to a new community (Linsky et al., 1985). Levels of social stress were found to be positively related to levels of alcohol consumption, the death rate for cirrhosis of the liver (a common condition among heavy drinkers), and the death rate due to alcoholism. These findings were consistent for both men and women.

In addition to the stress hypothesis, Bales' (1946) theory posited that culturally supported attitudes about alcohol and intoxication affect whether alcohol is used to relieve societal stress (the "normative hypothesis"). Thus, societal stress does not always lead to alcohol consumption, but rather, is dependent upon cultural norms. Relatedly, Bales hypothesized that alcohol abuse would be lower in cultures that provide alternative methods to relieve tension or stress. However, Bales' theory was criticized for not specifying the characteristics of a normative system that would result in high rates of alcoholism (Room, 1976).

Bales' hypotheses have been refined and tested to determine the overall relationship between alcohol norms and alcohol-behaviors, although the findings of these studies are mixed. To better understand how different alcohol norms relate to alcoholism, Larsen and Abu-Laban (1968) identified three normative structures that were then used to test Bales' normative hypothesis. Expanding on Bales' theory, the authors isolated four types of normative structures: proscriptive, prescriptive, nonscriptive, and ambivalent. Proscriptive norms indicate what behaviors individuals should *not* participate in (one should not drink at all), while prescriptive norms indicate how individuals should participate in particular behaviors (one should drink in moderation) (Mizruchi and Perrucci, 1962). Nonscriptive structures have little to no cultural norms on behavior (Linsky et al., 1986). In later research, these three types of structure were modified to add an ambivalent norm structure, whereby there are both proscriptive and prescriptive norms governing a behavior (Pittman, 1967). Quantitative research analyzing norm structures and differences in drinking patterns have produced mixed results. However, this research does depict a consistently significant relationship between social norms and individual drinking behaviors.

Using the categories of norm structures identified above, Larsen and Abu-Laben (1968) analyzed self-report surveys in Canada and found that respondents from proscriptive communities had the lowest rate of heavy drinking (15%), respondents in nonscriptive environments had the highest rate of heavy drinking (36%), and respondents from prescriptive communities had an intermediate rate of heavy drinking (29%). However, two weaknesses of the study should be noted. First, the study used a small sample from a single city. Second, the study used mail-survey techniques and reported a low overall response rate.

Using a sample of chronic alcoholics in a state hospital, Lafferty et al. (1980) found the opposite result. In this study, alcoholics were more likely to say their communities were characterized by proscriptive norm structures rather than by prescriptive norm structures. However, this survey measured social norms using only data from severe alcoholics. Critics of this study note that heavy drinkers commonly misperceive social attitudes toward alcohol use (Linsky et al., 1985).

A national study of alcohol consumption found significant differences in drinking and in alcohol-related behaviors across states as a function of differences in norm structures (Linsky et al., 1986). Consistent with the findings from Larsen and Abu-Laben, proscriptive states (identified as having large Fundamentalist Church and Mormon Church congregations, more "dry" areas, few per-capita liquor outlets, and significant restrictions on alcohol sales) had lower rates of heavy drinking and disease-related deaths. However, proscriptive states had higher rates of disruptive behavior related to alcohol, alcohol-related arrests, and DUI arrests. Importantly, DUI rates were uncorrelated with alcohol consumption.

The authors provided two possible explanations for the inverse relationship between proscriptive norms and DUI arrests (Linsky et al., 1986): social control and ambivalence-inoculation. First, the social control explanation posits that communities that are less tolerant of drinking will engage in stricter policing of drinking-related behaviors. Communities that are more tolerant about drinking may be more forgiving of alcohol-related behaviors and less likely to monitor or punish alcohol-involved offenses. This explanation suggests that true rates of alcohol-related behaviors do not differ between communities, but that differences in social response to alcohol-related behaviors result in different outcomes. In short, differences in DUI rates are explained by differences in the structure of formal social control.

Alternatively, the ambivalence-inoculation explanation posits that individuals who drink in proscriptive communities may be especially vulnerable to alcohol-related problems, due to the anxiety and guilt they experience from violating group norms, and the subsequent loss of control. Individuals who are raised in proscriptive environments are also not properly socialized to control their drinking and/or behaviors while intoxicated. Consequently, overall rates of consumption may be lower in proscriptive communities, but when drinking does occur, it is likely to be more dangerous and disruptive. These explanations for the relationship between norm structures and different alcohol related outcomes (e.g., rates of consumption, rate of alcoholism, rate of alcohol-related problem behaviors) suggest that apparent inconsistencies in research, such as the findings between Larsen and Abu-Laben and the findings from Lafferty et al., were due to differences in the samples and the operationalization of the dependent variable rather than a failure of the norm hypothesis.

Some research provides tentative support for the ambivalence-inoculation hypothesis. A study of regional drinking practices in the United States found that historically “dry” counties that change their drinking policies to allow alcohol use witness an increased per-drinker consumption rate, but maintain their conservative drinking patterns (Hilton, 1988). This study found that these unresolved tensions lead to more drinking in the home and higher levels of alcohol-related problems, such as belligerence, accidents, and trouble-with-the-police.

These theories indicate that consideration of and comparison between different cultural environments is necessary to understand why DUI rates differ across locations. However, additional studies at different levels of aggregation are needed to determine how proximity to different cultural norms influences behaviors. At the very least, existing research suggests that factors evidencing social norms should be included in future analyses of alcohol-related behaviors.

While Linsky et al. (1986) provided support for cross-state differences, it is unclear how local norm structures may moderate these effects. Significant heterogeneity in the demographic composition of urban, suburban, and rural communities in the United States may reveal intrastate variation in the applicability of Bales' hypotheses. Alternatively, states that are more demographically homogenous may have a more integrated norm structure that eliminates local variation in alcohol norms and alcohol-related behaviors. The same issues regarding homogeneity and heterogeneity also exist at the level of the country.

More recent research on drinking norms criticizes the previously discussed theories' reliance on macro-level characteristics. Savic and colleagues (2016) review the development of theories that seek to explain differences in "drinking cultures" and their influence on individual drinking behaviors. The authors posit that macro-level theories are insufficient for three reasons. First, there is often a focus on the harms of drinking (i.e., risky or harmful drinking) without consideration of the potential benefits or use of alcohol in cultural practices. Second, macro-level theories of drinking norms assume a static culture that applies to all interactions and behaviors in a given geographic space. Third, broad sweeping theories of drinking norms tend to assume homogeneity within a large geographic space, such as a nation, ignoring important differences within societies.

Considerations of drinking cultures and their influence on drinking-related behaviors must consider both macro-level and micro-level characteristics. Savic and colleagues (2016) suggest a new definition of drinking cultures:

> Drinking cultures are generally described in terms of the norms around patterns, practices, use-values, settings and occasions in relation to alcohol and alcohol problems that operate and are enforced (to varying degrees) in a society (macro-level) or in a subgroup within society (micro-level). Drinking culture also refers to the modes of social control that are employed to enforce norms and practices. Drinking culture may refer to the aspects concerned with drinking of a cultural entity primarily defined in terms of other aspects, or may refer to a cultural entity primarily defined around drinking. Drinking cultures are not homogeneous or static but are multiple and moving. As part of a network of other interacting factors (e.g. gender, age, social class, social networks, individual factors, masculinity, policy, marketing, global forces, place, etc.), drinking culture is thought to influence when, where, why and how people drink, how much they drink, their expectations about the effects of different amounts of alcohol, and the behaviours they engage in before, during and after drinking. The degree and nature of the influence that drinking cultures have on individuals is not inevitable but will depend on the configuration of factors in play in any given situation, and the nature of the relationships between the culture as a whole and smaller cultural entities as they affect the individual. (p. 280)

This new definition emphasizes the need to consider macro-level characteristics (e.g., criminal justice characteristics) and micro-level characteristics (e.g., demographics) to understand differences in alcohol consumption and alcohol-related behaviors.

Social networks are an important micro-level influence on drinking cultures and drinking behaviors. While drinkers may self-select into social networks with other drinkers, research has also found that alcohol consumption behaviors spread through social networks. One longitudinal study analyzing a network of 12,067 adults found that changes in alcohol consumption in an individual’s social network had a significant influence on individual’s subsequent drinking behaviors (Rosenquist et al., 2012). The relationship was bidirectional such that increases and decreases in the network’s alcohol consumption influenced subsequent increases and decreases in an individual’s alcohol consumption.

Additional research has found support for the diffusion of drinking behaviors through adolescent social networks generally (Ali and Dwyer, 2010) and through adolescent social networks that are formed from romantic relationships (Kreager and Haynie, 2014). Other research on the heterogeneity of drinking norms has focused on differences in the identification with general groups (e.g., being a woman, being white, being a sorority sister) and subsequent drinking behaviors (Neighbors et al., 2011). Recent advances in this literature highlight the need to consider how drinking and drinking-related behaviors vary both between and within larger social contexts. The following sections discuss general patterns in drinking among demographic groups in the United States and specific patterns in drinking-related behaviors, with an emphasis on DUI, among different groups in the United States.

Alcohol Consumption in the United States

There is a broad literature in journals related to alcohol use and addiction on alcohol consumption in the United States and on how alcohol consumption in the United States compares to use in other countries. These studies tend to review demographic trends in consumption over time, socioeconomic trends in consumption over time, and historical influences on present alcohol consumption. In addition, the National Institute on Alcohol Abuse and Alcoholism regularly releases updated national statistics on alcohol consumption.

The drinking culture in the United States is influenced by its history with prohibition and religious temperance movements. Protestant beliefs that alcohol use interferes with family and civic responsibilities, hard work, and self-control still inform moralistic perceptions of alcohol use (Bloomfield et al., 2002). However, immigration and the consequent importation of alternative drinking norms have reduced the strength of these norms over time (Bloomfield et al., 2002).

According to 2014 World Health Organization estimates of global alcohol consumption, on average males in the United States consume 13.6 liters of pure alcohol per capita and females consume 4.9 liters of pure alcohol per capita. Among those who drink, 30.9% of males report heavy episodic drinking[2] and 17.3% of females report heavy episodic drinking. A quarter of all males are abstainers (not consuming alcoholic beverages in the past 12 months) and a third of all females are abstainers. On the WHO patterns of drinking score,[3] the United States scores 2 out of 5 with 1 being least risky and 5 being most risky.

However, patterns of alcohol-related health problems paint a grim picture of alcohol use in the United States. The age-standardized[4] death rate (per 100,000) from liver cirrhosis is 14.9 for males and 7.1 for females. The age-standardized death rate (per 100,000) from road traffic accidents is 18.6 for males and 7.0 for females. About 11% of males in the United States have alcohol use disorders and around 4% of females have alcohol use disorders. On the WHO "years of life lost" score,[5] the United States received a score of 4 out of 5, with 1 being the least and 5 being the most.

Longitudinal analysis of drinking patterns in the United States shows a direct age effect, with alcohol consumption decreasing with age (Moore et al., 2005). There is also some evidence of a cohort effect, whereby more recent birth cohorts' alcohol consumption decreases more slowly with age than do older birth cohorts'. This finding may be reflective of a decrease in the commitment to the previously discussed Protestant values over time. Aside from age, research has identified other variables generally related to alcohol consumption through the life course including gender, marital status, education, income, and tobacco use (Moore et al., 2005). Males consume more alcohol than females. Whites and those who are not married consume more

[2] Defined as at least 60 grams or more of pure alcohol in a single occasion at least once in the last 30 days.
[3] This scale measures how people drink, rather than how much they drink. The scale is composed of several measures including the quantity of alcohol consumed per occasion, the amount of festive drinking, the proportion of drinking events when getting drunk, the proportion of drinkers who drink daily, the norms regarding drinking with meals, and the prevalence of drinking in public places.
[4] Age-standardized death rates are calculated using a weighted average of the death rates per 100,000 individuals in each age group. The weights are equal to the proportions of persons in each specific age group.
[5] This scale is based on alcohol-attributable years of life lost.

alcohol than non-whites and those who are married. Higher education and higher income levels also increase alcohol consumption. Individuals who smoke tobacco are also more likely to consume at higher rates of alcohol than those who do not smoke. Many of these characteristics also interact with age, such that males, non-whites, those who are not married, those with less education, and smokers are found to have steeper age-related decreases in alcohol consumption.

Unfortunately, this study included a simple white/non-white dichotomy, preventing any conclusions about longitudinal drinking patterns within other racial categories. In terms of race, cross-sectional research has found differences in alcohol use and alcohol abuse (DSM-IV) by race in the United States. The National Institute of Alcohol Abuse and Alcoholism (2006) found that current drinking is most prevalent among White and Hispanic men and lowest for Asian-American women. The highest rates of daily high-risk drinking among ethnic minorities are seen with Native Americans and Hispanics. Table 1-1 shows the percent of current drinkers by ethnic group and gender, as well as the percent of weekly and daily heavy drinkers within each category.

Table 1-1. Drinking Status and Heaving Drinking for United States Ethnic Groups by Gender, 2001-2002

Ethnic Group	U.S. Population Current Drinkers		Among Current Drinkers			
			Weekly Heavy Drinking		Daily Heavy Drinking	
	Male	Female	Male	Female	Male	Female
White*	74.27	65.10	18.51	13.85	30.74	23.73
	(0.73)	(0.79)	(0.55)	(0.47)	(0.63)	(0.59)
Black*	62.62	45.92	19.88	12.67	25.81	19.02
	(1.25)	(1.01)	(1.10)	(0.96)	(1.42)	(1.02)
Native American*	65.48	51.66	21.63	22.19	29.34	27.20
	(3.50)	(3.23)	(3.52)	(3.75)	(3.32)	(3.77)
Asian*†	61.51	36.11	10.83	8.24	18.84	19.77
	(2.58)	(2.67)	(1.79)	(1.90)	(2.30)	(2.27)
Hispanic	69.99	49.52	13.76	8.81	40.48	24.19
	(1.20)	(1.51)	(1.04)	(0.92)	(1.62)	(1.18)

Source: The National Institute of Alcohol Abuse and Alcoholism, 2006

These patterns differ for rates of alcohol use disorders. Whites have greater odds than Blacks, Hispanics, and Asians for DSM-IV alcohol abuse and dependence (Hasin et al., 2007). Native Americans have greater odds than Whites for life-time alcohol dependence, but the odds for lifetime alcohol abuse and alcohol abuse or dependence in the past-year are similar.[6] However, once individuals first develop a dependence, the effects appear to be more persistent for minorities. Specifically, Blacks (35.4%) and Hispanics (33.0%) have a greater prevalence than Whites (22.8%) of persistent or recurrent alcohol dependence (Dawson et al., 2005).

[6] Guidelines released in 2013 eliminated the distinction between alcohol abuse and alcohol dependence, creating a single category of alcohol use disorders (see Hasin et al., 2013). However, studies conducted under the old framework often analyzed abuse and dependence separately. In order to accurately report the findings in prior research, I use the same language and classifications tested in the articles.

More recent research has conducted robust longitudinal analyses simultaneously considering age, period, and cohort changes in the consumption of alcohol. One study analyzing two nationally representative surveys of adults in the U.S. found that the prevalence of drinking and monthly rates of heavy episodic drinking[7] among drinkers significantly increased from 2001-2002 to 2012-2013 (Dawson et al., 2015). Increases in consumption of alcohol were significant for all sociodemographic subgroups, including age, gender, race, marital status, and education status. Average daily consumption increased with most population subgroups, except for those aged 18-24 and 65 and older, Native Americans, Asians/Pacific Islanders, formally married individuals, and those with less than a high school degree. Increases in average daily consumption were highest among those aged 25-44, Blacks, and those with a high school degree but not college. Increases in heavy episodic drinking were present for all previously discussed sociodemographic subgroups except adults aged 18-24, Asians/Pacific Islander, and those who were formally married.

Put together, the findings from Dawson et al.'s (2015) comparison of drinking patterns reveal a complex relationship between period, cohort, and age effects. Every age group had an increase in the prevalence of drinking, indicating support for a period effect. These increases were attributed to a "wetter" climate and subsequent increases in the availability of alcohol. Increases in drinking were greatest for older age groups. The authors posited that the larger period effects for older drinkers may be the result of increased economic stress from the economic downturn in the mid-2000s that is less likely to affect younger drinkers. In addition, the authors found higher increases in consumption among those subgroups who had the lowest rates of consumption in early survey years. Studies which do not account for changes within

[7] Defined as "drinking 5+ drinks for specific beverages and drinking 5+/4+ drinks (for men and women, respectively) for all beverages combined," (Dawson et al., 2015, p. 4)

subgroups over time may underestimate the increase in consumption by analyzing only the changes in the differences between subgroups.

Drinking patterns are also likely to change through the life course in response to changes in social roles. Staff et al. (2014) analyzed a longitudinal dataset of 14,589 individuals from the same birth cohort in Britain and found that alcohol use decreases as individuals transition from adolescence to adulthood but increases in midlife. The study found that changes in alcohol use corresponded with changes in social roles, particularly those associated with family. As young adults entered into marriage and parenthood, alcohol use declined. As children aged and parents no longer had young children in the home, alcohol use increased. The authors provide three theoretical explanations for these changes. First, the authors use role incompatibility theory to suggest that alcohol use is incompatible with parenthood. Second, the authors use routine activities theory to suggest that marriage and parenthood limit unstructured leisure time and time spent with friends, reducing the likelihood of drinking. Finally, the authors use age-graded social control theory to suggest that marriage and parenthood lead to greater monitoring and social sanctioning of alcohol use.

Alcohol and Crime

Aside from affecting individuals' health, intoxication affects crime, particularly violent crime. Research finds that the consumption of alcohol is prevalent among offenders and during the commission of criminal acts. In the United States, over half of the homicides and assaults involve the use of alcohol (Murdock and Ross, 1990). Almost 40% of violent offenders incarcerated in state and local jails were drinking when they committed their offense. Roughly 25% of state prisoners are alcohol dependent (Greenfeld, 1998).

While some research suggests alcohol has a direct causal effect on criminal behavior, other research suggests that alcohol has an indirect causal association with crime by increasing the probability of criminal behavior or by creating the opportunity for crimes to occur. Research on the alcohol-crime association tends to focus on one of four factors: (1) the direct effects of alcohol on behavior, especially the lowering of inhibitions, (2) characteristics of the drinker that are the same as characteristics of offenders generally, (3) situational factors, and (4) cultural influences. Additionally, research tends to focus on violent crimes and/or aggression. Reviews of research on the alcohol-crime link has analyzed these four proposed explanations for the alcohol-crime link (see Graham and West, 2001, Martin, 2001, and Gmel and Rehm, 2003), and the main arguments for each theory are briefly discussed below.

Direct Cause Explanations

The consumption of alcohol has known pharmacological effects on the brain that affect the portions of the brain associated with decision-making and impulse control (Gustafson, 1994). Some research suggests that intoxication causes aggression by lowering inhibitions against aggressive behavior. Similarly, alcohol may cause cognitive, emotional, and/or psychological changes that affect an individual's perception of a particular situation or social interaction, increasing the likelihood of perceived provocations resulting in an aggressive response. However, despite these known pharmacological effects, experiments have largely failed to support a direct causal relationship between alcohol consumption and aggressive behaviors (Martin, 2001; Quigley and Leonard, 2006).

Common-Cause, or Spurious Explanations

The common-cause perspective suggests that the relationship between alcohol use and crime is spurious. That is, individuals who are likely to consume excessive amounts of alcohol or use illicit substances are the same individuals who are likely to commit crime. According to this hypothesis, alcohol has no effect on crime. For example, males are more likely than women to commit crime, and males are more likely than women to drink alcohol. Additionally, young persons are more likely than older persons to commit crime, but younger persons may also more likely than older persons to drink alcohol. The alcohol-crime relationship could merely be a reflection of an underlying likelihood to engage in problem behaviors in general (Jessor and Jessor, 1977).

Situational Explanations

Situational factors related to particular settings, situations, or interpersonal circumstances may explain the relationship between alcohol and crime (Steele and Josephs, 1990). For example, minor provocations may be more likely to escalate to aggression or violence when both individuals are intoxicated. Consequently, locations such as bars may create high-risk drinking environments where instances of violence are more likely to occur (Gruenewald et al., 2006). These conditions are exacerbated when there is a lack of institutional control facilitated by bar management and staff. Other research analyzing communities finds highly impoverished, inner-city neighborhoods with a high density of alcohol outlets are associated with increased levels of alcohol consumption and increased levels of violent crime.

Cultural Explanations

The relationship between alcohol and crime varies across cultures. Cross-cultural research tends to focus on norms dictating when the consumption of alcohol is permissible and/or the attitudes toward drinking and culpability for actions committed while intoxicated. Cultures vary in the degree to which they accept the consumption of alcohol as a mitigating factor for crimes committed while drinking. For example, in the United States, research finds that individuals generally believe that alcohol is causally related to violence; however, they generally reject intoxication as an excuse for violent behaviors (Wild, Graham, and Rehm, 1998).

Integrative Explanations

Finally, integrative theories combine the influence of individual, situational, and cultural factors to explain the relationship between alcohol and crime (see Martin, 2001). Studies find that causes of deviance and aggression, such as deviant attitudes, aggression and hostility, impulsivity, and problem-solving abilities, interact with alcohol consumption such that assault is more common for individuals with deviant attitudes who are heavy drinkers than for individuals with deviant attitudes who are light drinkers. These findings suggest that alcohol does not directly cause crime, but that it interacts with predispositions toward deviance or hostility to increase the likelihood of aggression.

Although research is generally supportive of an integrative theory for explaining the alcohol-crime relationship, it is not possible to know whether these findings explain *all* alcohol-involved criminal behaviors, or whether these findings apply only to crimes involving aggression and violence. For example, it may be true that individuals with a hostile predisposition are more likely to experience frustration and lash out aggressively at slight provocations when intoxicated.

However, this hostility predisposition may not explain why some individuals who are intoxicated choose to drive drunk. In addition, young males may be more likely to drink and to commit assault, but research suggests that DUI offenders tend to be older. Consequently, our knowledge of the alcohol-crime relationship is currently not sufficient to explain all alcohol-related criminal behaviors.

Driving Under the Influence in the United States

Research on DUI offenders is largely limited to studies conducted in the United States. If the United States is fundamentally different from other countries, then we cannot generalize the findings of existing research to other contexts. In addition, the absence of comparative research makes it difficult to distinguish between the independent effects of different variables and the interaction effects between those variables and their larger social context.

Research on punishments in the United States is rooted in what Tonry (1999) calls "American Exceptionalism." Rising incarceration rates amid falling crimes rates are a phenomenon unique to the United States and reflective of an approach to punishment that varies greatly from other countries. Tonry noted that conservative politicians and legislators often push for harsher punishments (e.g., three strikes laws and mandatory minimums) as crime rates are falling and then point to the decrease in crime rates as proof that these policies are successful. Similarly, policy decisions concerning DUI offenders are often clouded by "get-tough" rhetoric supported by politicians and community organizations such as Mothers Against Drunk Driving (MADD). In the early 1980s, MADD began lobbying state legislatures to pass harsher sentencing policies for drunk drivers. These organizations mobilized support using the emotional appeal of victim tragedies, and they pushed nationwide reforms against the "killer drunk driver" (Fell and Voas, 2006:199). Between 1981 and 1986, 729 new state drunk driving laws were created (Lerner, 2011). During this overhaul of state policies, the Reagan administration was also placing great emphasis on the immorality of drunk driving (Reinarman, 1988).

Nationally, arrests for driving under the influence decreased 37 percent from 1990-2010, with a 12 percent decrease from 2000-2010 (Snyder, 2012). Despite these long-term downward trends, organizations are still pushing for increasing punishments of drunk drivers. In 2015, members of Congress introduced a bill referred to as "Alisa's Law of 2015"[8] which would condition federal-aid highway funds to the states on the implementation of mandatory 180-day ignition interlock sentences for all DUI offenders.

In the United States, criminal justice systems are the primary institution tasked with addressing DUI offenders. The push to increase sanctions relies on a philosophy of just-deserts and incapacitation rather than a philosophy of rehabilitation. Emphasis is placed on restricting the ability of offenders to commit crimes rather than reforming individuals so they are no longer motivated to commit crimes. In general, these policies have only minimal success in reducing long-term recidivism. For example, a study released by the Centers for Disease Control and Prevention concluded that ignition interlocks reduce recidivism rates among DUI offenders. However, the CDC cautions that once the interlocks are removed, re-arrest rates largely revert back to levels that mirror comparison groups, suggesting that there are no long-term recidivism effects (Elder et al., 2011). The emphasis on incapacitation and crime control over rehabilitation and treatment is particularly problematic when dealing with DUI offenders who may be more likely to benefit from less severe sentences and prioritization of treatment options.

[8] H.R. 3501: Alisa's Law of 2015 is named after the daughter of MADD National President Jan Withers who was killed by a drunk driver in 1993 at the age of 15.

DUI Offenders in the United States

Within criminology and studies of sentencing, DUI offenders are usually seen as different from general offenders (Bowles, 2011; DeMichele and Payne, 2013), but no study has yet compared DUI offenders and non-DUI offenders in the same sample. Without such a test, it is impossible to know whether there are actually significant differences in the characteristics of DUI and non-DUI offenders.

In recent years, there has been a slight increase in criminological studies analyzing DUI offenders although most of this research has focused on categorizations of “one-time” and “chronic” DUI offenders. Drawing from addiction literature that categorizes individuals as “social drinkers” and “chronic drinkers,” DeMichele, Payne, and Lowe (2013) attempted to develop a typology of DUI offenders. The authors found that chronic DUI offenders are more likely to be white, male, between 30 and 44 years old, and employed, to have low education, to have previously attended outpatient treatments, and to be generally unwilling to change their attitude about punishment and criminal justice interventions. This profile has not been widely tested on other samples of DUI offenders and it is unknown whether or not these findings are generalizable. In addition, it is unclear whether these characteristics are related to the effectiveness of different criminal justice intervention approaches.

Official criminal justice statistics are not necessarily reflective of true crime rates. Given the low probability of arrest for DUI offenses (Anda, Remington, and Williamson, 1986; Liu et al., 1997), studies analyzing samples of DUI offenders who were arrested and/or convicted capture only a small percentage of individuals who drive under the influence. Consequently, the following summary of research relies on studies that analyze official statistics as well as alternative samples such as self-report surveys or surveys of individuals in treatment facilities.

Race

Nationwide self-report surveys find that white, non-Hispanic individuals are most likely to report a DUI episode (Liu et al., 1997). Black, non-Hispanic respondents are least likely to report a DUI episode. The gap between white non-Hispanic and minority groups other than blacks is narrower. However, because these statistics do not represent official arrest or conviction rates, disparity in the system may differ from the findings of these self-report studies.

Gender

Compared to males, females are more likely to be diagnosed with drug dependence (e.g., sedatives or opiates), while males are more likely than females to be diagnosed with alcohol and marijuana dependence (Maxwell, 2012). Similarly, substance use research finds that female DUI offenders are more likely than males to have psychological disorders (such as anxiety, depression, and post-traumatic stress disorder) that may underlie their initial decision to drink or use drugs (Laplante et al., 2008). Consequently, gender differences may be most pronounced in the analysis of different types of DUI offenses (i.e., drug vs. alcohol). These gender differences may also indicate the need for different forms of treatment for male and female DUI offenders. However, it should be noted that studies have not analyzed gender differences by characteristics of DUI offenses or by type of sentence.

Males are more likely than females to drive under the influence of drugs or alcohol. A study of DUI arrests from 1984 to 2004 found that the gender gap narrowed over time (Schwartz, 2008); however, this change most likely reflects changes in legal policies and law enforcement strategies rather than a true increase in female DUI offending. While arrest statistics showed an increase in female offending, the rates of females engaging in DUI offenses according to self-report surveys and the rates of females involved in fatal traffic accidents showed no change relative to males. These changes in the gender gap shown in official arrest statistics could have been a result of changes in the maximum BAC limits, which inadvertently increased the percent of females arrested for DUI (Schwartz, 2008). Some studies find that women average a lower BAC when drinking, which may explain the disproportionate increase in female arrests when the BAC limits were lowered (Mayhew et al., 2003). In other words, these findings represent a net-widening that resulted from changes in legal policy, creating the appearance of a demographic change in the population of DUI offenders.

Age

Research on the age-crime curve suggests that the distribution of age for DUI offenders peaks later, with more middle-aged offenders than is true for most property or personal crimes. In their seminal article explaining the age-crime curve, Steffensmeier et al. (1989) found that the median age for driving under the influence was 33, lower only than gambling and public drunkenness. The rate of decline in age for the DUI age-crime curve was also slower than for many other crimes. This gradual decline may represent persistence in DUI offending through the life course or may represent a second peak in DUI offending in older ages.

Longitudinal analyses of offenders from the Glueck study confirmed the unique age trends for drug and alcohol offenses. Laub and Sampson (2003) found that property and violent offenses decreased through the life course after peaking in early adulthood, but drug and alcohol crimes remained relatively stable between the ages of 20 and 47. This finding suggests that the gradual decline found in aggregate age-crime curve research may be influenced by DUI offenders who desist from serious crime in early adulthood but persist in anti-social behaviors, such as driving under the influence, through the life course.

A study analyzing self-report data found nearly 10% of alcohol-impaired driving episodes were among individuals between 18 and 20 years of age (Liu et al., 1997). Individuals between the ages of 21 and 34 reported the most alcohol impaired driving episodes. DUI episodes declined with age following a peak in early adulthood. Unfortunately, this study, like many others, grouped the age of respondents into categories (18-20, 21-34, 35-54, >55), thus precluding the ability to compare these findings to studies that do not use the same categories.

Data disaggregating the age-crime curve for DUI offenders based on prior criminal records finds significant differences between first-time DUI offenders with no prior arrests and those with prior arrests (Knoth, 2015). The age-crime curve for first-time DUI offenders with no criminal history is almost identical to patterns found among violent and property offenders (such as those found in Steffensmeier et al., 1989). For these offenders, arrest was most common in early adulthood (age 18-25) and rapidly declined with age. The age-crime curve for first-time DUI offenders with a prior arrest for a non-DUI crime peaked significantly later and showed a gradual decline with age. Combined, these findings suggest that there is heterogeneity between the type of offenders who commit DUIs at a young age and those who commit DUIs at an older age.

Prior Record

Other criminological DUI research distinguishes between two general types of DUI offenders based on their involvement in other criminal behaviors: problem drinkers who drive and problem drivers who drink (Marowitz, 1998). If DUI offenders are problem drinkers who drive, but otherwise do not engage in criminal behavior, then it may be true that existing criminological theories cannot explain DUI crimes. However, if DUI offenders are problem drivers who also drink, then existing theories of general criminality could possibly explain DUI crimes as well.

Research on DUI offenders rarely includes information about prior criminal history. Studies are most commonly conducted on data obtained from motor vehicle departments and are limited to information contained in an individual's prior traffic record. At best, research includes measures of significant prior traffic violations, but these records do not allow for an analysis of individuals' criminal careers. Given the findings previously discussed with regard to heterogeneity of age effects between offenders with and without prior criminal records, greater research using complete criminal data is necessary to understand important differences among DUI offenders.

Courtroom Context

Sentencing decisions may be influenced by courtroom or community characteristics. General research on sentencing finds that different "courtroom communities" establish norms or going rates and procedures for processing offenders, and that these norms vary between different courtroom workgroups (Eisenstein and Jacob, 1977). In addition, focal concerns theory posits that judges are likely to consider practical constraints such as the resources available within the community. For example, studies find that the amount of available county jail space predicts whether or not offenders receive incarceration sentences (Ulmer and Johnson, 2004).

County resources are one of the strongest determinants of the overall use of alternative sanctions (Tonry, 1990). The absence of resources for treatment can be particularly problematic for offenders with underlying drug or alcohol problems that may be related to their offending. Research on drug offenders finds that judges are likely to sentence drug offenders to jail rather than alternative programs when there is a lack of community drug treatment programs (Ulmer and Kramer, 1996).

In Pennsylvania, Bowles (2011) also found that county resources had an effect on judicial decision making. Specifically, county funding for intermediate punishments was related to an increase in the odds of receiving intermediate sanctions compared to incarceration. Overall, alternative sanctions were used most often for drug offenders, but the level of county funding for these programs had the greatest effect on the odds of property offenders receiving intermediate sanctions. Unfortunately, this study excluded DUI offenders.

In my prior research on first-time DUI offenders in Pennsylvania (Knoth, 2015), county funding for drug and alcohol intermediate punishment programs was not significantly related to sentencing decisions for first-time offenders. This finding may reflect the low rate of alcohol and drug use among first-time offenders (who thus have no need for substantial drug and alcohol treatment). Alternatively, it could be that intermediate punishment programs are unlikely to impact decisions for first-time DUI offenders since their sentences typically require probation sentences that are less serious than intermediate sanctions.

My research did find significant variation between counties for the sentencing of first-time DUI offenders. Specifically, there was significant variation in the use of guilty convictions and diversion programs between judicial districts. These findings provide preliminary support for the courtroom communities hypothesis. That is, these findings suggest that different districts have established different norms for granting acceptance into diversion programs.

DUI Sentencing Research in the United States

The criminal justice system is concerned with punishment of offenders, protection of the community from harm, and rehabilitation of offenders. Many criminological theories have been developed to explain how these concerns influence sentencing decisions. However, these theories have rarely been applied to explain sentencing patterns among DUI offenders. Because it is an offense defined by state law, punishment for DUI offenses differs greatly across jurisdictions in the United States. Sentences commonly include some combination of short incarceration sentences, probation, license suspension, substance use treatment, and economic sanctions. Consistent with research on non-DUI offenses, little research analyzes how DUI sentencing policies are developed by legislators and sentencing commissions (Baumer, 2013).

Prior research on sentencing and DUI offenders focuses largely on the effectiveness of different punishments (e.g., license suspension or incarceration) using samples of offenders in the United States and the U.K. Based on the theory of deterrence (Beccaria, 1764/1963), these studies tested whether severe punishments were effective in reducing recidivism among DUI offenders. In a review of research on DUI offenders, Ross (1992) concluded that administrative license revocation laws had a significant effect on reducing DUI offenses and recidivism. The use and publication of sobriety checkpoints and road safety stops have also been found to temporarily decrease DUI offending due to a perceived increase in the probability of being identified (Ross, 1977; 1984; Mercer, 1985). Another study found partial support for incarceration sentences (Weignrath and Gartrell, 2001), but was limited to a sample of older, chronic DUI offenders, many of whom had prior criminal convictions for predatory crimes.

Overall, findings about the effectiveness of different punishments for DUI offenders is mixed. This lack of consistency may be attributed to the general lack of perceived certainty that individuals will be caught for a DUI offense. A self-report study of adults in Michigan estimated that the probability of arrest for a DUI offense in Michigan was 1 in 250 (Anda, Remington, and Williamson, 1986). A nationwide self-report study estimated that the probability of arrest is closer to 1 in 82 but noted that there was significant variation between states (Liu et al., 1997). Differences in base rates of DUI events as well as differences in criminal justice organizations may explain the inconsistency between different jurisdictions. Whether the probability of arrest is 1 in 250 or 1 in 82, potential DUI offenders were unlikely to believe that they will be arrested for a DUI offense, thus greatly reducing the deterrent effect of severe punishments.

Some research finds that less serious punishments for DUI offenders are as effective or more effective than severe sanctions. Because offenders are unlikely to believe that they will be caught for a DUI offense, an arrest may be the only successful type of deterrent. A study of male drunk drivers from 1976 to 1979 found that individuals who were arrested for a DUI offense experienced an increase in their subjective probability of being arrested again in the future and did not recidivate (Shapiro and Votey, 1984). These findings were independent of the severity of the subsequent sanction. The small group of offenders who did recidivate deviated from the general patterns established by econometric models based on the assumption of rationality. The authors argued that repeat offenders may have an underlying alcohol or drug problem that causes them to behave irrationally.

Because most DUI offenses are victimless crimes that result in the safe arrival of the offender at the intended destination and many DUI offenders are not committed to criminal lifestyles, severe sanctions may actually increase recidivism. An important aspect of deterrence theory is the proportionality principle – that punishment must be severe enough to overcome the potential benefits that may be achieved from engaging in illegal activity, but not so severe that they are considered unjust (Beccaria, 1764/1963). Punishments violating the proportionality principle may lead to defiance (Sherman, 1993) or create barriers to reintegration (Braithwaite, 1989; Laub and Sampson, 1993). In either case, severe sanctions can result in an increase in recidivism.

Research on jail sentences for DUI offenders finds that incarceration is counter-productive to rehabilitating DUI offenders. A study testing the effects of mandatory jail sentences for first-time and repeat DUI offenders in Washington found that recidivism increased with more severe punishments (Salzberg and Paulsrude, 1983). Within incarceration sentences, longer sentences are associated with increases in recidivism (Homel, 1981; Weinrath and Gartrell, 2001). A study comparing DUI offenders sentenced to jail to DUI offenders sentenced to alternative sanctions found that alternative programs (such as weekend intervention programs) are a better deterrent than incarceration (Siegel, 1985).

Sanctions for DUI offenders can also have long-term effects on offenders resulting from the stigma of a permanent criminal label. The general sentencing literature argues that the costs associated with the commission of a crime are not always limited to formal legal sanctions. Braithwaite (2001) posited that shaming from peers and the exclusion from conventional roles due to the stigma associated with a criminal label create barriers to reintegration. As a result, stigmatizing shaming causes crime by promoting the development of criminal subcultures and blocking individuals from access to legitimate opportunities. Similar to theories of restorative justice, Braithwaite (1989) argued that criminal justice systems should rely on reintegrative shaming rather than stigmatizing shaming. Permanent criminal labels are inconsistent with reintegrative shaming approaches. Traditional court systems and sanctioning processes do not allow for offenders to discharge their criminal labels, leading to the long-term marginalization of individuals who carry the court-determined label of “criminal” (Erikson, 1962).

Consistent with these theories, research finds that DUI offenders given a permanent criminal label are more likely to recidivate. In many states, diversion programs are available for first-time DUI offenders, and offenders sentenced to diversion programs have their criminal records expunged following successful completion of their sentence. For example, a study of DUI offenders in Maryland found that first time DUI offenders were 27% more likely to recidivate if they had a guilty conviction compared to a diversion alternative. Similarly, my prior research (Knoth, 2015) analyzing differences in recidivism for first-time DUI offenders in Pennsylvania found that permanent criminal labels significantly increased the likelihood of recidivism for non-whites and women. Non-whites receiving a diversion sentence were significantly less likely to recidivate than were non-whites sentenced for a traditional guilty conviction. Females receiving diversion were significantly less likely to recidivate than were males receiving diversion, but there were no significant gender differences for offenders sentenced for a guilty conviction. These findings suggest that the effects of a permanent label on recidivism for DUI offenders are greatest for non-whites and for females.

In most states, prosecutors and judges have discretion over the disposition of DUI offenders. These decisions include whether or not to grant admission to diversion programs, as well as what type of sanctions to impose on a given offender. Few studies have analyzed what characteristics influence decision making at sentencing for DUI offenders. Consequently, criminological sentencing theories have yet to be examined in the context of DUI offenders.

Sentencing studies often analyze judicial decisions using the focal concerns theory. Focal concerns theory posits that judicial decisions at sentencing are driven by three concerns: blameworthiness, protection of the community, and practical constraints (Steffensmeier, Ulmer, and Kramer, 1998). Blameworthiness is informed by the seriousness of the offense and the culpability of the offender. Based in a philosophy of just deserts, this component of focal concerns suggests that punishments should be greater for more serious crimes and more serious offenders. Beyond punishment, judges must also protect the public from harm. Consequently, judges often consider the dangerousness of the offender and the likelihood that the offender will commit future crimes. Finally, judges are bound by practical constraints of the criminal justice system, including jail capacity, availability of treatment, and statutory restraints on discretion.

Focal concerns theory draws heavily from causal attribution theory (Albonetti, 1991). Judges make decisions using a limited amount of information. In order to reduce uncertainty, causal attribution theory and focal concerns theory suggest that judges rely on perceptual shorthand or stereotypes of offenders that judges develop based on characteristics of the offender as well as the offense committed. Research suggests that the stereotypes that inform perceived dangerousness may explain disparity in sentencing by gender, race, and/or age (Steffensmeier, et al., 1998; Spohn, 2000; Spohn and Holleran, 2000; Steen, Engen, and Gainy, 2005). Within subgroups of offenders, interactions between extralegal characteristics reveal even greater disparity, suggesting that these powerful stereotypes relate especially to particular combinations of characters. However, it should be noted that this same research finds that two legal factors, offense seriousness and criminal history, are the strongest predictors of sentencing outcomes.

Research has yet to extend the focal concerns perspective to explain differences in sentencing for DUI offenders. Only a limited amount of research analyzes differences in sentencing for DUI offenses by offender or offense characteristics. Thus, it is unclear whether judges apply the same types of stereotypes about blameworthiness and dangerousness for DUI offenders as for non-DUI offenders. In addition, DUI offenses have unique characteristics (e.g., blood alcohol content and substance use disorders) that could affect judges' perceptions of the dangerousness of DUI offenders. These differences warrant independent research on the sentencing of DUI offenders.

My research on the sentencing of first-time DUI offenders in Pennsylvania provides some support for general stereotypes of offender characteristics and dangerousness, but also confirms that legal characteristics have the largest impact on sentencing decisions (Knoth, 2015). Offenders with lengthy criminal records and offenders charged with driving under the influence of drugs were less likely to receive diversion than were offenders with no criminal history and those charged with driving under the influence of alcohol. Controlling for legal characteristics, there were some significant effects of extralegal factors on sentencing outcomes. White offenders were more likely than minority offenders to receive diversion. Female offenders were more likely than male offenders to receive diversion. Older offenders were more likely than younger offenders to receive diversion.

Similarly, Cherpitel and Bond (2003) found racial differences in the likelihood of conviction and referrals to treatment for DUI offenders. This study found that Mexican Americans were significantly more likely than whites to be convicted of a DUI offense but less likely than whites to be referred to a DUI treatment program. These patterns suggest that Mexican Americans are perceived as having less rehabilitative potential than whites. No additional research has analyzed the influence of gender and/or age on sentencing decisions for DUI offenders.

The demographic findings from Knoth (2015) and Cherpitel and Bond (2003) are consistent with sentencing research on non-DUI offenders (Ulmer, 2012) and provide tentative support for the application of focal concerns theory to the sentencing of DUI offenders. In general, criminology has much to learn about DUI offenders. Because DUI offenders are largely excluded from studies developing and testing criminological theories, we do not know either how these offenders compare to non-DUI offenders or whether or not our existing theories can explain patterns of DUI crime, recidivism, and sentencing.

DUI Offenders and Recidivism in the United States

Whether or not an offender will reoffend is a primary concern of criminal justice officials. Research finds that two-thirds of offenders in the United States will reoffend (Langan and Levin, 2002).[9] DUI offenders are an exception to these high recidivism rates. Recent analyses of offenders in the United States find that the rate of recidivism for DUI offenders is somewhere between 20% and 35% (Cornish and Marlow, 2003; Schell, Chan, and Morral, 2006).

Research on DUI offenders varies in the measure of recidivism. Some studies analyze re-arrests for DUI offenses only, others limit analyses to re-arrests for all traffic offenses, and a few others analyze re-arrests for all criminal offenses. No studies in the United States include a comparison of these different recidivism measures.

A study of DUI offenders in New South Wales found that about half of the offenders who recidivated were reconvicted for a DUI offense (Homel, 1981). A significant portion of the offenders who recidivated with a non-DUI offense were convicted of other traffic offenses such as speeding or negligent driving (Homel, 1981). Similar research needs to be conducted on samples of DUI offenders in the United States in order to identify possible differences in three groups: (1) types of offenders who continue to commit DUI offenses, (2) offenders who engage in more minor traffic offenses, and (3) offenders who engage in more serious non-DUI offenses.

[9] More recent critiques of the BJS methods for calculating recidivism find that only one-half of offenders recidivate in the United States (Rhodes et al., 2016).

Research on the general offending population suggests that a small group of offenders are responsible for the majority of crimes. This pattern may also be found for DUI offender populations, in that a small group of DUI offenders may be impervious to sanctions, regardless of how severe those sanctions are (Homel, 1981). Research does find some differences in the recidivism rate of DUI offenders based on individual or case characteristics. The following sections summarize these findings for five individual characteristics (race, gender, age, prior record, and blood alcohol content) and one contextual factor (location).

Race

Mentioned previously, Cherpitel and Bond (2003) found differences in recidivism among white and Mexican American offenders. This study concluded that Mexican Americans were significantly less likely than whites to recidivate when the offenders were arrested but not convicted. In contrast, Mexican Americans were more likely than whites to recidivate when offenders were arrested and convicted of a DUI offense. Racial differences were largely mediated by prior DUI convictions, but this study lacked additional controls for non-DUI criminal history.

My research on DUI offenders in Pennsylvania found significant racial differences in the recidivism rates of first-time DUI offenders (Knoth, 2015). Specifically, non-whites receiving a diversion sentence were significantly less likely to recidivate than were non-whites sentenced for a traditional guilty conviction. There was no difference in recidivism between whites receiving a diversion sentence and those receiving a traditional guilty conviction.

Gender

Males are more likely than females to be repeat DUI offenders (Meyer et al., 1993). Despite increasing rates of females arrested for DUI offenses, males are still nearly 5 times more likely than females to drive under the influence (Liu et al., 1997). A large study of DUI offenders in California found that males were 57% more likely than females to recidivate (Marowitz, 1998).

The gender difference in recidivism increases as the number of prior DUI offenses increases (Rauch et al., 2010). An analysis of DUI offenders in Maryland found that females account for 51% of drivers with no prior DUI record, 18% of drivers with one prior DUI offense, 13% of drivers with two prior DUI offenses, and only 8% of drivers with three or more prior DUI arrests. This study found that the relative risk of recidivism for males with no prior DUI convictions was 3.9 times higher than females with no prior DUI convictions. However, this study also found that the relative risk of recidivating among offenders with one, two, or three prior DUI arrests did not significantly differ by gender.[10] Similarly, Taxman and Piquero (1998) found that gender was not a strong predictor of recidivism for DUI offenders.

Studies of DUI offenders in treatment facilities find that gender differences in recidivism may be explained by additional factors. For example, Maxwell and Freeman (2007) found that social support was critical to the rehabilitation of female offenders. Females were less likely to complete treatment and more likely than males to live with another person who abused drugs or alcohol.

[10] The rate of DUI offending (per 1000 drivers) for male drivers with no prior DUIs was 5.5, while the rate of DUI offending for female drivers with no prior DUIs was 1.4. The rate of DUI offending for male drivers with one prior DUI was 25.3, while the rate of DUI offending for female drivers with one prior DUI was 21.0. Similar convergence was identified for the rate of offending among drivers with 2 or more prior DUIs.

Overall, the findings on gender and recidivism are inconsistent and sometimes null. Although gender is typically included as a standard covariate in DUI research, more research is needed to establish and understand gender patterns and possible interactions in recidivism among DUI offenders.

Age

Younger DUI offenders are more likely than older DUI offenders to recidivate. A study analyzing 21 million driver records between 1999 and 2004 found that the average age of offenders decreased as the number of prior DUI offenses increased (Rauch et al., 2010). Additional research finds that age is predictive of recidivism after the first DUI offense, but not after second or subsequent DUI offenses (Yu, 1994). This pattern suggests that while age at first DUI offense may be helpful in identifying which first-time offenders are likely to recidivate, it is less helpful in identifying the small group of career DUI offenders. Additional research needs to analyze the age of DUI offenders and recidivism as well as the interaction between age and prior criminal history.

Prior Record

Prior criminal history is consistently one of the strongest predictors of recidivism (Gendreau et al., 1996). DUI offenses are no exception. However, a substantial portion of studies analyzing DUI offenders uses incomplete criminal history information. Many studies rely on records of prior traffic convictions available through license records. Few have access to information about prior involvement in general criminal activity. Consequently, we do not know what characteristics of prior criminal histories are most predictive of recidivism for DUI offenders.

The likelihood of committing a DUI offense increases with each additional prior DUI. A study analyzing 21 million driver records in Maryland found that the rate of DUI offenses significantly increases as the number of prior DUIs increases (Rauch et al., 2010). The rate of DUI offenses (per 1,000 drivers) was 3.4 for individuals with no prior DUI arrests, 24.3 for individuals with one prior DUI arrest, and 35.9 for individuals with two prior DUI arrests.

Offenders with prior traffic violations are more likely to recidivate than offenders without prior traffic violations. A study of DUI offenders in New Jersey found that prior traffic records were the most significant predictors of re-arrest for a DUI offense (Cavaiola, Strohmetz, and Abreo, 2007). First-time DUI offenders who recidivated were more likely to have a history of license suspension prior to their initial DUI conviction (38% compared to 6%). Although this study found no significant differences for demographics or BAC level, with a sample of only 77 offenders, these null findings most likely reflect a lack of power to detect these relationships.

Prior criminal history may be able to identify the two types of offenders hypothesized by Marowitz (1998). In his study of convicted DUI offenders in California, Marowitz (1998) found that prior DUI convictions, prior accidents associated with a DUI, and prior non-DUI traffic convictions are predictive of recidivism. While other variables, such as BAC, predicted recidivism among first-time DUI offenders, prior traffic violations were the only variables to predict recidivism for repeat offenders. Consequently, Marowitz proposes that there are a small group of DUI offenders who are impervious to severe sanctions, while the majority of first-time offenders will desist from criminal behaviors following their first arrest. Additional research using more comprehensive measures of prior criminal offending could help further identify the small group of offenders likely to recidivate.

This lack of appropriate measure for prior criminal record echoes criticisms of early research analyzing the relationship between race, sentencing, and recidivism, and the call for comprehensive measures of prior criminal history (see Spohn 2000). Comprehensive measures of criminal history are critical for obtaining unbiased estimates of the relationship between demographic characteristics, which are often highly correlated with criminal records, and sentencing and recidivism outcomes. Consequently, criminological studies of DUI offenders have a unique opportunity to expand our understanding of these offenders and their processing through the criminal justice system.

Blood Alcohol Content

Many states use graduated sentencing structures for DUI offenders that are based on prior DUI arrests and blood alcohol content. BAC often determines the severity of the DUI charge (National Conference of State Legislatures, 2012) and the conditions of the offender's sentencing, including placement in particular forms of treatment (Voas, 2011). These policies are motivated by the belief that BAC is a signal for the seriousness of DUI offenses or an indicator of underlying alcohol dependence. However, these policies are not reflective of evidence-based sentencing, and there is a general lack of research analyzing the relationship between BAC, sentencing, and recidivism.

Some research finds that higher BAC levels correlate with more serious offending. A study of DUI offenders in New York found that offenders with higher BAC levels were more likely to recidivate than offenders with lower BAC levels (Yu, 1994). However, this study merely compared offenders who were impaired with a BAC between .05% and .07% to those with a BAC above .08%. Thus, this study is not able to differentiate between levels of BAC above the legal limit. At best, this study provides support for the current legal limit (.08%) but fails to provide support for graduated sentencing based on higher BAC limits.

Research analyzing different levels of BAC above the legal limit finds that the relationship between BAC and offense seriousness is curvilinear and contextualized by other offense related characteristics. Marowitz (1998) found that offenders with low BAC levels (.00% - .09%) and high levels (.35% and above) had a relatively high rate of recidivism compared to offenders with an intermediate BAC level (.09% - .29%). The findings for individuals with low BAC levels are likely driven by drug-impaired DUI offenders who often have a BAC of .00%.

Marowitz's research exposes the possible need to analyze the effects of BAC independently using a sample of only alcohol-impaired offenders. Understanding the differences between drug and alcohol offenders is necessary to determine whether the same risk factors are applicable to both populations. Research tends to use samples of alcohol-only DUI offenders or a mixture of drug and alcohol DUI offenders. In the latter, research often assumes that these offenders are homogeneous and that all DUI offenders can be analyzed in the same models using the same covariates. Given recent changes in states policies concerning the legalization of marijuana, there is an increasing need for research that analyzes drug-impaired DUI offenders in order to shape the inevitable rise of new criminal justice policies.

Other research finds that BAC is not a significant predictor of recidivism or of underlying alcohol dependence. A study analyzing 77 first-time offenders found that BAC was not predictive of recidivism (Cavaiola, et al., 2007). However, as noted earlier, these null effects may be due to a small sample size and insufficient statistical power to detect a relationship between BAC and recidivism. A similarly small study of 59 DUI offenders in Pennsylvania found no significant differences in BAC for first-time and repeat offenders (Dugosh et al., 2013). A third study analyzed evaluations of alcohol dependence for 235 DUI offenders and found no significant relationship between BAC and alcohol abuse, dependence, or problem drinking (Wierczorek et al., 1992).

Finally, my research analyzing the recidivism of first-time DUI offenders in Pennsylvania found that BAC was not predictive of recidivism (Knoth, 2015). Using the statutorily defined BAC categories, that study tested differences between drug offenders, alcohol offenders with a low BAC (.08% - .09%), intermediate BAC (.10% - .15%) and a high BAC (.16% or greater). The study found that drug-impaired offenders were significantly more likely than alcohol-impaired offenders to recidivate. However, no significant differences were found between different levels of BAC among alcohol-impaired offenders.

My research on offenders in Pennsylvania suggests that using BAC to signal seriousness of offenders and subsequent treatment may be misplaced. Offenders with a high BAC may have similar risk of recidivism compared to offenders with low BAC. However, the current sentencing guidelines for DUI offenders mandate more serious punishment for offenders with higher levels of BAC.

Location

In 2006, Kubrin and Stewart called for criminologists to consider the relationship between community characteristics and recidivism. Specifically, the authors noted that community characteristics influence the ability of offenders to reintegrate into society. Controlling for individual characteristics, the authors found that increases in community disadvantage were related to increases in recidivism, and that individuals returning to areas with high concentrations of wealth were less likely to recidivate than were offenders returning to areas with high concentrations of poverty.

Similarly, Braithwaite (1989) hypothesized that communities that are high in residential mobility and urbanization are less likely to reflect communitarian characteristics that protect against recidivism. The theory of reintegrative shaming posits that communitarian societies, compared to individualistic societies, have cohesive and interdependent characteristics that are necessary for the reintegration of offenders. Stability within communitarian societies fosters the conditions necessary for mutual obligation, trust, and group loyalty, each serving as protective factors against criminal behaviors. Thus, characteristics of the individuals within a community and their relationships to one another may influence DUI recidivism.

Research on DUI offenders tends to focus on individual characteristics, ignoring how community characteristics may also influence criminal behaviors and recidivism. It is possible that community characteristics are unrelated to recidivism because DUI offenses are mobile. That is, offenses may not be committed near the offender's residence. Alternatively, some non-economic, structural community characteristics, such as availability of public transportation, proximity of residential locations to alcohol establishments, and population density, may have a unique effect on the prevalence of DUI offenses and recidivism. Further research is needed to determine whether existing explanations used in the communities and crime literature are applicable to DUI offenders.

Assessing Risk

Policy makers and criminal justice officials are increasingly concerned with the risk of recidivism and threats to public safety. Despite the passage of several legislative mandates demanding the development and implementation of risk assessments at sentencing (see Monahan and Skeem, 2013), much of the academic literature is still focused on the a priori question of whether or not risk assessments should be used at all (Hannah-Moffat, 2013).

Critics of risk assessments view aggregate-based decision making as an extension of dangerous epistemological approaches that ignore individual characteristics and marginalize entire populations (Silver and Miller 2002; Harcourt 2003). Many opponents equate the use of aggregate-based decision making with increase disparity and discrimination in the criminal justice system (Starr, 2014; Tonry, 2014). Starr (2015) noted that actuarial risk assessment instruments are a method whereby the state labels groups of people dangerous because of who they are, not because of what they have done. These critics fear that risk assessments will become a sort of blinder for judges causing other individual characteristics, behaviors, or needs to be rendered irrelevant.

Proponents of using risk assessments argue that these tools can maximize safety of the public while preventing strain on state budgets. Risk assessments are increasingly used as a tool to reduce the cost of incarceration and to assist in the allocation of state and local resources (Silver and Miller 2002; Kleiman 2012). Some scholars and officials believe actuarial assessments are necessary to ensure appropriate services address individuals' specific risks and needs (Andrews and Bonta, 2010). Better understanding offender and offense characteristics that affect future actions of an individual allow for a more efficient allocation of resources (Taxman, 2006; Kleiman, 2012). These benefits can stem from incarcerating fewer offenders unnecessarily and from placing offenders into appropriate treatment programs.

Although actuarial risk assessment instruments are used throughout the criminal justice system, the use of these tools at sentencing is a relatively new development. It is unclear whether prior research risk assessment instruments used at other points of the criminal justice system are applicable to *sentencing* risk assessment instruments. In addition, a majority of the research on risk assessment instruments is limited to samples of offenders and scales developed in the United

States and the United Kingdom. Consequently, we know little about risk assessments outside of a particular court context.

The following sections describe the rise of risk assessment instruments throughout criminal justice systems in the United States, the difference between clinical and actuarial models, the development of sentencing risk assessment instruments, the types of variables included in risk assessment instruments, models used to develop risk assessment instruments, and the need for DUI-specific risk assessment instruments.

Risk Assessment Instruments in the Criminal Justice System.

From 1970 to 2014 prison populations in the United States rose from 200,000 offenders to over 1.5 million offenders (Harcourt, 2003; Kaeble et al., 2015). Between 1980 and 2014 the number of offenders on probation increased from 1.1 million to 3.8 million, and the number of offenders on parole increased from 220,438 to 856,900 (Silver and Miller, 2002; Kaeble et al., 2015). This rapid growth in incarceration and supervision increased strain on states struggling to balance small budgets and greater responsibilities. Between 1985 and 2004 average state expenditures on corrections rose by 200 percent, and costs for states and localities continue to rise (Kleiman, 2012).

Concurrent with the rise in supervision, criminal justice systems in the United States have undergone a gradual shift from a system of individualized punishment focused on rehabilitation, to fixed sentencing mechanisms, such as mandatory minimums, sentencing enhancements, sentencing guidelines, and three strikes laws, focused on retribution and prediction of future behavior (Harcourt 2003; Kleiman 2012). Policy makers increasingly emphasize the need to better predict and prevent criminal behavior and to promote consistency in the application of the law to offenders across jurisdictions.

Changes in criminal justice policy represented a larger philosophical shift in crime management. Feeley and Simon (1992) reflected on the changes in the criminal justice system in their discussion of *the new penology*. The authors stated that the new system seeks "to regulate levels of deviance, not intervene or respond to individual deviants or social malformations" (Feeley and Simon, 1992:452). The new penology replaced clinical and retributive language with probability and risk language resulting in a shift toward aggregate-based decision making and irrelevancy of individual characteristics (Feeley and Simon, 1992). Similarly, Bernard Harcourt (2003) noted that these changes reflect a "shift toward a new mode of bureaucratic management of crime involving a style of thought that emphasizes aggregation, probabilities, and risk calculation instead of individualized determination." (p. 106). Albert Alschuler (1991) warned that by speculating about group-based behavior, "we seem increasingly indifferent to individual cases and small numbers" (p. 904).

Risk assessments represent an extension of these changing perspectives with the goal of predicting the likelihood of criminal behavior based on an individual offender's group-based characteristics (Silver and Miller, 2002). Risk assessment instruments are not new to the criminal justice system. However, these instruments were largely abandoned by criminal justice officials in the 1980s due to the high false positive prediction rates and subsequent lack of faith in the existing statistical models (Silver and Chow-Martin, 2002). Resurgence in support for risk assessment tools began in the 1990s reflecting a change in societal understanding and acceptance of actuarially weighted models that were beginning to be used for other purposes, such as determining insurance premiums and college admissions (Simon, 2005).

Today, actuarial risk assessment instruments are used at nearly every stage of the criminal justice system. Risk assessment instruments are used in bail decisions, parole release decisions, charging decisions, sentencing decisions, and sexually violent predator classification decisions. Sentencing risk assessments are one of the newest forms of risk assessment tools in the criminal justice system. While actuarial sentencing tools have yet to be adopted on a national level, states are increasingly adopting these measures into their criminal justice systems (see Hannah-Moffatt, 2013, and Monahan and Skeem, 2013). National working groups have even been commissioned to study and promote the use of risk assessments in state courts (Casey, Warren, and Elek, 2011), and in 2014, the Department of Justice memo to the United States Sentencing Commission explicitly called for an increase in research on sentencing risk assessments.

Hyatt, Bergstrom, and Chanenson (2011) supported the expanded use of risk assessments arguing that these tools represent a positive change in criminal justice approaches:

The use of risk assessment at sentencing underscores an overall shift in the purposes of sentencing, moving from a backward-looking retributive approach with a focus on uniformity, proportionality, and reduction of unwarranted disparity to an approach that also incorporates a formalized, forward-looking utilitarian goal. (p. 266)

How sentencing risk assessments are used and whether or not their use translates into increased punishment remains to be seen. Limited research analyzes the use of sentencing risk assessments and no research has analyzed changes in actual sentencing decisions before and after the implementation of risk instruments. Despite the absence of this research, there is much research suggesting that actuarial models are preferable to current approaches to assessing risk of recidivism.

Clinical vs. Actuarial Models

Risk assessments evolved over time from purely clinical models to models that include clinical and actuarial approaches. Types of risk assessments are generally discussed according to their generation (Gendreau et al., 1996; Brennan, Dietrerich, and Ehret, 2009). First generation risk assessments are based solely on clinical judgment and do not use a formal scoring method. Research has repeatedly shown that these methods are not valid and may be influenced by a numerous errors and biases (Meehl, 1954; Meehl, 1986; Grove and Meehl, 1996; Hilton, et al., 2006).

Second generation risk assessments are actuarial models. These formal risk instruments assess static factors, such as gender and age. Risk factors are assigned a value that is used to calculate a final risk score for each offender. These scales tend to provide little direction for treatment decisions since they rely almost entirely on static factors (Gendreau et al., 1996; Andrews and Bonta, 2010).

Third generation risk assessments include both static and dynamic characteristics. Andrews, Bonta, and Wormith (2006) isolate two types of third generation scales: those that include dynamic factors that assess criminogenic needs, and those that include personality test scales where the majority of the items are dynamic. These scales are better for assessing treatment needs and assigning offenders to different types of treatment programs.

Finally, fourth generation risk assessments include a broader range of static and dynamic risk factors than previous generation models and also include measures of offenders' strengths. These risk assessments often include more complex statistical techniques that can be integrated with large agency databases in order to help manage offenders. These assessments are intended to follow offenders over time, through multiple stages of the criminal justice system. By integrating these techniques into agency databases, multiple assessments may be recorded and compared over time.

Risk tools used beginning in the 1960s were generally clinical and used for classification of the mentally ill; however, these procedures lacked empirical tests of validity, undermining their credibility, with many believing “expert risk prediction was no better than chance” (Simon, 2005:402). Risk assessments were largely abandoned in the 1980s due to the high false positive prediction rates that reinforced clinical skepticism of risk instruments. (Silver and Chow-Martin, 2002). As noted previously, support for risk assessments reemerged in the 1990s, as actuarial models were increasingly integrated into various aspects of society, such as determining insurance premiums and college admissions (Simon, 2005).

Actuarial predictions outperform human judgments in nearly all decision-making contexts. A review of research comparing actuarial prediction methods to clinical prediction methods found that actuarial methods are better for psychiatric judgments, graduate school admissions, and prognostic judgments made by sociologists and psychiatrists relative to parole-violations, parole board decisions, mental health and correctional case worker judgments of offender risk (see Grove and Meehl 1996 and Gottfredson and Moriarty, 2006). With regard to criminal justice and recidivism predictions, studies find that actuarial models consistently perform as well as or better than clinical judgments and structured professional judgments (Meehl, 1954; Grove and Meehl, 1996; Hanson and Morton-Bourgon, 2004; Campbell et al., 2007; Harris and Rice, 2015). As one scholar states, “There is no longer any serious debate about whether general criminal recidivism can be predicted among general criminal populations” (Hanson, 1998:50)

Clinical assessments are subject to error and bias (Grove and Meehl, 1996). Clinicians, particularly those in the criminal justice system, are often unaware of base rates (Carroll and Siegler, 1977), they may inappropriately weight factors that are predictive or give weight to factors that are not predictive (Gottfredson and Moriarty, 2006), and are often unable to distinguish between causal and spurious correlations (Monahan, 1981). In addition, individuals are likely to make different decisions at different times of the day, undermining the validity of their predictions (Meehl, 1992). In many ways, the decisions made by clinicians rely on a combined analysis of the same factors included in risk assessment instruments. The problem is that humans are poor at analyzing information for inferential purposes (Grove and Meehl, 1996).

An important advantage of actuarial risk instruments is that they can improve over time while clinical judgments do not. Despite the belief that clinicians "know from experience," research finds that experience adds little to accuracy of predictions (Hilton, Harris, and Rice, 2006). Clinicians are limited in the amount of information they receive (Grove and Meehl, 1996). For example, clinicians are exposed to only a small portion of offenders in the criminal justice system. In addition, in large criminal justice systems, clinicians may be assigned to handle only a particular type of offense, systematically biasing the types of characteristics they are exposed to. Finally, clinicians, particularly judges, often do not know the long-term outcomes of a given offender. That is, it is difficult for judges to develop opinions on which offenders are more likely to recidivate when they often do not know whether or not the offenders go on to commit crimes in the future. Judges are informed about recidivism only when the offender commits a violation while under supervision, or if the offender commits a new crime, is re-arrested, and is processed through the same judge's courtroom.

Of similar concern is the ability to test the accuracy of clinicians' estimates of risk. Bucahanan (2008) notes, "The clinician's estimate of risk is impossible to test because an adverse outcome does not make an assessment wrong and it is not possible to replicate the circumstances in order to conduct repeated trials" (p. 77). In addition, Buchanan notes that clinicians' judgments of risk are extremely sensitive to new information. Actuarial models are able to resolve these concerns. Actuarial instruments are developed using large samples and are retested on multiple samples in order to test their validity. In addition, the use of confidence intervals recognizes the imprecision of risk instruments. Finally, statistical methods can test the incremental increase to the validity of predictions for each individual variable (Hilton, Harris, and Rice, 2006). Variables that do not significantly contribute additional information to the risk model are excluded from consideration in the final calculation of the risk estimate.

Structured professional judgment (SPJ) was offered as an alternative to strict actuarial approaches by combining statistical and clinical judgments. SPJ approaches allow clinicians to make discretionary judgments about some risk factors and ultimately give clinicians the freedom to assign individuals to categories of low-, moderate-, or high-risk after a review of the factors included in the assessment. A review of the research on SPJ techniques found that SPJ methods are outperformed by both actuarial and clinical methods (see Hilton et al., 2006). Because SPJ instruments introduce human judgment, they are still subject to the errors and biases of clinical assessments that were previously discussed.

In addition, SPJ methods reduce transparency of risk instruments. Practitioners often do not have to explain how they arrive at a particular value for a discretionary variable, nor is there a clear method for determining who gets placed in each final risk category (Hannah-Moffat, 2013). Research on the use of SPJ methods shows poor interrater reliability of the final classifications, suggesting that the introduction of discretion into statistical models undermines the consistency and accuracy of these instruments (Hilton, et al., 2006).

Sentencing Risk Assessment Instruments

Sentencing risk assessments differ from risk assessments used at other stages of the criminal justice system, in that they are intended to identify the likelihood of recidivism, not to reduce recidivism (Monahan and Skeem, 2013). Other scales, such as those used to assign offenders to different treatment programs in prison or different levels of supervision on probation, are intended to reduce recidivism. In addition, sentencing risk assessments are not intended to reduce discretion, but rather to provide fully informed judicial decision making throughout the sentencing process (Hyatt et al. 2011; Kleiman 2012).

Sentencing risk assessments are used to inform judges when making a decision about the imposition of punishment. Consequently, it is important to understand the broader context of punishment decisions. Current sentencing structures in the United States are guided by a philosophy of limited retributivism. Advanced by Norval Morris (1974), limited retributivism posits that the seriousness of the offense and an offender's criminal history should determine a set range within which a punishment can be selected.[11] Utilitarian concerns, such as risk of recidivism and availability of treatment resources should be used only to determine the punishment within the predefined range.

Critics of sentencing risk assessment instruments fear that these tools will increase the severity of punishment for high-risk offenders (Hannah-Moffat, 2013). If systems used risk assessment instruments to impose harsher sentences than they would otherwise, these punishments would violate the premise of limited retributivism and those sentences would be unjust (Tonry, 2014). Although research on the impact of risk assessments is limited, an initial

[11] The influence of this approach to sentencing is evidenced by the use of offense seriousness and prior record in most state sentencing guidelines.

study suggests that risk assessments decrease rather than increase judicial perceptions of offender risk (Ruback et al., 2016).

States vary in how they use risk assessments at sentencing. For example, Pennsylvania's risk assessment instrument is intended to provide more information to judges, but there is no mandate directing how that information should be used. On the other hand, Virginia's risk assessment scale is used only to identify low-risk offenders who are eligible for diversion to non-incarceration sentences. Additional research is needed to assess how these types of policy differences may result in different effects on sentencing outcomes.

Risk Assessment Variables

Risk assessments rely on two types of characteristics to classify offenders: static factors and dynamic factors. Static risk factors include characteristics that do not change, or change only in a single direction (e.g., age, gender, offense information, and prior criminal history); dynamic risk factors include characteristics that can change over time (e.g., criminal thinking, joblessness, and level of education) (Hanson 1998; Andrews et al., 2006). For the most part, sentencing risk assessments rely on static factors.

Dynamic factors are those that can change, such as number of criminal friends, level of education, or substance use. While dynamic characteristics are helpful in identifying criminogenic needs and in determining the appropriate types of offender treatment (see Andrews and Bonta, 2010), dynamic characteristics tend to be poor predictors of recidivism (Virginia Criminal Sentencing Commission, 2012). Dynamic characteristics are most effective at predicting recidivism when they are measured multiple times. That is, it is not necessarily dynamic characteristics that predict recidivism, but rather changes in dynamic characteristics (e.g., a reduction in criminal associates) (Gendreau et al., 1996). Consequently, even if dynamic characteristics are predictive of recidivism, it does not make sense to include them in sentencing risk assessments that analyze only the characteristics of the offenders at the time of their disposition.

In general, judges already consider the factors included in most risk assessment instruments; however, judges are inconsistent in how they evaluate these factors (Hyatt et al., 2011; Skeem and Lowenkamp, 2015). Risk assessments serve to standardize information to maximize information-based decision-making, helping to eliminate cross jurisdiction disparities or inconsistencies within judge. In fact, the status quo approach to evaluating these characteristics may be more dangerous because there is variation in how judges perceive an individual's risk of recidivism. Therefore, similarly situated offenders committing similar offenses may be treated significantly differently depending on where they commit the offense or which judge is selected to hear their case (Grove and Meehl, 1996). In addition, judges may inappropriately give weight to extralegal characteristics (such as race), or characteristics not related to recidivism. Consequently, standardizing the calculation of risk using empirically valid actuarial methods may decrease disparity or the inappropriate consideration of extralegal characteristics.

Some of the factors used in actuarial risk assessments have raised a series of legal and ethical concerns. Although criminal history is widely accepted as a recidivism risk factor and is commonly found to be the most predictive risk factor (Gendreau et al., 1996), there is a debate over how criminal history should be operationalized. Number of prior arrests, number of prior convictions, number of prior incarcerations, and types of prior offenses are all variables that measure an offenders' criminal history. In addition, critics argue that criminal history, if measured inappropriately, is no more than a proxy for race (Harcourt, 2003; Frase, 2009; Starr, 2014, 2015).

Age is also generally accepted as a risk factor in risk assessment instruments (Scurich and Monahan, 2015). However, there are some opponents who believe that age should be included only as a mitigating factor for youthful offenders (Tonry, 2014). Most of the empirical research and existing scales indicate that age is predictive of recidivism in the opposite direction, such that young offenders are riskier than older offenders. These findings are consistent with general criminological literature on the age-crime curve and the concentration of crime among youthful populations followed by desistance through the life-course (Steffensemeier et al., 1989).

Race is universally excluded from risk assessments for constitutional issues (see Starr, 2015), although studies have found that race significantly increases forecasting validity (see Berk, 2009). The inclusion of gender is still somewhat controversial. Starr (2014) objects to the use of gender and claims that the use of gender reinforces unconstitutional gender discrimination. Other authors argue that the inclusion of gender is constitutional and that the exclusion of gender would actually cause gender discrimination (Skeem, Monahan, and Lowenkamp, 2016).

In addition to concerns about the predictive value of dynamic factors, some dynamic characteristics – such as marriage, college education, and employment – functionally punish individuals' lifestyle choices (Tonry, 2014). The ability to make these decisions is a key characteristic of living in a free society. Consequently, some authors argue that variables related to "lawful choices" should be excluded from risk assessment scales (Tonry, 2014). In addition, judges at sentencing often lack information about dynamic characteristics. Consequently, many states have excluded these characteristics from their sentencing risk assessments (see

Pennsylvania Commission on Sentencing, 2012 and Virginia Criminal Sentencing Commission 2012).

Approaches to Modeling Risk

Development of Statistical Models

Methodological approaches to developing risk assessments vary widely. Studies comparing different approaches to modeling risk find little to no difference in the predictive validity of different techniques (Gottfredson and Gottfredson, 1980). The Burgess method is the most common method for developing risk scales, and studies find it is as predictive as or more predictive than other methods (Gottfredson and Gottfredson, 1994; Silver and Miller 2002). In the Burgess method, regression techniques identify which variables are significantly related to recidivism and an additive scale is constructed by assigning values to different characteristics (see Gottfredson and Snyder, 2005). Increasing scores on the scale are associated with an increasing likelihood of recidivism.

In unweighted Burgess models, equal weight is assigned to characteristics that are found to be predictive in the logistic regression. For example, if males are likely to recidivate more than females, then males would receive one point and females would receive no points. If offenders with a prior property arrest are more likely to recidivate than offenders with no prior property arrests, then offenders with a prior property arrest would receive one point and offenders with no prior property arrests would receive no points. The total points from all significant characteristics are then added to construct an individual’s final risk score.

In weighted Burgess models, the value assigned to characteristics varies based on the strength of the relationship in the multivariate analysis. Therefore, variables that more strongly predict the outcome are more heavily weighted in the final risk scale. In general, research finds that unweighted Burgess models perform as well as weighted Burgess models, and the simplicity of the unweighted models makes them the preferred choice (Gottfredson and Snyder, 2005; Pennsylvania Commission on Sentencing, 2012).

Scores on the scale may be assigned a variety of cutoffs in order to create broad classifications of offenders. Some scales use as many as 3 cutoffs to create four categories of offenders: poor, below average, average, above average. Other scales have two cutoffs to create three categories: low-, medium-, and high-risk. Scales used to identify offenders for diversion programs use a single cutoff point to identify only low-risk offenders. Using statistical methods to identify an acceptable ratio of false positives to false negatives may identify cutoffs or policy makers may decide where cutoffs should apply. In addition, the meaning of these categories and how judges interpret them may be explicitly guided by legislative mandates or they may be left purely to the discretion of each judge.

Selecting Factors and Assigning Points to Factors

Deciding which variables should be included in risk assessment instruments necessitates a consideration of theory, statistical significance, and incremental improvements in validity. First, theory about correlates of recidivism should be consulted to determine which variables are appropriate for risk assessment instruments. Despite the increasing developments of statistical methods, theoretical considerations should still guide research designs (Firebaugh, 2008).

Second, regression instruments are used to determine which variables have a statistically significant relationship to the outcome of interest. In most cases, development of scales depends on logistic regression models where the outcome is a dichotomous measure of re-arrest or no re-arrest (Gottfredson and Snyder, 2005). Importantly, independent variables in the logistic model should be dichotomous or categorical. These types of variables allow for the assignment of discrete points for the final risk assessment scale. For example, if age was included in a logistic model as a continuous variable and found to be significant, it would be inappropriate to assign 99 points for age, decreasing one point for each year. Additionally, it is unlikely that there is a real difference between each individual year of age such that offenders aged 32 are more likely to recidivate than offenders aged 33. Consequently, age should be entered as a categorical variable (e.g., less than 21, 21 to 29, 30 to 39, 40 to 49, and 50 and older), and the same point value should be assigned to all offenders falling within a particular age category.

Finally, risk assessment instruments should be parsimonious and include only those variables that uniquely increase the ability to predict recidivism (Hilton, Harris, and Rice, 2006). Rather than including all of the significant variables from the logistic regression, scales should be developed starting with the variables that have the greatest predictive effect (age and prior arrests) and follow with an incremental addition of variables in order of their strength of prediction.

Assessing Predictive Validity

Receiver operating characteristics (ROC) offer a statistical method to assess the predictive validity of a scale (Rice and Harris, 1995; Gottfredson and Moriarty, 2006). ROCs for two different scales can be compared to test whether the predictive ability of the two scales is significantly different. If a scale including one variable does not predict significantly better than a scale omitting that variable, there is a statistical justification to exclude that variable.
Using methods to test the unique contribution of variables to predictive validity is important particularly for controversial variables. For example, if gender is significant in the logistic regression, but does not significantly improve predictions in the risk assessment scale, there is no need to include gender in the final scale (although it is controlled for).

Alternatively, these methods may reveal that not including a particular variable significantly reduces forecasting accuracy. Maximizing forecasting accuracy is particularly relevant given the applications of these scales to predict criminal behaviors. For example, Berk (2009) illustrated how the removal of a controversial variable (race) from a risk instrument predicting homicide increased forecasting error such that 5 or 10 homicides or attempted homicides would no longer be predicted accurately. Consequently, the development of risk assessment instruments necessitates not only an understanding of statistical differences, but also how those statistical differences translate into real world consequences.

The Need for DUI Risk Assessments

Risk assessments should be developed on populations of offenders that represent the populations on which the instruments will be used. Some critics argue that risk assessments are too often developed on populations of incarcerated white males, limiting their generalizability to non-whites, females, and less serious offenders (Hannah-Moffat, 2013). Gottfredson and Moriarty (2006) noted, “Prediction methods are intended to estimate, based on some group of people available for study, how other members of other similar groups will behave” (p. 185). Thus, limiting the sample to similar offenders (e.g., DUI offenders only) can increase the strength of predictions. Additionally, the relationship between offender characteristics and types of criminal behaviors may vary. Developers of risk assessments recognized this crime-specific heterogeneity and responded by developing specific scales for sex offenders and violent offenders (Quinsey et al., 1998; Hanson and Morton-Bourgon, 2009).

For sentencing risk assessments, some states limit the development and application of risk scales to certain types of offenders. For example, Virginia’s sentencing risk assessment applies only to offenders convicted of larceny, fraud, or drug offenses (Ostrom et al., 2002). Furthermore, separate scales are used for drug offenders and for larceny and fraud offenders.

Pennsylvania pursued an alternative approach to recognizing offender-offense heterogeneity by creating a separate risk assessment instrument for each level of offense serious in the sentencing guidelines (Pennsylvania Commission on Sentencing, 2015). The resulting scales reveal significant heterogeneity in the variables used to predict recidivism and provide support for risk assessment instruments tailored to the type of offense committed by the offender. Importantly, DUI offenders were removed from these samples and the resulting scales will not be used at sentencing for DUI offenders in Pennsylvania.

Risk assessments are a unique way of integrating academic research and policy. To date, no jurisdictions have developed a risk assessment instrument for DUI offenders. As discussed earlier, research on the characteristics of DUI offenders suggests that there are significant differences between DUI offenders and non-DUI offenders. Developing a unique scale for DUI offenders would better capture the unique characteristics of DUI offenders and maximize the predictive validity of a risk assessment instrument. For example, the previously discussed literature suggests that the relationship between age and DUI is non-linear. Consequently, while most general scales have linearly decreasing points for increasing age categories, the same point structure may not be appropriate for DUI offenders and DUI offenses.

DUI offenders are less likely to recidivate than the general offending population. Risk assessments would allow practitioners to identify the small group of DUI offenders who are most likely to recidivate and to target resources towards those offenders. Alternatively, these models may help distinguish between individuals who are likely to commit another DUI and those who are likely to commit other criminal offenses. Individuals likely to commit another DUI pose a risk to the safety of the general public but may also have underlying characteristics that make them more likely to drink. Consequently, identifying these offenders allows judges to sentence offender to treatment programs that can increase education about the dangers of drinking and driving as well as programs aimed toward treating substance use. However, these approaches may be less effective for offenders who are likely to recidivate with non-DUI offenses.

Chapter 2 DUI Offending and Risk of Recidivism in Pennsylvania

Despite being the most common offense for which individuals are arrested in the United States, DUI offenders are still an understudied population. Existing studies rely largely on data from Department of Motor Vehicles offices and are limited in their assessment of general criminal characteristics. Marowitz (1998) found support for a typology of problem drivers who drink and problem drinkers who drive. DeMichele, Payne, and Lowe (2013) offered an alternative typology of "social drinkers" and "chronic drinkers." I posit that both of these typologies are insufficient for understanding the different types of DUI offenders. This chapter establishes a broader typology of offenders that accounts for general criminal offending in addition to drinking and driving behaviors.

This chapter also addresses the issue of determining the recidivism risk of DUI offenders. To date, no state has implemented a DUI-specific risk assessment instrument. These gaps are especially evident in Pennsylvania, where the correlates of recidivism have been analyzed and risk assessment instruments have been developed by the Pennsylvania Commission on Sentencing for all offenders *except* DUI offenders. Research in Pennsylvania that does analyze DUI offenders often excludes a large portion of offenders by analyzing only the DUI offenders who are convicted of a DUI offense and excluding offenders who are diverted from prosecution.[12] This chapter assesses how existing methods could be used to predict general recidivism and DUI-specific recidivism among DUI offenders. In addition, this chapter questions whether the existing methods are sufficient for assessing the risk of recidivism for this unique population of offenders.

[12] The PCS does not collect information on diverted sentences. Therefore, they are unable to include these cases in their research using PCS data.

This chapter begins with a discussion of the hypotheses tested throughout this study. I next include a detailed description of the procedures I used to construct the final dataset. The analyses then proceed in four parts: (1) Descriptives and Bivariates, (2) The Development of a Risk Assessment for Any Reconviction, (3) The Development of a Risk Assessment for Repeat DUI offenders, and (4) An Alternative Approach to Specialized Risk Assessments. I conclude with a summary of the findings and a discussion of the theoretical and policy implications from the research.

Hypotheses

Hypothesis 1: (a) First-time DUI offenders, especially those who are convicted of an alcohol-impaired DUI, will be less likely to recidivate than DUI offenders with any criminal history, and (b) Offenders who have prior convictions for non-DUI offenses, especially those who are convicted of a drug-impaired DUI, will be more likely than first-time offenders and alcohol-impaired offenders to recidivate with a non-DUI offense.

In other words, I posit that there are three types of offenders: (1) generally non-criminal offenders with no drug or alcohol use disorder who commit a DUI but are unlikely to engage in any continued criminal behaviors, (2) offenders who are likely to be repeat DUI offenders, perhaps as a result of an underlying alcohol use disorder, and (3) general offenders for whom the DUI offense is one of many types of offenses they are likely to engage in.

The first type of offenders, one-time offenders, are likely to be either younger offenders who have no criminal history but who episodically binge-drink[13] at social gatherings or older offenders who have no criminal history but who episodically binge-drink in response to

[13] According to the National Institute on Alcohol Abuse and Alcoholism, binge drinking is defined as, "a pattern of drinking that brings blood alcohol concentration (BAC) levels to 0.08 g/dl." (NIAAA, n.d.)

unexpected social stresses (e.g., sudden unemployment or divorce) or as a result of changing social roles (e.g., transitioning out of parenthood). It is unlikely that these offenders are motivated by the factors associated with general criminal offending (e.g., financial gain) and may have more prosocial bonds that make them responsive to criminal sanctions. For this group of offenders, I expect there to be a significant population of DUI offenders with low rates of overall or DUI-specific recidivism. This group is most similar to DeMichele, Payne, and Lowe's (2013) classification of "social drinkers."

For the second group of offenders, offenders with an underlying alcohol use disorder it is likely that the underlying alcohol use disorder was the primary contributor to their DUI.[14] These offenders are also unlikely to have any criminal history, however, if they do have prior convictions, they are likely for prior DUI or other alcohol related offenses (e.g., public drunkenness). Offenders in this group are generally law-abiding but may have a problematic relationship with alcohol and are at a higher risk of committing a subsequent DUI offense. This group of offenders is most similar to Marowitz's (1998) problem drinkers who drive and DeMichele, Payne, and Lowe's (2013) "chronic drinkers."

The third group of offenders are general offenders who engage in a broad range of criminal offenses, including DUI offending. These offenders are likely to have a diverse criminal history and are more likely to be convicted of a drug-impaired DUI, given that drug-impaired DUIs necessarily require participation in other types of criminal offending (i.e., illicit drug use). Similar to the findings in the later Glueck studies (Laub and Sampson, 2003), this group may consist of serious offenders who generally desist from crime, but who continue to engage in anti-

[14] I specify alcohol-impaired DUI offenses because drug-use is likely representative of a willingness to engage in other types of criminal offending. While alcohol is a legal substance in the United States, most drug-impaired DUI offenses are associated with illicit drug use (as opposed to legal prescription drug use).

social behaviors such as binge drinking and driving under the influence. Alternatively, this group may include young offenders who have a high frequency of offending generally. Further, this group may include individuals with a substance use disorder that is associated with other types of criminal offending, whether that is illicit drug use or property crimes associated with a drug addiction. This group of offenders is likely to have higher rates of recidivism generally and of non-DUI recidivism specifically.

Hypothesis 2: Risk assessment instruments developed using offender demographics, criminal history, and primary offense characteristics will be able to predict the likelihood of any reconviction better than chance.

Research has demonstrated the ability to predict recidivism among general offenders and among particular types of offenders (see Campbell et al., 2007; Monahan and Skeem, 2013; Harris and Rice, 2015). General research on risk assessments indicate that actuarial instruments consistently outperform clinical judgments and provide estimates that are better than chance (Grove and Meehl, 1996). Even if DUI offenders are different from the general offending population on average, it is unlikely that patterns of recidivism are completely random. Despite the potential differences from the general offending population, prior research has identified strong patterns in recidivism among DUI offenders particularly for age (Yu, 1994; Rauch et al., 2010) and criminal history (Marowitz, 1998; Rauch et al., 2010). Burgess risk models constructed based on offender demographic, criminal history, and primary offense characteristics should be sufficient for distinguishing between offenders with high- and low-risk of recidivism.

Hypothesis 3: Risk assessments predicting any reconviction will be more accurate than risk assessments predicting DUI-specific recidivism.

The ability to predict outcomes ultimately depends on the heterogeneity of the population and the overall base rate of the outcome being predicted (Berk et al., 2017). Outcomes with a lower base rate are more difficult to predict and there is some evidence indicating that predictions of rare events may actually result in more classification errors than chance (Meehl and Rosen, 1955). Not all DUI offenders recidivate. When offenders do recidivate, not all of them will recidivate with a DUI. Given that the base rate of the outcome in a model predicting DUI recidivism will be lower than the base rate predicting any recidivism, I expect that the predictions for DUI-specific recidivism will be less accurate.

Data and Methods

AOPC Data Request

In December 2017, in conjunction with the Pennsylvania Commission on Sentencing (PCS), I submitted requests for data from the Administrative Office on Pennsylvania Courts (AOPC). At the time, the PCS and the AOPC were undergoing the development of a new data transfer process overseen by a third-party software company, BrickSimple. The data request for my dissertation data was the first request submitted through the new partnership with BrickSimple.

Under this new system, the data request process is initiated by a “candidate list” of offenders created by the PCS and sent to BrickSimple. The candidate list includes five identifiers: first name, last name, state identification number (SID), offense tracking number (OTN), and date of birth. BrickSimple then submits the information for offenders on the candidate list to the AOPC, which uses these identifiers to search CPCMS (Common Pleas Case

Management System) and MDJS (Magisterial District Judge System) for each offender. AOPC identified potential matches using four matching criteria: OTN, SID and name (first name and last name), SID and date of birth, and name (first name and last name) and date of birth. AOPC selects all criminal dockets for all offenders in CPCMS and MDJS who matched on at least one of the four selection criteria.

Selecting an Initial Candidate List

In order to request data, I first had to identify a candidate list of offenders who could potentially be included in my dissertation research. The PCS would typically use PCS sentencing data in order to identify a candidate list. However, the PCS does not receive information for ARD cases, because Common Pleas (CP) courts are required to report only conviction information into the PCS databases. As such, the PCS is missing information on a substantial portion (about half) of first-time DUI offenders. I decided to use existing AOPC datasets on statewide offenses sentenced in 2006 and 2007 to identify a candidate list for this dissertation. These records were previously obtained for research projects conducted by members of the PCS and the Penn State Criminology Department.

The original files included all dispositions for 2006 and 2007. There were two separate files: one for dispositions in Pennsylvania Courts of Common Pleas and one for dispositions in Philadelphia Municipal Courts. Due to differences in the availability of certain variables as well as differences in the formatting of variables that the files did share, I had to work with the two court databases separately. For each file, I first selected all dockets that had at least one charge for a DUI offense (either 75 Pa.C.S.A. § 3731 or 75 Pa.C.S.A. § 3802).

The next issue I faced concerned the changes in DUI laws passed by the Pennsylvania General Assembly in Act 24 in 2003. Act 24 included several important changes to DUI law in

Pennsylvania, including a reduction of the BAC standard from .10% to .08% and the introduction of a new sentencing grid (based on BAC level and number of prior DUIs) for DUI offenders.

Act 24 went into effect on February 1, 2004, meaning that section 3802 of the Vehicle Code replaced the previous offenses under section 3731. The problem I faced concerned the fact that my sample of 2006-2007 cases included offenses under both the old and the new DUI laws. Cases disposed in 2006 were more likely than cases disposed in 2007 to include a charge under the old DUI laws (75 Pa.C.S.A. § 3731).

I decided to select only offenders who were charged with an offense under the new DUI laws (75 Pa.C.S.A. § 3802) and whose cases were disposed in 2007. I made this decision for four reasons. First, as a result of changes following Act 24, it is difficult and inappropriate to compare DUI offenders sentenced under the old statutes to DUI offenders sentenced under the new statutes. Under previous laws, offenders driving with a BAC of .08% may not have been arrested for a DUI, but under current law, they would have been arrested and charged with a DUI. Including offenders sentenced under the old statutes would result in an over-count of offenders with a higher BAC level. Second, critical information such as BAC level is derived from the subsection under which an offender is charged. Subsections in section 3802 provide a more thorough classification of BAC level than the previous subsections in section 3731. Third, because this dissertation may be helpful for developing policies concerning current DUI offenders, I decided the research should be limited to an examination of offenders sanctioned under the current law. Finally, in order for offenders to have a case disposed in 2006 or 2007 for an offense under the old DUI law, the offense must have been committed prior to the enactment of Act 24 (February 1, 2004). As a result, the few cases with a charge for an offense in section

3731 likely represent a unique subset of cases that took an extraordinarily long time to process through the criminal justice system (at least 2 years).[15]

I submitted a request to BrickSimple and the AOPC for the criminal records for 52,285 offenders. This request included all offenders who had a CP or Municipal Court (MC) case disposed in 2007 with at least one DUI charge under the new DUI statutes. I requested a complete record of all criminal cases for each offender, including cases prior to their 2007 DUI case as well as cases after their 2007 DUI case.

Coding the AOPC Data

I requested information for all criminal (CR) dockets from the CPCSM and MDJS. The response from AOPC did not include juvenile or expunged dockets. In addition, I did not receive miscellaneous (MD), summary appeal (SA), or summary (SU) dockets from the CPCMS. Similarly, I did not receive non-traffic (NT), civil (CV), traffic (TR), or landlord/tenant (LT) dockets from the MDJS. The final data from AOPC should have included only those cases that were filed with a CR docket, limiting the analyses of this study to criminal history and recidivism of adult, criminal offenses.

As mentioned previously, the AOPC identified potential matches from our candidate list with cases in the CPCMS and MDJS using four match criteria: OTN, SID and name (first name and last name), SID and date of birth, and name (first name and last name) and date of birth. AOPC selected all criminal dockets for all offenders in the CPCMS and the MDJS who matched on at least one of the selection criteria. BrickSimple received individual XML data files for each

[15] For example, these cases may include individuals who failed to appear at a court hearing and had a warrant issued for their arrest.

match. BrickSimple parsed the data from the individual XML files into CSV files containing data for all matches.

I received 17 different files for all of the offenders who matched one or more of the selection criteria.[16] Each file contained different types of information for the matched cases. I used 3 of the 17 files – the offender file containing information about offenders, the case file containing information about particular cases, and the charge file containing information specific charges within a case – in order to construct measures of criminal history and recidivism.

I imported each of the CSV files into SPSS and used the SPSS merge command to combine the files. Each file contained a unique AOPC identifier for the particular case. In order to maintain all of the charge information for a case, I first merged the offender data to the case file and then merged the case information into the charge file. The resulting dataset was a long dataset, with each observation representing one charge in a specific case. The offender and case variables were the same for each charge in a specific case (e.g., docket number, county, case disposition), but the offense variables were different for each charge in a case (e.g., charge sequence number, offense description, and offense disposition). It is important to note that the offender file was not a broad file that could be linked to all cases for a particular individual, but rather, it was a case-specific file that provided the offender information for each case. As a result, offenders who had multiple cases also had multiple records in the offender file. The full set of merged data included 803,116 charges in 184,911 cases. The following is a discussion of how I processed the AOPC data to create a single file for analyses. I made a series of decisions that resulted in the removal of offenders, cases, OTNs, or charges.

[16] The 17 files received included: Other Factors, Bail, Defendant Balance, Case, Charge, Charge Sentence, Missing OTN Disposition, Offender address, offender external ID, Offender, Warrant, Response, Request, Request Status, Sexual Classification, Outstanding Warrant List, and Related Sanction.

Creating a Unique Identifier

AOPC and BrickSimple did not provide a unique identifier to easily link all of the cases that were associated with the same individual. Although SID is technically a unique identifier, it was often missing in the data we received from AOPC (15.3% of all charges). It is also possible that offenders could have been assigned multiple SIDs. I did not receive Social Security Numbers for offenders, eliminating it as a possible unique identifier. Finally, I did receive each offender's first, middle, and last name, as well as their date of birth. However, because there are often inconsistencies in the way an offender's name is recorded for different cases (e.g., with a middle initial, with a full middle name, married names vs. maiden names, hyphenated names, etc.), I had to create a unique identifier for each offender on the candidate list and match that identifier to each case I received from AOPC.

To create this unique person identifier, I replicated the selection process that AOPC used to identify potential matches in the CPCMS and the MDJS. First, I assigned a unique number to each person in my original candidate list. Second, I matched offenders in my candidate list to the cases received in the AOPC data using four match criteria: OTN, SID and name (first name and last name), SID and date of birth, and first name, last name, date of birth. Most of the charges matched my candidate list on OTN (N = 214,665), SID and Name (N = 608,029), SID and Date of Birth (N=555,394) or Name and Date of Birth (N=724,780).

Using all available matching techniques, I was able to match all but 38 of the charges to an offender on the candidate list (99.9% match rate). The unmatched charges were most likely due to the AOPC using their own unique identifiers to identify additional case matches that did not match on the four previously discussed criteria. Included in the AOPC data was a string variable labeled "aca_EventType." After examining this variable, I saw that this field identified the OTN or name on the candidate list that matched the data in the CPCMS or the MDJS. Unfortunately, the variable was truncated when the data were parsed. However, I was able to successfully destring the OTN information from this variable for most offenses. I remerged the person ID using the OTN from the candidate list and the OTN that was pulled from the aca_EventType variable. Nearly all charges (N=802,535; 99.9%) had an OTN in the event type field that matched an OTN on the candidate list.

When merging the unique identifier, I realized that several cases in the AOPC matched multiple different offenders in the candidate list. Upon further examination, I realized that the original candidate list included duplicate offenders who were not identified as the same individual when constructing the original candidate list. In some instances, an offender had an SID listed for one case, but did not have an SID listed for a second case. In other instances, there were minor spelling differences in the first or last name (e.g., Mathew vs. Matthew). In each case where a person in the AOPC data matched two or more offenders in the candidate list, I manually reviewed all relevant records to determine whether they were true duplicates. If the offenders on the candidate list were true duplicates, I merged the person IDs so that they would be included in my final sample only once. This reduced the sample in my candidate list from 52,285 offenders to 52,151 offenders.

After manually reviewing the charges that matched multiple offenders on my candidate list, I found there were still some offenders who had multiple IDs. I had to make a decision on how to handle these cases since I could not assign them a unique personal identifier. Rather than choosing to assign these cases to one offender or the other, I decided to remove these offenders from the sample altogether. I selected all of the cases where multiple IDs matched a single case, selected all other charges associated with each individual ID, and removed all of the selected charges. In total, I removed 2,701 charges associated with 10 IDs on the candidate list. I removed 38 charges that did not match any offender on the candidate list. In total, there were 44,966 unique offenders with 800,377 charges in the final AOPC dataset.[17]

Each arrest in Pennsylvania is assigned a unique offense tracking number (OTN) at the time of arraignment. This OTN can be used to track a case through the judicial system. The Pennsylvania Commission on Sentencing uses OTNs rather than arrests when calculating information about criminal history or recidivism. To be consistent with the PCS research, I also used OTN as a measure of "arrest" for purposes of criminal history and recidivism.[18] Any number of charges could be included in a single OTN (e.g., an OTN could include one burglary or ten burglaries). I used OTN and the unique person ID to aggregate charges into one event for individual offenders. The final AOPC dataset included 157,297 person-OTNs.

Removing Duplicate Cases

Before I began coding the data, I first checked to see if I received any duplicate cases. There were two different types of duplicate cases: true duplicates and duplicate OTNs in different court levels (e.g., MDJ and CP). True duplicates were instances where all of the information, including offender characteristics, case information (e.g., filing date, docket, document date), and charge information (e.g., charge sequence number, title, section, subsection, disposition) were all identical. While these duplicates would not affect the final calculations of

[17] There were 7,008 offenders on the candidate list who did not match charges in the AOPC dataset. These offenders were not removed from the sample.

[18] There were two alternatives to using OTN: arrest date and docket. However, date of arrest was missing in a substantial portion of the charges in my AOPC data. In addition, multiple arrests, or OTNs, may be disposed of in the same docket. Docket was also an insufficient identifier because a single arrest would have two separate dockets – one in the MDJ/MC and one in the CP. I needed an identifier that was consistent across court types. In addition, some prosecutors may decide to split charges from a single arrest event across multiple dockets. For example, if an offender is arrested and charged for committing 10 burglaries, the prosecutor may create 10 separate dockets to account for each of the separate burglaries even though they were part of the same arrest. If I used docket, I would overcount priors by counting offenders MC/MDJ and CP dockets for the same offense and by counting multiple dockets separately, even when they result from a single arrest.

any criminal history or recidivism variables, I removed the duplicates from the file in order to reduce the overall size of the file.[19] I removed a total of 10,910 charges that were true duplicates.

For duplicate OTNs in different court levels, I kept only the docket for the Court of Common Pleas (CP). Criminal cases in Pennsylvania undergo initial judicial review at the Magisterial District Court (MDJ) or Municipal Court (MC). Criminal charges that survive initial judicial review are held over for court in the appropriate Court of Common Pleas. The criminal charges are then handled and sentenced at the CP level. In most instances, I received only the CP case information for criminal charges. By keeping the CP docket for the OTNs for which I received both CP and MDJ/MC information, I kept the court records where the charges were eventually disposed. I ended up removing 19,114 cases and a total of 90,337 charges.[20]

Missing OTN

For this dissertation, criminal history and recidivism are calculated using unique OTNs. As such, I needed a valid OTN to identify criminal events. If an OTN was missing, I could not verify that the associated charge was a unique criminal event (i.e., not associated with other charges containing a valid OTN or other charges also missing an OTN), and I could not be sure that I did not have a duplicate court record already in the AOPC data (i.e., the associated MDJ/MC or CP docket for the same charges). I decided to remove charges that were missing an OTN. I removed 4,805 charges, representing 1,365 cases and 855 person-OTNs. OTN was missing in cases across all three court types (CP, MC, and MDJ) and in cases across a wide range of years (1968 – 2018). There was no identifiable pattern associated with the cases missing an

[19] These duplicates most likely occurred because of the duplicate offenders on the original candidate list. An explanation of these duplicate offenders was discussed in the previous section about creating a unique ID.
[20] Each OTN is assigned a unique case ID from AOPC at the MDJ/MC and at the CP. Consequently, when I removed these duplicates, the number of cases in the file decreased but the number of OTNs stayed the same.

OTN and offender- or offense-based characteristics. I concluded that this data was missing at random and removing these cases should have no substantial effect on the final results. In total, this step eliminated 0.69% of the charges in the AOPC data.

At this point, the file contained all valid OTNs for all offenders on my initial candidate list that matched the current AOPC records. The file included 694,325 charges in 162,256 court cases. These records represented 156,442 unique person-OTNs for 44,951 offenders. I decided to keep all of these records and code these data so that I had some record of arrests.

Coding Conviction Dispositions

For this dissertation, my measures of criminal history and recidivism include only convicted offenses. As such, I had to create an identifier for charges that resulted in conviction. I used the charge disposition to determine which charges to include in the conviction file.[21] I created a separate file with all of the different charge dispositions included in the AOPC data. I manually coded each of the dispositions consistent with the coding used by the Pennsylvania Commission on Sentencing for their broader risk assessment project. I limited the conviction sample to charges with one of the following seven dispositions: guilty, nolo contendere, Alford plea, probation without verdict (PWOV), accelerated rehabilitative disposition (ARD), drug court, and treatment court completed. While PWOV and ARD dispositions are not technically a conviction, they are dispositions that indicate the defendant was guilty of the alleged conduct. These types of diversionary dispositions are particularly common among drug and DUI offenders. Consequently, I chose to include diversionary dispositions in my measure of convictions for criminal history and recidivism.

[21] I could have used case disposition and selected the cases that resulted in conviction, but I wanted to be sure I was not coding data for charges for which offenders were not convicted.

Table 2-1 shows the number of non-conviction charges that I removed from the sample by different disposition groups. In some cases, I received the lower court docket where the charges were initially reviewed and held for court, but I did not receive the corresponding CP docket. I removed any lower court (MDJ/MC) charges where the charge disposition was "held for court" (N = 14,926). Similarly, I removed charges where the disposition indicated that the charge was moved to some other court, such as non-traffic or traffic court (N = 10,360). I also removed all charges that were dismissed, withdrawn, or nolle prossed (N = 365,082). These dropped charges represented the majority of all non-conviction dispositions (77.77%).

Table 2-1 Charge Dispositions Removed from Conviction Data

Disposition	N	%
Held For Court	14,926	3.18%
Transferred	10,360	2.21%
Dismissed	365,082	77.77%
Not Guilty	7,094	1.51%
Settled	183	0.04%
Mistrial	31	0.01%
Other	499	0.11%
Migrated	3,260	0.69%
Missing	68,017	14.49%

I removed offenses with a not guilty (N = 7,094) disposition. Not guilty dispositions were present for cases in both MC/MDJ and CP cases. Similarly, I removed offenses with a settled (N = 183) or mistrial (N = 31) disposition. All settled dispositions were for MC/MDJ cases and all mistrial dispositions were for CP cases. There was also a small number of other dispositions that did not indicate a conviction or finding of guilt. I removed all charges with these other dispositions (N = 499), which were all associated with CP cases.

Finally, I removed all charges where the disposition was migrated (N = 3,260) or missing (68,017). These dispositions lack the information necessary to determine whether the charges survived an initial judicial review. The CPCMS went live on a county-by-county basis starting in November, 2003 with the last county (Philadelphia) joining in September, 2006. Counties manually migrated cases prior to their "go-live" date into the new CPCMS. Offenses with a "migrated" disposition represent cases that counties migrated into the new CPCMS database with incomplete information. Offenses missing a disposition appeared to be missing at random. Offenses with a missing disposition were present in all three court types and ranged in case year from 1978 to 2018. Dispositions were missing in most counties. These missing dispositions may be the result of a clerical error or may be associated with cases that have not been disposed.

The final conviction data included 224,873 charges associated with 110,835 person-OTNs in 111,865 court cases for 41,458 unique offenders.

Coding the Primary Offense and Selecting the Final Sample

In order to split the data into prior offenses and recidivism offenses, I first had to identify the primary offense (i.e., the 2007 DUI) so that it would not be counted as either a prior offense or a recidivating offense. I returned to the original 2007 AOPC data, from which I identified the original candidate list for this study. This search also offered me the opportunity to identify my final sample of offenders. I made a series of decisions that resulted in the removal of some offenders from my sample.

At sentencing for a case in the Pennsylvania Court of Common Pleas, the current plan is for a judge to determine which risk assessment instrument to use based on the most serious offense in a judicial proceeding. Since the development sample for a risk assessment instrument ought to resemble the population of offenders for which the instrument would be used, I had to limit my sample to offenders whose most serious conviction offense was a DUI. Starting with the 2007 CP data file, I removed all non-conviction offenses using the same disposition coding that I used previously. I removed 121 offenders who had no conviction disposition in any CP OTN.

AOPC data do not include an indicator for the most serious offense. I decided to use grade and sequence number to select the most serious offense for each offender. I first coded grade such that homicide (H) was the most serious and summary (S) was the least serious. Ungraded misdemeanors were classified as the least serious misdemeanor, followed by M3, M2, and M1. Similarly, ungraded felonies were classified as the least serious felony, followed by F3, F2, and F1. Because courts typically enter the most serious offense as the first offense, I assumed the first offense was the most serious offense if there were multiple offenses with the same grade (i.e., multiple F1 offenses). If the resulting most-serious offense was not a DUI, I removed all charges from the associated OTN from the data. In total, I removed 3,419 offenders who had only OTNs that included at least one offense that was more serious than a DUI.

Finally, I selected the earliest offense for each offender. This step served two purposes. First, I had to ensure that each offender was in the sample only once to avoid statistical bias from oversampling offenders who had multiple arrests and sentences in a single year. Second, I selected their first offense so that subsequent offenses would be coded as recidivism.

I repeated this selection process for the offenders in the original MC case file. I removed 7 offenders who did not have any conviction dispositions in their MC OTNs and 715 offenders who did not have an OTN where a DUI was the most serious offense. The original MC dataset, from which I identified my candidate list, included all cases sentenced in 2006 and 2007. However, the data did not include a case disposition date. When I sent my original candidate list to AOPC, I included all DUI offenders, meaning that I received data for some offenders sentenced in 2006. Consequently, I needed to find some way to remove cases that were most likely sentenced in 2006 so that I was not oversampling cases from Philadelphia (since all other counties were limited to the cases disposed in 2007).

I selected the case disposition date and OTN from all data I received from the AOPC. Using this file, I merged case disposition into my sampling data using OTN. I removed 1,330 offenders whose MC cases were disposed in 2005 or 2006.

Of the remaining cases, 699 offenses did not match with the AOPC data, meaning that I still did not have a disposition date for these OTNs. Nearly all (98.2%) of the offenses that did not match were for offenders where the most serious DUI was an ARD. By statute, offenders who successfully complete ARD for a DUI will have their ARD records automatically expunged after 10 years. It is likely that the cases I was unable to match were associated with offenders whose records were expunged by the AOPC.

The 699 offenders who did not have a disposition date were not missing at random. These offenders were all from Philadelphia, they were almost all ARD cases, and they were likely expunged meaning that they did not commit any additional offenses in the 10 years after their DUI. Removing these cases from my sample would create non-ignorable bias, resulting in an under-sampling of less serious offenders in Philadelphia.

I decided to use the available information for other offenders in the data to determine a reasonable disposition date for missing cases. For these cases, I used 209 days, the average number of days between a DUI offense date and the associated disposition date for ARD cases in Philadelphia when the disposition date was not missing.[22] Using the complete and imputed

[22] This calculation put some case dispositions beyond the timeframe for the sampling frame. That is, some of this "filler" disposition dates were in 2007 (e.g., if an offense was committed in November, 2007, the disposition would be 209 days later, in May or June of 2018). I decided to keep these offenders in the sample since the data should have only included offenders sentenced in 2007.

disposition dates, I selected the earliest offense for each offender in the MC data and removed second or subsequent OTNs.

Next, I merged the CP and the MC data, stacking the cases into a single file.[23] Since it was possible that an offender committed an offense in Philadelphia and in a nearby county in the same year, it was possible that this combined dataset also included multiple OTNs for the same offender. Using the same approach that I used for the individual files, I selected the OTN with the earliest disposition date for each offender. I reviewed these cases and found that they were all cases from Bucks, Chester, Delaware, Montgomery, and Philadelphia counties, with the exception of one case from Centre County. All of the non-Philadelphia cases were removed because an earlier case was filed for the same offender in Philadelphia. These findings make sense, given that all of these counties (except Centre) are counties that border Philadelphia. In other instances, my data included the MC and CP case for the same offense (OTN). After merging these files, the total number of unique offenders was 46,448.

I aggregated information about the charges in the primary offense OTN so I could limit the file to one observation per offender. First, I created a count variable for the total number of conviction charges in each OTN. Next, I coded each type of DUI offense in an OTN using the offense subsection (see Appendix A). The AOPC data do not include a separate indicator of an offender's specific BAC level, but I was able to use the statutory subsection to determine the range within which an offenders BAC fell. I coded a separate variable for the highest BAC category, also using the offense subsection. Some offenders were charged under both the general impairment subsection as well as a specific BAC subsection (e.g., .08% - .09%, .10% - .15%, or .16% and greater). Other offenders were charged both with a drug DUI (subsection D) and an

[23] I modified the variables (names and formats) in the MC data to match the variables in the CP data prior to merging the datasets.

alcohol DUI (subsections A, B, and C). I coded a single variable for each offender for the most serious type of DUI conviction in the primary OTN with the least serious being an alcohol involved, general impairment offense, and the most serious being a drug-involved DUI (including drug and alcohol DUIs).

I aggregated additional indicator variables for DUI characteristics aside from the BAC or classification as a drug or alcohol DUI. Included in these measures was a variable indicating the presence of a minor (under 21) offender and a variable indicating whether the offender was charged with a DUI while driving a commercial vehicle or school vehicle. At this point, I also found several offenders who were included in the data, but who were actually charged with permitting a DUI, not committing a DUI themselves. In Pennsylvania, it is illegal to “authorize or knowingly permit a motor vehicle owned by him or under his control to be driven" by an offender who is under the influence of drugs or alcohol (75 Pa.C.S.A. 1575). While permitting a DUI is a separate offense in the vehicles code, these offenses were also recorded in the AOPC data using a special subsection under 75 Pa.C.S.A. 3802. These offenders did not themselves drive while under the influence of drugs or alcohol. I decided to remove these offenders (N = 3) from the sample.

The final primary offense file included 46,435 offenders. I selected the most serious DUI for each offender and removed all other charges. The file included information about all of the charges in the primary offense OTNs, but the data were aggregated such that each observation represented a unique offender.

<u>Identifying Prior Convictions and Recidivism</u>

In order to split the AOPC data into prior offenses (arrests and convictions) and recidivating offenses, I first had to identify the primary offense. I merged the OTNs and case disposition dates associated with the primary offense from the candidate list data into the long AOPC data containing all court data using the unique ID. I identified the primary offense for each offender by matching the primary offense OTN with the OTNs in the AOPC data. In the AOPC data, 161,674 of the offenses matched a primary offense based on the OTN. I did an additional match using offense date and matched 163,793 of the offenses in the AOPC with the offense date of a primary offense. I did an additional match with offense date where I selected all cases in the AOPC data for which the offense date fell within two days before or after the offense date in the primary offense data. Using this expanded offense date match criteria, 164,719 of the offenses were identified as a match with the offense date of a primary offense. In total, 181,065 of the offenses in the AOPC data matched an offense in the primary offense candidate list. I identified the primary offense in the AOPC data for 37,306 offenders. I removed the primary offenses from the AOPC data so I would not count these charges in the calculation of prior offenses or recidivism offenses.

Next, I split the AOPC data into two files: prior offenses and recidivism offenses. For prior offenses, I selected all offenses for which the file date was before the date of sentence for the primary offense. The file date is associated with the date that the charges were filed in a particular court (i.e., there are different file dates for the same case in MC/MDJ and CP courts). For recidivism offenses, I selected all offenses for which the document date was after the date of sentence for the primary offense. The document date represents the date that an initial criminal complaint was filed in the MC, MDJ, or CP.

I coded two measures of criminal history: prior arrests and prior convictions. For prior arrests, I summed the number of unique OTNs with a file date prior to the date of sentence for the primary offense. For convictions, I summed the number of unique OTNs with a conviction disposition and disposition date prior to the date of sentence. I used disposition date for the conviction OTNs to ensure that I counted only the convicted OTNs that would have been known to the judge at the time of sentencing for the primary offense.

For each arrest and conviction, I coded each offense into one of eight crime categories: personal/sex, property, drug, DUI, other traffic, public order, public administration, and firearms/weapons. I used the PCS crime category coding to code each offense based on the title and section of the offense. The PCS codes only the offenses in Title 18 (Crimes and Offenses), Title 23 (Domestic Relations), Title 35 (Health and Safety), and Title 75 (Vehicles), because nearly all misdemeanors and felonies are listed in these portions of the Pennsylvania Statutes. While the data did include some offenses outside of the aforementioned titles, these offenses were all summary offenses and were not included when coding the types of prior offenses in an offender's criminal history.

I aggregated criminal history information for each offender. The final criminal history file included a total count of prior arrests and convictions as well as a total count of arrests and convictions for offenses in each of the eight crime categories.

In order to identify recidivating offenses, I first had to identify when the exposure time for each offender would begin. I wanted to capture offenses that were committed and convicted after release from incarceration for the primary offense. The primary offense data I used included the disposition date for most offenses (see previous discussion of MC cases) but did not include details about sentencing, including the sentence type (e.g., probation or incarceration) or sentence length.

DUI offenders face unique mandatory sentences. These penalties, included in 75 Pa.C.S. 3804, range from diversionary probation (ARD) to a minimum incarceration of one year. I calculated the beginning of each offender's exposure time by adding the statutory minimum incarceration length for the most serious DUI in the offender's primary offense to the disposition date for the primary offense. Statutory minimums varied by subsection depending on the offender's DUI criminal history. The subsection included in AOPC data also included an asterisk after the subsection, indicating whether it was the offender's first, second, third, or subsequent DUI offense. I used the offense subsection and the asterisks listed in the AOPC data to calculate the statutory minimum for each offender. Appendix A provides the statutory minimum for each subsection in 75 Pa.C.S. 3802. Since offenders receiving ARD do not serve any period of incarceration, I calculated their exposure time beginning at the disposition date for the primary offense.

Most offenders (N = 26,784; 57.7%) faced no incarceration. An additional 14,432 (31.1%) faced a minimum incarceration sentence of less than 90 days. Offenders may be sentenced to a mandatory minimum incarceration sentence for one year if they are sentenced for their fourth or subsequent DUI with a high rate of BAC (.10% - .15%), their fourth or subsequent DUI while driving a commercial vehicle or school vehicle, their third or subsequent DUI with the highest rate of BAC (.16% or greater) or their third or subsequent DUI with controlled substances. Table 2-2 shows the distribution of offenders across different statutory minimum sentences.

Table 2-2 Maximum Statutory Minimum Sentence for Primary DUI, in Days

Days	N	%
0	26,784	57.7
2	3,814	8.22
3	7,224	15.56
5	1,494	3.22
10	559	1.2
30	1,341	2.89
90	4,260	9.18
365	942	2.03

It is possible that I overestimated or underestimated the release date for offenders for four reasons. First, offenders receiving an ARD are not sentenced to the mandatory minimum term of imprisonment as indicated by the type of DUI. As such, offenders would have been released prior to the release date I assigned the offender in the data. Second, offenders convicted under subsection A who refuse breath testing or blood testing are sentenced to the mandatory minimums specified for offenses under subsection C or D. Third, an offender convicted under subsection A who was involved in an accident resulting in bodily injury or damage to a vehicle or other property is subject to the mandatory minimums put forth for offenses under subsection B. My estimated release date would not account for breathalyzer refusals or accidents related to the DUI. Thus, my estimated release date could underestimate the actual incarceration sentence.

Finally, I calculated the statutory minimum based solely on the period of incarceration for the most serious DUI. It is possible that offenders also received incarceration sentences for co-offenses, but without variables indicating the sentence length for each offense and whether the different sentences were to be served concurrently or consecutively, I was unable to construct a measure for the total incarceration minimum for an OTN.[24] In these instances, it is possible that offenders were still incarcerated after the estimated release date that I calculated.

I coded two measures of recidivism: re-arrest and re-conviction. For re-arrest, I selected the first OTN for which the document date was after the release date for the primary offense. I then coded a count variable for the total number of charges in the first re-arrest. Using the same process previously described for coding prior offenses, I created indicator variables for the different types of offenses included within the first re-arrest OTN.

For reconvictions, I selected the first OTN for which the document date and the disposition date were after the release date for the primary offense and for which at least one offense had a conviction disposition.[25] I then coded a count variable for the total number of conviction charges in the OTN and created indicator variables for the different types of offenses included in the re-conviction OTN.

I merged the criminal history and recidivism files into the primary offense file using the unique offender ID. I also merged in a separate indicator for each offender identifying whether or not I received any records for the offender from the AOPC. It was possible that I received AOPC data for an offender, but that the offender had no prior offenses and that the offender was not arrested or convicted of a subsequent offense. In these instances, the offender would have

[24] Since my sample is limited to only those offenders whose most serious offense was a DUI, it is not likely that they received additional incarceration sentences for co-offenses. Less serious co-offenses were likely to be summary offenses or low-level misdemeanors that are not associated with a statutory minimum term of imprisonment. Using the statutory minimum for the most serious DUI offense reduces at least some of the bias that would arise from starting exposure during offenders' periods of exposure while they were incarcerated.

[25] The first re-arrest OTN may be different than the first re-conviction OTN for two reasons. First, an offender may have been re-arrested but not convicted of one offense and later re-arrested and convicted of a different offense. Second, it is possible that an offender has multiple arrests and that the charges in a second or subsequent OTN are disposed prior to the disposition for the initial re-arrest. For purposes of this research, I wanted the first conviction, so I chose to select re-convictions based on disposition date rather than document date or file date.

missing values for all criminal history and recidivism variables. I recoded missing values for these offenders to be 0, indicating that they had no prior arrests and that they did not recidivate.

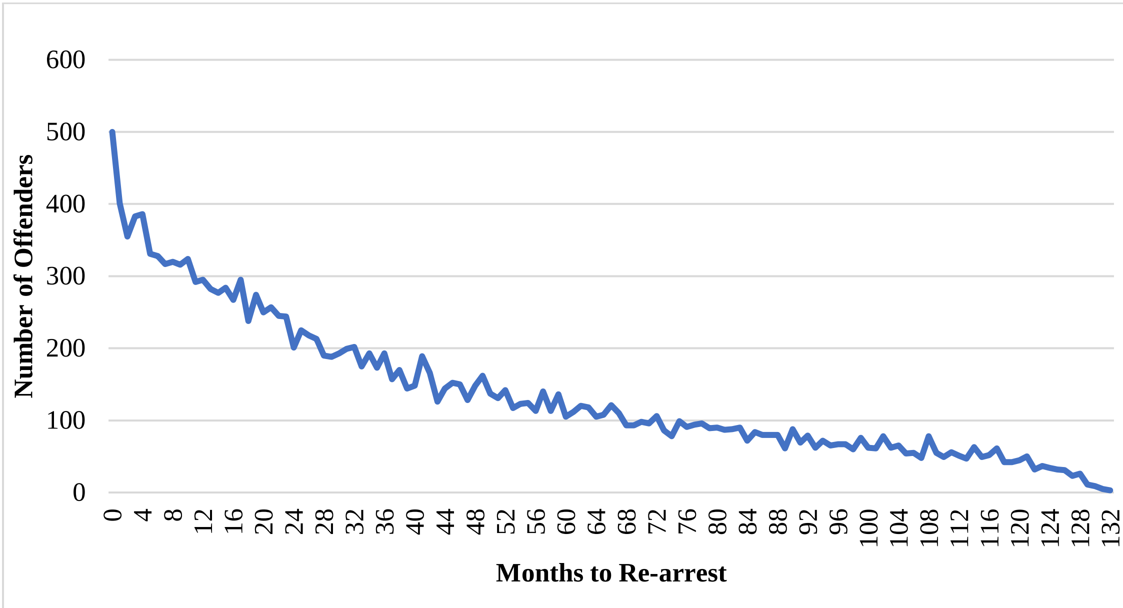
I received at least one AOPC record for 39,768 of the 46,418 offenders on my final candidate list (85.67%). I reviewed the case disposition for the offenders who did not match any records in the CPCMS or MDJS and found that nearly all of the offenders were processed with an ARD for their 2007 DUI. Because DUI offenses may be expunged after 10 years, I made the assumption that these offenders had no prior offenses and did not recidivate.[26] I kept these offenders in my final sample and coded their missing values for all criminal history and recidivism to be 0, indicating that they had no prior arrests and that they did not recidivate.

Coding Exposure Times

Once these files were merged, I coded the remainder of the recidivism variables indicating the time to failure for offenders who recidivated. The compiled dataset included the release date for each offender's primary offense and the document date, file date, and disposition date for each offender's first arrest and first conviction after his/her primary offense. For re-arrests, I calculated the time to failure as the time between the release date for the primary offense and the document date for the first re-arrest. For re-convictions, I calculated the time to failure as the time between the release date for the primary offense and the disposition date for the first re-conviction.

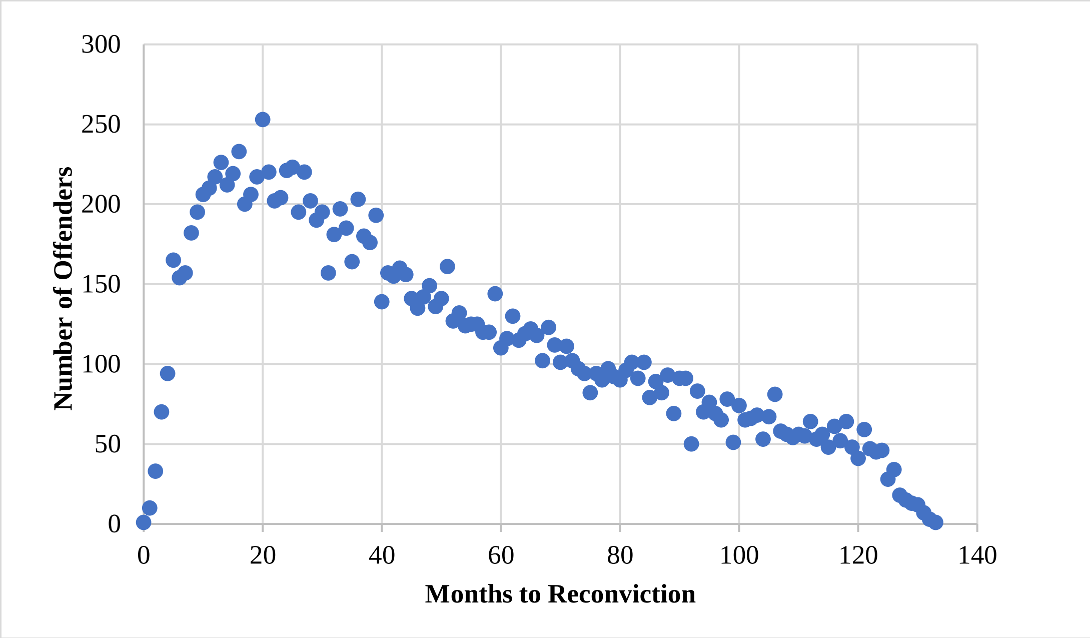
[26] It is possible that I am underestimating criminal history or recidivism. However, there were other ARD offenders for whom I received criminal history and recidivism data. Thus, there is good reason to believe that these missing values are legitimate. The use of casewise deletion would have almost certainly resulted in an overestimate of offenders with a criminal history or offenders who recidivated. The use of imputation for these variables was also inappropriate given that these data were not missing at random.

Figure 2-1. Months to Re-arrest



Of the sample, 39.4 % of offenders were re-arrested and 32.9% of offenders were re-convicted. Among recidivists, the average time to re-arrest was 40.9 months and the average time to re-conviction was 49.5 months. Figure 2-1 shows the distribution of time to failure, in months, for those who were re-arrested and Figure 2-2 shows the distribution of time to failure, in months, for those who were re-convicted. The number of offenders re-arrested was highest in the months immediately following release and declined over time. In terms of reconviction, the number of offenders reconvicted peaked 20 months after release (N = 253) and declined over time. The differences in the distribution of recidivism represents the time it takes to process cases from an arrest to a conviction.

Figure 2-2. Months to Failure - Reconviction



For this dissertation, I am operationalizing recidivism as a conviction for a criminal offense. Traditional recidivism research uses a 3-year follow-up period for offenders and operationalizes recidivism as a re-arrest. I chose to expand my follow-up period to include 5 years from the time of release for two reasons. First, offenders who are convicted within 5 years are likely to have been re-arrested within the first 3 or 4 years. By extending the follow-up period to account for the delay between an arrest and a conviction, this dissertation will be more comparable to prior research on recidivism. Second, a five-year follow-up period captures the majority of recidivism with a reconviction (65.94%). If I were to use a three-year follow-up period, I would capture only 43.35% of recidivism. By underestimating recidivism, my analyses would include a disproportionate number of false negatives.

I calculated a final failure variable for re-convictions where 1 represents that an offender was reconvicted within 5 years of release and 0 represents that an offender was not reconvicted within 5 years of release. In total, 21.5% of all offenders recidivated. I used the qualitative variables for the type of recidivism to create an additional measure indicating whether the initial reconviction was for a subsequent DUI offense. Only 11.2% of all offenders were reconvicted of a subsequent DUI offense. Among all recidivists (N = 9,960), 52.3% were reconvicted of a subsequent DUI offense. While these findings do indicate some specialization, they also suggest that DUI offenders are equally as likely to engage in a range of criminal behaviors.

Imputing Missing Data: Gender, Race, and Age

The data that I used for my initial sample selection did not include offender gender or offender race information. However, the offender files in the AOPC data that I received from BrickSimple did include these key demographics. I merged gender and race into my final dataset using the unique offender ID.[27]

For my research, I was also interested in the age of the offender when they were sentenced for the primary offense. I used date of birth and the disposition date for the primary offense to calculate the offender's age at the date of sentence. I calculated the number of days between an offender's disposition date and date of birth and divided the total by 365.25. I truncated the resulting number to an integer without rounding such that individuals who were 27.2 years old and offenders who were 27.9 years old were both listed as 27 years old.[28]

Gender, race, and age were all missing for some observations in the data. As noted previously, I did not receive AOPC data for all offenders in my sample. There were additional offenders for whom I did receive AOPC data, but who were missing on the values for gender,

[27] There were some instances where an offender's gender or race was missing for some OTNs but present in other OTNs. I aggregated the gender and race information to be sure that I captured these demographics if they were available in any AOPC cases for an offender.
[28] The methods in this dissertation use categorical variables for age. Consequently, all offenders are treated the same based on their total years of age. I could have left age as a continuous measure, but I chose to truncate the variable for ease of presentation in frequency tables and graphs.

race, and/or date of birth. In total, 9,928 offenders were missing gender, 7,034 offenders were missing race, and 703 offenders were missing age. I decided to impute the data for gender, race, and age rather than dropping offenders from my sample. Prior to imputing, I had to decide whether I should recode any variables and what type of imputation strategy I would use.

Coding Gender, Race, and Age Variables

I first reviewed the complete information for the offenders who were not missing on gender, race, or age. Table 2-3 reports the descriptive statistics for each of these demographic factors. Gender was reported as either male or female and required no subsequent changes. Race was reported using 4 categories: White, Black, American Indian, and Asian. The categories of American Indian and Asian had very few offenders (N = 18 and N = 278, respectively). Due to the small sample sizes, I would be unable to establish stable estimates for these racial groups in any multivariate analyses. As such, I followed the Pennsylvania Commission on Sentencing strategy to collapse American Indian and Asian offenders with White offenders. I ended up with a binary variable for race with White/Other Race and Black as the two groups.

Table 2-3 Missing Demographics

	N	%
Gender		
Male	31,255	67.3%
Female	8,129	17.5%
Missing	7,034	15.2%
Race		
White	32,614	70.3%
Black	3,580	7.7%
American Indian	18	0.0%
Asian	278	0.6%
Missing	9,928	21.4%
Date of Birth		
Complete	45,715	98.5%
Missing	703	1.5%

It is important to impute values for variables as they will be used in the final analyses. I knew that I would be conducting logistic regression where all variables are either binary or categorical. Rather than imputing a continuous measure for age and then coding a categorical variable based on the results, I chose to impute a single categorical age variable. There is some evidence suggesting that the passive creation of categorical variables using imputed values for continuous measures may actually introduce more bias into the data than directly imputing the value for the categorical variable, particularly when the data are not missing completely at random (Wagstaff, Kranz, and Harel, 2009).[29]

I considered both theory and statistical methods when creating a categorical variable for age at date of sentence. First, these offenders were all sentenced for an offense involving the consumption of alcohol. As such, I grouped all offenders under the age of 21. Offenders who

[29] Passive imputation creates imputed values (i.e., non-observed values) for categorical variables based on other imputed data instead of imputing the categorical variable based on all observed values for non-imputed variables.

were 21 at the date of sentence may have been younger than 21 when the offense was actually committed but were above the legal drinking age at the time of their disposition. Offenders aged 21 at the time of their disposition may have a greater risk of recidivism than offenders younger than 21 given their legal access to alcohol. I decided to classify offenders aged 21 as their own group. In order to determine the cut-points for age groups among the remaining offenders, I looked at the failure rates across age. My goal was to create relatively equal groups while also collapsing offenders who had similar patterns of recidivism. I decided to collapse offenders between the age of 22 and 24 into a single group. Beginning with offenders aged 25, I collapsed age groups in 5-year intervals (25-29, 30-34, 35-39, 40-44, 45-49) until age 49. Finally, I collapsed all offenders over the age of 50 into a single category.

I reviewed the distribution of offenders across the final age categories and confirmed that the categories were significantly different with respect to recidivism (χ^2 (8) = 785.55; $p < 0.000$). The group containing offenders who were 21 at the date of sentence stood out as the smallest group, but their rate of recidivism (30.47%) was noticeably different from the offenders aged 22-24 (24.52%). Given the theoretical justifications for evaluating offenders aged 21 as a distinct group of offenders, I decided to move forward with the imputation on these final 9 age categories.

Selecting an Imputation Method

I used multiple imputation through chained equations to predict values for gender, race, and age, when they were missing. Chained imputation techniques in STATA allow for the specification of the type of regression model used to impute each missing variable. In addition, chained imputation methods provide a value that is possible on the original scale for binary and categorical variables. Alternative methods, such as multivariate normal models rely on linear models, which can result in nonsense values for binary or categorical variables (e.g., .04 or .05 rather than 0 or 1). I used logistic regression to predict gender and race and multinomial logistic regression to predict the age-group at date of sentence.

Chained imputation techniques use iterative processes to fit multiple regression equations in which the missing variable is the outcome variable and completed data are used as predictor variables (Johnson and Young, 2011). Random error components are introduced in each iteration and the predicted value and the random error component are used to substitute for the missing values. Each iteration produces a new set of data. Subsequent analyses are conducted on each imputed dataset and the results are pooled to create a single point estimate and standard error estimate.[30] By pooling the estimates across multiple imputed datasets, these techniques reduce the bias introduced from missing data.

I made the assumption that my data are missing at random. That is, I assumed that the probability of missing values was not dependent on any unobserved characteristics, an assumption that underlies the use of multiple imputation techniques. My completed data included variables that would likely be correlated with gender, race, and age, such as criminal history, recidivism, types of criminal behaviors, and county-based characteristics. I used the available data on offender demographics, primary offense characteristics, criminal history characteristics, and recidivism characteristics to predict missing values for all three demographic variables.[31] In addition to the criminal history and recidivism variables modeled using convictions, I also used

[30] STATA uses the combination rules established by Rubin, 1987 for analyses of imputed datasets.
[31] I used the following variables in the imputation models: county, multiple charges, total conviction charges in primary offense, whether the primary offense included a charge for a DUI for a minor, total prior arrests, total prior convictions, most serious BAC in the primary offense, most serious type of DUI charge in the primary offense, prior personal conviction, prior drug conviction, prior DUI conviction, prior other traffic conviction, prior public order conviction, prior public administration conviction, whether the offender received ARD for the primary offense, whether the offender was reconvicted in the first 5 years following release for the primary offense, and whether the offender was reconvicted of a DUI in the first 5 years following release for the primary offense.

criminal history and recidivism variables modeled using arrests to increase the effectiveness of the imputation models.

I used new methods created by von Hippel (2018) to determine how many datasets I should impute. Traditionally, scholars suggested that between 2 and 10 imputations was sufficient to reduce bias and to produce replicable findings (Rubin, 1987). However, von Hipple's (2018) newest publication argues that the seemingly random sample of imputed datasets creates imputation variation and results in non-replicable findings. While imputation variation may have negligible effect on point estimates, research finds it can result in unreliable standard errors.

Von Hipple's approach to calculating the desired number of imputed datasets relies on a two-stage calculation. First, I conducted a pilot imputation where I imputed only 5 datasets. Second, I estimated a preliminary logistic regression (modeled on the analyses I would later use in the final development of a risk scale) and used a new post-hoc STATA command (***how_many_imputations)*** to determine the number of imputations needed to create stable standard errors. This command assesses how much the standard errors for point estimates would change if the data were imputed again. The command indicates the number of imputed datasets necessary to achieve confidence in the replicability of the standard error at the .95 level.

The two-stage calculation indicated a need for 11 total imputed datasets. The fraction of missing information was .07 (95% CI: 0.02, 0.21). I replicated the initial chained imputation procedures to add 6 additional imputed datasets. My final dataset included the initial, incomplete dataset, and 11 imputed datasets with complete values for all variables. The results presented in this dissertation were conducted on the 11 imputed datasets.

Imputation Diagnostics

I reviewed the imputed data to ensure that there were no extreme or skewed values and to be sure that there was general consistency across the imputed datasets. Table 2-4 shows the proportion of offenders in each category for gender, race, and age, for the observed, imputed, and completed data in each imputed dataset.

Table 2-4 Proportion of Offenders in Each Demographic Category, for Each Imputed Dataset

	Male		White/Other		Age at Date of Sentence								
	0	1	0	1	<21	21	22/24	25/29	30/34	35/39	40/44	45/49	50+
m=1													
Observed	0.206	0.794	0.098	0.902	0.070	0.043	0.147	0.178	0.111	0.109	0.111	0.102	0.130
Imputed	0.278	0.722	0.099	0.901	0.060	0.038	0.156	0.206	0.100	0.100	0.083	0.094	0.164
Completed	0.217	0.783	0.098	0.902	0.070	0.043	0.147	0.179	0.111	0.108	0.110	0.101	0.131
m=2													
Observed	0.206	0.794	0.098	0.902	0.070	0.043	0.147	0.178	0.111	0.109	0.111	0.102	0.130
Imputed	0.266	0.734	0.095	0.905	0.038	0.027	0.132	0.183	0.119	0.095	0.114	0.090	0.201
Completed	0.215	0.785	0.098	0.902	0.069	0.043	0.146	0.178	0.111	0.108	0.111	0.101	0.131
m=3													
Observed	0.206	0.794	0.098	0.902	0.070	0.043	0.147	0.178	0.111	0.109	0.111	0.102	0.130
Imputed	0.278	0.722	0.092	0.908	0.061	0.040	0.134	0.166	0.101	0.117	0.111	0.100	0.171
Completed	0.217	0.783	0.097	0.903	0.070	0.043	0.146	0.178	0.111	0.109	0.111	0.102	0.131
m=4													
Observed	0.206	0.794	0.098	0.902	0.070	0.043	0.147	0.178	0.111	0.109	0.111	0.102	0.130
Imputed	0.280	0.720	0.100	0.900	0.040	0.018	0.135	0.213	0.114	0.108	0.085	0.111	0.175
Completed	0.218	0.782	0.099	0.901	0.069	0.043	0.146	0.179	0.111	0.109	0.110	0.102	0.131
m=5													
Observed	0.206	0.794	0.098	0.902	0.070	0.043	0.147	0.178	0.111	0.109	0.111	0.102	0.130
Imputed	0.273	0.727	0.090	0.910	0.041	0.043	0.141	0.192	0.088	0.091	0.111	0.115	0.178
Completed	0.216	0.784	0.096	0.904	0.069	0.043	0.146	0.179	0.110	0.108	0.111	0.102	0.131
m=6													
Observed	0.206	0.794	0.098	0.902	0.070	0.043	0.147	0.178	0.111	0.109	0.111	0.102	0.130
Imputed	0.278	0.722	0.099	0.901	0.060	0.038	0.156	0.206	0.100	0.100	0.083	0.094	0.164
Completed	0.217	0.783	0.098	0.902	0.070	0.043	0.147	0.179	0.111	0.108	0.110	0.101	0.131
m=7													
Observed	0.206	0.794	0.098	0.902	0.070	0.043	0.147	0.178	0.111	0.109	0.111	0.102	0.130
Imputed	0.266	0.734	0.095	0.905	0.038	0.027	0.132	0.183	0.119	0.095	0.114	0.090	0.201
Completed	0.215	0.785	0.098	0.902	0.069	0.043	0.146	0.178	0.111	0.108	0.111	0.101	0.131
m=8													
Observed	0.206	0.794	0.098	0.902	0.070	0.043	0.147	0.178	0.111	0.109	0.111	0.102	0.130
Imputed	0.278	0.722	0.092	0.908	0.061	0.040	0.134	0.166	0.101	0.117	0.111	0.100	0.171
Completed	0.217	0.783	0.097	0.903	0.070	0.043	0.146	0.178	0.111	0.109	0.111	0.102	0.131
m=9													
Observed	0.206	0.794	0.098	0.902	0.070	0.043	0.147	0.178	0.111	0.109	0.111	0.102	0.130
Imputed	0.280	0.720	0.100	0.900	0.040	0.018	0.135	0.213	0.114	0.108	0.085	0.111	0.175
Completed	0.218	0.782	0.099	0.901	0.069	0.043	0.146	0.179	0.111	0.109	0.110	0.102	0.131
m=10													
Observed	0.206	0.794	0.098	0.902	0.070	0.043	0.147	0.178	0.111	0.109	0.111	0.102	0.130
Imputed	0.273	0.727	0.090	0.910	0.041	0.043	0.141	0.192	0.088	0.091	0.111	0.115	0.178
Completed	0.216	0.784	0.096	0.904	0.069	0.043	0.146	0.179	0.110	0.108	0.111	0.102	0.131
m=11													
Observed	0.206	0.794	0.098	0.902	0.070	0.043	0.147	0.178	0.111	0.109	0.111	0.102	0.130
Imputed	0.274	0.726	0.100	0.900	0.054	0.044	0.169	0.183	0.084	0.081	0.105	0.094	0.185
Completed	0.217	0.783	0.099	0.901	0.070	0.043	0.147	0.178	0.110	0.108	0.111	0.101	0.131

For each imputed dataset, the proportion of female offenders was greater in the imputed data than in the observed data. This finding is consistent with prior research, which finds that females are more likely than males to receive ARD and are less likely than males to have any criminal history or recidivism. Offenders who were missing gender were most often missing because they received ARD for the primary offense (i.e., the 2007 DUI) and they did not have any prior criminal history or subsequent recidivism.

The imputed datasets were less consistent for race. In 5 of the 11 imputed datasets, imputed values had a higher proportion of Black offenders than observed values. However, the proportions of Black offenders in the imputed values varied by only 1% across imputed datasets (.900 - .910). The imputed values for race had little impact on the final proportions in the completed data in each imputed dataset. The proportion of offenders who were Black in the observed data varied from the proportion of offenders who were Black in the completed data by less than .3% in each imputed dataset.

Imputed values for age tended to be older than observed values for age. These findings were consistent with prior research which finds that older DUI offenders are more likely to receive ARD and less likely to recidivate (Knoth, 2015). As with race, the imputed values had very little effect on the proportions in the completed data. Age was missing less often than gender and race (N = 703). The proportions in each age category for the observed and completed data varied at most by .1% across each of the imputed datasets.

Analyses

This chapter includes three sets of analyses. First, I split the data into two samples – development and validation – and review the descriptive and bivariate statistics. Second, I develop and validate a risk assessment instrument predicting a reconviction for any criminal offense within 5 years of release for the primary offense. Third, I develop and validate a risk assessment instrument predicting a reconviction for a DUI offense within 5 years of release for the primary offense. The analyses are followed by a summary of the overall findings and a discussion of the theoretical and policy implications of the research.

Selecting a Development and Validation Sample

I used random sampling to split the data into two equal samples: development (N = 23,209) and validation (N = 23,209). The analyses presented in this chapter were conducted on the development sample and validated using the validation sample. While conducting descriptive statistics, I tested for significant differences between the development and validation samples. I compared the distributions for each variable between the development and validation samples using chi-square tests for categorical variables and t-tests for continuous variables. There were no significant differences between the development and validation samples on any of the variables analyzed for this research.

Part I: Descriptives and Bivariates

First, I conducted descriptive statistics for the development and validation samples. As discussed previously, these descriptive comparisons allowed for an evaluation of the effectiveness of my random sampling methods. In addition, these descriptive statistics allowed for a review of the general characteristics of DUI offenders. I compared the descriptive statistics for my sample to similar descriptive statistics published by the PCS on non-DUI offenders.

Next, I conducted three sets bivariate statistics for the development sample. First, I compared offenders who were reconvicted of any offense to offenders who were not reconvicted. Second, I compared offenders who were reconvicted of a DUI offense to all other offenders, including those who were reconvicted of a non-DUI offense and those who were not reconvicted. Finally, I compared offenders who were reconvicted of a DUI with offenders who were reconvicted of a non-DUI offense.

Descriptive Statistics

My sample was disproportionately White (90.3% in development and 90.0% in validation) and male (79.4% in development and 79.3% in validation). Offenders were most likely to fall between the ages of 22 and 29. However, the average age in each sample was 34.7 years. Over half of the offenders (54.0% in the development sample and 53.8% in the validation sample) were arrested in an urban county other than Allegheny and Philadelphia. Nearly a third of the offenders (30.1% in both samples) were arrested in rural counties. Around 10% of offenders were arrested in Allegheny County and only 6% of offenders were arrested in Philadelphia County.

Table 2-5. Descriptive Statistics for the 2007 Development (N =23,209), 2007 validation (N=23,209) samples.

	Number		Percent		*Sig.*		Number		Percent		Sig.
	Dev	Val	**Dev**	Val	***Dev & Valid***		**Dev**	Val	**Dev**	Val	**Dev & Valid**
Race*					*0.373*	**Type of prior arrest(s)**					
White/Other	16,520	16,390	50.2	49.8		**Prior personal/sex**					0.602
Black	1,769	1,811	49.4	50.6		Yes	1,556	1,528	6.7	6.6	
Gender*					*0.726*	No	21,653	21,681	93.3	93.4	
Male	15,663	15,592	50.1	49.9		**Prior property**					0.190
Female	4,056	4,073	49.9	50.1		Yes	1,606	1,535	6.9	6.6	
Age**					0.32	No	21,603	21,674	93.1	93.4	
<21	1,638	1,559	7.2	6.8		**Prior drug**					0.797
21	996	983	4.4	4.3		Yes	1,599	1,585	6.9	6.8	
22/24	3,307	3,394	14.5	14.8		No	21,610	21,624	93.1	93.2	
25/29	4,097	4,055	17.9	17.7		**Prior DUI**					0.334
30/34	2,502	2,562	10.9	11.2		Yes	3,259	3,187	14.0	13.7	
35/39	2481	2485	10.9	10.9		No	19,950	20,022	86.0	86.3	
40/44	2,466	2,595	10.8	11.4		**Prior Other traffic**					0.945
45/49	2362	2,282	10.3	10.0		Yes	1,787	1,791	7.7	7.7	
50+	3003	2,948	13.1	12.9		No	21,422	21,418	92.3	92.3	
Mean	34.7	34.7			*0.841*	**Prior Public Order**					0.139
County					*0.853*	Yes	1,076	1,010	4.6	4.4	
Rural	6,994	6,978	30.1	30.1		No	22,133	22,199	95.4	95.6	
Other Urban	12,523	12,478	54.0	53.8		**Prior Public Administration**					0.133
Allegheny	2,266	2,322	9.8	10.0		Yes	499	547	2.2	2.4	
Philadelphia	1,426	1,431	6.1	6.2		No	22,710	22,662	97.8	97.6	
Multiple charges					*0.661*	**Prior firearms/weapons**					0.700
Yes	15,144	15,189	65.3	65.4		Yes	272	281	1.2	1.2	
No	8,065	8,020	34.7	34.6		No	22,937	22,928	98.8	98.8	
Total prior convictions					0.78		23,209	23,209	100.0	100.0	
0	17,038	17,097	73.4	73.7							
1	3,416	3,411	14.7	14.7		**Diversion Disposition**					0.089
2	1,358	1,330	5.9	5.7		Yes ARD	11,775	11,958	50.7	51.5	
3	596	589	2.6	2.5		No ARD	11,434	11,251	49.3	48.5	
4	285	310	1.2	1.3			23,209	23,209	100.0	100.0	
5	202	169	0.9	0.7							
6	102	103	0.4	0.4							
7	72	67	0.3	0.3		**Reconviction Within 5 Years**					0.403
8+	140	133	0.6	0.6		Yes	4,943	5,017	21.3	21.6	
						No	18,266	18,192	78.7	78.4	
Mean	0.54	0.53			*0.459*		23,209	23,209	100.0	100.0	
Blood Alcohol Content					*0.647*						
none	1,084	1,140	4.7	4.9		**DUI Reconviction Within 5 Years**					0.354
general impair	5,150	5,052	22.2	21.8		Yes	2,575	2,638	11.1	11.4	
.08- <.10	1,106	1,121	4.8	4.8		No	20,634	20,571	88.9	88.6	
.10- <.16	5,814	5,834	25.1	25.1			23,209	23,209	100.0	100.0	
.16+	10,055	10,062	43.3	43.4							
Drug DUI					*0.106*						
Yes	1,436	1,521	6.2	6.6		**Rearrest Within 3 Years**					0.928
No	21,773	21,688	93.8	93.4		Yes	4,914	4,922	21.2	21.2	
Drug and Alcohol DUI					*0.824*	No	18,295	18,287	78.8	78.8	
Yes	508	501	2.2	2.2			23,209	23,209	100.0	100.0	
No	22,701	22,708	97.8	97.8							

Two-thirds of offenders had multiple conviction charges in the primary offense. Given that my sample included only the offenders for whom the DUI was the most serious offense, the co-offenses were likely to be summary offenses (e.g., traffic violations) or other low-level misdemeanor offenses. Most DUI offenders were convicted of an alcohol-impaired DUI. Only 6.6% of offenders in the development sample and 7.0% of offenders in the validation sample were convicted of a drug DUI. Fewer still, only 2.2% of offenders were convicted of a drug- and alcohol-impaired DUI.

Although the exact BAC was not available in the AOPC data, I was able to derive the range of an offender's BAC using the subsection for his/her DUI offense. Offenders were least likely to have a BAC of .08% or .09% (4.8% in both samples) and most likely to have a BAC of .16% or greater. An additional quarter of offenders (25.1% in both samples) had a BAC between .10% and .15%. Other offenders charged with an alcohol-impaired DUI were charged under the general impairment classification (22.2% in the development sample and 21.8% in the validation sample).

The majority of offenders (73.4% in the development sample and 73.7% in the validation sample) had no prior convictions. In both samples, 14.7% of offenders had only one prior conviction. An additional 5.9% of offenders in the development sample and 5.7% of offenders in the validation sample had only two prior convictions. The remaining 6% of offenders had between 3 and 26 prior convictions. The most common type of prior conviction was for a DUI (14.0% in the development sample and 13.7% in the validation sample) while the least common type of prior conviction was for a firearms or weapons offense (1.2% in both samples). Prior convictions for a non-DUI traffic offense were the second most common type of prior conviction

(7.7% in both samples). Just under 7% of offenders in each sample had at least one prior conviction for a personal/sex, property, and/or drug offense.

Half of the offenders (50.7% in the development sample and 51.5% in the validation sample) received ARD for their primary DUI offense. This finding is consistent with other descriptive statistics indicating that many offenders were first time offenders who had no prior DUI conviction. Only 21.3% of offenders in the development sample and 21.6% of offenders in the validation sample were reconvicted within 5 years of release for the primary offense. These rates of recidivism were similar to the rates of re-arrest within 3 years of release (21.2% in both samples). About half of the offenders who were reconvicted were reconvicted of a DUI offense (11.1% in the development sample and 11.4% in the validation sample).

Comparing DUI Offenders to Non-DUI Offenders

My data included only DUI offenders. Consequently, I was unable to make direct statistical comparisons between DUI offenders and non-DUI offenders. However, I was able to compare the descriptive statistics from my sample to similar descriptive statistics published by the Pennsylvania Commission on Sentencing for non-DUI offenders. Figure 2-3 presents the descriptive statistics published in Table 2 of the PCS Risk/Needs Assessment Project Interim Report 7 (2013). The original PSC risk assessment used a sample of all offenders sentenced in 2004, 2005, and 2006, excluding DUI offenders. The PCS also divided their total sample into two equal parts – development and validation. As with my data, there were no significant differences between the development and validation samples. For ease of interpretation, I am comparing only the development samples from the original PCS study and my study.

Figure 2-3. PCS Reported Descriptive Statistics

Table 2. Descriptive statistics for the development (N = 17,798) and first validation sample (N = 17,750). [1]

	Development N	Validation N	Development %	Validation %	Sig.
Race					0.496
White	7,901	7,969	44.4	44.9	
Black	8,112	7,957	45.6	44.8	
Hispanic	1,583	1,608	8.9	9.1	
Other	202	216	1.1	1.2	
	17,798	17,750	100.0	100.0	
Gender					0.596
Male	15,223	15,217	85.5	85.7	
Female	2,575	2,533	14.5	14.3	
	17,798	17,750	100.0	100.0	
Age					0.530
< 21	3,151	3,154	17.7	17.8	
21 - 24	3,169	3,160	17.8	17.8	
25-29	2,900	2,805	16.3	15.8	
30-34	2,238	2,224	12.6	12.5	
35-39	2,157	2,142	12.1	12.1	
40-44	1,951	1,933	11.0	10.9	
45-49	1,245	1,250	7.0	7.0	
> 50	987	1082	5.5	6.1	
	17,798	17,750	100.0	100.0	
Mean	31.12	31.3			0.158
County					0.998
Philadelphia	3,961	3,959	22.3	22.3	
Allegheny	2,574	2,575	14.5	14.5	
Other urban	8,308	8,280	46.7	46.6	
Rural	2,955	2,936	16.6	16.5	
	17,798	17,750	100.0	100.0	
OGS					0.504
1	177	194	1.0	1.1	
2	707	722	4.0	4.1	
3	3,529	3,518	19.8	19.8	
4	439	454	2.5	2.6	
5	3,237	3,222	18.2	18.2	
6	4,918	4,878	27.6	27.5	
7	3,605	3,489	20.3	19.7	
8	1,186	1,273	6.7	7.2	
	17,798	17,750	100.0	100.0	
Mean	5.30	5.29			0.751
PRS					0.381
0	5,322	5,278	29.9	29.7	
1	2,059	2,064	11.6	11.6	
2	2,089	2,018	11.7	11.4	
3	1,256	1,281	7.1	7.2	
4	2,194	2,108	12.3	11.9	
5	3,879	3,926	21.8	22.1	
RFEL	999	1,075	5.6	6.1	
	17,798	17,750	100.0	100.0	
Mean	2.48	2.50			0.313
Multiple charges					0.939
Yes	8,445	8,415	47.4	47.4	
No	9,353	9,335	52.6	52.6	
	17,798	17,750	100.0	100.0	
Prior arrest(s)					0.249
Yes	15,208	15,090	85.4	85.0	
No	2,590	2,660	14.6	15.0	
	17,798	17,750	100.0	100.0	

	Development N	Validation N	Development %	Validation %	Sig.
Total prior arrests					0.317
0	2,590	2,660	14.6	15.0	
1	2,163	2,068	12.2	11.7	
2-4	5,056	4,945	28.4	27.9	
5-12	5,969	6,032	33.5	34.0	
13+	2,020	2,045	11.3	11.5	
	17,798	17,750	100.0	100.0	
Mean	5.68	5.74			0.375
Type of prior arrest(s)					
Prior personal/sex arrest(s)					0.331
Yes	9,391	9,457	52.8	53.3	
No	8,407	8,293	47.2	46.7	
	17,798	17,750	100.0	100.0	
Prior property arrest(s)					0.780
Yes	11,991	11,934	67.4	67.2	
No	5,807	5,816	32.6	32.8	
	17,798	17,750	100.0	100.0	
Prior drug arrest(s)					0.587
Yes	9,670	9,593	54.3	54.0	
No	8,128	8,157	45.7	46.0	
	17,798	17,750	100.0	100.0	
Prior firearms/weapons arrest(s)					0.474
Yes	3,117	3,160	17.5	17.8	
No	14,681	14,590	82.5	82.2	
	17,798	17,750	100.0	100.0	
Prior other arrest(s)					0.457
Yes	12,346	12,248	69.4	69.0	
No	5,452	5,502	30.6	31.0	
	17,798	17,750	100.0	100.0	
Current offense type (most serious)					0.742
Personal-- Felony	1,562	1,553	8.8	8.7	
Personal-- Misdemeanor	1,179	1,171	6.6	6.6	
Sex offense-- Felony	359	323	2.0	1.8	
Sex offense-- Misdemeanor	98	115	0.6	0.6	
Drug-- Felony (PWID)	6,459	6,382	36.3	36.0	
Drug-- Misdemeanor (Possession)	1,130	1,078	6.3	6.1	
Burglary	1,060	1,079	6.0	6.1	
Other property offense	4,079	4,194	22.9	23.6	
Firearms/other weapons	739	712	4.2	4.0	
Other offense	1,133	1,143	6.4	6.4	
	17,798	17,750	100.0	100.0	
Type of sentence					0.139
Prison	2,192	2,306	12.3	13.0	
SIP	12	6	0.1	0.0	
Jail	10,019	10,036	56.3	56.5	
CIP	1,911	1,827	10.7	10.3	
Probation	3,432	3,363	19.3	18.9	
Other	232	212	1.3	1.2	
	17,798	17,750	100.0	100.0	
Recidivism					
One Year					0.460
Yes	4,874	4,923	27.4	27.7	
No	12,924	12,827	72.6	72.3	
	17,798	17,750	100.0	100.0	
Two Year					0.625
Yes	7,618	7,552	42.8	42.5	
No	10,180	10,198	57.2	57.5	
	17,798	17,750	100.0	100.0	
Three Year					0.882
Yes	9,276	9,237	52.1	52.0	
No	8,522	8,513	47.9	48.0	
	17,798	17,750	100.0	100.0	

Source: Pennsylvania Commission on Sentencing, 2013

There are two notable differences between my sample and the PCS sample that may affect the ability to make meaningful comparisons. First, the samples are taken from different years. My sample includes offenders sentenced in 2007 while the PCS data includes offenders sentenced from 2004 through 2006. It is possible that there are systematic differences in the populations of offenders based on the years in which they were sentenced. However, it is unlikely that there were any significant social or structural changes that could cause systematic differences in the distributions of offenders in one year.

Second, the PCS operationalized criminal history and recidivism using arrests while I used convictions.[32] These differences will not affect general demographic comparisons, including race, gender, age, and county. My descriptive statistics included measures of re-arrest in three years, allowing for a direct comparison of recidivism measures. For criminal history variables, the PCS sample will likely report more priors, both for the total numbers of priors and the indicator variables for types of priors, than my sample. Each conviction in my sample must have an arrest, but not necessarily every arrest will result in a conviction. It is likely that offenders have more prior arrests than they do convictions. In order to make more accurate comparisons, I conducted additional descriptive statistics in my sample using arrests rather than convictions.

The general offending population in Pennsylvania includes far more Black offenders (45.6%) than the DUI offending population (9.7%). Similarly, non-DUI offenders were more likely than DUI offenders to be male (85.5% and 79.4%, respectively) than female (14.5% and 20.6%, respectively). DUI offenders were more likely to be arrested and sentenced in rural

[32] The PCS later decided to use convictions for criminal history measures but used arrests as the measure of recidivism. The Commission has not yet published the descriptive statistics for their newest studies using convictions for criminal history measures.

counties (30.1%) than were non-DUI offenders (16.6%). DUI offenders and non-DUI offenders were most likely to be arrested and sentenced in other urban counties (46.7% and 54.0%, respectively), which may simply be a reflection of the concentration of Pennsylvania populations in other urban counties. Non-DUI offenders were more likely to be arrested and sentenced in Philadelphia County (22.3%) than in Allegheny County (14.5%). DUI offenders were more likely to be arrested and sentenced in Allegheny County (9.8%) than in Philadelphia County (6.1%). These differences may be due to differences in public transportation systems. Philadelphia County has the largest public transportation network including buses, rapid transit subways, commuter rails, and trolleys. Allegheny County has only buses and light rail.

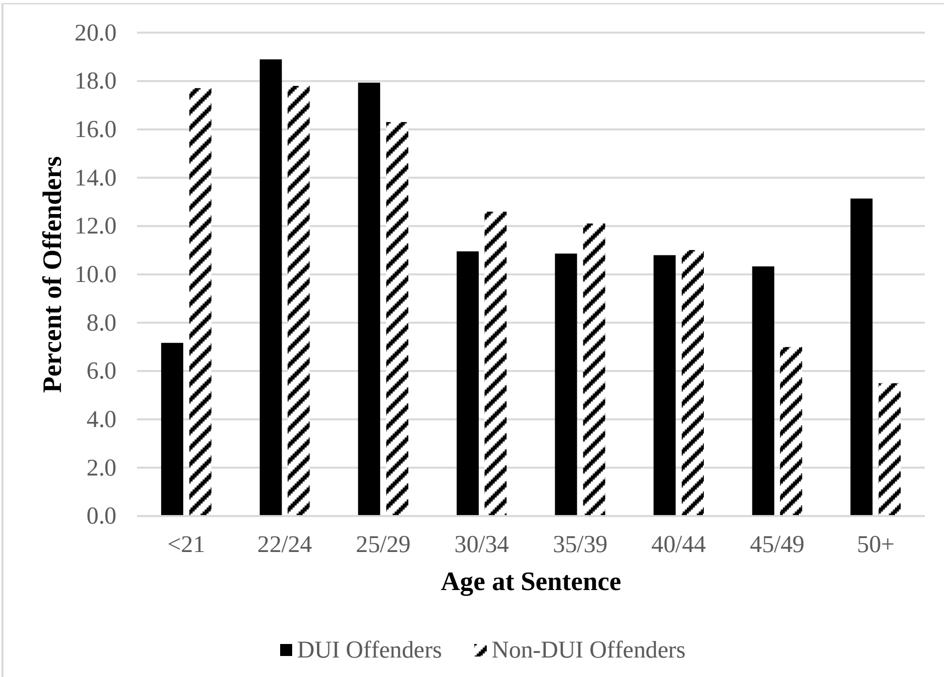
Non-DUI offenders were generally younger than DUI offenders, although both populations showed large concentrations of offenders between the ages of 21 and 29 (see Figure 2-4). The largest differences for age were among offenders under the age of 21 (17.7% for non-DUI offenders and 7.2% for DUI offenders) and offenders 50 years and older (5.5% for non-DUI offenders and 13.1% for DUI offenders). Discrepancies among the youngest offenders are likely due to the legal restrictions on driving and on drinking. It is more difficult for young offenders to get access to the elements necessary to commit a DUI offense than to get access to the elements necessary for other offenses, such as property or personal crimes.

There are several possible explanations for the differences in DUI and non-DUI offending for older offenders. The consistent decline in non-DUI offending with age reflects the maturation effect that results in desistance for most criminals. For DUI offenders, drinking and driving persists through the life course with offending initially declining in early adulthood and remaining flat through midlife.[33] The second peak of DUI offending in midlife may be explained

[33] The apparent increase in offending for offenders aged 50 and older is the result of a collapsing all offenders 50 years of age and older into a single category. I was unable to disaggregate the older age group because I imputed

by drinking and driving that follows instances of binge drinking that are motivated by times of stress, such as unemployment or divorce. Alternatively, this peak may be explained by changing social roles as children age and parents have more unstructured leisure time.

Figure 2-4. Distribution of Age for DUI and Non-DUI Offenders in Pennsylvania



The majority of non-DUI offenders had at least one prior arrest (85.4%) while the majority of DUI offenders had no prior arrests (60.8%). 73.2% of non-DUI offenders had 2 or more prior arrests while only 20.9% of DUI offenders had 2 or more prior arrests. Among non-DUI offenders, the average number of prior arrests was 5.68. Among DUI offenders, the average number of prior arrests was 1.02. Over half of all non-DUI offenders had at least one prior personal, property, and/or drug offense. For DUI offenders, the rates of prior personal, property, and drug offenses were all 15% or less. Firearms offenses were the least likely prior offenses in both samples.

missing age values based on the categories for age instead of the absolute age. See Appendix B for age distribution for DUI offenders when age was not missing (N = 45,715)

Non-DUI offenders were more likely than DUI offenders to be re-arrested within three years (52.1% and 21.2%, respectively). Interestingly, fewer DUI offenders were reconvicted in 5 years (21.3%) than the percent of non-DUI offenders re-arrested within one year (27.4%). The PCS data did not include any specifics about the types of recidivism, so I was unable to compare the quality of recidivism between the two samples.

Descriptive Conclusions

These descriptive statistics provide some support for the belief that DUI offenders are a "unique" population of offenders. DUI offenders were more likely than non-DUI offenders to be white, female, and older. The offenders in my sample were unlikely to have any prior criminal history and were unlikely to recidivate. Those who did have any criminal history or subsequent recidivism were likely to have a prior conviction for a DUI and to recidivate with a subsequent DUI, indicating some specialization among this population. In addition, DUI offenses were more likely than non-DUI offenses to occur in rural areas and less likely than non-DUI offenses to occur in dense urban centers.

Despite the stark differences between DUI and non-DUI offenders, the descriptive statistics do indicate that there is a small portion of DUI offenders who are likely very similar to non-DUI offenders. The offenders in my sample were still more likely to be male than to be female and to be younger than to be older. Although there was some indication of specialization of offenders in criminal history and recidivism measures, there were other offenders exhibiting more general patterns of offending. Offenders in my data had prior convictions for a range of behaviors including personal, property, drug, public order, public administration, and firearms offenses. In addition, nearly half of the offenders who recidivated were reconvicted of a non-DUI offense. Risk assessments analyzing correlates of criminal offending may be especially useful for the population of DUI offenders exhibiting general offending patterns. In addition, the differences between non-DUI offenders and DUI offenders provide support for the development of a specialized risk assessment developed on and used for only DUI offenders.

Bivariate Statistics

This chapter of the dissertation focuses on an analysis of the correlates of recidivism among DUI offenders in Pennsylvania. Prior to engaging in multivariate analyses, I conducted bivariate comparisons between the characteristics of DUI offenders and recidivism. For each of the offender and offense characteristics, I conducted three sets of bivariate analyses: 1) those who were reconvicted of any criminal offense and those who were not, 2) those who were reconvicted of a DUI offense and those who were not, and 3) those who were reconvicted of a non-DUI offense and those who were reconvicted of a DUI offense. I conducted each of these bivariate comparisons on both the development and validation samples. For brevity, I discuss only the bivariate comparisons for the development sample.

Recidivists vs. Non-Recidivists

The bivariate comparisons between offenders who recidivated with any criminal offense and those who did not are presented in Table 2-6. Black offenders (32.7%) were significantly more likely than white offenders or offenders of another race (25.0%) to recidivate. Male offenders (25.7%) were significantly more likely than females to recidivate (22.0%), but the actual rates of recidivism were similar. DUI offenders in Philadelphia County were most likely to recidivate (26.2%). Offenders in other urban counties, Allegheny County, and rural counties had similar rates of recidivism (19.2%, 20.9%, and 21.8%, respectively).

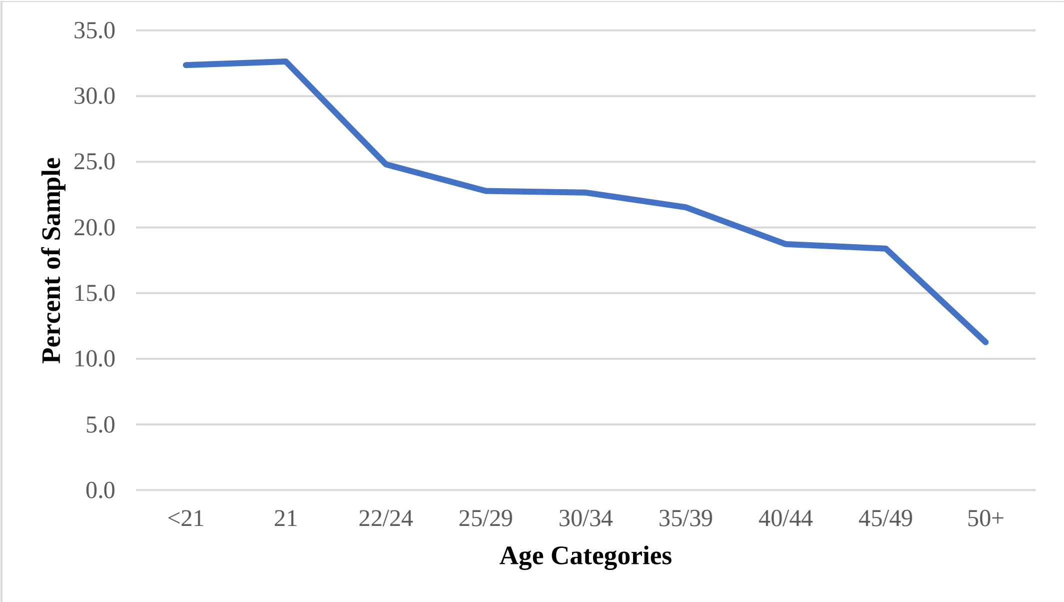
Table 2-6. 2007 DUI Offender Recidivism Rates for Any Reconviction

	Development Sample (N = 23,209)					Validation Sample (N = 23,209)				
	Percent		Number			Percent		Number		
	Clean	Failure	Clean	Failure	sig	Clean	Failure	Clean	Failure	sig
Race					***					***
White/Other	75.0	25.0	12,384	4,136		74.5	25.5	12,205	4,185	
Black	67.3	32.7	1,191	578		64.8	35.2	1,173	638	
Gender					***					***
Male	74.3	25.7	11,632	4,031		73.6	26.4	11,477	4,115	
Female	78.0	22.0	3,164	892		78.2	21.8	3,186	887	
Age					***					***
<21	67.6	32.4	1108	530		66.1	33.9	1,030	529	
21	67.4	32.6	671	325		71.7	28.3	705	278	
22/24	75.2	24.8	2,487	820		75.8	24.2	2,571	823	
25/29	77.2	22.8	3,164	933		76.8	23.2	3,115	940	
30/34	77.3	22.7	1,935	567		75.8	24.2	1,942	620	
35/39	78.5	21.5	1,947	534		77.7	22.3	1,931	554	
40/44	81.3	18.7	2,004	462		79.8	20.2	2,071	524	
45/49	81.6	18.4	1,928	434		83.1	16.9	1,897	385	
50+	88.7	11.3	2,665	338		87.7	12.3	2,585	363	
mean			35.5	31.8	***			35.4	32	***
County					***					***
Rural	78.2	21.8	5471	1523		77.7	22.3	5422	1556	
Other Urban	79.1	20.9	9911	2612		78.8	21.2	9834	2644	
Allegheny	80.8	19.2	1,832	434		80.8	19.2	1,876	446	
Philadelphia	73.8	26.2	1,052	374		74.1	25.9	1,060	371	
Multiple charges										
Yes	78.7	21.3	11,950	3226		78.4	21.6	11,888	3269	
No	78.6	21.4	6,316	1,717		78.3	21.7	6,304	1,748	
Prior Conviction					***					***
0	82.4	17.6	14,044	2994		82.5	17.5	14,106	2991	
1	74.5	25.5	2,544	872		72.7	27.3	2,481	930	
2	66.8	33.2	907	451		64.6	35.4	859	471	
3	57.2	42.8	341	255		58.4	41.6	344	245	
4	58.2	41.8	166	119		59.4	40.6	184	126	
5	55.4	44.6	112	90		49.1	50.9	83	86	
6	55.9	44.1	57	45		57.3	42.7	59	44	
7	40.3	59.7	29	43		43.3	56.7	29	38	
8+	47.1	52.9	66	74		35.3	64.7	47	86	
mean		.	0.43	0.96	***	29.3	70.7	0.41	0.99	***
DUI Type					***					***
General Impairment	75.8	24.2	3,720	1187		75.8	24.2	3,649	1,162	
.08-.09	78.5	21.5	833	228		79.6	20.4	853	219	
.10-.15	81.2	18.8	4,610	1,067		80.5	19.5	4,611	1,115	
.16+	81.1	18.9	8,018	1,865		81.1	18.9	7,981	1,864	
Drug involved	64.5	35.5	1,085	596		62.6	37.4	1,098	657	
Type of Prior Offense [yes indicated]										
Personal/Sex	59.8	40.2	930	626	***	58.8	41.2	899	629	***
Property	58.4	41.6	938	668	***	55.9	44.1	858	677	***
Drug	57.2	42.8	914	685	***	55.6	44.4	881	704	***
DUI	74.2	25.8	2418	841	***	74.1	25.9	2360	827	***
Traffic	69.1	30.9	1,234	553	***	67.7	32.3	1,213	578	**
Public Order	60.1	39.9	647	429	***	58.3	41.7	589	421	***
Public Admin	55.5	44.5	277	222	***	55.9	44.1	306	241	***
Firearms/Weapons	58.0	42.0	156	113	***	55.2	44.8	155	126	***
ARD Disposition					***					***
Yes	83.6	16.4	9847	1928		83.4	16.6	9970	1988	
No	73.6	26.4	8,419	3,015		73.1	26.9	8,222	3,029	

** Significant at .05 level   ** Significant at .01 level   *** Significant at .001 level*

The rates of recidivism declined slowly with age. The youngest offenders were most likely to recidivate (32.4% for offenders under the age of 21) and the oldest offenders were most likely to recidivate (11.3% for offenders 50 years of age and older). Figure 2-5 presents a visual representation of recidivism rates by age. Although the rate of recidivism declines overall with age, recidivism rates appear to decline quickly before age 22 and after age 49 but decline slowly from ages 22 through 49. These findings suggest there are three meaningful categories of age for offenders: young offenders (21 and younger), middle-aged offenders (22 through 49), and older offenders (50 and older). Rates of recidivism were statistically significantly different across age categories. T-tests also found that the mean age of non-recidivists (35.5) and recidivists (31.8) were significantly different, with recidivists being significantly younger.

Figure 2-5. Rate of Recidivism by Age



Drug-impaired DUI offenders were the most likely to recidivate (35.5%). Rates of recidivism for alcohol-impaired drivers decreased as the BAC increased. Offenders charged under the general impairment subsection were most likely to recidivate (24.2%) followed by offenders with a BAC of .08% - .09% (21.5%) and offenders with a BAC of .10% - .15%

(18.8%) or .16% and higher (18.9%). Recidivism rates were significantly different for the different types of DUI offenses. There were no significant differences in the number of charges for recidivists and non-recidivists. Offenders who received an ARD for their primary DUI offense were less likely than offenders who did not receive an ARD to recidivate (16.4% and 26.4%, respectively).

Rates of recidivism increased as the number of prior convictions increased. First-time offenders (i.e., those with no prior convictions of any crime) were the least likely to recidivate (17.6%). Offenders with 7 prior convictions were the most likely to recidivate (59.7%).[34] There was a noticeable difference in the rates of recidivism for offenders with no prior convictions (17.6%), one prior conviction (25.5%) and two prior convictions (33.2%). Rates of recidivism appeared to plateau for offenders with 4 or more prior convictions. The average number of prior convictions between recidivists (1.0) and non-recidivists (0.4) were significantly different but varied by less than one prior conviction.

I analyzed recidivism rates for each type of prior conviction. Recidivism rates were highest for offenders with at least one prior public administration conviction[35] (44.5%) and lowest for offenders with a prior DUI conviction (25.8%). In general, only 21.3% of offenders recidivated, but offenders with a prior personal or sex conviction, property conviction, drug conviction, non-DUI traffic conviction, public order conviction, or firearms convictions all had

[34] Offenders with 8 or more prior convictions were less likely than offenders with 7 prior convictions to recidivate. However, the small sample sizes for offenders with a large number of prior convictions likely contributed to less reliable estimates. In the validation sample, offenders with 8 or more prior convictions were more likely than offenders with 7 prior convictions to recidivate.

[35] The public administration category was comprised mostly of offenses in Article E of Title 18 in the Pennsylvania Consolidated Statutes. This includes offenses such as bribery, perjury, falsification and intimidation, and obstruction of justice.

rates of recidivism greater than the base rate (40.2%, 41.6%, 42.8%, 30.9%, 39.9%, and 42.0%, respectively).

DUI Recidivists vs. Non-Recidivists and Non-DUI Recidivists

The findings for bivariate comparisons between DUI recidivists and those who did not recidivate at all or who recidivated with a non-DUI offense are presented in Table 2-7. The correlates of DUI recidivism differed from the patterns of general recidivism. First, there were no significant racial or gender differences in the likelihood of recidivating with a DUI offense. Second, although there were statistically significant differences in DUI recidivism across the age categories, these differences were not substantively meaningful. Offenders who were 21 or younger were the most likely to recidivate with a DUI (15.1% and 14.2%, respectively) and offenders who were 50 years of age or older were least likely to recidivate with a DUI (7.6%). The range of recidivism for offenders between the ages of 22 and 49 varied little (10.8% - 12.3%). The average age of DUI recidivists (33.1) was 1.8 years younger than the average age of non-DUI recidivists and non-recidivists (34.9). There were no statistically significant differences in recidivism across different counties. However, offenders in Philadelphia County were least likely to recidivate with a subsequent DUI offense (9.7%).

Table 2-7. 2007 DUI Offender Recidivism Rates for DUI Reconviction

	Development Sample (N = 23,209)					Validation Sample (N = 23,209)				
	Percent		Number			Percent		Number		
	Clean	Failure	Clean	Failure	sig	Clean	Failure	Clean	Failure	sig
Race										
White/Other	86.7	13.3	14,325	2,195		86.2	13.8	14,133	2,257	
Black	87.0	13.0	1,539	230		86.0	14.0	1,557	254	
Gender										*
Male	87.0	13.0	13,632	2,031		86.3	13.7	13,462	2,130	
Female	86.9	13.1	3,526	530		87.8	12.2	3,575	498	
Age					***					***
<21	85.8	14.2	1406	232		86.0	14.0	1,340	219	
21	84.9	15.1	846	150		85.8	14.2	843	140	
22/24	87.7	12.3	2,899	408		87.6	12.4	2,972	422	
25/29	89.0	11.0	3,647	450		88.9	11.1	3,606	449	
30/34	88.7	11.3	2,219	283		88.1	11.9	2,258	304	
35/39	88.0	12.0	2,184	297		87.6	12.4	2,177	308	
40/44	89.2	10.8	2,199	267		88.1	11.9	2,287	308	
45/49	89.0	11.0	2,103	259		89.6	10.4	2,045	237	
50+	92.4	7.6	2,774	229		91.5	8.5	2,697	251	
mean			34.9	33.1	***			34.8	33.4	***
County										
Rural	88.7	11.3	6202	792		88.2	11.8	6158	820	
Other Urban	89.0	11.0	11140	1383		88.7	11.3	11068	1410	
Allegheny	88.5	11.5	2,005	261		88.5	11.5	2,055	267	
Philadelphia	90.3	9.7	1,287	139		90.1	9.9	1,290	141	
Multiple charges										
Yes	88.8	11.2	13,475	1701		88.6	11.4	13,424	1733	
No	89.1	10.9	7,159	874		88.8	11.2	7,147	905	
Prior Conviction					***					***
0	89.4	10.6	15,236	1802		89.3	10.7	15,260	1837	
1	88.7	11.3	3,029	387		87.9	12.1	2,999	412	
2	85.6	14.4	1,163	195		86.0	14.0	1,144	186	
3	86.6	13.4	516	80		85.6	14.4	504	85	
4	87.0	13.0	248	37		88.4	11.6	274	36	
5	86.1	13.9	174	28		84.6	15.4	143	26	
6	88.2	11.8	90	12		87.4	12.6	90	13	
7	77.8	22.2	56	16		79.1	20.9	53	14	
8+	87.1	12.9	122	18		78.2	21.8	104	29	
mean		.	0.53	0.65	***	43.3	56.7	0.52	0.68	***
DUI Type					**					**
general impairment	88.4	11.6	4,338	569		88.0	12.0	4,236	575	
.08-.09	90.5	9.5	960	101		90.3	9.7	968	104	
.10-.15	89.8	10.2	5,100	577		89.6	10.4	5,133	593	
.16+	88.2	11.8	8,717	1,166		88.0	12.0	8,668	1,177	
Drug involved	90.4	9.6	1,519	162		89.2	10.8	1,566	189	
Type of Prior Offense [yes indicated]										
Personal/Sex	84.8	15.2	1,320	236	***	85.1	14.9	1,301	227	***
Property	86.4	13.6	1,388	218	**	85.9	14.1	1,318	217	***
Drug	86.4	13.6	1,382	217	**	85.1	14.9	1,349	236	***
DUI	88.4	11.6	2881	378		88.2	11.8	2810	377	
Traffic	86.9	13.1	1,553	234	**	85.8	14.2	1,536	255	***
Public Order	86.0	14.0	925	151	**	84.6	15.4	854	156	***
Public Admin	85.0	15.0	424	75	**	81.5	18.5	446	101	***
Firearms/Weapons	85.3	14.7	232	40		83.3	16.7	234	47	**
ARD Disposition										
Yes	89.0	11.0	10477	1298		88.8	11.2	10614	1344	
No	88.8	11.2	10,157	1,277		88.5	11.5	9,957	1,294	

** Significant at .05 level   ** Significant at .01 level   *** Significant at .001 level*

The likelihood of DUI recidivism varied significantly by the type of DUI offense. Offenders convicted under the general impairment statutes or with a BAC of .16% or greater were the most likely to recidivate with a DUI (11.6% and 11.8%, respectively). Drug-impaired DUI offenders and alcohol-impaired DUI offenders with a BAC of .08% or .09% were least likely to recidivate with a DUI (9.6% and 9.5%, respectively). These findings likely have two different explanations. Offenders convicted of a drug-impaired DUI offense may be more likely to recidivate with a non-DUI offense, whereas offenders convicted of an alcohol-impaired DUI offense with a low-level BAC are unlikely to recidivate at all.

The rates of DUI reconvictions were similar for all types of prior convictions. Offenders with a prior personal or sex offense were most likely to recidivate with a DUI offense (15.2%) while offenders with a prior DUI offense were least likely to recidivate with a DUI offense (11.6%). There was no statistically significant difference in the rates of DUI recidivism between those who had a prior DUI conviction and those who did not. These findings suggest that the qualitative characteristics of an individual offender's criminal history is unlikely to be predictive of a particular type of recidivism.

Finally, rates of DUI reconviction were the same for offenders who received an ARD (11.0%) and those who were sentenced for a guilty conviction (11.2%). The low rate of DUI recidivism for offenders who receive an ARD may indicate that judges effectively identify the offenders with the lowest risk of recidivism, while the low rate of DUI recidivism for offenders who were sentenced for a guilty conviction may reflect a higher risk for non-DUI recidivism.

DUI Recidivism vs. Non-DUI Recidivism

The previous bivariate comparisons were complicated by the combination of non-recidivists and non-DUI recidivists. The significant or non-significant findings in the previous section were likely driven by the large population of offenders who did not recidivate. I conducted a third set of bivariate comparisons between offenders who recidivated with a non-DUI offense and offenders who recidivated with a DUI offense. These comparisons allow for a better understanding of the different types of DUI offenders who recidivate and may help identify general offenders from repeat DUI offenders.

Table 2-8 presents the bivariate comparisons between non-DUI recidivists and DUI recidivists. The samples for these comparisons are limited to only those offenders who were reconvicted within 5 years of their release (development sample $N = 4,943$; validation sample $N = 5,017$). These bivariate comparisons were highly statistically significant ($p < .001$) for each variable except for the indicator variable for multiple conviction charges in the primary offense.

Table 2-8. 2007 DUI Offender Recidivists, DUI vs Non-DUI Recidivism

	Development Sample (N = 4,943)					**Validation Sample (N = 5,017)**				
	Percent		Number			Percent		Number		
	Non-DUI	DUI	Non-DUI	DUI	sig	Non-DUI	DUI	Non-DUI	DUI	sig
Race					***					***
White/Other	46.9	53.1	1,941	2,195		46.1	53.9	1,928	2,257	
Black	60.2	39.8	348	230		60.2	39.8	384	254	
Gender					***					*
Male	49.6	50.4	2,000	2,031		48.2	51.8	1,985	2,130	
Female	40.6	59.4	362	530		43.9	56.1	389	498	
Age					***					***
<21	56.2	43.8	298	232		58.6	41.4	310	219	
21	53.8	46.2	175	150		49.6	50.4	138	140	
22/24	50.2	49.8	412	408		48.7	51.3	401	422	
25/29	51.8	48.2	483	450		52.2	47.8	491	449	
30/34	50.1	49.9	284	283		51.0	49.0	316	304	
35/39	44.4	55.6	237	297		44.4	55.6	246	308	
40/44	42.2	57.8	195	267		41.2	58.8	216	308	
45/49	40.3	59.7	175	259		38.4	61.6	148	237	
50+	32.2	67.8	109	229		30.9	69.1	112	251	
mean			30.4	33.1	***			30.5	33.4	***
County					***					***
Rural	48.0	52.0	731	792		47.3	52.7	736	820	
Other Urban	47.1	52.9	1229	1383		46.7	53.3	1234	1410	
Allegheny	39.9	60.1	173	261		40.1	59.9	179	267	
Philadelphia	62.8	37.2	235	139		62.0	38.0	230	141	
Multiple charges										
Yes	47.3	52.7	1,525	1701		47.0	53.0	1,536	1733	
No	49.1	50.9	843	874		48.2	51.8	843	905	
Prior Conviction					***					***
0	39.8	60.2	1,192	1802		38.6	61.4	1,154	1837	
1	55.6	44.4	485	387		55.7	44.3	518	412	
2	56.8	43.2	256	195		60.5	39.5	285	186	
3	68.6	31.4	175	80		65.3	34.7	160	85	
4	68.9	31.1	82	37		71.4	28.6	90	36	
5	68.9	31.1	62	28		69.8	30.2	60	26	
6	73.3	26.7	33	12		70.5	29.5	31	13	
7	62.8	37.2	27	16		63.2	36.8	24	14	
8+	75.7	24.3	56	18		66.3	33.7	57	29	
mean		.	1.3	0.65	***	65.7	34.3	1.3	0.68	***
DUI Type					***					***
general impairment	52.1	47.9	618	569		50.5	49.5	587	575	
.08-.09	55.7	44.3	127	101		52.5	47.5	115	104	
.10-.15	45.9	54.1	490	577		46.8	53.2	522	593	
.16+	37.5	62.5	699	1,166		36.9	63.1	687	1,177	
Drug involved	72.8	27.2	434	162		71.2	28.8	468	189	
Type of Prior Offense [yes indicated]										
Personal/Sex	62.3	37.7	390	236	***	63.9	36.1	402	227	***
Property	67.4	32.6	450	218	***	67.9	32.1	460	217	***
Drug	68.3	31.7	468	217	***	66.5	33.5	468	236	***
DUI	55.1	44.9	463	378	***	54.4	45.6	450	377	***
Traffic	57.7	42.3	319	234	***	55.9	44.1	323	255	***
Public Order	64.8	35.2	278	151	***	62.9	37.1	265	156	***
Public Admin	65.3	34.7	147	78	***	58.1	41.9	140	101	**
Firearms/Weapons	65.5	34.5	76	40	***	62.7	37.3	79	47	**
ARD Disposition					***					***
Yes	32.7	67.3	630	1298		32.4	67.6	644	1344	
No	57.6	42.4	1,738	1,277		57.3	42.7	1,735	1,294	

** Significant at .05 level   ** Significant at .01 level   *** Significant at .001 level*

White offenders and offenders of another race who recidivated were significantly more likely than Black offenders who recidivated to be reconvicted of a DUI offense (53.1% and 39.8%, respectively). Female offenders who recidivated were more likely than male offenders who recidivated to be reconvicted of a DUI offense (59.4% and 50.4%, respectively). Recidivating offenders convicted of a DUI offense in Philadelphia County were least likely to recidivate with a DUI offense (37.2%), while recidivating offenders convicted of a DUI offense in Allegheny County were most likely to recidivate with a DUI offense (60.1%). Recidivating offenders convicted of a DUI offense in a rural county or other urban county had similar rates of DUI recidivism (52.0% and 52.9%, respectively).

Older offenders were more likely than younger offenders to recidivate with a DUI offense. Offenders under the age of 21 were least likely to recidivate with a DUI offense (43.8%) and offenders who were 50 years of age or older were most likely to recidivate with a DUI offense (67.8%). The likelihood of recidivating with a DUI offense gradually increased with age. On average, DUI recidivists were significantly older (M = 33.1) than non-DUI recidivists (M = 30.4).

Offenders convicted of a drug-impaired DUI offense most likely to recidivate with a non-DUI offense (72.8%). Offenders convicted of an alcohol-impaired DUI offense with the highest rate of BAC (.16% or higher) were most likely to recidivate with a DUI offense (62.5%). For alcohol-impaired offenders, the likelihood of recidivating with a DUI offense increased as BAC increased. Recidivating offenders who were processed through an ARD were more likely to be reconvicted of a DUI offense (67.3%) than a non-DUI offense (32.7%). In contrast, recidivating offenders sentenced for a guilty conviction were more likely to be reconvicted of a non-DUI offense (57.6%) than a non-DUI offense (42.4%).

For each type of prior conviction, recidivating offenders were more likely to be reconvicted of a non-DUI offense than a DUI offense. However, offenders who had a prior DUI offense were most likely to be reconvicted of a subsequent DUI offense (44.9%). Offenders who had a prior property conviction or prior drug conviction were least likely to be reconvicted of a subsequent DUI offense (32.6% and 31.7%, respectively).

Bivariate Discussion

Patterns of general recidivism for DUI offenders appeared to be consistent with recidivism research for general offenders. Minority offenders, male offenders, younger offenders, and offenders with more prior convictions were most likely to recidivate. However, some distinct patterns did appear. First, the gender gap in recidivism was minimal (3%). The absence of a significant gender gap suggests that gender-based barriers to general criminal offending are not present for DUI offending. Second, recidivism for DUI offenders was equally as common in rural and urban areas, with the exception of Philadelphia. These findings may represent differences in the availability of alternative transportation methods such as public transportation or taxis. Alternatively, these findings could reflect differences in the driving conditions (e.g., straighter roads, more well-lit roadways, shorter driving distances) that make it less likely for impaired drivers in many urban areas to be detected by law enforcement. The urban exception of Philadelphia may reflect a more significant law enforcement presence or a higher base rate of overall criminality.

Third, recidivism rates declined slowly with age and appeared to plateau through middle age. While offenders may rapidly age out or mature out of more serious criminal behaviors, DUI offending appears to persist through the life course. DUI offending may be a response to stressful life events (e.g., divorce or unemployment) but may also foster conditions (debt, poverty, the knifing off of prosocial bonds) that lead to continued criminal behavior (recidivism). Alternatively, DUI offending in midlife may represent changing social roles as individuals transition out of parenting roles for young children and have more time to socialize and drink with adults.

Fourth, recidivism rates varied little for offenders with 3 or more prior convictions. Further, the average number of prior convictions varied by less than one prior conviction. The base rate of criminal history among DUI offenders was low, with 73.4% of all offenders having no prior convictions. The absence of significant differences in recidivism by criminal history characteristics likely reflects the small sample of serious, career criminals in my dataset. These findings are consistent with the relatively low rate of recidivism for DUI offenders.

Bivariates for general recidivism also indicated some interesting characteristic specific to DUI offenders. First, drug-impaired DUI offenders were more likely than alcohol-impaired DUI offenders to recidivate, regardless of the BAC level. Given that drug-use itself is illegal, it is likely that drug-impaired DUI offenders have more criminal tendencies than alcohol-impaired DUI offenders. It was surprising that the likelihood of recidivism among alcohol-impaired DUI offenders decreased as the BAC increased. This finding is antithetical to the general belief that a higher BAC signifies a more serious offender. The rates of recidivism between the categories of BAC varied by only 5.4%. These findings suggest that there is little substantive difference in the likelihood of recidivism by BAC. Second, DUI offenders with a prior DUI were less likely to recidivate than DUI offenders with any other type of prior criminal offense (e.g., personal, property, drug, or public order). These findings suggest that general offenders, for whom a DUI offense is just one type of offense in a broader criminal history, are more likely to recidivate than those who engage in only DUI offending.

Analyses comparing the type of recidivism indicated that White and Other Race offenders, female offenders and older offenders were more likely than Black offenders, male offenders, and younger offenders to recidivate with a DUI offense. Alternatively, Black offenders, male offenders, and younger offenders were more likely to engage in more general patterns of criminal offending. Younger offenders who commit a DUI may be motivated by a general lack of self-control or lack of maturity – characteristics that are also associated with general offending. In addition, younger offenders may be less likely to have an established substance use disorder. On the other hand, older offenders may be more likely to commit a DUI following increased alcohol consumption onset by stressful life events or as a result of prolonged substance use. Other types of criminal offending (such as property or personal offenses) likely do not have the same stress-relieving benefits of substance use. The increase and stability of DUI offending through the life course could also reflect changes in social roles as adults transition into and out of parenthood.

County differences in recidivism showed that offenders in Philadelphia were more likely to recidivate with non-DUI offenses. Surprisingly, offenders in Allegheny were most likely to recidivate with a DUI offense. The differences in these two large urban areas highlight the complexity of understanding DUI offending behaviors. While both Philadelphia and Allegheny are dense urban areas, the public transportation network in Philadelphia is more sophisticated than in Allegheny. It is also possible that these differences in recidivism are driven by higher rates of drug-consumption in Philadelphia (in which recidivism for a drug offense would be coded as non-DUI recidivism). Additionally, the city center in Philadelphia is located closer to the state border than the city center of Pittsburgh. Consequently, it is possible that some DUI recidivism in Philadelphia County is missing from my data because they were identified and convicted in another state.[36]

Drug-impaired DUI offenders were most likely to recidivate with a non-DUI offense (72.8%). Offenders convicted of a drug-impaired DUI necessarily engaged in the use of illegal substances. The higher likelihood of non-DUI recidivism may reflect an increased likelihood to be arrested and convicted of a subsequent illegal drug charge or another criminal offense related to their illegal substance use (e.g., property offenses motivated by a need to obtain money to pay for illegal drugs). Alternatively, alcohol-impaired DUI offenders with a BAC of .16% or greater were most likely to recidivate with a DUI offense (62.5%). Offenders with a high level of BAC may be more likely to have an alcohol use disorder issue resulting in frequent, heavy drinking. An underlying alcohol use disorder may be more likely to be associated with alcohol-related offending, such as DUI, rather than general offending.

Offenders who had any prior convictions were more likely to recidivate with a DUI offense than a non-DUI offense. This pattern was confirmed both with the quantitative criminal history variables (number of prior convictions) and the qualitative criminal history variables (types of prior convictions). However, across all of the types of prior convictions, offenders with a prior DUI conviction were most likely to recidivate with a subsequent DUI offense. Offenders with a prior property and/or drug conviction were the most likely to recidivate with a non-DUI offense. These findings suggest there may be two distinct groups of DUI offenders and recidivists: those who engage in DUI offending but do not engage in other crimes, and those who engage in a range of criminal behaviors including DUI.

[36] My data included convictions only from courts in Pennsylvania.

Part II: Developing a Risk Assessment for Any Reconviction

For this study, I use unweighted Burgess methods to develop and validate a risk assessment instrument. I used unweighted Burgess methods rather than alternative methods for three reasons. First, research comparing the unweighted Burgess method with more complicated methods, such as weighted Burgess models or regression tree methods, finds that the basic Burgess method performs equally well, if not better (Gottfredson and Gottfredson, 1980). Second, unweighted Burgess methods are more parsimonious and transparent than alternative risk assessment methods. There has been increasing concern, both in the media and the courts, about the lack of transparency for some risk instruments such as the Northpointe COMPASS risk instrument (Freeman, 2016). Unweighted Burgess models avoid many of these concerns over transparency and may be more likely to withstand a legal challenge. Third, the Pennsylvania Commission on Sentencing uses unweighted Burgess methods to construct risk assessment instruments for non-DUI offenders. Because my dissertation examines whether the Commission could use a similar instrument to predict the likelihood of recidivism for DUI offenders, I chose to use methods that allow for a direct comparison to existing Pennsylvania Risk Scales.

The development of an unweighted Burgess risk instrument proceeds in three steps. First, I conduct multivariate analyses using logistic regression to identify the significant predictors of recidivism. Second, I construct a discrete, additive scale by assigning points to significant risk factors and validate the scale using the validation sample. Third, I analyze the predictive ability and overall accuracy of the scale.

Logistic Regression

Unweighted Burgess models use the findings from a logistic regression model to determine the factors included in the scale and the points associated with each significant factor.

Burgess models assign discrete point values (e.g., 1 or 2 points) to different risk factors. Subsequently, all factors included in the logistic regression must be coded into discrete categories rather than continuous measures. I first review the predictor variables and create categories for the number of prior convictions.

This section develops a risk assessment instrument predicting the likelihood of any reconviction. The dependent measure is a binary indicator of a reconviction for any offense within 5 years of release from the primary DUI. I predict failure based on a combination of offender and offense characteristics including demographics, prior record, and primary offense type.

Coding Variables

All variables for this analysis were converted into categorical variables. Gender, multiple charges, and types of prior offenses were already coded using indicator variables. Prior to imputing age, I created a categorical variable with 9 distinct age groups. Number of prior convictions was the only remaining continuous variable.

I coded a categorical variable for the number of prior convictions using the same methods previously discussed for coding age categories. I chose the categories for number of prior convictions using both theory and method. First, there is a conceptual difference between first-time offenders and offenders with any criminal history. Thus, I kept offenders with no prior convictions as a separate group. Second, there appears to be some difference between offenders with only one prior conviction and offenders with multiple prior convictions (see Table 2-9), with 7.7% more of the latter group recidivating in the development sample. Similarly, offenders with three prior convictions were 9.59% more likely to recidivate than offenders with only 2 prior convictions. I kept offenders with one prior conviction and offenders with two prior convictions as separate groups. There were few offenders with 3 or more prior convictions (6% of the development sample). Based on rates of recidivism, I created three additional groups: 3-4 prior convictions, 5-6 prior convictions, and 7 or more prior convictions. A chi-square test of the final categories confirmed that there were significant differences ($p < .000$) in the rates of recidivism across the 6 groups of prior convictions (see Table 2-10).

Table 2-9. Prior Convictions by Recidivism, Development Sample (N=23,209)

	Clean		Fail		Total
	N	%	N	%	N
0	14,044	82.43	2,994	17.57	17,038
1	2,544	74.47	872	25.53	3,416
2	907	66.79	451	33.21	1,358
3	341	57.21	255	42.79	596
4	166	58.25	119	41.75	285
5	112	55.45	90	44.55	202
6	57	55.88	45	44.12	102
7	29	40.28	43	59.72	72
8	17	38.64	27	61.36	44
9	18	56.25	14	43.75	32
10	9	45.00	11	55.00	20
11	10	50.00	10	50.00	20
12	3	37.50	5	62.50	8
13	1	20.00	4	80.00	5
14	0	0.00	1	100.00	1
15	2	66.67	1	33.33	3
16	1	100.00	0	0.00	1
17	2	66.67	1	33.33	3
18	1	100.00	0	0.00	1
19	1	100.00	0	0.00	1
26	1	100.00	0	0.00	1
Total	18,266		4,943		23,209

Table 2-10. Prior Conviction Categories by Recidivism, Development Sample

	Clean		Fail		Total
	N	%	N	%	N
0	14,044	82.43	2,994	17.57	17,038
1	2,544	74.47	872	25.53	3,416
2	907	66.79	451	33.21	1,358
3-4	507	57.55	374	42.45	881
5-6	169	55.59	135	44.41	304
7+	95	44.81	117	55.19	212
	18,266	78.70	4,943	21.30	23,209

Base Model and Categorical Reference Rotations

Table 2-11 presents the results for the initial logistic regression model predicting a reconviction for any criminal offense within 5 years of release for the primary DUI offense. The original model included each of the relevant demographic, offense, and criminal history information for each offender. For age, offenders who were 50 years of age and older were the reference group, and for prior convictions, offenders with no prior convictions were the reference group.

Table 2-11. Logistic Regression Predicting Reconviction Within 5 Years. Development Sample (N = 23,209)ǂ

Male	1.167***
White/Other Race	0.851*
County	
Other Urban	0.938
Allegheny	0.852*
Philadelphia	0.840*
Age	
<21	3.905***
21	3.982***
22/24	2.628***
25/29	2.088***
30/34	2.064***
35/39	1.956***
40/44	1.675***
45/49	1.663***
Multiple Convictions	0.989
Type of DUI	
BAC .08% - .09%	0.904
BAC .10% - .15%	0.813***
BAC .16%+	0.886*
Drug-Impaired	1.461***
No. of Prior Conv.	
1 Prior Conv	1.668***
2 Prior Conv	2.344***
3-4 Prior Conv	2.935***
5-6 Prior Conv	2.799***
7+ Prior Conv	3.844***
Prior Personal	1.311***
Prior Property	1.191*
Prior Drug	1.304***
Prior DUI	0.701***
Prior Traffic	1.087
Prior Public Order	1.129
Prior Public Administration	1.144
Prior Firearm	0.985
Constant	0.120***

ǂ Model conducted using 11 complete, imputed datasets.
*p < .05 ** p < .01 *** p < .001
Reference categories: Black for race; rural for county; 50+ for age; general impairment for Type of DUI; 0 prior convictions for No. of Prior Conv.

Male offenders and black offenders were significantly more likely than female offenders and white offenders to recidivate. Offenders in Allegheny and Philadelphia Counties were less likely than offenders in rural counties to recidivate. Younger offenders were more likely than older offenders to recidivate. Offenders convicted of a drug-impaired DUI were more likely than offenders convicted of an alcohol-impaired DUI to recidivate. Offenders with a higher blood alcohol content were more likely than offenders with a lower blood alcohol content to recidivate. The likelihood of recidivating significantly increased as the number of prior convictions increased. Offenders with a prior conviction for a personal offense, property offense, or drug offense were more likely to recidivate. However, offenders with a prior DUI conviction were less likely to recidivate.

For categorical variables (i.e., age, type of DUI, and number of prior convictions), the base model provides only the significant differences between different categories and the reference category. I conducted additional logistic models with the reference category individually rotated for each category for age, number of prior convictions, and type of DUI. Table 2-12 shows an example of this method for the type of DUI offense. Using these rotations, I identified significant differences between different groups in categorical variables.

Table 2-12. Logistic Regressions Predicting Reconviction Within 5 Years. Rotating Reference Category for Type of DUI. Development Sample (N = 23,209)ǂ

	Model 1	Model 2	Model 3	Model 4	Model 5
Male	1.167***	1.167***	1.167***	1.167***	1.167***
White/Other Race	0.851*	0.851*	0.851*	0.851*	0.851*
County					
Other Urban	0.938	0.938	0.938	0.938	0.938
Allegheny	0.852*	0.852*	0.852*	0.852*	0.852*
Philadelphia	0.840*	0.840*	0.840*	0.840*	0.840*
Age					
<21	3.905***	3.905***	3.905***	3.905***	3.905***
21	3.982***	3.982***	3.982***	3.982***	3.982***
22/24	2.628***	2.628***	2.628***	2.628***	2.628***
25/29	2.088***	2.088***	2.088***	2.088***	2.088***
30/34	2.064***	2.064***	2.064***	2.064***	2.064***
35/39	1.956***	1.956***	1.956***	1.956***	1.956***
40/44	1.675***	1.675***	1.675***	1.675***	1.675***
45/49	1.663***	1.663***	1.663***	1.663***	1.663***
Multiple Convictions	0.989	0.989	0.989	0.989	0.989
Type of DUI					
BAC <.08%	Ref.	1.107	1.230***	1.129*	0.684***
BAC .08%-.09%	0.904	Ref.	1.112	1.02	0.618***
BAC .10%-.15%	0.813***	0.9	Ref.	0.918	0.556***
BAC .16%+	0.886*	0.98	1.09	Ref.	0.606***
Drug-Impaired	1.461***	1.617***	1.797***	1.649***	Ref.
No. of Prior Conv.					
1 Prior Conv	1.668***	1.668***	1.668***	1.668***	1.668***
2 Prior Conv	2.344***	2.344***	2.344***	2.344***	2.344***
3-4 Prior Conv	2.935***	2.935***	2.935***	2.935***	2.935***
5-6 Prior Conv	2.799***	2.799***	2.799***	2.799***	2.799***
7+ Prior Conv	3.844***	3.844***	3.844***	3.844***	3.844***
Prior Personal	1.311***	1.311***	1.311***	1.311***	1.311***
Prior Property	1.191*	1.191*	1.191*	1.191*	1.191*
Prior Drug	1.304***	1.304***	1.304***	1.304***	1.304***
Prior DUI	0.701***	0.701***	0.701***	0.701***	0.701***
Prior Traffic	1.087	1.087	1.087	1.087	1.087
Prior Public Order	1.129	1.129	1.129	1.129	1.129
Prior Public Adm.	1.144	1.144	1.144	1.144	1.144
Prior Firearm	0.985	0.985	0.985	0.985	0.985
Constant	0.120***	0.108***	0.097***	0.106***	0.175***

ǂ Model conducted using 11 complete, imputed datasets. Boxes around coefficients indicate no significant difference.

*p < .05 ** p < .01 *** p < .001

The significant differences for age showed 5 distinct groups: 21 and younger, 22 – 24, 25 – 39, 40-49, and 50 and older. The likelihood of recidivism decreased as age increased such that offenders 21 and younger were the most likely to recidivate and offenders aged 50 and older were the least likely to recidivate.

The rotations for type of DUI and number of prior convictions did not identify clear differences between the individual groups. Type of DUI, alcohol-impaired offenders with a BAC less than .08% were not significantly different from offenders with a BAC of .08% - .09% but were significantly different from offenders with a BAC .10% or above and drug-impaired DUI offenders. Alcohol-impaired offenders with a BAC of .08% - .09%, .10% - .15%, and .16% or greater were not significantly different from each other, but were significantly different from drug-impaired DUI offenders. There were two possible categorizations for these significant differences: (1) drug-impaired offenders vs. all other offenders or (2) offenders with a BAC <.10%, offenders with a BAC of .10% or greater, and drug-impaired offenders.

The likelihood of recidivism increased as the number of prior convictions increased. However, there were not clear statistical differences between offenders with 2 or more prior convictions (see Table 2-13). Offenders with no prior convictions were significantly less likely to recidivate than all other offenders. Offenders with one prior conviction were significantly more likely to recidivate than offenders with no prior convictions and significantly less likely to recidivate than offenders with 2 or more prior convictions.

Table 2-13. Coefficients for Number of Prior Convictions from Logistic Regressions Predicting Any Reconviction Within 5 years. Development Sample (N = 23,209)ǂ

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
No Prior Convictions	Ref	0.600***	0.427***	0.341***	0.357***	0.260***
1 Prior Conv	1.668***	Ref	0.711***	0.568***	0.596***	0.434***
2 Prior Conv	2.344***	1.406***	Ref	0.799*	0.838	0.610**
3-4 Prior Conv	2.935***	1.760***	1.252*	Ref	1.049	0.764
5-6 Prior Conv	2.799***	1.678***	1.194	0.954	Ref	0.728
7+ Prior Conv	3.844***	2.304***	1.639**	1.309	1.373	Ref

ǂ Model conducted using 11 complete, imputed datasets. Overall model specification is the same as the basic logistic model presented in Table 2-11. All other coefficients were the same as those presented in Table 2-11.

*p < .05 ** p < .01 *** p < .001

Offenders with 2 prior convictions were significantly more likely to recidivate than offenders with no prior convictions, one prior conviction, 3-4 prior convictions, or 7 or more prior convictions. Offenders with 2 prior convictions did not significantly differ from offenders with 5-6 prior convictions.

<u>Constructing a Burgess Scale</u>

Using the results from the logistic regression, I constructed a discrete scale predicting the likelihood of being reconvicted for any offense within 5 years of release. Table 2-14 shows the total number of points assigned to each risk factor in the scale. The final scale ranged from 0 to 11.[37] For binary variables a point was assigned to the group of offenders who were significantly more likely to recidivate. For example, males were significantly more likely than females to recidivate (OR = 1.167, *p* < .001), so males receive one point for gender on the Burgess scale and females receive no points for gender on the Burgess scale.

[37] Although there is a factor that results in -1 point (prior DUI), offenders could receive the -1 only if they also received a positive point value from the quantitative variable for the number of prior convictions. That is, offenders could not have 0 prior convictions but also have a prior DUI conviction. As such, it is impossible for any offender to have a negative point value on the final scale.

Table 2-14. Burgess Risk Scale Predicting Any Reconviction (0-11)

Factor	Within Group Points	Total Factor Points	Factor	Within Group Points	Total Factor Points
Gender		**1**	**Prior Convictions**		**2**
Male	1		0	0	
Female	0		1	1	
Age		**4**	2	2	
<21	4		3-4	2	
21	4		5-6	2	
22/24	3		7+	2	
25/29	2		**Prior Property**		**1**
30/34	2		Yes	1	
35/39	2		No	0	
40/44	1		**Prior Personal**		**1**
45/49	1		Yes	1	
50+	0		No	0	
Type of DWI		**1**	**Prior Drug**		**1**
BAC <.08	0		Yes	1	
BAC .08-.09	0		No	0	
BAC .10-.15	0		**Prior DUI**		-1
BAC .16+	0		Yes	-1	
Drug	1		No	0	

For categorical variables, points were assigned based on the significant differences and direction of the odds ratios for each individual group. As noted previously, the categories for age were collapsed in distinct categories based on significant differences. Offenders 21 and younger received 4 points for age, more than any other age group. Offenders aged 22 to 24 received 3 points. Offenders aged 25 through 39 received 2 points. Offenders aged 40-49 received 1 point. Offenders aged 50 and older received no points. These findings for age are consistent with the descriptive and bivariate statistics that showed a relatively flat, slow decline in recidivism among middle-aged offenders.

For number of prior convictions, I collapsed offenders with 2 or more prior convictions. Despite the significant differences between offenders with 2 prior convictions and those with 3-4 and 7 or more prior convictions, offenders with 2 prior convictions were not different from offenders with 5-6 prior convictions. Assigning fewer points to offenders with only 2 prior convictions would unfairly inflate the risk of offenders with 5-6 prior convictions. By assigning the same number of points to all offenders with 2 or more prior convictions, the Burgess scale is true to the significant findings while providing the benefit to defendants with more prior convictions.

For type of DUI, I individually tested the two potential categories identified from the logistic regression rotations. I created two scales, one with two categories for type of DUI (drug-impaired DUI vs. all other) and one with three categories for type of DUI (general impairment, BAC .08%+, and drug-impaired). The truncated scale, with only two categories for type of DUI, performed significantly better ($x2(1) = 795.14$, $p < 0.000$). Thus, I continued with the binary category for type of DUI whereby drug-impaired DUI offenders received one point and all other offenders received no points for type of DUI.

Offenders received a point if they had a prior personal, property, or drug offense. Alternatively, offenders with a prior DUI offense had their score reduced by 1 point (and offenders without a prior DUI received 0 points). Assigning a negative value for points in the scale introduces additional policy concerns, which are discussed later. However, this finding is consistent with the research which indicates that offenders who specialize in DUI offending are more likely to desist than more general criminal offenders. In order for offenders to receive a point for the qualitative prior convictions variables (e.g., prior personal, property, drug, or DUI), they must also receive at least one point for the quantitative prior convictions variable. In this scale, offenders who have a criminal record, but who have only prior DUI offenses are less likely to recidivate than offenders who have a criminal record, but only for non-DUI offenses. In this way, the quantitative and qualitative points work together to identify the more serious repeat offenders from the less serious repeat offenders.

The negative prior DUI effect may also reflect differences in sentencing and treatment. Sentences for DUI offenders in Pennsylvania are decided by a separate sentencing guideline grid that includes mandatory minimums and the need for treatment based on drug and alcohol assessments. As noted previously, there are mandatory minimum sentences of incarceration for DUI offenders based on BAC and the number of prior DUIs. For offenders who have a history of DUI offending and who have a high level of BAC, the statutory minimum incarceration sentence ranges from 5 to 365 days (see Appendix A). Drug and DUI offenders are some of the most likely to receive restrictive intermediate punishment (RIP) instead of a traditional prison sentence (Orth, 2017). RIP programs combine more intensive supervision than probation (e.g., incarceration with work release and house arrest with electronic monitoring) and intensive alcohol or drug treatment (e.g., partial hospitalization, halfway house, or short-term residential facility). Research evaluating RIP in Pennsylvania, particularly for DUI offenders, has found these sanctions to be effective at reducing recidivism (Orth, 2017). The negative effect for a prior DUI could reflect the effective use of alternative sanctions for offenders who have a prior record and are more likely to be sentenced to a period of incarceration.

The need for drug and alcohol treatment for DUI offenders is also determined by the CRN and full drug and alcohol assessments. One factor on the CRN is the number of prior DUIs for an offender. Offenders who are repeat DUI offenders are likely to score higher on the CRN, indicating the need for additional treatment. Studies analyzing the use of treatment programs as a part of sanctions for second- and third-time DUI offenders have found significant reductions in recidivism (Deyoung, 1997; Taxman and Piquero, 1998). Once again, the lower likelihood of recidivism for offenders with a prior DUI may reflect a higher likelihood to be sentenced to more intensive drug or alcohol treatment even in instances when the offender is not sentenced to incarceration. I validated the scale using the validation sample. Using receiver operating characteristics (ROC) comparisons, I tested for significant differences in the ability to predict recidivism for the development and validation samples. ROC analyses are not currently supported with multiple imputation commands in STATA. Consequently, I conducted the ROC analyses on the 11 imputed datasets combined, resulting in a sample size of 255,299 observations for the development and validation samples.[38] The ROC comparison between the development and validation samples are presented in Table 2-15. A chi-squared test of the area under the curve found no significant difference between the scale's ability to accurately predict recidivism in the development and validation samples. This test confirms the validation of the scale and indicates that the scale was not over-fit to the development sample.

Table 2-15. AUC Comparison - Burgess Scale - Any Reconviction - Development and Validation, Imputed Samples

	N	ROC AUC	Std Err	95% CI	
Validation	255,299	0.6544	0.0013	0.6518	0.657
Development	255,299	0.6554	0.0013	0.65285	0.65805
chi2(1)	=	0.31	Prob>chi2	0.5763	

In traditional risk methods, offenders are classified into different groups based on their final risk score. Following the methods used by the Pennsylvania Commission on Sentencing, I classified offenders into one of three categories: low-risk, average-risk, and high-risk. I classified

[38] By artificially increasing the sample 1100%, it is likely that the standard errors are underestimated, which may result in false positives when hypothesis testing. Although I did not find a significant difference in the ROC comparison, I replicated the analysis on each imputed sample individually. Consistent with the findings from the collapsed dataset, I did not find any significant differences in the AUC for the development and validation samples in any individual imputed dataset (N = 11).

offenders as average-risk if they fell within one standard deviation above or below the average risk score. Offenders were classified as low-risk if they had a score less than one standard deviation below the mean. Offenders were classified as high-risk if they had a score greater than one standard deviation above the mean. For classification purposes, I used the mean and standard deviation of the scores from the full sample (development and validation combined).[39] When implemented, judges are instructed to order a pre-sentence investigation for offenders classified as low- or high-risk. For average-risk offenders, judges are instructed to proceed as usual.

The average risk score for any reconviction was 3.20 with a standard deviation of 1.65. The mean plus one standard deviation was 4.85 and the mean minus one standard deviation was 1.55. I classified offenders with a risk score of 0 or 1 as low-risk, offenders with a score of 2 to 4 as average-risk, and offenders with a score of 5 to 11 as high-risk.[40]

Evaluating Accuracy

Table 2-16 presents the distribution of recidivists and non-recidivists across the three risk categories.[41] As expected, nearly two-thirds of the sample was classified as average-risk, with the remaining third split among low- and high-risk categories. For this scale, more offenders were classified as high-risk (21.37% of the full sample) than low-risk (15.18% of the full sample). Offenders who recidivated were more likely to be classified as high-risk (38.46%) than low-risk

[39] The mean and standard deviation from the development sample would have created the same cut points for the low, average, and high groups of offenders.
[40] The cut points were based on the absolute value of the upper and lower limit established from the mean plus/minus one standard deviation.
[41] These results are presented using the 11 imputed datasets. Offenders with imputed data for gender or age may have different scores in different imputed datasets, though their scores should be similar. By conducting these analyses using all imputed datasets, I maintain the information from the original, complete observations without biasing the information included from the individual imputed datasets.

(7.54%). Offenders who did not recidivate were slightly more likely to be classified as low-risk (17.26%) than high-risk (16.70).

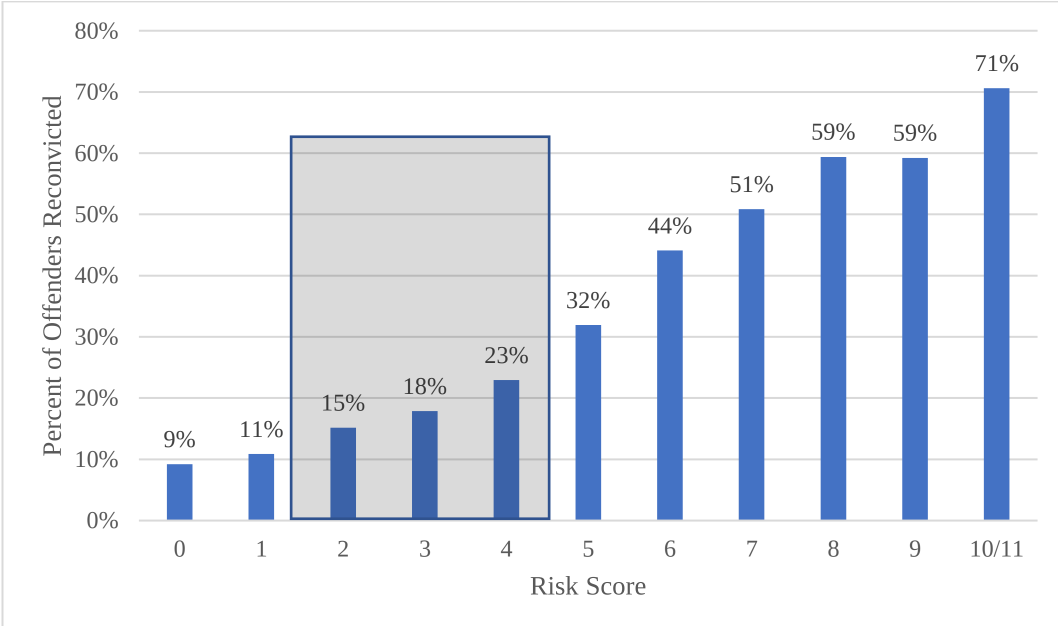
Table 2-16. Burgess Risk Groups – Risk of Any Reconviction – Full imputed Sample

Risk Group	Clean		Failure		Total	
	N	%	N	%	N	%
Low	69,225	17.26	8,261	7.54	77,486	15.18
Average	264,849	66.04	59,166	54.00	324,015	63.46
High	66,964	16.70	42,133	38.46	109,097	21.37
Total	401,038	100.00	109,560	100.00	510,598	100.00

In addition to these classifications, Pennsylvania risk assessment techniques present judges with a figure detailing the percent of offenders who recidivate within each risk score. Figure 2-6 shows the rate of recidivism for each individual risk score, with offenders in the highest two risk categories (10 and 11) collapsed.[42] Scores that are "in the box" represent offenders with an average risk score. Scores below the box are considered low-risk and scores above the box are considered high-risk. Note that the distribution of offenders appears heavily skewed toward offenders in high-risk categories. While there were more offenders classified as high-risk than as low-risk, the overall distribution was heavily concentrated in lower scores on the scale. As such, the individual sample sizes for each risk score in the high-risk classification (5 through 11) are much smaller than the sample sizes for each risk score in the low- or average-risk classifications.

[42] There were no offenders in my sample who had a risk score of 11. Consequently, I collapsed the two highest categories in the final figure.

Figure 2-6. Rate of Recidivism for Any Offense by Risk Score



Sentencing risk assessments are still relatively new in the criminal justice system. As such, there is little consensus on how the accuracy of any given risk assessment instrument should be measured. Most authors agree that the AUC test provides a robust assessment of the overall accuracy of a risk assessment instrument. However, the AUC may be insufficient for understanding the nuance of a sentencing risk assessment for two reasons. First, the AUC tests the effectiveness of the overall scale, while some jurisdictions may use only parts of the scale (e.g., high or low-risk groups). Second, the AUC treats all error similarly. That is, false positives and false negatives are given equal weight. If a scale does relatively well overall, but performs poorly for low- or high-risk, then it may have unintended consequences for particularly vulnerable groups.

Other approaches to assessing the accuracy of risk assessment instruments focus on the rates of false positives and false negatives based on 2 (predicted to fail, predicted to succeed) x 2 (actual failure or actual success) confusion tables (Berk et al., 2017). Analyses based on confusion tables require an absolute prediction for behavior – in this case, that an offender will recidivate or that an offender will not recidivate. This is problematic for two reasons. First, my scale is not intended to make an absolute prediction of behavior, but rather, to predict the *likelihood* than an offender will recidivate (Monahan and Skeem, 2014). Second, a 2 x 2 confusion table would either ignore the classification of average-risk offenders or require an additional split whereby average-risk offenders were included in either low- or high-risk.

The overall uncertainty of my prediction for offenders in each risk score is included in the findings presented in Figure 2-6. For example, offenders with a risk score of 5 recidivate 32% of the time, but offenders with a risk score of 5 do not recidivate 68% of the time. Given the low base-rate of recidivism for this population (21%), a 32% probability of recidivism is above average. However, it is still the case that less than half of the offenders with a risk score of 5 or 6 recidivated. It would be problematic to make a declarative statement about offenders in the high-risk category (e.g., that high-risk offenders will recidivate) given these findings. In addition, by presenting the recidivism rate for each individual risk score, this figure also provides some information about the heterogeneity of offenders in each group. For this scale, the rate of recidivism for offenders in the high-risk category ranged from 32% to 71%.

The Pennsylvania Commission on Sentencing approach to risk assessment is primarily concerned with high- and low-risk offenders. The risk assessment instrument is intended to identify offenders with a lower than average or higher than average likelihood of recidivism. Table 2-17 shows the accuracy of the predictions for high- and low-risk offenders, assuming that a “correct” prediction of low-risk means that an offender did not recidivate and that a “correct” prediction of high-risk means that an offender did recidivate. This chart is most akin to the confusion charts previously discussed.

Table 2-17. Accuracy for High- and Low-risk

	% Correct prediction
High and Low-risk	59.7%
High-risk	38.6%
Low-risk	89.3%

Overall, the scale accurately predicts the behavior of offenders in low- and high-risk categories 59.7% of the time. This accuracy measure is about 6% lower than the overall accuracy measure obtained from an AUC analysis (AUC = 0.655) which includes an assessment of the classification for average-risk scores. In addition, the overall accuracy appears to be driven largely by the offenders classified as low-risk (89.3% accurate) and not the offenders classified as high-risk (38.6%). Despite the relatively high accuracy of predictions in some of the higher scores on the scale (e.g., offenders with a risk score of 10 or 11 recidivated 71% of the time), the overall predictions in the high-risk group were poor. These findings emphasize the problems associated with making declarative statements about any particular group of offenders. While it may be appropriate to say that low-risk offenders will probably not recidivate, it would be misleading to say that high-risk offenders probably will recidivate.

These accuracy measures do not indicate that there is something wrong with the scale or with the methods used to calculate the offenders' risk scores. Even though offenders in the high-risk category recidivated only 38.6% of the time, this was still significantly higher than the overall rate of recidivism for DUI offenders (21.5%). Thus, this model did successfully identify the population of offenders with a higher-than-average rate of recidivism.

Part III: Developing a Risk Assessment for Repeat DUI Offending

Prior analyses of Pennsylvania sentencing data (Knoth, 2015) suggest that 29.94% of first-time DUI offenders are arrested for a new DUI. Other research suggests that a small population of DUI offenders account for a significant portion of all DUI offenses (Homel, 1981). Repeat DUI offenders may pose a greater risk to society given that each additional incidence of DUI represents a new threat to pedestrians or other members of the public. In addition, repeat DUI offenders may have an underlying substance use disorder that contributes to their criminal behaviors (DeMichele, Payne, and Lowe, 2013). Targeted treatment for substance use disorders may be able to reduce the likelihood of future offending.

There may also be offenders who engage in a broad range of criminal behaviors, including DUI. These general offenders may have a higher propensity to engage in any criminal behavior that poses a threat to individual persons or property. However, in contrast to DUI offenders with substance use disorders, general offenders may not have a substance use disorder and may be less likely to respond to treatment programs or punishment.

This section develops and validates an additional risk assessment scale that predicts the likelihood of a reconviction for a subsequent DUI within 5 years of release from the primary DUI offense. The methods used in this section were modeled on the Pennsylvania Commission on Sentencing's approach to specialized risk assessments predicting the likelihood that an offender will recidivate with an offense against a person. The development of DUI risk instrument follows the same approach as the development of a general risk instrument. First, I conduct multivariate analyses using logistic regression to identify the significant predictors of DUI recidivism. Second, I construct a discrete, additive scale by assigning points to significant risk factors and validate the scale using the validation sample. Third, I analyze the predictive ability and overall accuracy of the scale. In addition to these analyses, I review the overlap of offender risk categories for the general recidivism scale and the DUI recidivism scale.

Logistic Regression – Base Model and Categorical Rotations

The DUI risk assessment instrument included the same offender demographic, criminal history, and current offense variables as predictors of DUI recidivism. The categories for age and type of DUI were unchanged from the original logistic models. However, there were meaningful differences in the recidivism rates by number of prior convictions. Table 2-18 shows the rate of DUI recidivism by number of prior convictions.[43] The rate of DUI recidivism was between 12% and 14% for offenders with two to six prior convictions. Consequently, I changed the categories in the quantitative prior convictions variable to be 0 prior convictions, one prior conviction, two to six prior convictions, and seven or more prior convictions.

Table 2-18. Prior Convictions by DUI Recidivism, Full Sample (N = 46,418)

	Clean		Failure		Total
	N	%	N	%	N
0	30,496	89.34%	3,639	10.66%	34,135
1	6,028	88.30%	799	11.70%	6,827
2	2,307	85.83%	381	14.17%	2,688
3	1,020	86.08%	165	13.92%	1,185
4	522	87.73%	73	12.27%	595
5	317	85.44%	54	14.56%	371
6	180	87.80%	25	12.20%	205
7	109	78.42%	30	21.58%	139
8+	226	82.78%	47	17.22%	273
Total	41,205	88.77%	5,213	11.23%	46,418

Table 2-19 shows the results for the basic logistic model predicting a DUI reconviction within 5 years of release for the primary offense. There were no significant differences for gender, race, or county. Findings for age were consistent with the general patterns for any

[43] The base rate for DUI recidivism was low (11.23% in the full sample). I decided to use the full sample to analyze the best cutpoints for number of prior convictions in order to obtain more stable estimates of recidivism.

recidivism such that older offenders were less likely than younger offenders to recidivate with a DUI. The initial model showed that drug-impaired DUI offenders were less likely to recidivate than alcohol-impaired offenders charged under the general impairment statutes. There were no significant differences in DUI recidivism for any of the BAC categories. There appeared to be some differences by number of prior convictions, such that offenders with more prior convictions for any offense were more likely to recidivate with a DUI. Offenders with a prior personal conviction were more likely to recidivate with a DUI than offenders without a prior personal conviction. Offenders with a prior DUI conviction were less likely to recidivate with a DUI than offenders without a prior DUI conviction.

Table 2-19. Logistic Regression Predicting DUI Reconviction Within 5 Years. Development Sample (N = 23,209)ǂ

Male	1.042
White/Other Race	1.001
County	
Other Urban	0.982
Allegheny	1.025
Philadelphia	0.852
Age	
<21	2.179***
21	2.256***
22/24	1.750***
25/29	1.480***
30/34	1.517***
35/39	1.609***
40/44	1.444***
45/49	1.471***
Multiple Convictions	1.014
Type of DUI	
BAC .08-.09	0.826
BAC .10-.15	0.905
BAC .16+	1.106
Drug-Impaired	0.770**
No. of Prior Conv.	
1 Prior Conv	1.152
2-6 Prior Conv	1.449**
7+ Prior Conv	1.723*
Prior Personal	1.235*
Prior Property	0.953
Prior Drug	1.03
Prior DUI	0.831*
Prior Traffic	1.073
Prior Public Order	0.987
Prior Public Admin	1.054
Prior Firearm	1.106
Constant	0.074***

ǂ Model conducted using 11 complete, imputed datasets.
*p < .05 ** p < .01 *** p < .001
Reference categories: Black for race; rural for county; 50+ for age; general impairment for Type of DUI; 0 prior convictions for No. of Prior Conv.

The rotations for age categories did not show distinct groups based on statistical significance. Table 2-20 shows the coefficients for the different age categories with the reference category rotated. The two youngest age categories (<21 and 21) had significantly greater odds of recidivism than all other offenders. The oldest age category (50 and older) had significantly lower odds of recidivism than all other offenders. Offenders between the age of 25 and 49 were not significantly different from each other. However, offenders aged 22-24 were significantly different from younger offenders (21 and younger), offenders aged 25/29, and offenders 40 years of age and older and not significantly different from offenders aged 30 to 40. Given the absence of consistent differences for middle aged offenders and young adults, I collapsed all offenders between age 22 and 49. Thus, there were three age groups: 21 and younger, 22 to 49, and 50 and older.

Table 2-20. Coefficients for Age Categories from Logistic Regressions Predicting DUI Reconviction Within 5 years. Development Sample (N = 23,209)ǂ

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
<21	Ref.	0.966	1.245*	1.472***	1.436***	1.354**	1.509***	1.481***	2.179***
21	1.035	Ref.	1.289*	1.524***	1.487***	1.402**	1.563***	1.533***	2.256***
22/24	0.803*	0.776*	Ref.	1.182*	1.153	1.087	1.212*	1.189*	1.750***
25/29	0.679***	0.656***	0.846*	Ref.	0.975	0.92	1.025	1.006	1.480***
30/34	0.697***	0.673***	0.867	1.025	Ref.	0.943	1.051	1.031	1.517***
35/39	0.739**	0.713**	0.92	1.087	1.06	Ref.	1.115	1.094	1.609***
40/44	0.663***	0.640***	0.825*	0.975	0.951	0.897	Ref.	0.981	1.444***
45/49	0.675***	0.652***	0.841*	0.994	0.97	0.914	1.019	Ref.	1.471***
50+	0.459***	0.443***	0.572***	0.676***	0.659***	0.621***	0.693***	0.680***	Ref.

ǂ Model conducted using 11 complete, imputed datasets. Overall model specification is the same as the basic logistic model presented in Table 2-19. All other coefficients were the same as those presented in Table 2-19. Boxes around coefficients indicate clear age categories that are not significantly different.

*p < .05 ** p < .01 *** p < .001

Rotations for the reference category of prior convictions showed that there was no significant difference in the likelihood of DUI recidivism for offenders with no prior convictions and offenders with only one prior conviction. There was a significant difference between offenders with no prior convictions or one prior conviction and offenders with two to six prior convictions. Offenders with seven or more prior convictions were not significantly different from offenders with 1 to 6 prior convictions. In order to maintain the benefit for defendants with only one prior conviction, I chose two categories for prior convictions: offenders with no prior convictions or only one prior conviction and offenders with 2 or more prior convictions.

Type of DUI did not cleanly predict DUI recidivism. Table 2-21 shows the coefficients for Type of DUI categories across different logistic regressions rotating the reference group. Offenders convicted under the general impairment statute or with a BAC between .08% - .15% did not have significantly different odds of DUI recidivism. Offenders with a BAC of .16% or greater were not significantly different from offenders charged under the general impairment statute but were significantly more likely than offenders with a BAC between .08% and .15% and drug-impaired offenders to recidivate. Drug-impaired offenders were the least likely to recidivate with a DUI but were not significantly different from offenders with a BAC between .08% and .15%. Due to the absence of clear and consistent differences across the different types of DUI, I decided not to assign any points for type of DUI.

Table 2-21. Coefficients for Type of DUI (BAC %) from Logistic Regressions Predicting DUI Reconviction Within 5 years. Development Sample (N = 23,209)ǂ

	Model 1	Model 2	Model 3	Model 4	Model 5
General Impairment		1.211	1.105	0.904	1.299**
BAC .08-.09	0.826		0.912	0.747**	1.073
BAC .10-.15	0.905	1.096		0.818***	1.176
BAC .16+	1.106	1.339**	1.222***		1.437***
Drug-Impaired	0.770**	0.932	0.85	0.696***	

ǂ Model conducted using 11 complete, imputed datasets. Overall model specification is the same as the basic logistic model presented in Table 2-19. All other coefficients were the same as those presented in Table 2-19.

*p < .05 ** p < .01 *** p < .001

Constructing a DUI Burgess Scale

Using the results from the logistic regressions and subsequent rotations, I constructed a discrete scale predicting the likelihood of being reconvicted for a DUI offense within 5 years of release.[44] Table 2-22 shows the number of points assigned to each risk factor in the scale, including the individual groups within categorical risk factors. The final scale ranged from -1 to 4. Unlike the scale for any reconviction, it was possible for offenders to have a negative score on the final DUI risk scale. If an offender was 50 years or older and had one prior conviction for a DUI offense, their total risk score would be -1.[45]

Table 2-22. Burgess Risk Scale Predicting DUI Reconviction (-1 - 4)

Factor	Within Group Points	Total Factor Points	Factor	Within Group Points	Total Factor Points
Age		**2**	**Prior Convictions**		**1**
<21	2		0	0	
21	2		1	0	
22/24	1		2-6	1	
25/29	1		7+	1	
30/34	1		**Prior Personal**		**1**
35/39	1		Yes	1	
40/44	1		No	0	
45/49	1		**Prior DUI**		-1
50+	0		Yes	-1	
			No	0	

The final DUI recidivism scale included far fewer factors than the scale predicting any reconviction. Gender, type of DUI, prior property convictions and prior drug convictions were not predictive of DUI recidivism. While age and number of prior convictions were significantly

[44] As a reminder, this model is predicting whether the offender's first recidivism after release was with a DUI offense. It is possible that other offenders recidivated with a non-DUI offense and later committed a DUI within the 5-year follow-up period. Because I captured data from only the first reoffense, second and subsequent offenses in the follow-up period were not recorded.

[45] Negative risk scores may be confusing to practitioners. For implementation purposes, it may be necessary to add a constant to all offenders (e.g., all offenders start with one point) so that all final scores are positive values.

related to recidivism, the number of distinct categories for these variables was smaller than the number of distinct categories when predicting any recidivism.

I validated the scale using the validation sample. AUC comparisons between the effectiveness of the DUI risk instrument indicated that the scale performed significantly better on the development sample than the validation sample ($\chi^2(1) = 8.47$, $p = 0.0036$). These initial analyses suggested that my scale did not validate. However, this AUC comparison was conducted using all of the observations across the 11 imputed datasets. As noted previously, STATA multiple imputation commands currently do not support ROC analyses.

By conducting comparisons using the data from all 11 imputed datasets, the estimates of the standard errors were most likely artificially deflated. By artificially increasing the statistical power in my sample, the confidence in the AUC estimates were heavily biased, resulting in a higher probability of rejecting the null hypothesis.[46] In order to test whether this significant difference was real or the result of biased standard errors, I conducted ROC comparisons individually on each of the 11 imputed datasets.

[46] It is for this reason that regression analyses on imputed data are conducted using special regression methods, adjusting for the imputed data and providing more realistic estimates statistical significance for coefficients in the model.

Table 2-23. Testing Significant AUC Differences for DUI Recidivism Scale on Development and Validation Samples, by Imputed Dataset.

	AUC		
Dataset	Development	Validation	Sig.
MI 1	0.550	0.544	0.381
MI 2	0.551	0.544	0.364
MI 3	0.550	0.544	0.381
MI 4	0.550	0.544	0.388
MI 5	0.550	0.544	0.381
MI 6	0.550	0.544	0.381
MI 7	0.551	0.544	0.364
MI 8	0.550	0.544	0.382
MI 9	0.550	0.544	0.388
MI 10	0.550	0.544	0.382
MI 11	0.550	0.544	0.393
Full MI	0.550	0.544	0.004

Table 2-23 reports the overall AUC for the development and validation samples using the combined imputed datasets as well as the individual AUC estimates for the development and validation samples for each of the individual imputed datasets. None of the comparisons conducted on the individual imputed datasets identified statistically significant differences between the development and validation samples. The AUC for the development and validation samples in the individual imputed datasets was essentially the same as the AUC for the development and validation samples in the combined imputation data. The consistency across the individual datasets confirmed that there was no significant difference in the performance of the scale on the development and validation samples and that the findings in the sample including all imputed datasets were the result of over-confidence in the AUC estimates.

The average risk score for the DUI recidivism scale was 1.03 with a standard deviation of 0.69. The upper and lower bounds for the average-risk group were 1.72 and 0.33, respectively.

Offenders with a score of -1 or 0 were classified as low-risk. Offenders with a risk score of 1 were classified as average-risk. Offenders with a risk score of 2, 3, or 4 were classified as high-risk.

Evaluating Accuracy

The AUC for the DUI risk assessment instrument (AUC = 0.547) indicated that the scale performed poorly overall. The scale was able to predict DUI recidivism only slightly more often than a simple coin flip. Given that DUI recidivism was a rare event (11.2%), it is unlikely that the scale performed equally well for low-, average-, and high-risk groups.

Table 2-24 presents the distribution of the sample across the three risk groups by recidivism. Nearly two-thirds of the sample (62.81%) were classified as average-risk, with the remaining 37.19% split between low- and high-risk. Slightly more of the sample was classified as high-risk (19.32%) than low-risk (17.87%). Offenders who recidivated with a DUI offense were almost twice as likely to be classified as high-risk (24.69%) than low-risk (13.10%). However, offenders who did not recidivate with a DUI were equally likely to be classified as low-risk (18.47%) and high-risk (18.64%).

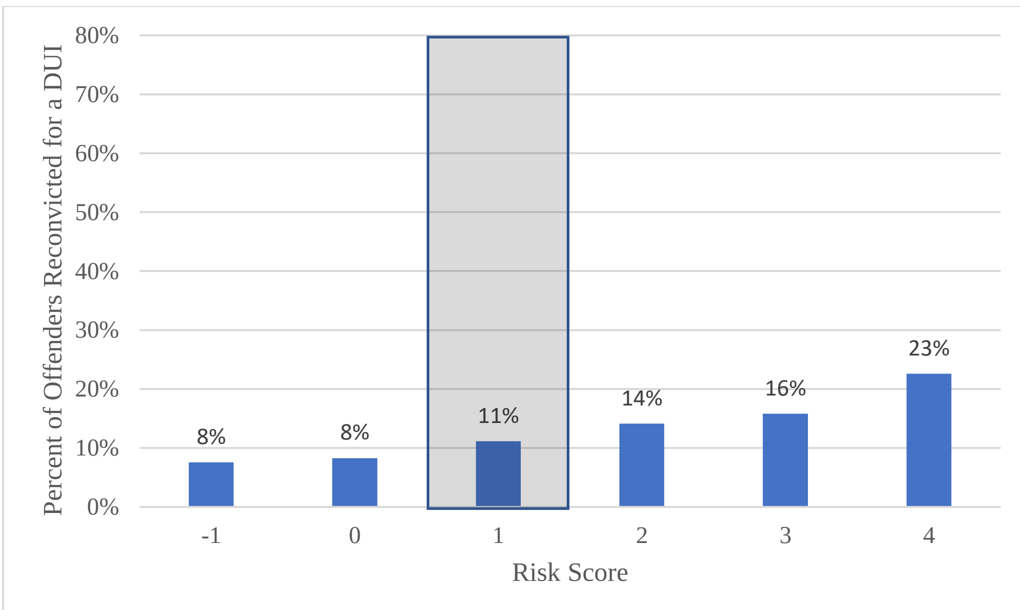
Table 2-24. Burgess Risk Groups for DUI Recidivism - Full Imputed Sample

Risk Group	Clean*		Failure		Total	
	N	%	N	%	N	%
Low	83,716	18.47	7513	13.10	91,229	17.87
Medium	285,031	62.89	35,673	62.21	320,704	62.81
High	84,508	18.64	14,157	24.69	98,665	19.32
Total	453,255	100.00	57,343	100.00	510,598	100.00

*Clean offenders were those who did not recidivate with a DUI, including offenders who recidivated with a non-DUI offense

Figure 2-7 presents the rate of recidivism for each risk score on the DUI risk assessment scale. This figure uses the same scaling for the Y axis as the previously reported figure for any reconviction. The low probability of DUI recidivism across risk scores further demonstrates the rarity of DUI recidivism. Among high-risk offenders, the largest likelihood of DUI recidivism was only 23%.

Figure 2-7. Rate of DUI Recidivism by Risk Score



The DUI risk scale performed well for low-risk offenders but performed poorly for high-risk offenders. Table 2-25 shows the accuracy of predictions in low- and high-risk categories, assuming that an accurate prediction for low-risk occurred when an offender did not recidivate with a DUI and that an accurate prediction for high-risk occurred when an offender did recidivate with a DUI. The combined effectiveness for high- and low-risk predictions was lower than the previously reported AUC. Although the scale accurately predicted low- and high-risk offenders half of the time, this success rate was driven by the ability to effectively predict who would not recidivate with a subsequent DUI.

Table 2-25. Accuracy for High- and Low-Risk Groups

	% Correct prediction
High- and Low-Risk	51.5%
High-Risk	14.3%
Low-Risk	91.8%

Under the current, proposed sentencing guidelines for risk assessment instruments in Pennsylvania, judges would receive information on a specialized risk assessment scale (i.e., a scale predicting a particular type of recidivism) only if the offender is first identified as being high-risk for any recidivism. I conducted additional accuracy analyses for the DUI recidivism instrument using only those offenders who were high-risk on the general reconviction risk instrument.

Table 2-26. Burgess Risk Groups for DUI Recidivism Only for Offenders Who Were High-Risk of Any Recidivism

Risk Group	Clean*		Failure		Total	
	N	%	N	%	N	%
Low	374	0.40	33	0.21	407	0.37
Medium	21,265	22.78	3,344	21.25	24,609	22.56
High	71721	76.82	12,360	78.54	84,081	77.07
Total	93,360	100.00	15,737	100.00	109,097	100.00

*Clean offenders were those who did not recidivate with a DUI conviction, including offenders who recidivated with a non-DUI conviction

Table 2-26 shows the distribution of offenders who were high-risk of any recidivism (21.37% of the full sample), across their risk groups for the DUI recidivism scale. The majority of offenders (77.07%) who were classified as high-risk for recidivism with any offense were also classified as high-risk for recidivism with a DUI offense. Less than one percent (0.37%) of this sample was classified as low-risk for recidivism with a DUI offense.

The accuracy of the DUI recidivism predictions for low- and high-risk offenders is included in Table 2-27. Once again, the scale performed better for low-risk predictions (91.9% accuracy) than for high-risk predictions (14.7% accuracy). However, the concentration of the sample in the high-risk category significantly reduced the overall accuracy of low- and high-risk predictions combined (15.1% accuracy).

Table 2-27. Accuracy for High- and Low-Risk Groups - Only Offenders Who Were High-Risk for Any Recidivism

	% Correct prediction
High- and Low-Risk	15.1%
High-Risk	14.7%
Low-Risk	91.9%

Overall, these findings highlight the difficulty in predicting rare events. The accuracy for the DUI recidivism scale was significantly lower than the accuracy for the general recidivism scale. In addition, the predictions that were accurate were largely concentrated in the low-risk offender groups. The inability to accurately identify DUI recidivists may be due to the limitations in the predictor variables. If DUI offenders are different, there may be important predictors for DUI recidivism that are not included in these scales (e.g., substance use information). Alternatively, the methods developed by the Pennsylvania Commission on Sentencing may be insufficient for developing specialized risk assessments. In the next section, I suggest an alternative approach to developing a recidivism instrument, which may be more effective at predicting subsequent DUI offending.

Part IV: An Alternative Approach to Specialized Risk Assessments

The PCS method of developing a specialized risk assessment relies on a comparison of two groups: 1) a specific type of recidivist and 2) all other recidivists and those who do not recidivate. As a result, the PCS general recidivism and specialized recidivism scales ask two separate questions: (1) What is the likelihood that an offender will recidivate at all?, and (2) What is the likelihood that an offender will recidivate with a particular type of offense?

There are three problems with using the PCS approach to specialized risk assessment instruments to construct a DUI recidivism scale. First, there is a relatively small number of non-DUI recidivists (10.2% of the Development sample) compared to the number of non-recidivists (78.7% of the Development sample). Consequently, the offenders who do not recidivate are likely to drive any of the statistically significant differences with the population of DUI recidivists. Ultimately, this approach provides only a weaker comparison of recidivists with non-recidivists than does a comparison between DUI recidivists and non-DUI recidivists. This finding was confirmed by the general consistency between the significant factors in the general recidivism scale and the DUI-specific recidivism scale.

Second, using the PCS approach, the general recidivism scale and the DUI-specific scale must be viewed independently of one another. That is, the general recidivism scale provides the overall probability of recidivism for any offense, and the DUI-specific recidivism scale provides the overall probability of DUI recidivism. However, the PCS approach would provide the DUI-specific recidivism scale only if certain conditions were met under the general recidivism scale, creating the perception that the scales should be interpreted in tandem. The PCS approach does not ask, “If the offender does recidivate, what type of offense are they most likely to commit?”

Third, the PCS approach does not allow for an evaluation of the DUI offenders who are likely to recidivate with a non-DUI offense. Under current statutes, all DUI offenders in Pennsylvania must receive a CRN (Court Reporting Network) evaluation, which screens for potential drug- or alcohol-dependence. If an offender is identified as potentially having a substance use disorder, the offender must undergo further drug- and alcohol-use assessments. Given that repeat DUI offending is most likely to occur with individuals who have a substance use disorder, individuals who are most at-risk for a subsequent DUI should already be captured under current screening practices.[47] A risk assessment that does not test for the different likelihoods of engaging in non-DUI vs. DUI recidivism provides little to no unique information to the courts.

For this study, I pursued an alternative approach to developing a specialized DUI risk assessment instrument. In this section, I develop and validate a second risk assessment instrument predicting the likelihood of recidivism with a DUI among those offenders who did recidivate. I used the same methods for development and validation as previously discussed in Parts II and III, however, I limited my sample to only those offenders who were reconvicted within 5 years of release for their primary DUI offense (Development N = 18,266; Validation N = 18,192). As with the previous sections, I conducted all analyses using the 11 imputed datasets for each offender.

<u>Logistic Regression – Base Model and Categorical Rotations</u>

I used the same predictor variables for this model including offender demographics, criminal history, and primary offense characteristics. I once again reviewed the categories for prior convictions to determine whether there was a better specification for the number of prior convictions after limiting the sample to only the offenders who recidivated. Removing offenders who did not recidivate meant that I primarily removed offenders with no criminal record. Thus, instead of the six-category variable that I used for the prior scale construction (Part III) the best

[47] As noted earlier, this CRN evaluation is not available to the PCS or the AOPC and therefore cannot be used in a risk assessment instrument.

fit for the categories of prior convictions was a 5-category variable: 0 prior convictions, 1 prior conviction, 2 prior convictions, 3 to 6 prior convictions, and 7 or more prior convictions.

Table 2-28 presents the basic logistic regression predicting a reconviction for a DUI within 5 years of release among only those offenders who did recidivate (N = 4,943). Unlike the previous section, the comparison group on the dependent variable is offenders who recidivated with a non-DUI offense. The findings in this model may be interpreted as the odds of recidivating with a DUI instead of a non-DUI offense.

Table 2-28. Logistic Regression Predicting DUI Reconviction Within 5 Years. Development Sample, Recidivists Only (N = 4.943)ǂ

Male	0.86
White/Other Race	1.296*
County	
Other Urban	0.86
Allegheny	1.296*
Philadelphia	0.852
Age	
<21	0.371***
21	0.376***
22/24	0.447***
25/29	0.499***
30/34	0.532***
35/39	0.627**
40/44	0.678*
45/49	0.749
Multiple Convictions	1.046
Type of DUI	
BAC .08%-.09%	0.935
BAC .10%-.15%	1.251*
BAC .16%+	1.613***
Drug-Impaired	0.459***
No. of Prior Conv.	
1 Prior Conv	0.537***
2 Prior Conv	0.537***
3-6 Prior Conv	0.340***
7+ Prior Conv	0.368**
Prior Personal	0.971
Prior Property	0.805
Prior Drug	0.809
Prior DUI	1.161
Prior Traffic	1.013
Prior Public Order	0.943
Prior Public Admin	0.945
Prior Firearm	1.306
Constant	1.977***

ǂ Model conducted using 11 complete, imputed datasets.
*p < .05 ** p < .01 *** p < .001
Reference categories: Black for race; rural for county; 50+ for age; general impairment for Type of DUI; 0 prior convictions for No. of Prior Conv.

White offenders and offenders of another race (non-Black) were more likely than Black offenders to recidivate with a DUI. Offenders in Allegheny County were more likely to recidivate with a DUI than were offenders in rural counties, other urban counties, or Philadelphia County. There was no significant difference in the type of recidivism by gender.

Younger offenders were significantly less likely than older offenders to recidivate with a DUI. The relationship for age in this model was in the opposite direction from the relationships with age and recidivism identified in Part II and Part III. The models rotating the reference category for age identified four different age groups: 21 and younger, 22-34, 35-44, and 45 and older.[48] In this model, the youngest age group (21 and younger) had the lowest likelihood of recidivism with a DUI while the oldest age group (45 and older) had the highest likelihood of recidivism with a DUI.

Drug offenders were least likely to recidivate with a DUI offense. Among alcohol-impaired offenders, those with a BAC of .16% or greater were the most likely to recidivate with a subsequent DUI. Alcohol-impaired offenders with a BAC of .15% or less were more likely than drug-impaired offenders to recidivate with a DUI but less likely than highly intoxicated offenders to recidivate with a DUI.[49]

Offenders with no prior convictions were the most likely to recidivate with a DUI offense. There was no difference in the likelihood of recidivism with a DUI for offenders with one or two prior convictions. Offenders with three or more prior convictions were least likely to

[48] There was one alternative coding for age: 24 and younger, 25-34, 35-49, and 50 and older. However, subsequent comparisons of the AUCs for scales using each of the two age specifications found that that the alternative model performed significantly worse.

[49] Offenders charged under general impairment statutes were significantly less likely to recidivate with a DUI than offenders with a BAC between .10% and .15%; however, the difference was significant only at the .05 level. In addition, both offenders convicted under general impairment statutes and offenders convicted with a BAC between .10% and .15% were not significantly different from offenders convicted with a BAC of .08% or .09%. I combined all three categories due to the ambiguity in significant differences and in order to maintain the benefit for all defendants.

recidivate with a DUI.[50] There were no significant differences in the likelihood of DUI recidivism by the type of prior convictions. However, it is interesting that the direction of the relationship between a prior DUI conviction and subsequent DUI recidivism was positive. That is, offenders with a prior DUI conviction were more likely than offenders without a prior DUI conviction to recidivate with a DUI. In all previous models, the relationship between a prior DUI conviction and recidivism was negative.

Constructing a DUI Burgess Scale

Based on the results from the logistic regressions, I constructed a discrete scale predicting DUI recidivism among offenders who were reconvicted of a criminal offense within 5 years of release. The final scale (presented in Table 2-29) ranges from 0 to 7 based on points from only three risk factors: age, type of DUI, and number of prior convictions.

The oldest offenders (45 and older) received three points for age while the youngest offenders (21 and younger) received no points for age. Young adults (aged 22 – 34) received one point and middle-aged offenders (35 – 44) received two points for age. Drug-impaired DUI offenders received no points for the type of DUI offense. Alcohol-impaired DUI offenders with a BAC less than .16% received one point while those with a BAC of .16% or greater received two points. Offenders with no criminal history received two points. Offenders with one or two prior convictions received one point. Offenders with the longest criminal records (3 or more prior convictions) received no points.

[50] Offenders with seven or more prior convictions were not significantly different from offenders with one, two, or three to six prior convictions. However, the inability to find significant differences was likely due to small sample sizes given that only 117 offenders in this sample had seven or more prior convictions. I decided to collapse these offenders with offenders who had 3 to six prior convictions based on the direction of the relationship and significant differences between other categories of prior convictions.

Table 2-29. Burgess Risk Scale Predicting DUI Reconviction for Recidivist Offenders (0-7)

Factor	Within Group Points	Total Factor Points	Factor	Within Group Points	Total Factor Points
Age		**3**			
<21	0				
21	0				
22/24	1				
25/29	1		**Prior Convictions**		**2**
30/34	1		0	2	
35/39	2		1	1	
40/44	2		2	1	
45/49	3		3-6	0	
50+	3		7+	0	
Type of DWI		**2**			
BAC <.08	1				
BAC .08-.09	1				
BAC .10-.15	1				
BAC .16+	2				
Drug	0				

Missing from this scale were any significant qualitative prior conviction factors. In both of the previous scales (general recidivism and DUI-specific recidivism) a prior DUI was negatively related to recidivism. However, in this scale, the logistic regression showed no significant difference between DUI and non-DUI recidivists with a prior DUI. Despite the absence of a significant finding, the relationship between prior DUIs and DUI recidivism was positive, such that offenders with a prior DUI were more likely to recidivate with a DUI than a non-DUI offense.

I validated the scale using the validation sample but limited the analysis to only those offenders in the validation sample who recidivated.[51] There was no significant difference in the AUC for the development and validation samples ($\chi^2(1) = 2.14$, $p = 0.144$). I conducted additional AUC comparisons on each of the imputed datasets. This sensitivity analysis confirmed

[51] Validation analyses were conducted using the imputed datasets.

that there were no significant differences in the AUC for the development and validation samples across imputed datasets.

On average, offenders had a risk score of 4.07 with a standard deviation of 1.39. The upper and lower bounds of the average-risk category were 5.46 and 2.68, respectively. Offenders with a risk score of 0 – 2 were classified as low-risk, and offenders with a risk score of 6 or 7 were classified as high-risk.

Evaluating Accuracy

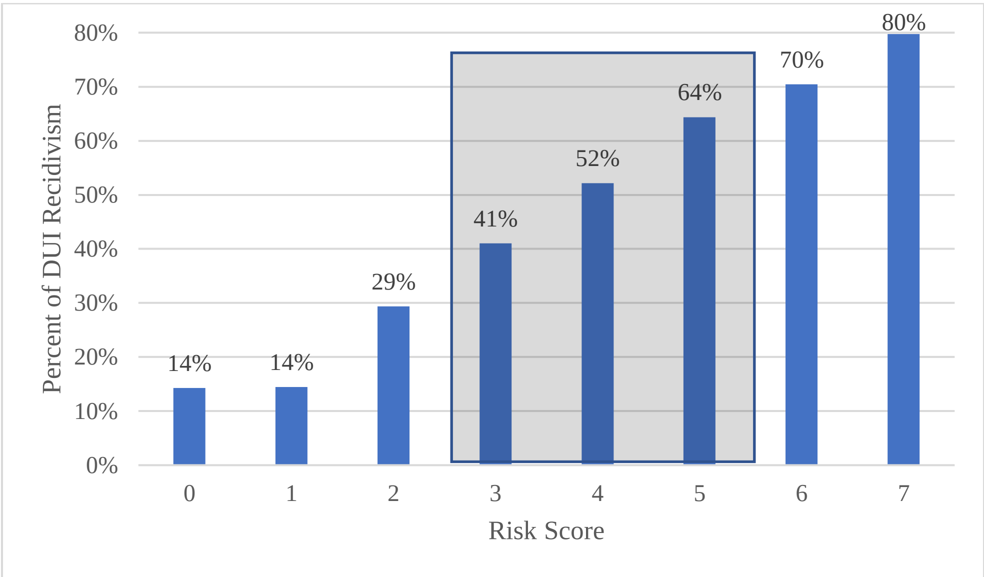
Table 2-30 presents the distribution of offenders across the three risk groups. Nearly three quarters of all offenders (72.0%) were classified as average-risk, while 12.66% of offenders were classified as low-risk and 15.34% of offenders were classified as high-risk. Offenders who recidivated with a DUI were more likely to be classified as high-risk (21.45%) than as low-risk (6.37%). Offenders who recidivated with a non-DUI offense were more likely to be classified as low-risk (19.57%) than as high-risk (8.64%).

Table 2-30. Burgess Risk Groups for DUI Reconviction - Recidivists Only

Risk Group	Non-DUI Failure		DUI Failure		Total	
	N	%	N	%	N	%
Low	10,219	19.57	3652	6.37	13,871	12.66
Average	37,486	71.79	41,393	72.18	78,879	72.00
High	4512	8.64	12,298	21.45	16,810	15.34
Total	52,217	100.00	57,343	100.00	109,560	100.00

Figure 2-8 shows the rate of recidivism by risk score. The rate of DUI recidivism ranged from 14% to 29% for low-risk offenders and 70% to 80% for high-risk offenders. The increased ability to detect high-risk offenders is not surprising. The base-rate of DUI failure for this population was 52.10%, much higher than the base rate of failure for the any recidivism scale and for the DUI recidivism scale developed using the full sample.

Figure 2-8. Rate of DUI Recidivism by Risk Score - Recidivists Only



This scale, predicting the type of recidivism among recidivists, showed the highest accuracy for the low- and high-risk categories. Table 2-31 presents the percent accuracy for the low- and high-risk groups as well as the overall accuracy across these two groups combined. While other models performed exceptionally well for low-risk offenders but poorly for high-risk offenders, this scale made accurate predictions 73% of the time for both groups.

Table 2-31. Accuracy for High and Low Risk Groups

	% Correct prediction
High- and Low-Risk	73.4%
High-Risk	73.2%
Low-Risk	73.7%

While this scale was developed using only the offenders who recidivated, it would be used to make predictions about the likelihood of recidivism of offenders at the time of sentencing. One way to use this scale is to show the DUI risk scale for only those offenders who are at high-risk of any recidivism. Judges would first identify offenders who are most likely to recidivate and then use this scale to obtain more information about the type of offense they are likely to commit if they do recidivate.

Table 2-32 shows the DUI recidivism classifications for offenders classified as high-risk of any reconviction. Almost all offenders were classified as low-risk (24.79%) or average-risk (74.79%). Less than one percent of all high-risk offenders were classified as high-risk of DUI recidivism (0.42%).[52] The distribution of offenders between the three risk categories was almost identical for offenders who did and did not recidivate with a DUI.

Table 2-32. Burgess Risk Groups for DUI Reconviction for Offenders Who Were High-Risk of Any Recidivism

Risk Group	Non-DUI Failure/Clean		DUI Failure		Total	
	N	%	N	%	N	%
Low	23,492	25.16	3553	22.58	27,045	24.79
Average	69,475	74.42	12,118	77.00	81,593	74.79
High	393	0.42	66	0.42	459	0.42
Total	93,360	100.00	15,737	100.00	109,097	100.00

Table 2-33 reports the accuracy of the high- and low-risk predictions for DUI recidivism among offenders who were high-risk of any recidivism. Among the general high-risk offenders, the scale was more accurate at identifying offenders who were low-risk of DUI recidivism

[52] It is important to note that these tables report the risk classification for offenders in each of the 11 imputed datasets. To establish a rough estimate of the actual number of offenders in each cell, divide the reported sample size by 11. For example, the actual number of offenders who were classified as high-risk of DUI recidivism and who actually did recidivate with a DUI is around 6.

(86.9% accurate) than offenders who were high-risk of DUI recidivism (14.4%). However, the disproportionate classification of offenders in low-risk rather than high-risk drives the overall accuracy for the combined high- and low-risk predictions.

Table 2-33. Accuracy for High- and Low-Risk Groups - Only Offenders Who Were High-Risk for Any Recidivism

	% Correct prediction
High- and Low-Risk	85.7%
High-Risk	14.4%
Low-Risk	86.9%

As a final evaluation of this scale, I reviewed the distribution and accuracy of risk categories for the full sample. Table 2-34 shows the distribution of offenders across risk categories by recidivism, while Table 2-35 presents the accuracy of the predictions for offenders classified as low- or high-risk of DUI recidivism. Offenders were disproportionately classified as high-risk (26.05%) compared to low-risk (5.51%). The majority of offenders were classified as average-risk (68.44%).

Table 2-34. Burgess Risk Groups for DUI Reconviction, Full Imputed Sample (All Offenders)

Risk Group	Non-DUI Failure/Clean		DUI Failure		Total	
	N	%	N	%	N	%
Low	24,478	5.40	3,652	6.37	28,130	5.51
Average	308,061	67.97	41,393	72.18	349,454	68.44
High	120,716	26.63	12,298	21.45	133,014	26.05
Total	453,255	100.00	57,343	100.00	510,598	100.00

Table 2-35. Accuracy for High and Low Risk Groups, Full Sample

	% Correct prediction
High and Low Risk	22.8%
High Risk	9.2%
Low Risk	87.0%

Among high- and low-risk offenders, the model accurately predicted DUI recidivism 22.8% of the time. However, the overall accuracy was driven largely by the offenders classified as low-risk (87.0% accurate) rather than those classified as low-risk (9.2% accurate). The accuracy for the high-risk classifications fell below the overall base rate for DUI recidivism (11.2%).

Alternative Presentation Methods

The methods for presenting the DUI recidivism scale developed on only recidivist offenders emphasizes the risk of recidivating with a subsequent DUI offense. However, there is an alternative presentation method for this scale which would emphasize non-DUI recidivism. While half of all offenders who recidivated did so with a DUI offense, the other half of recidivists were reconvicted for a non-DUI offense, such as a property or personal offense.

Current evaluation practices for DUI offenders are likely to identify offenders with an underlying substance use disorder who may be likely to become a repeat-DUI offender. However, these evaluations do not include an assessment of overall criminality and the propensity to engage in a broad range of criminal behaviors.[53] Consequently, sentencing risk

[53] The CRN includes information only about previous DUIs or license suspensions.

assessments for DUI offenders may be most useful when they are able to identify the individuals who are general offenders and who pose a broader threat to the community.[54]

For the DUI risk assessment instrument developed on recidivist offenders, the dependent variable was a dichotomous indicator of DUI or non-DUI failure. In the analyses presented above, the dichotomous variable was coded such that a value of 1 represented DUI recidivism. It is also possible to present the analyses with the values on the dependent variable switched, such that a value of 1 represents non-DUI recidivism. The magnitude and significance of the relationships reported in the logistic regressions would be the same, but they would be in the opposite direction. The scores on the risk scale and the subsequent risk classifications would be reversed. That is, those classified as high-risk of DUI recidivism would be classified as low-risk for non-DUI recidivism.

Assessing accuracy of predictions is more complicated. Because the “clean” group includes offenders who did not recidivate and offenders who recidivated only with a DUI offense, I had to recalculate the risk groups and percent of successful predictions using a dependent variable classified where 1 represents a non-DUI failure and 0 represents either no recidivism or recidivism with a DUI. Table 2-36 presents a comparison of the accuracy in high- and low-risk predictions using the previous method, which predicts DUI failure, and the current method, which predicts non-DUI failure, for both the full sample and for offenders who were classified as high-risk of any recidivism

[54] While DUI offenders may also pose a threat to property or persons, the overall rate of accidents among impaired-driving trips is low (CDC, 2017). Other offenses, such as theft or assault, pose a more direct threat to property and persons.

Table 2-36. Percent of Correct Predictions for Recidivist Only Scale Predicting DUI Failure or Non-DUI Failure

	Full Sample		High-Risk Any Reconviction	
	DUI Failure	Non-DUI Failure	DUI Failure	Non-DUI Failure
High- and Low-Risk	22.8%	86.1%	85.7%	37.6%
High Risk	9.2%	36.3%	14.4%	36.8%
Low Risk	87.0%	96.6%	86.9%	83.2%

.

Overall, the scale predicting non-DUI recidivism appears to perform best for high- and low-risk offenders combined for the full sample of offenders, while the scale predicting DUI recidivism appears to perform best for the offenders who are high-risk of any reconviction. The disaggregation of these overall success rates reveals substantial differences, particularly for predictions of high-risk offenders. The scale predicting DUI recidivism accurately predicts only 9% of the high-risk offenders in the full sample and only 14.4% of the high-risk offenders who were high-risk of any reconviction. The scale predicting non-DUI recidivism accurately predicts just over 36.0% of the high-risk offenders in both samples.

In addition to the differences in accuracy, these scales would have a different impact on offending populations. Table 2-37 shows the approximate number of offenders in each risk classification for the scale predicting DUI recidivism and the scale predicting non-DUI recidivism. The table includes the distribution for the full sample and the distribution for only the offenders classified as high-risk of any recidivism. Notably, the number of offenders in low- and high-risk classifications are inverted between the DUI failure and non-DUI failure scale. This table emphasizes that the differences between the two scales have nothing to do with the types of factors or the significance of the factors in the scale, but rather, the classification of the dependent variable. Offenders who are low-risk of DUI recidivism are, by statistical necessity, high-risk of a non-DUI failure and vice versa.

Table 2-37. Distribution of Offenders in Risk Groups for Recidivist Only Scale Predicting DUI Failure or Non-DUI Failure. Approximate Offender Estimates*

	Full Sample		High-Risk Any Reconviction	
	DUI Failure	Non-DUI Failure	DUI Failure	Non-DUI Failure
Low-Risk	2,557	12,092	2,459	42
Average-Risk	31,769	31,769	7,418	7,418
High-Risk	12,092	2,557	42	2,459

*Numbers of offenders are approximate. These values were calculated by dividing the frequency across all imputed datasets by 11 (the number of imputed datasets)

These analyses clearly identify significant differences resulting from differences in the presentation and use two risk scales developed using the same logistic models. One possible goal of risk assessments could be to identify offenders who are high-risk of any recidivism and likely to commit a particular type of offense. Under this framework, the specialized risk scale predicting DUI recidivism would be used for approximately 42 offenders statewide in a given year. Under the same framework, a specialized risk scale predicting non-DUI recidivism would be used for approximately 2,459 offenders statewide in a given year. By using the non-DUI recidivism scale, judges would more often receive information regarding the specific type of recidivism likely to be committed by high-risk offenders.

Summary of Findings

The purpose of this chapter was to explore the correlates of offending and recidivism for DUI offenders and to determine whether risk assessment instruments could accurately predict their recidivism. This chapter expanded upon prior literature by analyzing DUI offenders through a criminal context. Previous research tends to focus on drug and alcohol use characteristics and the success or failure of treatment options for DUI offenders. It is undeniable that DUI offenders likely benefit from substance use treatment. However, without analyzing the criminal correlates of DUI offenders, it is difficult to know whether our current approaches to DUI offenders are sufficient.

Current approaches to assessing risk for DUI offenders focus on substance use. While jurisdictions are beginning to implement sentencing risk assessments for other offenders, there is still a question about whether or not the courts could benefit from a risk assessment for DUI offenders. This study tested the ability to develop static risk assessment instruments for DUI offenders to predict the likelihood of any recidivism and of DUI-specific recidivism. While traditional methods created scales with underwhelming predictive accuracy, I proposed alternative approaches that may provide more value to practitioners. The following is a discussion of the overall findings from this study as they pertain to the individual hypotheses proposed at the beginning of the chapter.

Hypothesis 1: (a) First-time offenders, especially those who are convicted of an alcohol-impaired DUI, will be less likely to recidivate than offenders with any criminal history, and (b) Offenders who have prior convictions for non-DUI offenses, especially those who are convicted of a drug-impaired DUI, will be more likely than first-time offenders and alcohol-impaired offenders to recidivate with a non-DUI offense.

<u>SUPPORTED</u>

DUI offenders are a unique group of offenders. But, DUI offenders are not a homogenous population. The majority of offenders did not recidivate and had no criminal history. Among those who did recidivate, there were significant differences between offenders who recidivated with a subsequent DUI offense and those who recidivated with a non-DUI offense.

Offenders who recidivated with a DUI offense had shorter criminal histories, were more likely to reside in rural areas, were more likely to be white and female, and were older at the time of their primary DUI. Notably, DUI recidivists also had higher levels of BAC and were unlikely to be convicted of a drug-impaired DUI. When DUI recidivists did have a criminal record, they were most likely to have a prior conviction for a DUI. The logistic regressions identified differences between the likelihood of committing another crime and the likelihood that a recidivating offense would be a DUI. While younger offenders were more likely to recidivate overall, older offenders were significantly more likely to recidivate with a DUI. While offenders with more extensive criminal histories were more likely to recidivate overall, offenders with little to no criminal history were significantly more likely to recidivate with a DUI.

Offenders who recidivated with a non-DUI had characteristics that mirrored the general offending population. Non-DUI recidivists were more likely to be Black, to be male, to be younger, to reside in dense urban areas, to have more extensive criminal histories, and to have experience with drug-use. Non-DUI recidivists had a diverse criminal record, with prior convictions for property, personal, drug, public order, public administration, and firearms offenses. The correlates of non-DUI recidivism were confirmed in the multivariate comparisons. The patterns for recidivism generally were similar to the patterns for non-DUI recidivism. This was particularly true for young offenders and for offenders with extensive criminal records.

Based on these results, it is apparent that the Marowitz (1998) typology of problem drivers who drink and problem drinkers who drive ignores both the large population of one-time DUI offenders who do not exhibit other problematic behaviors and serious criminal offenders who engage in a broad range of criminal offenses. Similarly, the DeMichele, Payne, and Lowe (2013) typology, which classifies offenders based on their drinking habits ("social drinkers" and "chronic drinkers") and assumes that an offender's likelihood to drink is the sole factor relevant in the classification of the DUI population, is insufficient. The DeMichele et al. typology ignores general offenders who may drink casually, or who may be more likely to use illicit substances rather than consume alcohol.

Thus, from my analyses, I conclude that there are three distinct groups of DUI offenders: (1) non-criminal, one-time DUI offenders, (2) offenders who are likely to be repeat DUI offenders, perhaps as a result of an underlying alcohol use disorder, and (3) general offenders who engage in DUI as well as other crimes.

Hypothesis 2: Risk assessment instruments developed using offender demographics, criminal history, and primary offense characteristics will be able to predict the likelihood of any reconviction better than chance. <u>PARTIALLY SUPPORTED</u>

I successfully constructed a Burgess risk instrument predicting any reconviction using offender demographics, criminal history, and primary offense information. Subsequent tests for accuracy indicated that the scale performed significantly better than chance (AUC = 0.6544). Among the high- and low-risk populations, predictions of recidivism were accurate in 59.7% of cases.

While the overall findings support the hypothesis that actuarial risk instruments will predict recidivism better than chance, disaggregation by predictions found inconsistencies in the accuracy across risk classifications. The general risk instrument was more accurate at predicting low-risk offenders (89.3%) than high-risk offenders (38.6%).

It appears that the predictions for any recidivism were also affected by the base rate problem. Only 21.5% of the total sample recidivated with a conviction for any criminal offense. This low base rate made it difficult to identify high-risk offenders with a high degree of certainty. It is true that the predictions for recidivism in the high-risk group were lower than chance (e.g., less than 50%). However, the accuracy should actually be compared to the overall base rate, or overall probability of recidivism. Absent a risk instrument, practitioners may make their decisions based on an understanding that 21% of all DUI offenders will recidivate.

With this risk scale, the model identifies the population of offenders with a probability of recidivism that is greater than the overall base rate. In this way, the model is able to somewhat discern those offenders with a higher-than-average risk of recidivism. The policy implications of these findings are discussed in the next section.

Hypothesis 3: Risk assessments predicting any reconviction will be more accurate than risk assessments predicting DUI-specific recidivism. **<u>SUPPORTED</u>**

As expected, the overall rarity of DUI recidivism made it difficult to accurately predict DUI-specific recidivism. Only 11.2% of the sample recidivated with a DUI offense. The overall scale predicted DUI recidivism only slightly better than chance (AUC = 0.547). Predictions for high- and low-risk offenders were accurate in only 51.5% of cases. While the scale was highly accurate for low-risk offenders (91.8%), the scale performed poorly for high-risk offenders (14.3% accurate). This scale added little value above simply providing judges with the base rate of DUI recidivism for DUI offenders, 11.2%.

The ability to accurately predict DUI failure was further complicated by the types of methods used to develop crime-specific recidivism scales. Current methods used by the Pennsylvania Commission on Sentencing require that DUI recidivists are compared to a group including both non-recidivists and those who recidivate with a non-DUI offense. Given the low base rate of non-DUI recidivism, the models were essentially identifying weaker correlates of recidivism generally. That is, the comparison between non-DUI recidivists and DUI recidivists was washed out by the large population of offenders who did not recidivate at all.

Alternative methods proposed in Section IV found that developing a crime-specific recidivism scale based on only the offenders who recidivate may provide more meaningful information to practitioners. This is particularly true if the crime-specific scale is intended to be used on only the offenders who are high-risk of any recidivism.

Scales predicting DUI failure among recidivists only had similar rates of accuracy for the scale predicting DUI failure among all offenders. Subsequent analyses found that by switching the values of the dependent variable and developing a model predicting non-DUI recidivism, the accuracy of low- and high-risk predictions substantially increased. While the DUI-recidivism scale provided little benefit beyond the overall base rate, the non-DUI-recidivism scale identified populations of high-risk offenders with overall probabilities of non-DUI-recidivism that were three times larger than the overall base rate. Similarly, the non-DUI-recidivism scale identified populations of low-risk offenders with overall probabilities of non-DUI-recidivism that were nearly one-fourth of the overall base rate. The policy implications of these findings are discussed in the following section.

One other significant difference between the DUI-specific recidivism risk assessment developed from the full sample and the DUI-specific recidivism risk assessment developed from the recidivist only sample was the relationship between prior DUIs and DUI-specific recidivism. The general recidivism instrument and the DUI-specific recidivism instrument developed on the full sample found a significant, negative relationship between prior DUIs and recidivism. However, the DUI-specific instrument developed on the recidivist-only population found no significant relationship between prior DUIs and recidivism. Although the relationship was not significant, the direction of the relationship indicated that offenders with a prior DUI who did recidivate were more likely to recidivate with a DUI rather than a non-DUI offense.

The different findings for prior DUIs and recidivism are particularly important. The findings show support for my argument that a DUI-specific recidivism instrument developed on the full sample is just a weaker instrument predicting recidivism generally. If it was true that offenders with a prior DUI were less likely than offenders with no prior DUI to recidivate with a DUI offense instead of some other offense, the relationship would have been even stronger in the model limited to only the offenders who recidivated. The finding in the DUI-specific risk instrument developed on the full sample is likely driven by the fact that offenders who engage solely in DUI offending are less likely to recidivate than the general offending population. From a statistical perspective, this model is picking up selection effects of recidivism in general, not recidivism with a DUI specifically.

The alternative approach to developing a specialized risk-assessment does not capture the underlying likelihood of recidivism (selection effects), but rather assesses the type of offending that recidivists are likely to engage in. While it is somewhat surprising that prior DUI offending was not significantly related to DUI recidivism (which would indicate specialization), it was in a positive direction. The absence of a significant finding could be because of the significant portion of the sample who were first-time offenders and a lack of statistical power to identify a significant difference in recidivism patterns based on the type of prior offending.

In addition to the differences in the findings for prior-DUI offenses and recidivism, age and number of prior arrests also had inverse relationships with DUI-recidivism in the scale developed on the full sample and the scale developed on only the offenders who recidivated. Combined, these findings indicate that current methods for developing specialized risk assessments (i.e., those used by the PCS) are insufficient due to confounding with the likelihood of recidivism generally. This chapter proposes one alternative model for developing specialized risk assessment instruments. Future research must consider the purpose of specialized risk assessment instruments and whether there are alternative methods to account for selection into recidivism generally before making assessments about a specific type of recidivism risk.

Discussion

This study fills important gaps in the literature analyzing DUI offenders. By focusing on the criminal correlates of DUI offenders, this dissertation begins the process of expanding criminological theories to include explanations of impaired-driving. By testing the best practices for developing risk instruments predicting the likelihood of recidivism for DUI offenders, this dissertation explores new tools that may help practitioners to better distribute criminal justice resources. The following sections discuss the various theoretical and policy implications of this research.

Theoretical implications

By establishing a broader typology of offenders that is not solely reliant on substance-use behaviors, we can move toward a more nuanced understanding of DUI offenders. While current criminological theories explaining the causes of criminal behaviors and recidivism may not be sufficient to explain the behaviors of non-criminal, one-time DUI offenders, they may be able to explain the behaviors of general offenders who engage in DUI as well as other crimes. For example, chronic, general offenders may exhibit lower levels of self-control, leading to a higher likelihood of all types of criminal offending (Gottfredson and Hirschi, 1990). Alternatively, non-criminal, one-time DUI offenders and repeat DUI offenders with underlying alcohol use disorders may have higher levels of self-control that inhibit criminal offending generally.

However, when individuals imbibe or consume illicit substances, the underlying levels of self-control are impaired, leading to occasional instances of DUI offending.

Much of the prior literature on DUI offenders focused on alcohol or drug use and/or substance use disorders (e.g., DeJong and Hingson, 1998; Nochajski and Stasiewicz, 2006; Maenhout et al., 2014). However, drug and alcohol use and treatment for substance-use disorders may be less relevant for understanding the behavior of non-criminal, one-time DUI offenders and general offenders who engage in a range of criminal offenses. By focusing on substance-use and repeat DUI offenses, studies ignore both the offenders who are unlikely to need expensive substance-use treatments and the offenders who may pose a more serious threat to the public as a result of their general offending behaviors. In addition, criminological theories discussing turning points (Teruya and Hser, 2010), social bonds (Laub and Sampson, 2003), and strain (Merton, 1938) may benefit from a more in-depth integration of the relationship between life events (such as unemployment, divorce, or transitions out of parenting roles), substance use, and DUI offending.

Furthermore, the typology identified in this study indicates that it is insufficient to continue analyzing DUI offenders using datasets that are restricted to DMV records. Future research must consider the criminal characteristics of DUI offenders. While prior research has found that problem drivers with a history of traffic violations may be more likely to commit a DUI (Marowitz, 1998; Cavaiola, Strohmetz, and Abreo, 2007), these findings may be spurious. That is, problem drivers may not be more likely to commit a DUI, but their poor driving skills may make them more likely to be identified while driving under the influence of drugs or alcohol.

By expanding offending histories to include robust measures of general criminal offending, we can better identify the population of offenders who are chronic offenders and who do not fit the typical DUI offender profile. In addition, existing criminological theories may be able to explain the behaviors of this subset of DUI offenders. We know from prior research that there are some serious, chronic offenders who desist from general offending, but who may continue engaging in anti-social behavior such as excessive alcohol or drug use (Laub and Sampson, 2003). Given their previous commitments to criminal behaviors and their frequent exposure to the criminal justice system, these offenders may be less responsive to standard DUI punishments but may also be less responsive to drug- and alcohol-treatment programs. By restricting the measures of prior offending to include only traffic offenses, many studies are likely to combine these serious offenders with less, serious, one-time DUI offenders.

It is inaccurate to say that DUI offenders are universally a "different" type of offender and it is inappropriate to exclude DUI offenders from broader criminological research. While it may be true that DUI offenders are less likely to exhibit general criminal tendencies than the non-DUI offending population, there appear to be many similarities between DUI and non-DUI offenders. Additional research which directly compares DUI offenders to non-DUI offenders is necessary to further explore the similarities and differences between these types of offenders.

Policy Implications

This study begins the process of expanding risk assessment instruments based on static characteristics to predict the likelihood of recidivism among DUI offenders. Given that DUI offenses comprise a significant portion of the total arrests in the United States every year, it is critical that policy makers include DUI offenders when developing new tools to assist in the allocation of criminal justice resources. The findings from this study suggest that traditional methods for developing risk instruments may be sufficient for predicting the likelihood of general recidivism among DUI offenders, but that new methods may be needed to help identify the different types of DUI recidivists.

Practitioners are faced with the responsibility of identifying which offenders pose the greatest danger to society (Steffensmeier, Ulmer, and Kramer, 1998). While DUI offenses may result in the injury or death of innocent bystanders, fatal accidents account for a very small portion of all DUI offenses. The Centers for Disease Control and Prevention reports that there were 111 million self-reported instances of alcohol-impaired DUIs in 2016 and only 10,497 deaths resulting from alcohol-impaired crashes.[55] Consequently, offenders who may be likely to recidivate with a non-DUI offense (such as a property or personal offense) may be more dangerous to society than offenders who may be likely to recidivate with a DUI offense.

The findings for this research introduce three important policy questions that must be addressed before risk assessments may be developed and implemented for DUI offenders. First, what percent of accuracy is acceptable for a risk assessment instrument? Second, how should general recidivism scales and DUI-specific recidivism scales be used?

Accuracy of Predictions – What is Acceptable?

DUI offenders tend to have very low rates of recidivism. Of the offenders who do recidivate, about half of them recidivate with a subsequent DUI offense, indicating some degree of specialization among DUI offenders. However, the low overall base rate of recidivism for this population makes it difficult to develop an accurate and effective risk assessment instrument (Meehl and Rosen, 1955; Berk et al., 2017).

[55] Not all of these traffic fatalities were innocent bystanders. However, the CDC did not publish a separate breakdown of the fatalities for impaired-drivers and pedestrians. https://www.cdc.gov/motorvehiclesafety/impaired_driving/impaired-drv_factsheet.html

All of the scales presented in this chapter predicted the likelihood of recidivism better than chance (AUC > .50). The scales consistently identified a meaningful division of low-, average-, and high-risk offenders, with roughly two-thirds of offenders classified as average-risk and the remaining third of offenders divided between low- and high-risk classifications. Given the low base rate of recidivism, all scales performed exceptionally well for predicting the likelihood of recidivism for low-risk offenders (accuracies ranged from 73.7% for the recidivists only scale to 91.8% for the full sample DUI recidivism scale).

The classification of high-risk offenders consistently identified groups of offenders with a higher-than-average risk of recidivism. The base rate of general recidivism was 21.3%. The likelihood of recidivism for high-risk offenders was 38.6%. The base rate of DUI-specific recidivism was 11.2%. The likelihood of DUI recidivism for high-risk offenders was 14.3% in the model developed on the full sample.

While the models did accurately identify groups of offenders with higher-than-average risks of recidivism, it may be misleading to classify these offenders as "high-risk." Ruback et al., (2016) found that criminal justice practitioners (e.g., judges, defense attorneys, prosecutors, etc.) have low rates of numeracy. It may be difficult for practitioners to understand that, while high-risk offenders are higher-than-average, their absolute rates of recidivism are still less than 50%. More often than not, DUI offenders will not recidivate. Labeling offenders as "high-risk" may cause judges to overestimate the danger that these offenders pose to society.

Policy makers must determine what is an acceptable level of accuracy for sentencing risk assessment instruments. That is, what is the rate of false-positives and/or false-negatives that is acceptable for a sentencing risk assessment instrument? The findings from this study are consistent with the findings from other risk assessment instruments currently used to identify rare events. For example, violence risk assessment tools have been found to be accurate at predicting moderate- and high-risk offenders 41% of the time while sex offense risk assessment tools have been found to be accurate at predicting moderate- and high-risk offenders only 23% of the time (Fazel, Singh, Doll, and Grann, 2012).

Implementing General and DUI-Specific Risk Assessment Instruments

There are currently no generally accepted standards for using general and specialized risk assessment instruments. In Pennsylvania, the current method is to assess all offenders on a general recidivism risk instrument and to assess offenders on a specialized recidivism risk instrument (risk of a personal offense) for only the offenders who are high-risk of any recidivism. Furthermore, judges see the specialized risk assessment instrument only if the offender is classified as low-risk.

Despite the conditional use of the specialized risk assessment instrument in Pennsylvania, the two scales were developed independently and are not to be interpreted in tandem. The current study explored an alternative approach to developing and using specialized risk assessment instruments. If specialized risk assessment instruments will be presented for only the offenders who are high-risk of any recidivism, then it may be more beneficial to limit the specialized risk assessment to offenders who recidivate. By limiting the development of the specialized risk assessment to recidivists, I was able to make more meaningful predictions about the type of behaviors an offender may engage in.

Risk assessment instruments are sensitive to the base rate of the outcome being predicted. By developing a risk assessment predicting DUI recidivism among the full sample of DUI offenders, the base rate of the outcome is only 11.2%. However, by developing a risk assessment predicting DUI recidivism among recidivists only, the base rate of the outcome is nearly 50%.

As such, the risk assessment instrument developed on recidivists only has greater power to identify significant differences in the correlates of DUI and non-DUI recidivists.

Risk assessment instruments are also sensitive to the different classifications of the outcome variable. By developing a risk assessment predicting DUI recidivism among the full sample of DUI offenders, the model is predicting offenders who will recidivate with a DUI rather than not recidivate or recidivate with a non-DUI offense. The findings from this study showed that this method essentially models a weaker prediction for the likelihood of any recidivism. The factors that were significant for the general recidivism model were the same factors that were significant for the DUI-specific recidivism model. Further, the direction of the relationships between significant factors and recidivism were also the same.

When judges make decisions about a particular offender, it is likely that they want to know whether an offender will recidivate and, if they will, what type of recidivism they are likely to engage in. As the focal concerns theory posits, judges often consider the danger than an offender poses to general society (Steffensmeier, Ulmer, and Kramer, 1998). Not all recidivist offenders pose the same threat to society. An offender who is likely to commit a violent offense poses a greater threat to society than an offender who is likely to commit a DUI offense. It is unlikely that judges consider separately the underlying likelihood of recidivism and the underlying likelihood of DUI-specific recidivism.

By developing a DUI-specific recidivism scale on a sample of only the offenders who recidivate and by using the specialized risk instrument for only the offenders who are high-risk of any recidivism, the risk assessment instruments follow the logic used by practitioners who will make decisions based on the risk assessment findings.

Given the differences between DUI and non-DUI offenders, policy makers may want to consider alternative implementation methods for sentencing risk assessment instruments for DUI offenders. There are two possible alternative uses for DUI risk assessment instruments: (1) using risk instruments to identify candidates for diversion and (2) using risk instruments to identify individuals who are likely to recidivate with a non-DUI offense.

DUI offenders in many states are eligible for diversionary sentences that, if completed successfully, leave no permanent criminal record for an offender. However, research indicates that not all diversion-eligible offenders receive diversion, and that the acceptance into diversion programs vary across judges and courts (Knoth, 2015). Risk assessment instruments may be helpful to identify low-risk offenders who should receive diversion and may help create consistency across different jurisdictions. A similar method is currently used to identify diversion-eligible offenders arrested for certain types of offenses in Virginia (Ostrom et al., 2002).

All of the models in this chapter were better at identifying offenders who were low-risk of recidivism than offenders who were high-risk of recidivism. Given the low base rate of general recidivism and the even lower base rate of DUI-specific recidivism, the scales had high rates of false positives among offenders who were classified as high-risk. Even the model predicting general recidivism made accurate predictions of high-risk offenders only 38.6% of the time. This means that 61.4% of the classifications for high-risk were actually false-positives. Other models with similar rates of false positives have been deemed unacceptable by policy makers in some states (see Pennsylvania). By restricting the use of risk assessment instruments to classifications for low-risk offenders, practitioners would use only the parts of the scale with high levels of predictive accuracy.

DUI offenders often undergo drug and alcohol use evaluations as a part of their sentencing. These evaluations are necessary to identify underlying substance use disorders and to determine whether offenders should be required to complete drug and alcohol treatment programs as a part of their sentence. In Pennsylvania, offenders undergo an initial CRN (Court Reporting Network) evaluation assessing their drug and alcohol use. Offenders with a certain score on CRN are then recommended to complete a full drug and alcohol assessment to determine the type of treatment needed to address an offender's substance use behaviors. While these assessments evaluate the likelihood that an offender has a problematic relationship with drugs and/or alcohol, they do not include any characteristics of general criminality, such as the number or type of prior convictions.

The risk assessment instruments in this study did not include any measures of drug or alcohol use. The goal of this study was to assess whether DUI offenders could be evaluated based on their correlates of general criminal behavior rather than their correlates of drug and alcohol use. In this way, the risk assessment instrument provides information beyond the type of information that judges already receive through a CRN or a full drug and alcohol assessment.

It is possible that these different assessments could be synthesized to maximize the information available to the courts. One approach is to use the incorporate the information from the CRN into the development of a DUI risk assessment instrument. Variables measuring drug and alcohol use may be helpful for predicting the likelihood of general recidivism and the likelihood of repeat DUI offending. Judges would then receive one comprehensive risk assessment instrument which uses criminal correlates and substance use correlates to predict future offending.

Alternatively, risk assessments may be used to provide more information for offenders who do not have an underlying drug or alcohol use disorder. Repeat DUI offenders who are motivated by substance use are likely to be identified on the CRN and the full drug and alcohol assessment. However, these assessments are unlikely to identify the population of DUI offenders who are general criminal offenders and who are likely to recidivate with a non-DUI offense. Part IV of this chapter illustrates the ways that risk assessments may be used to predict the likelihood of non-DUI recidivism rather than DUI recidivism. The model predicting non-DUI recidivism had higher rates of accuracy than the model predicting DUI recidivism for predictions of high-risk and low-risk offenders. Since current evaluation practices already identify the population of DUI offenders with problematic relationships with drugs and alcohol, the unique value of adding an additional assessment based on criminal characteristics may come from its ability to identify general offenders who are likely to commit a wide range of criminal offenses.

Conclusion

This chapter lays the foundation for a new approach to understanding DUI offenders. The findings in this research provide support for the belief that some DUI offenders are different from the general offending population, while others exhibit characteristics that are similar to the general offending population. Additional research which directly compares DUI offenders to non-DUI offenders is necessary to confirm these findings and to provide additional details about the convergence and divergence of the correlates for DUI and non-DUI offending and recidivism.

This chapter is limited by its focus on a population of offenders in the United States. Despite being a global problem, there is little research on DUI offenders outside of the United States. Additional research in jurisdictions outside the United States is necessary to determine whether there are universal characteristics of DUI offenders and whether the likelihood of recidivism for DUI offenders is consistent across different structural and cultural contexts.

This chapter also evaluated the usefulness of risk assessment instruments for predicting the behavior of DUI offenders. While it is possible to use traditional methods to predict the likelihood of general recidivism and DUI-specific recidivism for DUI offenders, alternative methods may be more useful in jurisdictions with lower base rates of recidivism. It is clear that there may not be a universally acceptable method for developing risk assessment instruments. Rather, policy makers and researchers must work together to determine how risk assessments will ultimately be used and what methods may be best to achieve a particular policy goal. Small differences in the development or presentation of risk instruments have significant differences in the impact of risk assessment instruments in the courts.

Chapter 3 : The Case for Comparative Criminology: Finland and The United States

Research needs to compare the correlates of DUI offending and recidivism across different geographic and cultural contexts. Understanding differences between and within groups of individuals nested within a larger social context can help researchers and policy makers understand how different characteristics influence criminal behavior and recidivism. Cross-national study is necessary to strengthen this research and to provide a more thorough understanding of DUI behaviors and sentencing risk assessment instruments. Observed differences in the findings across two countries may indicate differences in the way offender and offense characteristics are related to the commission of crime and recidivism. Such differences would suggest the need for the development or modification of theories that account for legal, cultural, and sociological factors.

International Comparative Criminology

Despite increasing attention to cross-national criminological research, the focus of such research is largely limited to a few crimes (Bennett, 2009). In addition, most studies tend to be descriptive, qualitative, and cross-sectional (Bennett, 2009), particularly the studies focusing on criminal justice systems. In the past few decades, researchers have increasingly called for international comparative research, particularly on topics covering criminal careers and criminal justice systems.

In her American Society of Criminology Presidential Address, Freda Adler (1996) called for an increased pursuit of comparative criminology research studies. Specifically, Adler noted, “Humankind seeks perfection by comparison, adaptation, and adoption.” This dissertation seeks to spread awareness of risk prediction models to a new country (Finland) while allowing for the new, international evaluation of techniques typically developed and tested in the United States.

Consequently, the results of this dissertation are mutually beneficial to knowledge production in both the United States and Finland.

In his call for research in the next millennium, David Farrington (1999) cited the need for cross-national comparative longitudinal research analyzing criminal careers. Cross-national risk prediction studies can help answer this call. Risk prediction analyses are rooted in an attempt to better understand who is likely to desist from criminal behaviors. Risk tools themselves rely on an understanding of the variables related to recidivism and criminal careers. For example, Farrington notes that understanding differences in the prevalence of offending by age is key to understanding criminal careers. Risk assessment instruments seek to analyze the relationship between age and crime by determining which age groups are associated with the highest risk of repeated criminal activity. Similarly, Farrington discusses the need to conduct research to determine whether there is specialization or versatility in offending. Risk assessment models can be modified to predict the likelihood of general reoffending or the likelihood of specialized reoffending.

My dissertation specifically seeks to answer these calls for comparative research. It compares the relationships between key demographic characteristics (e.g., age and gender), patterns of criminal history (e.g., age of first offense, number of prior convictions, types of prior convictions), and recidivism. In addition, as noted in the prior chapter, it seeks to understand the differences between general reoffenders and repeat-DUI offenders. Finally, it examines the stability of these relationships across different international contexts.

Following Bennett's (2009) typology for comparative criminological research, this dissertation is a descriptive and analytical, national, quantitative, longitudinal analysis of recidivism and risk assessment prediction instruments. It describes the different systems present in Pennsylvania and Finland, while also using statistical analyses to understand how each system works and how criminal recidivism within these structures differs between countries[56]. Using longitudinal data on offenders in each jurisdiction, the analyses analyze the different relationships between crime correlates and recidivism among DUI offenders convicted over several years.

Cross-national research has a unique ability to influence both theory and practice. First, it has repeatedly been noted that one, if not the most significant, benefit of comparative research is the ability to test the generalizability of theories (Bennett, 1980; Kohn, 1987). Theories are often developed with an implicit recognition that the explanation for the observed phenomena is constrained by the social, cultural, and political structures under which the phenomena were observed (Bennett, 2009). Even when differences are not found, cross-national research can strengthen existing theories by establishing consistency in the relationships between observed phenomena under different social and cultural conditions.

Cross-national research is needed to better understand theories of criminal careers. According to Farrington (1999):

> An advantage of cross-national comparative studies is that they would help to establish how far criminal careers, risk factors, and intervention effects are the same or different in participating countries. To the extent that results are similar, they might strengthen our confidence in universal findings and theories. To the extent that results are different, the challenge would be to explain the differences, perhaps by reference to features of national contexts.

Similarly, Adler (1996) remarks:

> The comparative approach forces upon us an intellectual process that we should embrace: the transference from the descriptive case to generalization. The process leads us from

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[56] I recognize that Pennsylvania is not a country. However, by using Pennsylvania, we are able to test one system within the United States to one system within Finland. Although the comparison is not perfect, the unique structure of the criminal justice system in the United States (e.g., the partition between federal and state courts) prohibits a truly cross-national study with the United States. For simplicity, I refer to this study as cross-national, or a comparison of systems in two countries given the absence of an alternative term.

micro-analysis to macro-analysis. Globalization affords us the opportunity to do cross-cultural testing and development of criminological theory

Our understanding of DUI offenders and of sentencing risk assessment instruments is currently limited by the absence of comparative research. Consequently, this dissertation presents a unique opportunity to test and to challenge existing theories in criminological research.

Moreover, studies analyzing criminal justice tools in different criminal justice systems can test for best practices and may also indicate how certain tools may be modified to work more effectively (Bennett, 2009). For example, different countries may have access to different types of information. Through a comparative analysis, one can test the added value of additional variables. For instance, in Finland, court data includes a robust indicator for the number of co-offenders for any given offense. Thus, in Finland, we could test whether information on co-offenders assists in the prediction of recidivism. Co-offenders may signal that an individual is more likely to recidivate because he or she is embedded in a larger criminal network. Analyses of offenders in Finland may reveal ways that jurisdictions in the United States could improve or expand upon in their data collection efforts.

There is a particular need for comparative research on risk assessment instruments. To date, most of the research on actuarial risk assessments is limited to samples in the United States and the UK. Consequently, our understanding of these assessments is limited to the data available in these two countries. In addition, it is not always easy to compare the results of studies conducted independently in different locations. Often each study uses a different operationalization of a particular variable (e.g., the way that age or criminal history is coded) or a different method to select the sample for a study (e.g., using data from the DMV vs. criminal court data). Comparative research, such as this dissertation, ensures that the most robust comparisons can be made across jurisdictions.

Culture vs. Structure

Central to a comparative criminology is an understanding of the relative influence on criminal behavior of objective structural conditions versus cultural values and norms. Some theories focus only on one or the other construct, whereas other theories attempt to synthesize cultural and structural effects.

Drawing from Durkheim's writings on society, Robert Merton (1938) proposed strain theory to explain both the balance between culturally prescribed goals and institutional means and the ways in which deviance is a "normal" response in some intersections of culture and structure. Specifically, when societies emphasize cultural goals, but there is not equal emphasis on the availability of institutional means, individuals will make adjustments or adaptations to reduce the negative impacts of social pressure.

Merton (1938) posited that some individuals will engage in retreatism, whereby individuals give up on both the goals and the efforts to achieve them. Merton included alcoholics, drug addicts, and vagrants in this category. Agnew (1992) extended Merton's work to construct a general strain theory that similarly suggests alcohol and drug use may be a way to cope with negative emotions fostered by societal strain. Both of these theories rest heavily on the assumption that individual beliefs and behaviors are influenced by their relation to broader social norms and values.

Alternatively, social learning theories (e.g., Sutherland's [1947] theory of differential association and Akers's [2009] social learning model) suggest that norms, values, and attitudes are developed through interaction with other individuals. Associations and interactions with others who engage in certain types of behaviors influence our own attitudes or meanings that we ascribe to particular behaviors. Akers (2009) notes that social structural factors have an indirect effect on social learning in that they shape the organization of social groups and social pressures on groups that influence general learning contexts.

Control theories maintain that culture is largely irrelevant when explaining criminal behavior. Challenging social learning and strain theories, control theories posit that individuals are motivated to commit crime but choose not to because of the influence of social controls. In their construction of a general theory of crime, Gottfredson and Hirschi (1990) posited that self-control alone predicts delinquency. Self-control – the differential tendency to avoid acts whose long-term costs exceed their immediate or short-term benefits – is developed through early parental socialization and remains relatively stable through the life course. Those with low self-control are likely to commit crime when opportunities are available.

Age-graded informal social control theories were developed to explain changes in criminal behaviors through the life course (Laub and Sampson, 1993). The premise of this control theory is that while individuals may have a propensity to engage in delinquency that is developed in adolescence, social bonds developed through adulthood influence continuity and desistance in criminal behaviors over time. Social bonds function as a form of informal social control that influences individual behaviors. This theory also recognizes the value of formal social control institutions (e.g., the criminal justice system), but suggests that methods of formal social control may negatively affect social bonds, resulting in a weakening of informal social control. Thus, criminal justice responses to crime should be analyzed in conjunction with their effects on offenders' relationships to their peers.

In general, criminological theories have not been tested with DUI offenders. Studies that do offer a theoretical explanation for the behaviors of DUI offenders are generally limited to criminal justice theories (e.g., deterrence) rather than the previously mentioned criminological theories. In 1993, Keane and colleagues offered a test of Hirschi and Gottfredson's self-control theory to explain DUI offending. The authors posited that DUI offenses may be a manifestation of impulsivity and risk-taking behaviors associated with individuals who lack self-control. The study analyzed self-report surveys from individuals stopped at nighttime police checkpoints in Canada and found risk-taking behaviors (such as not wearing a seat belt) and measures of impulsivity (e.g. choosing to drive despite being discouraged to do so by others) were positively related to higher BAC levels. These findings were robust, even among individuals who recognized they were impaired and believed the certainty of punishment to be high. Thus, the authors concluded that a lack of self-control - evidenced by impulsivity, risky behaviors, hedonistic tendencies, and short-term orientations - rather than the absence of deterrence is the best predictor of DUI offending.

Cross-national studies offer a unique opportunity to test differences in culture and structure. Often, studies of crime in the United States are limited to a homogenous sample from a single city (or smaller sampling unit such as school) or a comparison of several relatively similar cities. These limitations often make it difficult to test differences in cultures and normative structures and in how they relate to criminal or conforming behaviors. In addition, studies using samples in the United States are limited in the types of structural comparisons that can be made. While jurisdictions may have slight differences in criminal justice policies (such as the use of different rehabilitation or treatment programs), courts in the United States generally operate using a similar perspective on crime and punishment (namely one of crime control and deterrence).

One example of an intra-national study capable of analyzing structural differences in criminal justice policies are those that assess the effectiveness of alternative court programs. Specialized courts, such as those for drugs, mental health, and veterans, are an exception to the general court structure in the United States. However, the limited jurisdiction of these courts as well as prosecutorial discretion over who gets access to these courts restricts the amount of comparative research that can be conducted. In addition, offenders who are processed through specialized courts still have interactions with police and probationers who are a part of the general criminal justice system. Thus, while tests of particular rehabilitation programs or sentencing options (e.g., incarceration vs. probation) may be possible, tests of issues reflecting the larger criminal justice system are more limited in the absence of cross-national research.

Finland as a Comparison Group

Comparative criminology benefits from the use of extreme comparison groups. Studies that compare and contrast similar crimes (e.g., DUI offending) and policy tools (e.g., risk assessments) across significantly different social environments best reveal the unique effect of social structures on deviant behavior. In addition, the use of extreme comparison groups allows for simultaneous differentiation of effects of multiple variables as well as the impact of different interactions of particular variables. For these epistemological reasons, Finland is the second site of research for this cross-national dissertation. As a part of the Nordic region, the Finnish criminal justice system differs greatly from the United States, while the beliefs about alcohol consumption and high rates of alcohol consumption differentiates Finland from other Nordic countries.

DUI offenders in the United States and Finland are, in many ways, equal and opposite. The rate of DUI offending is similar in both countries. The likelihood of being caught and arrested is similar in both countries. The threat posed by DUI offenders is the same in both countries. However, Finland treats its DUI offenders more seriously than the United States, both formally and informally. DUI offenders recidivate more often in Finland than the United States. Most importantly, both countries lack research comparing DUI offenders and DUI recidivism to non-DUI offenders and non-DUI recidivism. This dissertation combines research in each country, with tests of the consistency of the correlates for DUI offending and DUI offending across different structural and cultural conditions.

Structure

Finland has one of the lowest rates of criminal recidivism in the world; the United States has one of the highest. Despite these differences, rates of recidivism for DWI[57] are higher in Finland (33%) than they are in the United States (25%) (Portman, 2014; Warren-Kigenyi & Coleman, 2014). The Nordic region, in general, has low rates of recidivism, in part because of these countries' emphasis on rehabilitative and reintegrative programs.

The Nordic region is considered a pioneer in criminal justice policies, including alcohol-related policies. During the late 20th century, most of the Nordic countries, including Finland, liberalized their penal policy, significantly reducing the use of incarceration for treatment of offenders (Lappi-Seppälä, 2009). In lieu of incarceration sentences, the use of economic sanctions and suspended sentences significantly increased. These changes resulted in a drastic drop in the incarceration rate for DWI offenders; almost 90% of DUI offenders were sentenced

[57] In Finland, impaired-driving is defined by statutes governing "Driving While Impaired." To be consistent with the literature in Finland, I use DWI in the following sections that discuss Finland-specific impaired-driving research.

to incarceration in the 1960s, but by the mid-1990s, the use of incarceration for DWI offenders had dropped to roughly 10% (Lappi-Seppälä, 2009).

The Nordic countries were also the first to pass *per se* DWI laws, those for which the behavior is automatically illegal without having to prove any additional facts. For DWI, establishing a certain BAC level defined by law is sufficient to prove alcohol impairment. *Per se* DWI laws are now the norm in most developed countries, including the United States. Countries in the Nordic region are also known to use randomized breath testing, a type of police strategy that does not require the establishment of probable cause in order to test an individual for alcohol consumption. And, the likelihood of being stopped at an alcohol checkpoint is higher in Finland than almost all other European countries (Meesmann, Martensen, and Dupont, 2015). Randomized breath testing is banned in other jurisdictions, including the United States where the 4th amendment to the Constitution prohibits searches without probable cause. Many state and local law enforcement agencies in the United States use sobriety checkpoints to identify drunk drivers. However, these stops do not allow for breath testing without other evidence of intoxication. As a result, it is possible for individuals with a blood alcohol content above the legal limit to pass through these checkpoints undetected.

Culture

Nordic countries are distinct from other Western countries in that they are sparsely populated, are demographically homogenous, and maintain the highest standard of living in the world (Osterberg and Karlsson, 2011). However, even though Nordic countries share principles informing criminal justice processes, there are some cultural differences that lead to differences in crime patterns in these countries. Specifically, Finland has the highest rate of alcohol consumption per capita among Nordic countries, slightly higher than the European average, and higher than the United States (Skjælaaen, 2010).

Despite its similarities with other Nordic countries, alcohol consumption in Finland has uniquely increased following a series of structural changes beginning in the 1960s. Overall economic growth that increased the purchasing power of citizens, as well as changes in national policies that increased the general availability of alcohol, resulted in levels of consumption by Finns that are much greater than other countries in the Nordic region or Western Europe (Karlsson et al., 2010). In addition, Finland's membership in the European Union facilitated the reform of various policies that led to an increase in the importation of cheaper liquor from neighboring countries, such as Russia and Estonia. In the 1990s, the Finnish government repeatedly reduced taxes on alcohol, removing economic barriers to purchasing alcohol, and passed laws, including the Alcohol Act of 1995, allowing for alcohol to be sold in grocery stores, kiosks, cafes, and gas stations (Alavaikko & Osterberg, 2000; Karlsson, 2009).

Differences in alcohol culture also contribute to the high rate of alcohol consumption in Finland. Coinciding with structural changes in alcohol policy, the drinking culture in Finland has changed significantly in the last 40 years. Mäkelä and colleagues (2012) described the cultural changes that were associated with a 300% increase in per capita alcohol consumption in Finland in the last 40 years. Prior to reforms in the 1960s, Finland was classified as a dry and ambivalent drinking culture – characterized by a low volume of consumption, large population of abstainers, high rate of binge drinking, conflicting social norms about drinking, and significant gender differences in drinking. Today, Finland could be classified as a wet and permissive drinking culture. All subgroups in the population have seen an increase in the prevalence of drinking. The largest increases have been among women, but the gender gap is still large. Despite these changes, drinking still takes place largely in the home and in the evenings and weekends, and there has been an increase in the frequency of very heavy drinking. Mäkelä et al. (2012) conclude:

> Many aspects of the Finnish drinking culture have remained similar over the past 40 years, while at the same time significant changes have occurred. Alcohol is used as a social lubricant and intoxication's role in the drinking culture is still central. This means that alcohol is not embedded in ordinary everyday life, but rather offers a break from it. (p. 839)

The Finnish culture on drinking is characterized by instances of binge drinking, or in which the intention is to get drunk (Rehm et al., 2003). The consumption of alcohol is reserved for leisure time or celebratory gatherings and occurs largely on the weekends. Thus, the high overall rate of alcohol consumption is driven not by consistent low amounts of daily consumption, as in many European countries, but by an infrequent consumption of large quantities of alcohol that leads to high rates of drunkenness. As described in a report by the Finnish National Institute for Health and Welfare: "Intoxication has an established position in Finnish social intercourse" (Karlsson, 2009).

The exceptionally high prevalence of binge drinking in Finland presents a challenge for understanding and responding to criminal behaviors. While rates of offending are generally low, rates of offending while intoxicated are especially high. Offenders are intoxicated in 80% of homicides and 70% of assaults committed in Finland (Kivivuouri and Lehti, 2006; Granath, 2011). These rates, particularly for homicide, greatly exceed the rates of intoxicated offenders involved in homicides and assaults in other Nordic countries.

At an aggregate level, Finland has the highest rate of homicides and the second highest rate of assaults among the Nordic countries (Denmark, Finland, Norway, and Sweden), (Osterberg and Karlsson, 2011).[58] In addition, Finland has the highest rate of homicides by liter of alcohol consumed and the second highest rate of assaults by liter of alcohol consumed. Importantly, Finland accounts for the greatest percent of alcohol consumption among the Nordic Countries (Osterberg and Karlsson, 2011).

Despite the cultural promotion of binge drinking, Finland has an overwhelmingly negative perception of DWI offending. In 2016, the ESRA (European Survey of Road users' safety Attitudes) project released the findings from a European-wide survey analyzing drivers' perceptions of DWI. The design of this survey was partially modeled after the U.S.-based AAA Foundation for Traffic Safety's Traffic Safety Culture Index. Most recent findings from the AAAFTS Survey were published in 2017. These two studies allow for some comparisons about the population attitudes toward drinking and driving in Finland and the United States.

Among European countries, Finnish citizens reported the lowest personal acceptability rate of drunk driving (0.6%) and the lowest level of perceived social acceptability of drunk-driving (1.8%). In addition, Finnish citizens reported the highest rate of disapproval for DWI by acquaintances or friends (92%, compared to the 78% European average). In the United States, respondents were four times more likely to rate drunk-driving as personally acceptable (2.4%), but the United States survey did not ask about perceived social acceptability.

Perceived social disapproval and personal disapproval of drunk-driving appears to have a stronger effect on behavior in Finland than in the United States. In Finland, only 1% of respondents indicated that they had driven a vehicle when they may have been over the legal limit. In the United States, 12.7% of respondents reported driving when their BAC was above the

[58] Differences in reporting crime statistics for assaults in Sweden raise questions about the validity of this comparison. Swedish statistics for assault include any reported assault, many of which may be unfounded by the police. Thus, it is possible that Finland actually has the highest rate of assault as well.

legal limit at least once in the 12 months prior to the survey, with 16.3% of those respondents reporting that the drunk-driving incident occurred within 30 days prior to the survey.

Analyzing the correlates of DWI offending and recidivism in Finland and making comparisons to studies in the United States allows for the investigation of several important questions. For example, a cross-national comparison of DWI risk assessments allows for a unique analysis of characteristics that may be associated with recidivism. As noted above, some research finds that blood alcohol content is predictive of recidivism. In the United States, individuals are guilty of DUI if they are driving with a BAC at or above .08%. Analysis of BAC in Pennsylvania can be made by using only the statutory cut-points. However, the Finnish penal code uses different cut points for BAC. For example, individuals are guilty of DWI if their BAC exceeds .05% and aggravated DWI if their BAC exceeds .12%. Thus, conducting DWI research in Finland allows for new comparisons to better understand the relationship between BAC and DWI recidivism.

In addition to these legal comparisons, there is reason to believe that the characteristics of recidivists in Finland are different from those in the United States. For example, in the United States males are more likely than females to recidivate after the first DUI offense (Marowitz, 1998). However, there is little gender difference in heavy drinking in Finland, which may be due to the presence of greater gender equity in the Nordic region (Bloomfield, Grittner, Kramer and Gmel, 2006). For both men and women in Finland, a small portion of the population accounts for a large portion of the overall consumption of alcohol. Specifically, the top 10% of men and women consume, respectively, 45% and 50% of the total alcohol consumed by each gender. Consequently, the greater gender equity in Finland raises questions both about theories developed (primarily in the United States) to explain gender differences in crime, which largely indicate that females are less likely than males to commit crime, and about whether these theories may be applicable to DWI offenders in Finland.

Although the differences between samples in cross-national studies are advantageous in that they allow for unique comparisons, these same differences may pose potential problems for drawing generalizable policy conclusions. Cross-national studies must give careful consideration to structural differences (such as legal differences) that make it difficult to directly compare the two samples, in that the confounding of law and country makes comparability between countries more difficult. For example, if DWI offenders with a blood alcohol content between .05 and .08 are systematically different from offenders with a higher BAC, differences identified in demographic characteristics between United States and Finland may be the result of Finland having a lower BAC rather than true differences in demographic effects.

Driving Under the Influence Trends in Finland

Impaired driving is a serious public health concern in Finland. Alcohol-impaired crashes resulting in the injury of one or more persons account for around 10% of all road accidents (Skjaelaaen, 2010), and a quarter of all fatal accidents involve impaired offenders (Karki, 2002). In addition, increasing rates of drug use in all Nordic countries, including Finland, have raised significant concern over the rising number of drug-impaired DWIs (Impinen et al., 2009). Recent longitudinal studies of offenders in Finland have found that arrests for DWI are significantly related to short-term and long-term increases in subsequent social disadvantage (Karjalainen et al., 2014). DWI offenders in Finland are more likely than individuals not arrested for DWI to be unemployed, divorced or living alone, and facing severe debt problems (Portman et al., 2013; Karjalainen et al., 2014; Oksanen, Aaltonen, & Kivivuori, 2015). Further, the mortality rate for DWI arrestees is significantly higher than the mortality rate of non-arrestees (Impinen et al., 2010, Skurtveit et al., 2002).

Despite changes in policy and culture, the rate of DWI offenders in Finland has stayed relatively stable since the early 1990s. Just over 20,000 impaired offenders are arrested each year, and over half of those arrests are near the capital, Helsinki (Karki, 2002). Self-report surveys have found that official arrest statistics for driving under the influence grossly underestimate the prevalence of this behavior. In Uusimaa Province alone, research estimates that there are nearly 1.26 million DWI events annually, but less than .5% of those events are detected by law enforcement (Portman et al., 2013). Despite efforts to increase enforcement of DWI offenses using randomized breath testing, impaired individuals may drive up to 227 times before being apprehended by law enforcement (Portman et al., 2013).

Members of the Finnish government, practitioners, and academics have called for more research about DWI in Finland, characterizing DWI as a serious public health issue (Karlsson et al., 2010). Most of the emphasis has been on the effectiveness of various national policies in reducing the widespread availability of alcohol. However, absent the adoption of severe prohibition policies, this high alcohol consumption rate in Finland will likely continue because of the strong drinking culture. Thus, greater attention should be paid to how different systems react to incidents of driving under the influence.

A general lack of research on DWI offenders in Finland precludes a significant discussion of the correlates of DWI offenders, the correlates of sentencing for DWI offenders, and the correlates of DWI recidivism in Finland. In fact, many of the studies that do analyze DWI offenders in Finland rely on studies of DUI offenders in the United States as the basis for their literature review. The following sections provide brief overviews of what we currently know while simultaneously highlighting the need for substantial research on DWI offenders in Finland.

DWI Sentencing Research in Finland

According to the Ministry of Justice in Finland, standard DWI offenses (BAC .05% - .11%) are punishable by a fine or up to six months of incarceration. Aggravated DWIs (BAC > .12%) are punishable by a minimum of sixty day-fines or up to two years of incarceration. Penalties are increased if the DWI offense causes an accident resulting in bodily injury or homicide. Courts may also temporarily or permanently suspend the offender's driver's license. To date, there is no research analyzing offender or offense characteristics and the likelihood of a particular sentence. In addition, there is no research comparing the effectiveness of economic sanctions and incarceration sentences on recidivism among DWI offenders.

Contrary to their national focus on rehabilitation, there are no statutory requirements for participation in rehabilitation or treatment programs for DWI offenders, although researchers are calling for an increase in early intervention programs for substance use, as well as the adoption of alternative punishment options for DWI offenders (Karjalainen et al., 2014). Small pilot programs were implemented to test the effectiveness of ignition interlock systems for DWI offenders in Finland. A four-year pilot program conducted by the Finnish Transport Safety Agency found that recidivism rates for offenders opting to use ignition interlocks were significantly lower (5.7%) than recidivism rates for all DWI offenders (30%) (Loytty, 2013). In addition, offenders with ignition interlock reported lower rates of alcohol consumption and many suggested that the interlock system assisted in their desistance from alcohol consumption. Surprisingly, some offenders opted to keep the interlock system beyond the mandatory period.

Alternative research finds that there are no long-term effects of ignition interlock systems on DWI offending. A survey study in Finland found that drivers are likely to return to drinking and driving behaviors once the interlock systems are removed from their vehicle (Radun et al., 2014). These findings are consistent with the CDC's study of ignition interlock systems in the United States (Elder et al., 2011). Absent the ability to actually reform behaviors, it is unclear whether ignition interlock systems are an effective response to DWI offending. As of now, Finland has not adopted a national policy on ignition interlocks and these systems have been used only in lieu of driver's license suspension policies.

DWI Offenders in Finland

Most of the research on DWI offenders in Finland relies on longitudinal analysis of register-based crime data. Studies often combine criminal databases with other databases containing information on social status and/or social disadvantage. Alternatively, research depends on road-survey data collected during police stops in which individuals were administered a breathalyzer test. Six notable associations have been found in these data.

First, DWI offenders often come from socially disadvantaged backgrounds (Karjalainen et al., 2011). However, because socio-economic disadvantage is related to substance use, the relationship between social disadvantage and DWI offending may be spurious. The same study found that the majority of DWI offenders are young, which is consistent with patterns that show intoxication and substance use generally begins at an early age.

Second, although DWI offenders are most likely to be under the influence of alcohol (83%) (Statistics Finland, 2013), rates of drug-impaired DWI offenses in Finland have recently increased (Ojaniemi et al., 2009). The number of drug-involved DIU offenses has grown substantially since the adoption of zero-tolerance drugs-and-driving policies enacted in 2003.

Benzodiazepines and amphetamines are the most common drugs found in blood and urine samples of drug-impaired DWI offenders, but research finds that many of the drug-impaired DWI offenders are polydrug users (Karjalainen, 2011).

Third, DWIs are more often committed by males (91.3%) than by females (8.7%) (Portman et al., 2013). In addition, males had an average BAC (.10%) that was significantly higher than the average BAC for females (.09%). The mean age for male DWI offenders was 41.2 while the mean age for female DWI offenders was 40.0.

Fourth, DWI offenses were most common for those between the ages of 40 and 49 for males and between the ages of 30 and 54 for females (Portman et al., 2013). Young DWI offenders were more likely to be driving on Saturdays from 9 p.m. to 1 a.m., while older DWI offenders were more likely to be driving on weekdays from 7 a.m. to 11 a.m.

Fifth, over half of the DWI offenders were married (45%) or cohabiting (13%) (Portman et al., 2013). About 17% of the DWI offenders were divorced, and 24% were unmarried and lived alone. Sixth, only 11% of DWI offenders were unemployed, although the mean BAC was higher for this group than for DWI offenders who were employed. Forty percent of DWI offenders indicated they thought the risk of being caught was very high or high, while 20 percent estimated the risk to be small, very small, or non-existent.

Sixth, about half of all DWI offenders began their drive from their house, rather than a bar or public place (Portman et al., 2013). In addition, about half of impaired drivers noted that their drive was less than 10 km. DWI offenders were commonly alone (50%) or with only one passenger (25%).

In sum, Portman and colleagues (2013) depicted the "profile" of a Finnish drunk driver as:

> A man aged between 40 and 49 years who has a driving license and drives his own car, usually alone, with a blood alcohol level of 0.1% [.10 in U.S. metrics]. He drives between 20,000 and 50,000 km per year. He is a skilled employee or junior salaried employee in a permanent employment relationship and is married or cohabiting. Such a typical drunk driver is on the road on weekdays, either leaving home or going home; on his way to work in one in five cases and going home from work in just over 10% of cases. The percentage of women among drunk drivers varied randomly between 3.3% and 16.5% but did not change during the period studied. Indeed, the profile of a typical drunk driver remained the same throughout the 18-year study period. (p. 26)

DWI Offenders and Recidivism in Finland

As noted previously, recidivism rates for DWI offenders in Finland surpass those for DUI offenders in the United States. The particularly high rate of recidivism for DWI offenders has garnered the attention of policy makers, criminal justice practitioners, and members of the public. Identification of the correlates for DWI recidivism and the development of successful interventions is critical to the individual well-being of DWI offenders, members of their family, and the general public. No studies to date have analyzed re-arrest for DWI offenders. Consequently, our knowledge of post-sentencing behaviors of DWI offenders is limited to other life outcomes such as employment, family relations, and financial stability, all of which may be related to future criminal behaviors.

Arrest for a DWI offense may either serve as a “wake-up” call, reducing the likelihood of future arrests, or lead to substantial forms of social disadvantage, increasing the likelihood of recidivism. A longitudinal study of DWI offenders in Finland found that an arrest for DWI may cause individuals to face underlying substance use disorders, resulting in positive reforms that increased employment (Karjalainen et al., 2014). However, the same study found that an arrest for DWI simultaneously leads to social disadvantage, measured by family relations. The authors did not directly measure for recidivism, but suggest that these differences likely influence heterogeneity in recidivism among DWI offenders.

Another longitudinal study of first-time DWI offenders in Finland contradicted the "wake-up call" hypothesis by analyzing post-sentencing debt problems, divorce, and income instability (Oksanen et al., 2015). This study found that convictions for DWI offending acted as a negative turning point, significantly increasing the likelihood of financial and marital problems. The authors posit that arrest and conviction for a DWI leads to a "downward spiral," significantly worsening the offender's life chances. It is reasonable to expect that these negative outcomes on financial stability and familial relations would lead to an increase in criminal behaviors.

Substance use is strongly associated with general re-arrest in Finland. About one-fifth of first-time prisoners in Finland are diagnosed as alcoholics. However, two-thirds of offenders in prison for the sixth time are diagnosed as alcoholics (Joukamaa, 1995). The most common offenses among substance abusing offenders are violent crimes (manslaughter, assault, rape), property crimes (arson, robbery) and drunk driving.

Chapter 4 : DWI Offending and Risk of Recidivism in Finland

Driving while intoxicated[59] is a global problem. This chapter seeks to expand our understanding of driving under the influence of alcohol or drugs by analyzing a population of offenders in Finland. This chapter advances the literature on DWI offenders in two ways. First, this chapter provides a comparison of the correlates of DWI offenders with non-DWI offenders as a way to test the applicability of general criminological facts and theories. Second, this chapter develops a risk assessment instrument to test for the correlates of recidivism for DWI offenders in a distinct European country. Finally, this chapter tests how additional variables or alternative specifications of variables may increase the predictive accuracy of risk instruments.

Hypotheses

Despite the cultural and structural differences discussed in Chapter 1, Finland and the United States are both W.E.I.R.D. (Western, Educated, Industrialized, Rich and Democratic) societies. Consequently, there is reason to believe that the widely known criminological facts and theories that were largely developed on populations in the United States and the United Kingdom ought to apply to Finnish populations. The first section of this study focuses on the comparison of DWI to non-DWI offenders in Finland. The second section of this study focuses on patterns of recidivism among DWI offender in Finland and uses the correlates of recidivism to develop and validate a risk assessment instrument predicting the likelihood of general and DWI specific recidivism among DWI offenders in Finland. The third section tests alternative ways of specifying risk factors (e.g., criminal history), and whether these alternative specifications may increase the predictive validity of risk assessment instruments. Below is a brief discussion of

[59] I use the term DWI in this chapter to be consistent with the laws in Finland.

each of the hypotheses tested throughout this chapter as well as a brief review of the literature that supports each of the proposed hypotheses.

Part One: DWI and Non-DWI Offenders

Gender

Hypothesis 1: (a) Males will be more likely than females to commit all offenses, however, (b) the gender gap will be narrower for DWI offending than for non-DWI offending.

Males are more likely than females to commit crimes. Criminologists have gone so far as to state that the "gender gap in crime is universal: Women are always and everywhere less likely than men to commit criminal acts" (Steffensmeier and Allan, 1996: 459). Research suggests that this gender gap is also common among DWI offenders, although reductions in legal BAC limits have corresponded with a narrowing of the gender gap in official DWI offending rates (Schwartz, 2008). In addition, there is some research that suggests that females are more likely than males to have a serious drug dependence (e.g., opiates) and females are more likely than males to have psychological disorders (e.g., anxiety, depression, PTSD) which may be associated with higher rates of alcohol or drug use (Laplante et al., 2008; Maxwell, 2012).

Changes in the drinking culture in Finland have been characterized by an increase in the consumption of alcohol among women (Mäkelä et al., 2012). One study on the consumption of alcohol in Finland noted, "That alcohol has permeated the lives of women of all ages is to be regarded as the most important change in the Finnish drinking culture." (Mäkelä et al., 2012, p. 838). Consistent with these significant increases in the consumption of alcohol by women, I expect that the gender gap will be narrower for DWI offending than for non-DWI offending.

Age

Hypothesis 2: (a) On average, DWI offenders will be older than non-DWI offenders, and (b) the age of DWI offenders will peak later and decline more slowly than non-DWI offenders.

In general, research on the age-crime curve finds that the age of offending peaks in early adulthood and declines rapidly with age (Greenberg, 1985, Laub and Sampson, 2003). While this general pattern holds for most offenses, prior research does find some variation across crime types (Steffensmeier et al., 1989). Specifically, “low-yield,” high-risk types of offenses such as burglary, robbery, and vandalism tend to peak at an earlier age and decline more rapidly. Alternatively, expressive crimes, such as homicide and assault, peak at an older age and decline more slowly. Finally, drug- and alcohol-related offenses are likely to peak at an older age and remain relatively stable through the life course (Laub and Sampson, 2003).

Location

Hypothesis 3: (a) Non-DWI offenses will be more likely to occur in urban areas than in rural areas, but (b) DWI offenses will be more likely to occur in rural areas than in urban areas.

Crime rates are higher in urban and suburban areas than in rural areas in the United States (FBI, n.d.). Additional international comparisons have found that the urban-rural crime disparity is a global phenomenon (Van Dijk, 1999; Marshall & Johnson, 2005). Theories about urbanization and crime posit that crime is more likely to occur in urban areas than rural areas as a result of weakened social bonds (such as local kinship and friendship networks) and increased population density and presence of mixed-use neighborhoods which increase the opportunity for crime (Stark, 1987; Sampson and Groves, 1989).

Most of the research on crime and place is limited to violent and property crimes. DWI offenses do not rely on the presence of deviant social networks or increased crime targets (i.e., persons or property). Urban and suburban neighborhoods often have greater public transportation networks (e.g., buses, trams, subways, and taxis) than rural neighborhoods (Velaga et al., 2012). In addition, some studies find that, although the overall likelihood of consuming alcohol is lower in rural areas than in urban areas, the likelihood of having an alcohol disorder or consuming more than the recommended daily limit of alcohol among reported drinkers is higher in rural areas than in suburban areas (Borders & Booth, 2007). Consistent with integrative theories of the alcohol-crime relationship, rural citizens may be more likely to become intoxicated and have less access to structural means to prevent DWI behaviors. Consequently, DWI offending may be more likely to occur in rural than in urban areas.

Co-offending and Solo Offending

Hypothesis 4: DWI offenders will be more likely to be solo-offenders than non-DWI offenders.

DWI offending does not benefit from the presence of multiple people. Other offenses, such as burglary, may net greater rewards as a result of co-offending. It is possible that an individual may lend a drunk person their car, resulting in a charge of "permitting" a DWI, but that type of co-offending is not the same as a co-offending burglary network that works together to commit more meaningful burglaries. Additionally, DWI offenders may actually be more likely to be dissuaded from committing a crime (driving under the influence) if they are in the presence of other people. Consequently, DWI offenders should be less likely to be co-offenders than solo-offenders.

Frequency of Prior Offending

Hypothesis 5: On average, DWI offenders will have fewer prior convictions than non-DWI offenders.

If it is true that DWI offenders are a “different” type of offender, meaning that they are generally less serious criminals than other types of offenders, they should have fewer prior arrests and convictions than non-DWI offenders. Consistent with Marowitz’s (1998) theory of DWI offenders, it is likely that a substantial portion of DWI offenders are problem drinkers who drive, but who otherwise do not engage in criminal behavior. Consequently, DWI offenders should have fewer prior convictions than non-DWI offenders.

Types of Prior Offending and Specialization

Hypothesis 6: DWI offenders are more likely than non-DWI offenders to specialize in one particular type of offending.

Most offenders are general offenders and do not specialize in one particular type of offending (Piquero, Farrington and Blumstein, 2003). Studies that have identified some level of specialization tend to focus on short time intervals rather than the entirety of an offender’s criminal career (Sullivan et al., 2006). Marowitz’s (1998) typology of DWI offenders suggests that some DWI offenders may engage in a range of problematic behaviors, including driving under the influence of alcohol and/or drugs. However, Marowitz notes that there are other DWI offenders who are problem drinkers who drive, and who are unlikely to engage in other types of criminal offending. Similarly, research on DWI offenders alone indicates that the likelihood of DWI offending significantly increases with each additional prior DWI arrest (Rauch et al., 2010). Additional research finds that DWI offenders who recidivate are likely to be reconvicted for a new DWI offense or other traffic offense (Homel, 1981). Taken together, this research suggests that DWI offenders will be more likely than non-DWI offenders to engage in specialization.

Types of Sentences

Hypothesis 7: DWI offenders will receive (a) fewer incarceration sentences than non-DWI offenders but (b) more intermediate punishments than non-DWI offenders.

In general, DWI offenses are less serious than property or personal offenses (exceptions obviously exist, such as when the DWI is associated with an accident involving serious injury or death). Consequently, under the focal concerns framework, DWI offenders should be less likely to receive severe incarceration sentences than non-DWI offenders (Steffensemeier, Ulmer, and Kramer, 1998). However, increasing public focus on DWI behaviors may result in an increase of intermediate sanctions for DWI offenders. In Finland, where impaired driving was declared a public health concern (Karlsson et al., 2010), I expect that there will be more severe, non-incarceration sentences for DWI offenders than for non-DWI offenders.

Recidivism

Hypothesis 8: DWI offenders will be less likely than non-DWI offenders to recidivate.

Prior research finds that a small group of DWI offenders account for the majority of recidivism among DWI offenders (Homel, 1981; Marowitz, 1998). An arrest for a DWI may force individuals to acknowledge an underlying substance use disorder, resulting in an increase in substance use treatment and a decrease in the likelihood of impaired driving (Karjalainen et al., 2014). In addition, research finds that a single arrest for a DWI offense may be a successful deterrent for future DWI offending (Shapiro and Votey, 1984). Alternatively, an arrest for a DWI may serve as a negative turning point, increasing the likelihood of financial and marital problems, resulting in an increased likelihood of recidivism (Oksanen et al., 2015). While the negative effects associated with an arrest and criminal record are likely to apply to all types of offenders, the benefits of receiving substance use treatment are more likely to be present for DWI offenders. Consequently, I hypothesize that DWI offenders will be less likely to recidivate than non-DWI offenders.

<u>Part Two: DWI Offenders and Risk of Recidivism</u>

General Recidivism

Hypothesis 9: DWI offenders who recidivate will be more likely than non-recidivists (a) to be males than females, (b) to be younger than older, and (c) to have more prior convictions.

Consistent with the previously discussed theories, males are more likely to commit crimes than females, younger offenders are more likely to commit crimes than older offenders, and offenders with a prior criminal record are more likely to commit crimes than individuals with no criminal history. The limited research on recidivism among DWI offenders suggests that these relationships should be present in recidivism analyses. Specifically, male DWI offenders are more likely than female DWI offenders to recidivate (Meyers et al., 1993), and younger DWI offenders are more likely than older DWI offenders to recidivate (Rauch et al., 2010). In addition, prior traffic and DWI offenses have consistently been identified as a strong predictor of recidivism among DWI offenders (Marowitz, 1998; Cavaiola, Strohmezs, and Abreo, 2007). In general, prior criminal history is consistently one of the strongest predictors of recidivism (Gendreau et al., 1996), and there is no reason to believe that this relationship would be any different for DWI offenders.

DWI Specific Recidivism

Hypothesis 10: DWI offenders who recidivate with a DWI will be more likely than non-recidivists and recidivists who recidivate with a non-DWI offense (a) to be younger than older, (b) to have fewer prior convictions, and (c) to have a prior DWI conviction.

Prior research on DWI offenders finds that the average age of offenders decreases as the number of prior DWI offenses increases (Rauch et al., 2010) suggesting that younger DWI offenders should be more likely to recidivate with a DWI offense. Consistent with Marowitz's (1998) typology of DWI offenders, specialization may be present among DWI offenders who are merely problem drinkers who drive rather than problem drivers who may have an underlying propensity to engage in antisocial behaviors. Consequently, I hypothesize that repeat DWI offenders will have fewer criminal convictions, but when they do have prior criminal convictions, it is more likely that those prior criminal convictions will be for DWI offenses.

Hypothesis 11: Risk assessment instruments will be able to predict general recidivism more accurately than DWI-specific recidivism.

As the base rate of a particular event or behavior decreases, the difficulty of accurately predicting the likelihood that the event or behavior will occur increases (Singh, 2013; Gottfredson, 1987). Difficulty in establishing accurate predictions significantly increases if the base rate falls below 50% (Meehl and Rosen, 1955). Even though DWI offenders are more likely to specialize than other types of offenders, the base rate of DWI recidivism will still be significantly less than the base rate of recidivism generally. Consequently, I hypothesize that the risk assessment instrument predicting DWI-specific recidivism will be significantly less accurate than the risk assessment instrument predicting general recidivism.

Part Three: Finland Sensitivity Analyses

Finland Specific Risk Assessment Variables

Hypothesis 12: Alternative specifications of criminal history that are specific to the Finnish Criminal Justice System will significantly increase the predictive ability of the risk assessment instrument.

The Finnish criminal justice system varies from the United States criminal justice in several ways. Less serious offenses (e.g., misdemeanors) are processed using summary penal judgments while more serious offenses (e.g., felonies) are processed with formal court convictions. Given these structural differences, it is possible that an alternative specification for criminal history may increase the predictive ability of a Finnish risk assessment instrument. Andrews and colleagues (2006) note, "at least modest gains may be expected in predictive criterion validity through continuing work on the incremental value of strength ratings and expanded or refined assessments of criminal history" (p. 20). By creating alternative criminal history specifications that capture more of the unique aspects in the Finnish criminal justice system, I hypothesize that the predictive ability of the risk assessment instrument will increase.

Hypothesis 13: Adding independent variables for prior incarceration and co-offending will significantly increase the predictive ability of the risk assessment instrument.

Judges in the Finnish criminal justice system have access to additional offender and offense information which may be helpful in predicting recidivism. I test whether adding a measure for prior incarcerations and a measure for whether or not the current offense involved any co-offenders will significantly increase the predictive ability of the risk assessment instrument. Prior incarcerations may serve as an additional measure of the seriousness of an offender's criminal history. If offenders continue to commit criminal behavior following an incarceration sentence, they may be impervious to additional criminal justice interventions. Consequently, I hypothesize that these offenders will be more likely to recidivate than other offenders who have not been previously incarcerated.

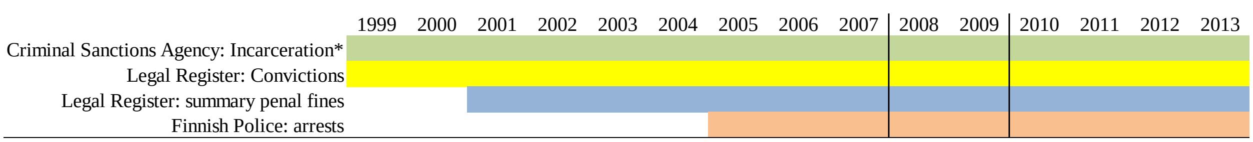
Prior research finds that co-offenders commit more crimes and commit crimes for a longer period of time than solo offenders (Knight and West, 1975; McCord and Conway, 2002). A measure of co-offending may represent a measure of embeddedness in larger delinquent networks, increasing the likelihood of future recidivism. Although co-offending is rare with DWI offenders, I still hypothesize that this measure will be significantly related to recidivism and significantly increase the predictive validity of a risk assessment instrument for DWI offenders.

Data and Methods

The data for this research was provided by the Institute of Criminology and Legal Policy (Krimo) at the University of Helsinki. I worked closely with the IT department at Krimo to extract data from the "register of crimes and sanctions" (RST: in Finnish, "Rikosten ja seuraamusten tutkimusrekisteri"). The RST includes data from various sources, including data from the Finnish Police (police-reported crimes), the Legal Register Centre (convictions and fines), and the Criminal Sanctions Agency (periods of incarceration). The RST includes information about court convictions and summary penal judgements in all Finnish courts. The data are updated annually, and the raw data are processed into an Oracle/SQL database. In addition to being stored in a program format that I was unfamiliar with, all of the data were stored in Finnish. Consequently, I worked with a member of the Krimo IT department to extract the dataset for my specific research.[60] Following the final extraction, the member of the Krimo IT department translated the variable names and values into English.

Data availability depends on the original source, with Criminal Sanctions Agency data going back the furthest (1992). Police data (police-reported crimes and arrests) are available only from 2005 onwards. Figure 4-1 depicts the availability of data from various sources. For purposes of this research, I wanted to maximize the amount of data available for constructing criminal history profiles while maintaining enough post-conviction data for an adequate recidivism follow-up period. The most recent, complete year of data available was 2013. In order to ensure a 4-year follow-up period, I chose to select offenders convicted between 2008 and 2009.[61]

Figure 4-1. Finland Data Availability



Note: Shaded areas represent the years for which data were available from the specific source. The black box represents the years selected for the sample of offenders for this research.
*Data range from 1992 - 2013.

Original Data Files

I received the data in 5 separate datasets: primary offenses, co-offenses, prior criminal convictions and summary penal judgments, prior incarcerations, and recidivism.[62] These datasets were individually extracted, beginning with the primary offenses file. The sample includes all

[60] In the following discussion, “we” refers to work I conducted in direct collaboration with the Krimo IT department. Olli-Pekka Aaltonen was responsible for extracting my data from the large SQL database. I worked closely with Aaltonen to review the variables available in the database and to determine how cases should be selected for each of the individual datasets. For each file, Aaltonen extracted the data from the database and provided me with a copy of the extracted data in a text file. I then converted these text files to SPSS files.
[61] Incarceration sentences are relatively rare in Finland compared to incarceration sentences in the United States. Thus, estimating a four-year follow-up period from the date of conviction should capture the overwhelming majority of offenders.
[62] See Appendix C for a complete list of the variables included in each original data file.

offenders convicted in district courts in Finland between January 2008 and December 2009. Each offender's first conviction during the sample time frame was selected for the primary offenses file. Individual offenders were easily identified using the Finnish PIN number. Similar to our social security numbers, Finnish PIN numbers are unique, eleven-character combinations of numbers, letters, and/or symbols.[63] Finnish identification numbers are assigned at birth. Immigrants and temporary residents whose stay exceeds the 90-day tourism allowance are also assigned a Finnish PIN (for example, I received a Finnish PIN during my Fulbright stay). The PIN numbers identified in the primary offenses file were used to extract the remaining four data files.[64]

The primary offenses file includes only the most serious offense.[65] The second dataset (co-offenses) is a compilation of all co-offenses in each offender's primary conviction. We identified co-offenses by using the Finnish PIN and sentence ID variables from the primary offenses file. The sentence ID is similar to judicial proceeding identifiers in Pennsylvania. The co-offenses file was a vertical file with each observation representing a separate offense.

We extracted two different criminal history files. First, we extracted all prior convictions and summary penal fines prior to the primary offense. As noted previously, this was not a complete criminal history. Rather, the database includes convictions from 1999 onward and summary penal judgments from 2001 onward. A complete record of court convictions *and*

[63] The first 6 characters are the individual's date of birth (DDMMYY). The 7th character indicates the century of birth ('-' for 1900-1999; 'A' for 2000-2099). The 8th, 9th, and 10th characters are numbers, ranging from 002-899. The 10th character is odd for males and even for females. Finally, the 11th digit is a control character based on the previous 10 digits. The control character may be a number or letter. An example of a Finnish PIN is 270490-123U.
[64] In order to maintain confidentiality of Register data, all analyses were conducted on a secure computer in a secure room (the "safe room") at the Institute. Data were stored on USB drives stored in a safe located in the safe room. Once the final files were compiled, all PIN variables were removed from the data.
[65] Most serious offenses were identified using an SQL clause that selects the lowest priority code from all of the offenses in a sentence ID. Priority codes are reverse coded such that the highest priority offense has the lowest priority code.

summary penal fines represent a complete criminal history. Thus, I chose to use criminal history data beginning on January 1st, 2001. Including the additional two years of conviction information would have resulted in a criminal history measure that was disproportionately driven by criminal convictions (i.e., it would appear as though offenders had zero summary penal fines during the first two years of their criminal record). The convictions and summary penal judgments file is a vertical file where each observation represents an individual offense. The dataset includes an indicator for the type of conviction (court conviction or summary penal fine), the crime code for each offense, and the sentence ID associated with each offense.

All offenses sentenced prior to the primary offense were coded as prior offenses. Offenses committed prior to but sentenced after the sentencing date for the primary offense were removed. In Finland, an offender's criminal history includes only convicted offenses. Consequently, although these crimes are technically *prior offenses*, they are not a part of an offender's criminal history.[66]

Second, we extracted data from the Criminal Sanctions Agency about each offender's prior incarcerations. The prior incarcerations data does not include a sentence ID. Consequently, these sentences cannot be matched with offenses in the criminal history dataset. The dataset is a vertical dataset with each observation representing an incarceration sentence. Each observation includes the first date of imprisonment, the date of release from imprisonment, and the type of imprisonment. This file includes information for standard prison sentences, as well as pre-trial imprisonment, juvenile detention, and prison for unpaid fines.

[66] One may argue that judges still consider outstanding charges that have not been sentenced. However, the RST contains information only for convicted offenses. Thus, my analyses must be limited to true convictions. Any other approach would require information on all outstanding charges, including those that do not end in a conviction. As a result of excluding outstanding charges, my analyses may underestimate the effect of criminal history, but they correctly capture the legal basis for judges' use of prior record.

Finally, we extracted data for the recidivism file. For the recidivism file, we extracted all convictions and summary penal judgments for offenses committed after the date of sentence for the primary offense.[67] Unfortunately, the information system used by the Finnish courts changed in June, 2013. When this switch happened, the structure of the data in the RST changed. As a result, there are two separate recidivism files that were ultimately combined. The first dataset includes convictions and summary penal fines from 2008 through May, 2013. The second dataset includes convictions and summary penal fines from June, 2013 through December, 2013.

The first recidivism file was a vertical file with each observation representing an offense. Offenders may have multiple offenses within a single sentence ID, and offenders may have multiple sentence IDs in the follow-up period. The second dataset was a vertical file with each observation representing a sentence ID. Information on co-offenses is available in the database, but it is not possible to extract an offense level dataset. Specific crime code information was provided for the most serious offense in the sentence ID. In addition, we extracted a dichotomous indicator flagging sentence IDs that included a DWI or aggravated DWI co-offense.

I restructured the initial recidivism file such that each observation represented a unique sentence ID. To match the information in the second recidivism file, I maintained the crime-specific information for the most serious offense and created an indicator for DWI or aggravated DWI co-offenses. The two recidivism files were merged to create a single recidivism file including information for all recidivism sentence IDs between 2008 and 2013.

[67] The question for risk assessments is whether or not the offender is likely to reoffend after being sentenced for a given offense. Thus, I needed to be sure that the recidivism file represented *new* crimes. Crimes sentenced after the primary offense sentencing date may have been committed prior to the primary offense, or after the primary offense but prior to sentencing date for the primary offense.

Restructuring and Merging Data

Four of the five datasets were structured using a vertical format where each observation was either an individual offense or sentencing ID. In order to combine the datasets, each file was coded and restructured such that offense and sentence ID variables were aggregated to the person-level. I then merged the files to create a comprehensive dataset. Using the person_id, all of the six datasets were merged into a single file, beginning with the primary offense file. It is possible that some offenders had no co-offenses, no prior criminal record, no prior incarcerations, or no recidivism. After each merge, I reviewed the file for offenders who were missing on the merged variables. I recoded missing values to represent the absence of a given variable. For example, after merging the prior convictions and summary penal judgments file, 26,169 offenders had missing values for the criminal history variables. These offenders had no prior convictions or summary penal judgments. Thus, the prior conviction variables were recoded as ‘0.’

Some observations were removed during the restructuring and merging processes. Table 4-1 details the removal of cases in each file. As noted previously, I started with the primary offenses file. While the Legal Register Centre collects information on the imposed sentence, they do not collect information on prison sentences, such as the amount of time actually served, or the release date from incarceration. These dates were recorded by the Criminal Sanctions Agency, but these data do not contain a sentence ID. Consequently, it is impossible to link the Criminal Sanctions Agency incarceration data to the corresponding offense in the Legal Register data.

The absence of an official release date is complicated by the appeals process. In Finland, each offender has the right to appeal his or her finding of guilt or sentence from the district court to the court of appeals. In most instances, the appeals court affirms the decisions made by the district court. In some cases, the appeals court may alter the sentence given by a district court judge, but it is rare that an appeals court overturns a finding of guilt from the district court. In my data, about 9% of the offenders appealed their case (N = 7,477). In some cases, offenders appeal their case in order to delay the imposition of a sentence. For example, if an offender is sentenced to 6 months in prison, he or she may appeal the case, knowing that the appeal will delay the imposition of the prison sentence for at least a few months.

Using the date of sentence and the start date of incarceration, I attempted to link the incarceration data (from the Criminal Sanctions Agency) to obtain an official release date for offenders who were incarcerated for the primary offense. However, I was able to create a “match” in only 70% of the cases. I also created my own release date by using the district court sentence date plus the prison sentence included in the Legal Register data. In a majority of the cases matched with the Criminal Sanctions Agency, the difference between the “official” release date and the release date created using the sentencing data in the Legal Register was less than one month. Consequently, I decided to use the Legal Register sentencing data to construct the dates for the follow up period. I calculated the release date for offenders receiving a prison sentence as the district court sentencing date plus the prison sentence (in days).

Data for this study were available through December 31st, 2013. As a result, offenders who were released from incarceration after January 1st, 2010 would not have a complete, four-year follow-up period. Offenders who did not have a four-year follow-up period were removed from the data (N = 1,353, 1.55%). Some of these offenders recidivated prior to the end of their four-year follow-up. However, including these offenders would have disproportionately increased the number of recidivists in the file.

The analyses for this dissertation require information on the type of offense and the individual who committed the offense. I removed an additional 613 offenders (.70%) who were missing crime code information for their primary offense. While coding the types of offenses included in the primary offense file, I found 2,083 (2.38%) offenses that were Chapter 61 offenses, that is, offenses that are outside the criminal code and typically sentenced with a fixed fine. The most common Chapter 61 offenses were *61-3000* (traffic infraction; N = 1,676), *61-3010* (violation of social welfare legislation on road traffic; N = 146) and *61-5005* (violation of vehicle requirements; N=189). These offenses are not typically processed through criminal courts. It is likely that most of these offenses were for minor traffic offenses, such as speeding. The small percent of Chapter 61 violations that reach criminal courts are most likely for offenders who challenge the fixed fine.[68] I ultimately decided to remove these offenders from the analyses because there is incomplete information for these types of offenses and any findings for these offenses would be unreliable and biased in favor of the small group of offenders who chose to appeal their fixed fines.

I limited the sample to offenders sentenced in District Courts. When reviewing the data, I found that there were 289 cases with a court ID that was not a district court. While District Courts often serve as the court of first instance for criminal offenses, there are a few exceptions. For example, if judges are charged with corruption, Finnish Appeals Courts serve as the court of first instance. In addition, the Register included information for offenders who were convicted in another Nordic country but were serving their sentence in Finland. The Register does not include data on all cases sentenced in Appeals court or offenses sentenced in another Nordic Country. It is likely some of these cases represent reporting errors whereby a non-district court code was

[68] Appeals of fixed fines are decided using the criminal courts.

entered into the district court ID field. Thus, I removed the 289 cases where the court of first instance was not a Finnish District Court. The final sample of offenders for this research is 83,008 offenders (95.03% of the original full file).

Second, I moved to the co-offenses file. After reviewing the file, it became clear that this file included the primary (most serious) offense *and* all other offenses in a sentence ID. Consequently, I had to remove the primary offenses in this file. In total, 87,346 offenses were removed (equal to the number of offenses in the original primary offenses file). This resulted in the removal of 56,391 unique sentence IDs and offenders. The final co-offenses file included 66,948 offenses, and 30,955 offenders. 56,391 (64.56%) of the offenders in the original sample did not have a co-offense.

Third, I coded the criminal history file. This file was the largest original data file, containing 818,894 offenses, 472,812 unique sentence IDs, and 64,720 offenders. I removed offenses committed prior to and sentenced after the primary offense (N = 72,315 offenses; 33,937 sentence IDs; 1,621 offenders). I also removed prior sentence IDs not containing an offense in the criminal code (N = 67,617 offenses; 57,248 sentence IDs; 5,110 offenders). The final criminal history file represented information on all offenses and sentence IDs disposed after 2000 and prior to the sentencing date for the primary offense. In total, 57,989 offenders had a prior criminal record.

Fourth, I coded the prior incarcerations file. This file included an observation for each incarceration sentence in a person's criminal history. I kept each of these prior incarcerations, though I aggregated the information to the offender-level. In total, 16,343 offenders (18.7% of the original sample) had a prior incarceration record.

Finally, I coded the recidivism files. The first recidivism file (covering offenses convicted between 2008 and May, 2013) included information for each offense within a sentence ID. The second file (covering offenses convicted between June, 2013 and December, 2013) included information for the most serious offense in each of the sentence IDs convicted during the follow-up period. Similar to the criminal history file, I removed all sentence IDs that did not contain an offense in the criminal code. In total, 57,248 sentence IDs were removed from the first recidivism file (23.16%) and 13 sentence IDs were removed from the second recidivism file (<1%). After combining the files, I merged in the release date from the primary offense file to make sure that the recidivism offenses were committed during the official follow-up period. In total, 2,757 additional sentence IDs were removed because the file contained only offenses committed prior to the release date for the primary offense. These offenses may represent offenses committed while incarcerated. In addition, it is possible that these offenses were committed prior to the release date or to the primary offense, and that the authorities processed these offenses prior to the offender being released for the primary offense. Many of these offenders still ended up being failures in my dataset (i.e., they had recidivism offenses after the release date, within the four-year follow-up period).

Table 4-1. Summary of Files for Original Samples and Dropped Cases

Primary Offenses File

	Offenses		Sentence IDs		Offenders	
	N	%	N	%	N	%
Removed						
No 4-year follow up	1,353	1.55	1,353	1.55	1,353	1.55
Chapter 61 Primary Offense	2,083	2.38	2,083	2.38	2,083	2.38
Offense Information Missing	613	0.70	613	0.70	613	0.70
Final File	83,297	95.36	83,297	95.36	83,297	95.36
Total (original file)	87,346		87,346		87,346	

Co-Offenses File

	Offenses		Sentence IDs		Offenders	
	N	%	N	%	N	%
Removed						
Primary Offenses	87,346	56.61	56,391	64.56	56,391	64.56
Final File	66,948	43.39	30,955	35.44	30,955	35.44
Total (original file)	154,294		87,346		87,346	

Criminal History File

	Offenses		Sentence IDs		Offenders	
	N	%	N	%	N	%
Removed						
Post Primary	72,315	8.83	33,937	7.18	1,621	2.50
No Criminal Law	67,617	8.26	57,248	12.11	5,110	7.90
Final File	678,962	82.91	381,627	80.71	57,989	89.60
Total (original file)	818,894		472,812		64,720	

Table 4-1. Summary of Files for Original Samples and Dropped Cases (Continued)
Prior Incarcerations File

	Offenses		Sentence IDs		Offenders	
	N	%	N	%	N	%
Original/Final File	--		72283	100	16343	100

Recidivism File
2008 - May 2013

	Offenses		Sentence IDs		Offenders	
	N	%	N	%	N	%
Removed						
No Criminal Law	67,617	15.87	57,248	23.16	4,447	8.78
File for Merge	399,083	93.64	224,971	91.02	46,221	91.22
Total (original file)	426,173		247,168		50,668	

Recidivism File
June - December 2013

	Offenses		Sentence IDs		Offenders	
	N	%	N	%	N	%
Removed						
No Criminal Law	--		13	0.69	11	0.68
File for Merge	--		1,882	99.31	1,617	99.32
Total (original file)			1,895		1,628	

Combined Recidivism Files

	Offenses		Sentence IDs		Offenders	
	N	%	N	%	N	%
Removed						
Offenses Before Release Date	--		2,757	1.12	211	0.45
Final File	--		224,096	90.67	46,310	99.55
Total (original merged file)	--		247,168		46,521	

Analytic Strategy

This study consists of 3 separate parts. In Part 1, I discuss how each variable was coded and compare DWI offenders to non-DWI offenders using various descriptive and bivariate statistics. This descriptive section seeks to understand differences and similarities between DWI and non-DWI offenders in Finland. These comparisons are necessary to understand whether DWI offenders are truly "unique," and if so, in what ways the profiles of DWI offenders differ from the general offending population. This section includes comparisons between DWI offenders to all other non-DWI offenders as well as more focused comparisons between DWI offenders and more specific classifications of non-DWI offenders (e.g., property, personal, and drug offenders).

In Part 2, I develop Burgess risk assessment instruments for DWI offenders as a method of evaluating the correlates of recidivism among DWI offenders. I develop two risk assessments: one predicting the risk of recidivism for any offense and another predicting the risk of recidivism for another DWI. I limit these risk instruments to the factors commonly available to judges both in the United States and in Finland.

In Part 3, I expand the Burgess risk assessment instruments to include variables uniquely available to judges in Finnish courts. This section analyzes how much predictive ability may be gained by including additional offender and/or offense specific characteristics. This section also tests how sensitive risk assessments are to the coding mechanisms used for independent variables such as prior convictions.

Part 1: DWI and Non-DWI Offending

Offenders were first classified into their primary type of offense (e.g., DWI, drug, property, personal). This study uses two primary dependent variables – general recidivism and

DWI specific recidivism – and three types of independent variables - offender demographic characteristics (e.g., age and gender), offense characteristics (e.g., type of offense and whether or not there were multiple conviction charges), offender criminal history (e.g., number and type of prior convictions), and criminal justice responses (e.g., type of sentence). By comparing DWI offenders and non-DWI offenders across these four sets of independent variables, some prominent similarities and differences emerge. The comparisons between DWI and non-DWI offenders are available in Appendix D.

Type of Crime

I manually coded each crime into 11 crime categories: property, personal, sex crimes, public administration/public order, other traffic, alcohol, drug, weapons, driving while intoxicated (DWI), driving while seriously intoxicated (DWSI), and non-vehicular DWI (including waterway traffic intoxication, air traffic intoxication, rail traffic intoxication, and non-motor-powered traffic intoxication). I coded the crimes into categories using the numeric crime code and an English translation of the Finnish Crimes Code. Appendix E shows the 10 most frequent crimes in each crime category. The Finnish Crimes Code is succinctly divided into chapters based on the type of offense which made the coding of the offenses unambiguous (e.g., Chapter 15 is "Offences against the administration of justice" and all chapter 15 offenses were coded as "public administration" offenses.). For the few instances where a specific offense was unclear, I consulted with the data manager and one of the legal advisors at Krimo to determine how these offenses would be coded in Finnish courts.

DWI and DWSI were the most common offenses during the sample period (N = 13,263 and N = 16,619, respectively). The number of personal offenses (N = 16,548) surpassed normal DWIs, but not DWSIs. However, the personal offense category was largely driven by assaults (N

= 12,447, 75.22% of all personal offenses). There were also a substantial number of property offenses (N = 15,571). The most common type of property offenses were theft offenses (N = 3,781 theft and petty theft offenses), fraud (N = 2,692 fraud and petty fraud offenses), and criminal damage (N = 2,560 criminal damage and petty criminal damage offenses).

Other offense categories were less frequent. Other traffic offenses accounted for 7,969 offenders. There were only four types of other traffic offenses: causing a traffic hazard, causing a serious traffic hazard, operation of a vehicle without a license, and flight from the scene of a traffic accident. While most traffic crimes are processed outside of criminal courts, these offenses represent more serious traffic offenses for which offenders can receive for day fines or imprisonment.

Public administration and public order offenses accounted for 6,221 offenders. The most frequent offense in this category was relinquishing a vehicle to an intoxicated person. There were over 100 different types of offenses included in the public administration/public order category. In Finland, these crimes are largely classified as "crimes against public authority and public peace." This category also includes violations of various regulatory Acts and Decrees.

Less than five percent of offenders were convicted for a drug offense (N = 3,839; 4.62% of all offenders). Drug laws in Finland are more succinct than drug laws in the United States; there were only nine offenses included in this category. Drug offenses were largely driven by narcotics offenses (N = 2,751; 71.7% of all drug offenses). The narcotics offense crime code (chapter 50, section 1) includes all drugs included on lists I-IV in the 1961 Single Convention on Narcotic Drugs and the 1971 Convention on Psychotropic Substances (including, but not limited to, cannabis, coca plant, khat, Psilosybe mushrooms, opium poppy, hemp, cactus plants containing mescaline, and heroin).

Weapons offenses were rare (N = 1,353, 1.63% of all offenses). Firearms offenses accounted for most weapons crimes (N = 853 firearms, aggravated firearms, and petty firearms offenses). Non-vehicular offenses were also rare (N = 785, 0.95% of all offenses). Nearly all of the non-vehicular DWI offenses involved waterway traffic infractions (N=777). There were only 686 sex offenses in this sample (.83% of all offenses). Over half of these offenses involved sexual abuse of a child (N=409). Finally, there were 154 alcohol crimes (0.19% of all offenses).

In the following sections, I summarize the two comparisons I made. First, I compared DWI offenders with non-DWI offenders for each offender and offense characteristic in the dataset. Second, I made additional comparisons between DWI offenders and more specific categories of non-DWI offenders. Table 4-2 includes descriptive statistics by type of offense for DWI offenders (N = 29,882), property offenders (N = 15,571), personal offenders (N = 16,548), and drug offenders (N = 29,882). The following sections discuss important differences and similarities between DWI offenders and non-DWI offenders.

Table 4-2. Descriptive statistics for the Full Sample by Property (N = 15,571), Personal (N = 16, 548), Drug (N = 3,839) and DWI (N = 29,882) offenders

	DWI N	Property N	Personal N	Drug N	DWI %	Property %	Personal %	Drug %	Sig.
Gender									0.000
Male	25,880	11,998	14,083	3,252	86.6	77.1	85.1	84.7	
Female	4,002	3,573	2,465	587	13.4	22.9	14.9	15.3	
	29,882	15,571	16,548	3,839	100.0	100.0	100.0	100.0	
Age									0.000
< 18	2,125	1,737	1,541	188	7.1	11.2	9.3	4.9	
18-24	4,685	3,635	3,623	1,163	15.7	23.3	21.9	30.3	
24-29	3,052	2,306	2,399	971	10.2	14.8	14.5	25.3	
30-34	2,619	1,812	1,864	558	8.8	11.6	11.3	14.5	
35-40	2,493	1,441	1,584	339	8.3	9.3	9.6	8.8	
41-44	3,065	1,392	1,826	255	10.3	8.9	11.0	6.6	
45-49	3,269	1,181	1,434	170	10.9	7.6	8.7	4.4	
50-54	3,082	826	957	98	10.3	5.3	5.8	2.6	
55-59	2,638	626	635	56	8.8	4.0	3.8	1.5	
60+	2,854	615	685	41	9.6	3.9	4.1	1.1	
	29,882	15,571	16,548	3,839	100.0	100.0	100.0	100.0	
Mean	39.19	32.88	33.87	29.77					0.000
Location									0.000
Helsinki	4,548	3,918	3,575	1,274	15.2	25.2	21.6	33.2	
Urban	7,282	3,695	3,722	829	24.4	23.7	22.5	21.6	
Rural	18,052	7,958	9,251	1,736	60.4	51.1	55.9	45.2	
	29,882	15,571	16,548	3,839	100.0	100.0	100.0	100.0	
Cooffenders									0.000
Yes	1,630	5,096	4,973	1,239	5.5	32.7	30.1	32.3	
No	28,252	10,475	11,575	2,600	94.5	67.3	69.9	67.7	
	29,882	15,571	16,548	3,839	100.0	100.0	100.0	100.0	
Multiple conviction charges									0.000
Yes	12,376	5,772	5,633	1,390	41.4	37.1	34.0	36.2	
No	17,506	9,799	10,915	2,449	58.6	62.9	66.0	63.8	
	29,882	15,571	16,548	3,839	100.0	100.0	100.0	100.0	

Table 4-2. Descriptive statistics for the Full Sample by Property (N = 15,571), Personal (N = 16, 548), Drug (N = 3,839) and DWI (N = 29,882) offenders, continued

	DWI N	Property N	Personal N	Drug N	DWI %	Property %	Personal %	Drug %	Sig.
Total prior sentence Ids									0.000
0	11,228	4,063	5,036	937	37.6	26.1	30.4	24.4	
1	6,429	2,325	3,058	589	21.5	14.9	18.5	15.3	
2	3,638	1,502	1,984	402	12.2	9.6	12.0	10.5	
3	2,202	1,119	1,349	283	7.4	7.2	8.2	7.4	
4	1,434	859	965	226	4.8	5.5	5.8	5.9	
5	999	656	727	165	3.3	4.2	4.4	4.3	
6	701	545	564	140	2.3	3.5	3.4	3.6	
7	465	438	384	111	1.6	2.8	2.3	2.9	
8	375	311	331	109	1.3	2.0	2.0	2.8	
9	314	292	262	93	1.1	1.9	1.6	2.4	
10-14	842	1,006	767	252	2.8	6.5	4.6	6.6	
15-19	438	681	409	158	1.5	4.4	2.5	4.1	
20-24	256	453	198	105	0.9	2.9	1.2	2.7	
25-29	165	327	145	81	0.6	2.1	0.9	2.1	
30+	396	994	369	188	1.3	6.4	2.2	4.9	
	29,882	15,571	16,548	3,839	100.0	100.0	100.0	100.0	
Mean	2.97	7.69	4.33	6.72					0.000
Total Prior Court Convictions									0.000
0	16,680	7,133	8,345	1,651	55.8	45.8	50.4	43.0	
1	5,895	2,454	3,015	663	19.7	15.8	18.2	17.3	
2	2,779	1,421	1,577	381	9.3	9.1	9.5	9.9	
3	1,441	967	1,070	283	4.8	6.2	6.5	7.4	
4	853	702	685	187	2.9	4.5	4.1	4.9	
5	548	522	440	115	1.8	3.4	2.7	3.0	
6	337	371	323	105	1.1	2.4	2.0	2.7	
7	272	335	246	84	0.9	2.2	1.5	2.2	
8	214	277	187	58	0.7	1.8	1.1	1.5	
9	156	223	150	48	0.5	1.4	0.9	1.3	
10-14	457	699	331	174	1.5	4.5	2.0	4.5	
15-19	175	283	122	56	0.6	1.8	0.7	1.5	
20-24	54	118	44	20	0.2	0.8	0.3	0.5	
25-29	18	38	11	11	0.1	0.2	0.1	0.3	
30+	3	28	2	3	0.0	0.2	0.0	0.1	
	29,882	15,571	16,548	3,839	100.0	100.0	100.0	100.0	
Mean	1.30	2.56	1.69	2.47					0.000
Total Prior Summary Penal Fines									0.000
0	16,096	5,452	7,096	1,262	53.9	35.0	42.9	32.9	
1	6,063	2,724	3,498	716	20.3	17.5	21.1	18.7	
2	2,805	1,563	1,839	435	9.4	10.0	11.1	11.3	
3	1,460	1,054	1,102	267	4.9	6.8	6.7	7.0	
4	865	720	713	187	2.9	4.6	4.3	4.9	
5	541	539	438	148	1.8	3.5	2.6	3.9	
6	373	396	308	122	1.2	2.5	1.9	3.2	
7	260	329	239	80	0.9	2.1	1.4	2.1	
8	186	285	167	75	0.6	1.8	1.0	2.0	
9	154	213	144	67	0.5	1.4	0.9	1.7	
10-14	498	818	436	190	1.7	5.3	2.6	4.9	
15-19	225	465	208	118	0.8	3.0	1.3	3.1	
20-24	135	298	103	54	0.5	1.9	0.6	1.4	
25-29	82	187	74	36	0.3	1.2	0.4	0.9	
30-34	46	129	53	31	0.2	0.8	0.3	0.8	
35-39	27	96	25	13	0.1	0.6	0.2	0.3	
40+	66	303	105	38	0.2	1.9	0.6	1.0	
	29,882	15,571	16,548	3,839	100.0	100.0	100.0	100.0	
Mean	1.67	5.13	2.64	4.25					0.000

Table 4-2, continued. Descriptive statistics for the Full Sample by Property (N = 15,571), Personal (N = 16, 548), Drug (N = 3,839) and DWI (N = 29,882) offenders, continued

	DWI	Property	Personal	Drug	DWI	Property	Personal	Drug	
	N	N	N	N	%	%	%	%	Sig.
Age at first conviction									0.000
< 18	4,706	4,181	3,926	873	15.7	26.9	23.7	2.9	
18-24	4,732	3,457	3,446	1,410	15.8	22.2	20.8	36.7	
24-29	2,466	1,720	1,738	545	8.3	11.0	10.5	14.2	
30-34	2,417	1,421	1,611	371	8.1	9.1	9.7	9.7	
35-40	2,675	1,262	1,607	233	9.0	8.1	9.7	6.1	
41-44	3,034	1,160	1,434	160	10.2	7.4	8.7	4.2	
45-49	3,097	869	1,090	103	10.4	5.6	6.6	2.7	
50-54	2,665	658	733	84	8.9	4.2	4.4	2.2	
55-59	2,035	443	447	32	6.8	2.8	2.7	0.8	
60+	2,055	400	516	28	6.9	2.6	3.1	0.7	
	29,882	15,571	16,548	3,839	100.0	100.0	100.0	100.0	
Mean	36.17	29.19	30.43	25.75					0.000
Type of prior sentence(s)									
Prior personal sentence(s)									0.000
Yes	4,003	3,880	5,216	828	13.4	24.9	31.5	21.6	
No	25,879	11,691	11,332	3,011	86.6	75.1	68.5	78.4	
	29,882	15,571	16,548	3,839	100.0	100.0	100.0	100.0	
Prior sex sentence(s)									0.000
Yes	122	109	117	13	0.41	0.7	0.7	0.34	
No	29,760	15,462	16,431	3,826	99.6	99.3	99.3	99.7	
	29,882	15,571	16,548	3,839	100.0	100.0	100.0	100.0	
Prior property sentence(s)									0.000
Yes	6,370	8,052	5,420	1,711	21.3	51.7	32.8	44.6	
No	23,512	7,519	11,128	2,128	78.7	48.3	67.2	55.4	
	29,882	15,571	16,548	3,839	100.0	100.0	100.0	100.0	
Prior Alcohol sentence(s)									0.000
Yes	206	200	170	46	0.7	1.3	1.0	1.2	
No	29,676	15,371	16,378	3,793	99.3	98.7	99.0	98.8	
	29,882	15,571	16,548	3,839	100.0	100.0	100.0	100.0	
Prior drug sentence(s)									0.000
Yes	2,370	3,217	1,968	1,708	7.9	20.7	11.9	44.5	
No	27,512	12,354	14,580	2,131	92.1	79.3	88.1	55.5	
	29,882	15,571	16,548	3,839	100.0	100.0	100.0	100.0	
Prior firearms/weapons sentence(s)									0.000
Yes	2,202	2,785	2,171	809	7.4	17.9	13.1	21.1	
No	27,680	12,786	14,377	3,030	92.6	82.1	86.9	78.9	
	29,882	15,571	16,548	3,839	100.0	100.0	100.0	100.0	
Prior traffic sentence(s)									0.000
Yes	13,792	7,604	7,574	1,881	46.2	48.8	45.8	49.0	
No	16,090	7,967	8,974	1,958	53.8	51.2	54.2	51.0	
	29,882	15,571	16,548	3,839	100.0	100.0	100.0	100.0	
Prior Public Adm/Order sentence(s)									0.196
Yes	4,725	4,435	4,073	954	15.8	28.5	24.6	24.9	
No	25,157	11,136	12,475	2,885	84.2	71.5	75.4	75.1	
	29,882	15,571	16,548	3,839	100.0	100.0	100.0	100.0	
Prior DWI sentence(s)									0.000
Yes	5,143	2,494	2,064	707	17.2	16.0	12.5	18.4	
No	24,739	13,077	14,484	3,132	82.8	84.0	87.5	81.6	
	29,882	15,571	16,548	3,839	100.0	100.0	100.0	100.0	
Prior Serious DWI sentence(s)									0.000
Yes	6,997	2,610	2,648	511	23.4	16.8	16.0	13.3	
No	22,885	12,961	13,900	3,328	76.6	83.2	84.0	86.7	
	29,882	15,571	16,548	3,839	100.0	100.0	100.0	100.0	
Prior Non-Vehicular DWI sentence(s)									0.004
Yes	222	73	119	21	0.7	0.5	0.7	0.5	
No	29,660	15,498	16,429	3,818	99.3	99.5	99.3	99.5	
	29,882	15,571	16,548	3,839	100.0	100.0	100.0	100.0	

Table 4-2, continued. Descriptive statistics for the Full Sample by Property (N = 15,571), Personal (N = 16, 548), Drug (N = 3,839) and DWI (N = 29,882) offenders, continued

	DWI N	Property N	Personal N	Drug N	DWI %	Property %	Personal %	Drug %	Sig.
Prior Incarceration									0.000
Yes	2,970	2,580	1,940	557	9.9	16.6	11.7	14.5	
No	26,912	12,991	14,608	3,282	90.1	83.4	88.3	85.5	
	29,882	15,571	16,548	3,839	100.0	100.0	100.0	100.0	
Type of sentence (Most Serious)									0.000
Unconditional Prison	1,395	833	658	155	4.7	5.3	4.0	4.0	
Community Service	2,256	430	521	104	7.5	2.8	3.1	2.7	
Conditional Prison	12,662	3,545	3,764	687	42.4	22.8	22.7	17.9	
Other (including Fines)	13,569	10,763	11,605	2,893	45.4	69.1	70.1	75.4	
	29,882	15,571	16,548	3,839	100.0	100.0	100.0	100.0	
Average Length of Sentence									
Unconditional Prison	4.87	6.50[a]	7.45[a]	6.78[a]					0.000
Community Service	6.59	2.75[a]	3.20[a]	2.68[a]					0.000
Conditional Prison	26.19	36.14[a]	33.41[a]	33.08[a]					0.000
Other (including Fines)	34.59	22.89	27.47[a]	26.67[a]					0.000
Recidivism									
Four Year									0.000
Yes	13,949	9,308	8,742	2,355	46.7	59.8	52.8	61.3	
No	15,933	6,263	7,806	1,484	53.3	40.2	47.2	38.7	
	29,882	15,571	16,548	3,839	100.0	100.0	100.0	100.0	
DWI reconviction									0.000
Yes	4,052	774	988	190	13.6	5.0	6.0	4.9	
No	25,830	14,797	15,560	3,649	86.4	95.0	94.0	95.1	
	29,882	15,571	16,548	3,839	100.0	100.0	100.0	100.0	

Recidivism

Most recidivism studies in the United States use a three-year follow-up period and use arrest as the measure of recidivism. Using these standards, the majority of recidivist offenders are re-arrested within 3 years of their release from a prior sentence (Langan and Levin, 2002). However, there is still some disagreement, particularly in research on risk assessments, about whether recidivism should be measured as re-arrest or reconviction. The data for the current study were limited to convictions. Given this limitation, I had to decide whether a three-year follow-up period was sufficient to capture the majority of recidivists.

The average time between date of offense and date of conviction was 308.97 days (SD 455.75). However, the median was 159 days. Three-fourths of offenders (77%) were convicted within one year of the offense date. The time to conviction varied by type of crime. Table 4-3 shows the mean and mode for the days to conviction by type of offense. Sex offenses took the longest time to reach a conviction (mean 818.12 days; Median 491.50 days). DWI and DWSI offenses took the least amount of time to result in a conviction (Mean 88.13 and 120.19; Median 73.86 and 107.05, respectively). Table 4-3 also shows the percent of offenders convicted within one year for each crime type.

Using a three-year follow up period would exclude a large number of offenders who were re-arrested but are still going through the process of being convicted. Thus, I chose to use a four-year follow-up period. Given the previous findings that the average offender in my sample was convicted within one year after their arrest, a one-year extension in the follow-up period should capture the majority of offenders arrested within three years after their primary offense. This extended follow-up period makes the results of the study more comparable to research that uses a three-year follow-up with re-arrest as the measure of recidivism. In addition, it is likely that this research actually captures more than 77% of offenders who would be coded as recidivists if an arrest measure was available, since these calculations are from the date of offense, and there is often a delay between the date of offense and the date of arrest.[69]

[69] This delay may also explain the exceptionally lengthy time to conviction for sex offenses. Often, sex offenses are not reported immediately, and offenses such as sexual abuse of a child may be ongoing for months or years before being reported.

Table 4-3. Time to Conviction (Days from Offense Date)

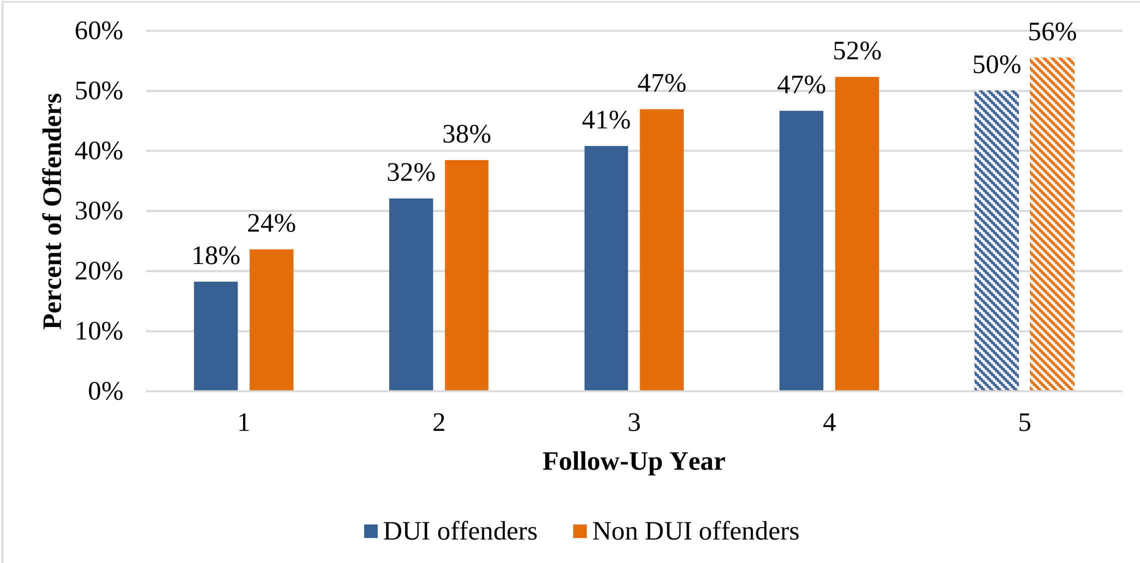
Primary Offense Crime Type	N	Mean	SD	Median	% Within 1 Year
Property	18.76	614.73	697.88	355	51.19
Personal	16,548	334.7	270.12	263	68.45
Sex Offenses	686	818.12	904.49	491.5	34.4
Public Adm/Order	6,221	507.07	630.29	293	58.23
Other Traffic	7,969	172.16	158.01	118	90.2
Alcohol	154	724.14	740.83	471	37.66
Drug	3,839	361.71	305.55	267	65.75
Weapons	1,353	485.89	911.41	218	69.48
DWI	13,263	88.13	73.86	69	98.94
Serious DWI	16,619	120.19	107.05	94	97.51
Non-Vehicular DWI	785	160.11	156.85	108	92.36
All Offenders		308.97	455.75	159	77

The majority of recidivist offenders were reconvicted within four years. An additional 4% of offenders were reconvicted after the four-year follow-up period.[70] Consistent with previous research, the number of offenders who recidivated decreased in each subsequent year. Offenders were most likely to recidivate in the first year following their release (22%) and over half of the offenders who recidivated did so in the first two years following their release (72% of those who recidivated within 4 years).

DWI offenders were less likely than non-DWI offenders to recidivate. Figure 4-2 shows the cumulative rate of failure for DWI and non-DWI offenders at each year in the follow-up period. Recidivism was significantly different for DWI and non-DWI offenders (chi2[5] = 402.4908, p < .000), but the patterns across time were similar.

[70] The number of offenders recidivating beyond the 4-year follow-up period may be an underestimate because of the lack of 5 years of follow-up data for some offenders.

Figure 4-2. Cumulative Recidivism Rate by Follow-Up Year

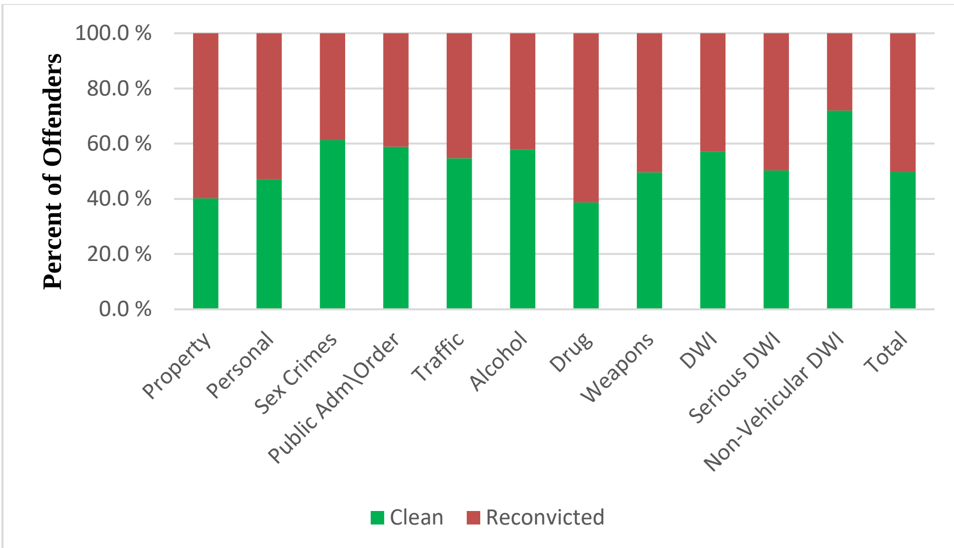


Literature often cites Finland as one of the countries with the lowest recidivism rate in the world (Ekunwe and Jones, 2012; Fazel and Worf, 2015). However, prior recidivism studies in Finland often limit their analyses to samples of prisoners and limit their analyses of recidivism to re-imprisonment. Due to the low rate of incarceration for offenders in Finland, limiting the analyses to prisoners and reimprisonment excludes the majority of criminals in Finland and underestimates the presence of criminal behaviors in Finland. This dissertation expands the analysis to include all offenders, regardless of whether or not they were sentenced to prison. In addition, this study defines recidivism as a reconviction, rather than reimprisonment.

Specialization vs. Generalized Offending

Recidivism rates varied by type of offense. Figure 4-3 depicts the recidivism rate by type of crime. Drug offenders (61.3%) and property offenders (59.8%) were most likely to recidivate. Just over half of personal offenders (52.8%) and weapons offenders (50.4%) recidivated. Non-vehicular DWI offenders (28.0%) were least likely to recidivate. Consistent with findings in other countries, sex offenders also had low recidivism rates (38.6%) relative to other types of offenders. Overall, 46.7% of DWI offenders were reconvicted. However, serious DWI offenders (49,7%) were more likely to recidivate than DWI offenders (43.0%). Recidivism rates for DWI offenders were most similar to recidivism rates for other traffic offenders (45.3%).

Figure 4-3. Recidivism by Crime Type



Overall, only 30.7% of offenders who recidivated were reconvicted for the same type of offense as their primary offense. The amount of specialization varied by type of crime. Table 4-4 shows the total distribution of offenders for the primary offense and for the type of recidivism offense. The final row of the table presents the percent of offenders who "specialized" in a type of crime defined as the percent of offenders who recidivated with the same type of offense as their primary offense. Traffic offenders were the only type of offender who showed a significant specialization. Almost two thirds of traffic offenders who recidivated were reconvicted for another traffic offense. Property offenders who recidivated were more likely to commit another property offense than any other type of offense (38.2%).

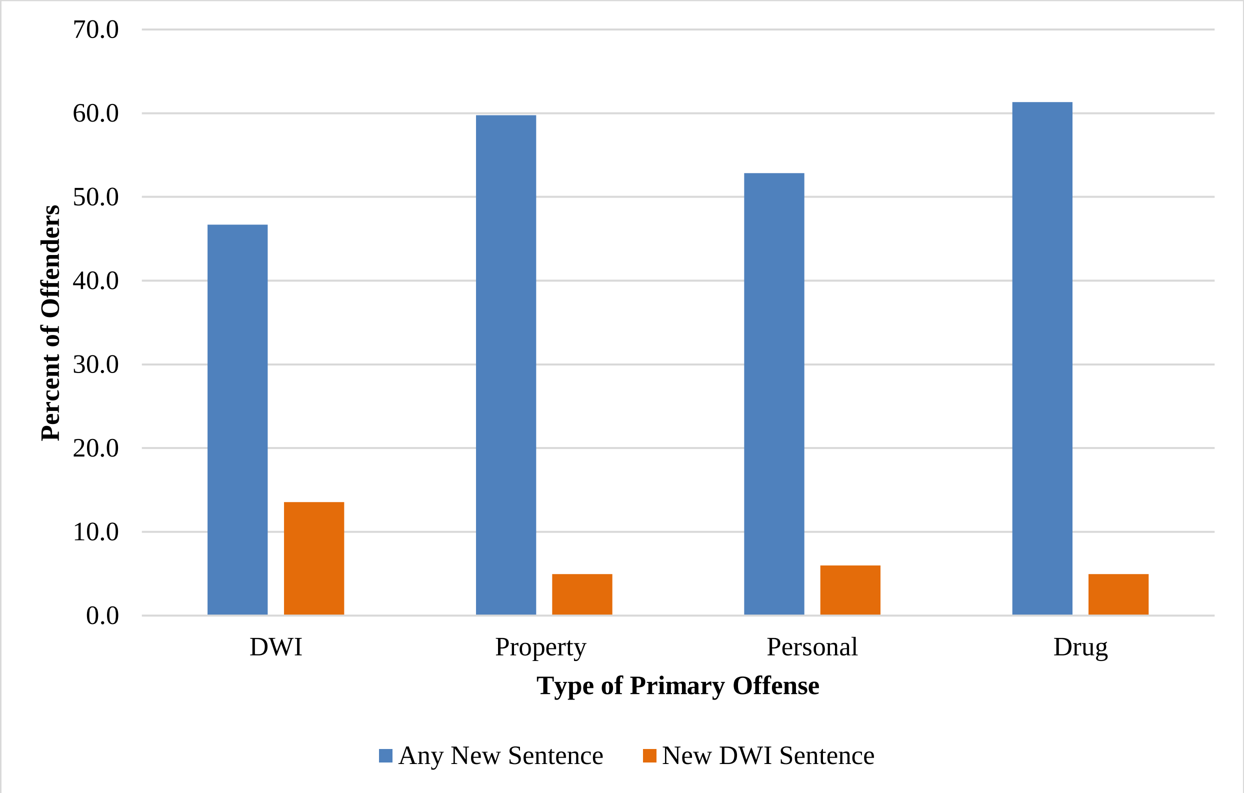
Table 4-4. Type of Current Offense by Type of Recidivism: Analysis for Specialization

	Primary Offense Crime Type											
Recidivism Crime Category	Property	Personal	Sex Crimes	Public Adm and Pub Order	Traffic	Alcohol	Drug	Weapons	DWI	Serious DWI	Non-Vehicle DWI	Total
Property	3,717	1,808	37	460	296	12	608	139	820	1,390	17	9,304
Personal	854	1,758	28	263	222	6	154	72	378	762	13	4,510
Sex Crimes	10	30	2	4	5	1	4	0	10	16	0	82
Public Adm and Pub Order	638	939	26	334	162	5	121	50	291	668	14	3,248
Traffic	2,690	2,910	136	1,077	2,741	31	611	269	2,544	2,672	93	15,774
Alcohol	16	14	1	11	14	3	0	2	26	28	1	116
Drug	582	456	14	130	98	4	680	49	347	245	10	2,615
Weapons	397	359	5	85	59	2	92	44	153	222	5	1,423
other unknown	0	2	0	1	0	0	0	0	0	0	0	3
DWI	318	346	14	133	132	5	112	34	719	772	24	2,609
Serious DWI	484	679	26	261	137	4	88	58	829	2,004	48	4,618
non-vehicle DWI	16	23	1	8	10	0	2	1	20	36	19	136
Total	9722	9324	290	2767	3876	73	2472	718	6137	8815	244	44438
% "specialization"	38.2 %	18.9 %	0.7 %	12.1 %	70.7 %	4.1 %	27.5 %	6.1 %	25.2 %	31.5 %	7.0 %	30.7 %

DWI Recidivism

This dissertation focuses on the behavior of DWI offenders. My research not only questions the characteristics of DWI offenders, but also the characteristics of offenders who recidivate with a DWI offense. Consequently, I analyzed patterns of recidivism for offenders who go on to commit a DWI or serious DWI within 4 years of their primary offense. Overall, 8.24% of offenders recidivated with a DWI offense.

Figure 4-4. Overall and DWI Specific Recidivism by Type of Primary Offense



All types of offenders recidivated with DWI offenses at least once (see Figure 4-4). Recidivism with a DWI was most common for DWI offenders. Nearly a third (29%) of all DWI offenders who recidivated, did so with another DWI offense. DWI recidivism was less pronounced for other types of offenders. Only 8% of the property and drug offenders who recidivated did so with a DWI, and 11% of personal offenders who recidivated did so with a DWI offense.

Gender

Gender and age are the only demographic factors included in Finnish court data. Court data included a measure for gender. Across crimes, the sample was overwhelmingly male (84.5%), and offenders were more likely to be male, regardless of whether they were a DWI or non-DWI offender. The proportion of females was significantly greater for non-DWI offenses (16.7%) than for DWI offenses (13.4%), χ^2 (1, N = 83,008) = 155.37, p = .000, but this difference was not substantively large. Surprisingly, the more specific crime category analysis showed that the gender gap was largest for DWI offending. However, the gender gap for personal offenders (85.1% male) and drug offenders (84.7% male) was similar to the gender gap for DWI offenders. Unsurprisingly, the smallest gender gap was for property offending (77.1% male). This finding is consistent with prior research on gender differences and offending which show that females are more likely to engage in small-scale property offending such as shoplifting or minor theft (Steffensmeier and Allan, 1996).

Age

Court data included the offender's date of birth, the date of offense, and the date of sentence for district and appellate court sentences. Using these variables across different datasets, I constructed a measure for the offender's age at initial sentence (district court) and the offender's age at the first conviction in the criminal history data.

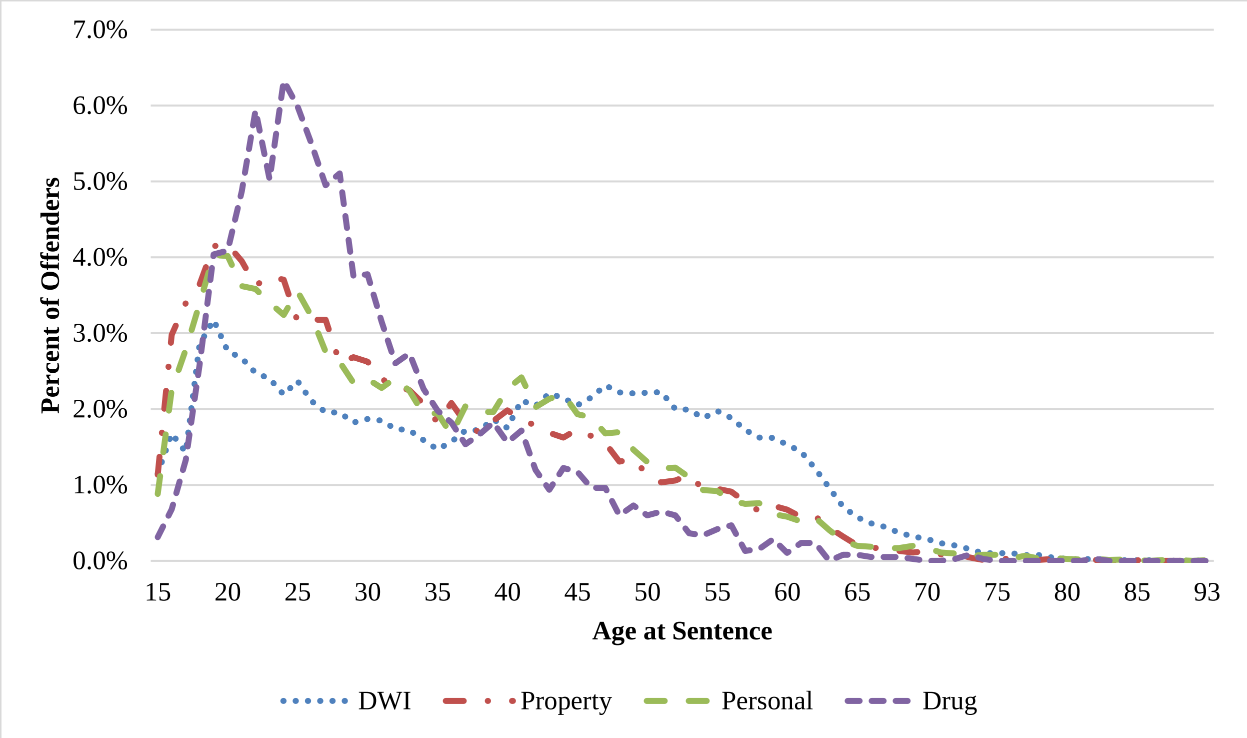
The distribution of age and crime was generally consistent with prior research on the age-crime curve. Figure 4-5 shows the distribution of age at sentencing for each of the four categories of crime. Offending for all crime types peaked in early adulthood (between ages 18 and 22) and declined through the life-course. This decline temporarily reverses for all crimes between the ages of 35 and 40. While drug offenses and property offenses quickly return to a decline, personal offenses and DWI offending appear to plateau for a longer period of time. Personal offenses begin declining again around age 45, while DWI offenses more slowly decline after 50 years of age.

Overall, DWI offenders had the oldest average age at date of sentence (39.19). Drug offenders had the youngest average age at date of sentence (29.77). This finding was slightly somewhat surprising given that DWI offenses may be drug-induced. Consequently, drug offending and DWI offending might be expected to be more highly correlated. However, despite recent increases, drug-induced DWI offending still represents a minority of all DWI offending. The mean age for property offending (32.88) and personal offending (33.87) were more similar and fell between the mean values of DWI and drug offending. An analysis of variance (ANOVA) test found significant differences in the average age for different types of offenders $F(3, 65836) = 1175.32$, $p = 0.000$.[71] A subsequent post-hoc Tukey-Kramer test confirmed that the average age for offenders in each category of offense was statistically significantly different from the average age of offenders in every other category of offense, $p = .000$.[72]

[71] The data violate two assumptions of ANOVA: heterogeneity of variance and equal sample sizes. However, the large sample sizes for each of the four groups reduces the risk of a type 1 error. I conducted additional nonparametric tests (Welch ANOVA and Brown-Forsythe tests) to confirm the findings. The Welch ANOVA test does not require equal sample sizes or heterogeneity of variance. The Brown-Forsythe test also adjusts for heterogeneity of variance. Findings converged across all three measures (ANOVA, Welch ANOVA and Brown-Forsythe tests) unless otherwise mentioned.

[72] Unlike Tukey HSD post-hoc tests, Tukey-Kramer tests include adjustments for unequal sample sizes.

Figure 4-5. Age Distribution at Sentencing by Type of Crime

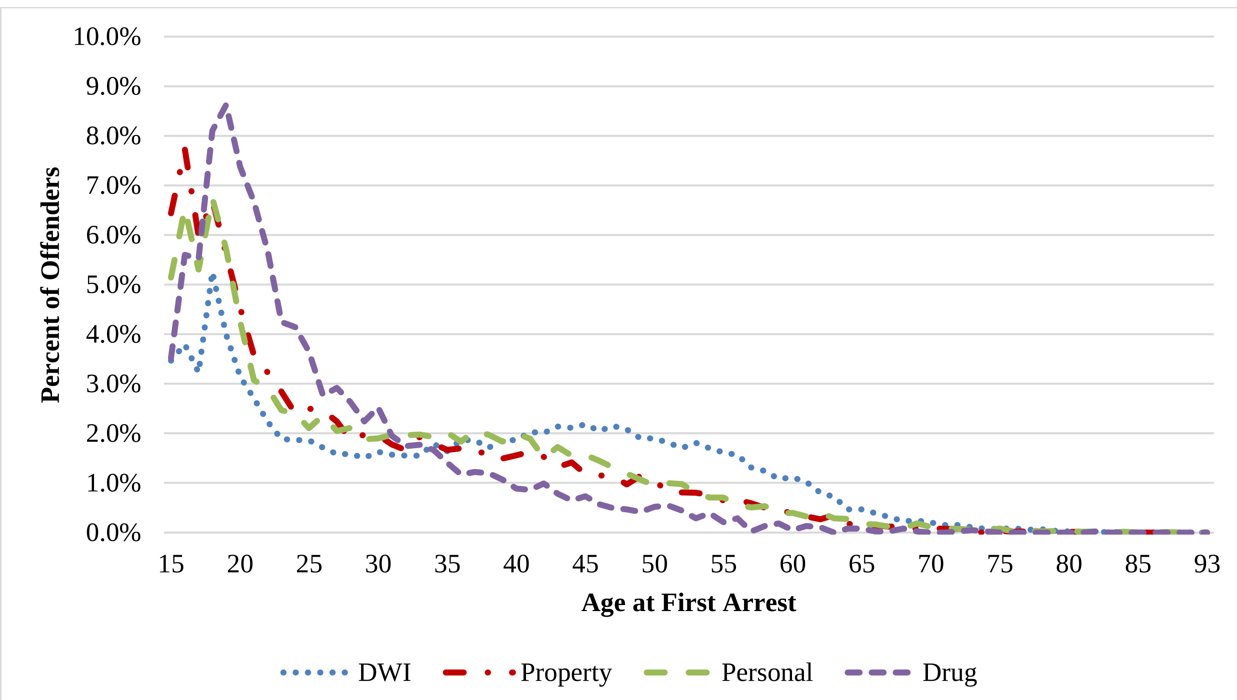


Age at first conviction followed similar patterns.[73] Figure 4-6 shows the distribution of offenders' age at their first conviction, separated by their type of primary offense. The offenders in each of these groups are the same offenders in corresponding groups in the prior figure. Offenders were most likely to begin offending during adolescence (ages 15-20). Onset of offending decreased with each additional year of age. However, DWI offenders were once again the exception to these patterns. DWI offenders were still most likely to begin offending in early ages, but age of onset plateaued at age 22 and temporarily increased between the ages of 36 and 50.

[73] It is important to remember that this is age at first conviction in the available criminal history data. Age at first conviction was calculated using the date of conviction for the oldest case in each offender's criminal history data. If an offender committed crimes prior to 2002, those offenses are not included in these data and their "first conviction" was counted as the first conviction after 2002.

Due to this group of late-onset offenders, the average age at first conviction was highest for DWI offenders (36.17 years). Consistent with the overall distribution at age conviction, drug offenders had the earliest average age at onset (25.75 years). Personal offenders (30.43 years) and property offenders (29.19 years) had a similar average age at onset and fell between DWI and drug offenders. An ANOVA test found significant differences in the average age for different types of offenders F(3, 65836) = 1386.76, p = 0.000. A subsequent post-hoc Tukey-Kramer test confirmed that the average age at onset for each category of offenders was statistically significantly different from every other category of offenders, p = .000.

Figure 4-6. Age Distribution for Age at First Arrest by Type of Primary Offense



There are two possible explanations for the differences in age at onset for DWI and non-DWI offenders. First, these results may simply confirm that DWI offenders are significantly different from the general offending population. These results suggest that DWI offenders are likely to be older, but also to begin offending later in the life course. Consequently, one would expect that DWI offenders are significantly less likely to have any criminal history. Those DWI offenders who do have a criminal history may begin offending later in the life course, or they may not engage in any criminal behaviors prior to their DWI. To analyze these differences, I re-estimated descriptive tables and ANOVA analyses using only offenders with a criminal history. The average age of onset reduced by only 2 or 3 years for each group of offenders, and general patterns and significant differences remained.

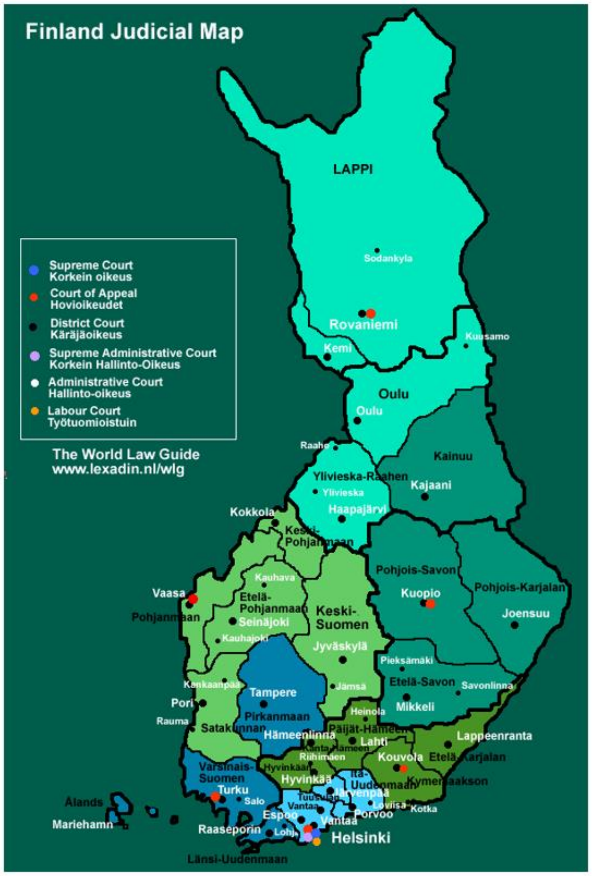
An alternative explanation could be due to the limited availability of criminal history data. Earlier analyses showed that DWI offenders were significantly older than non-DWI offenders. Our data are limited to 8 years prior to the primary offense. Consequently, for older offenders in the dataset, we do not have information on their offending, or lack thereof, in early adulthood. While this data limitation affects all groups of offenders, the impact on analysis of age at onset is greatest for offenses with larger numbers of older offenders. These limitations may exacerbate the differences in the average age at onset between DWI and non-DWI offenders and suggests that age at onset may not be a reliable measure for the rest of the analyses.

Region

Certain cities may have more criminal opportunities. Alternatively, some regions may have higher rates of crime because they have a larger law enforcement presence, increasing the probability that offenders are arrested. In addition, differences in court communities likely influence differences in patterns of sentencing and supervision. Thus, I wanted to include some measure of location in attempt to capture location-based differences in offending and recidivism.

The country of Finland was divided into 19 regions (maakunta) after abolishing the former province system in 2009. Around the same time, the district court system was restructured from 54 district courts to 27. The jurisdiction of each district court varies in land and population size. The data for this study included district IDs reflecting the old and new jurisdictions. I recoded all of the old district IDs to reflect the current District Court jurisdictions. Figure 7 shows the boundaries of each district court jurisdiction. Large black dots show the location of the court office. Smaller black dots reflect other significant cities in the court jurisdiction.

Figure 4-7. Map of Finnish District Court Jurisdictions



Finland largely consists of small- to medium-sized towns surrounded by large rural territories. Cities are more concentrated in the southern region and very few cities exist north of the Arctic Circle. Most of the classifications for rural and urban areas correspond to particular cities or small geographic areas (for example, Statistics Finland codes the country based on a 250m x 250m grid system). Neither of these classifications directly correspond with District

Court jurisdictions. Consequently, I used information from Statistics Finland and the Organization for Economic Co-operation and Development (OECD) to determine how to classify Finnish District courts into three categories: urban, semi-urban, and rural.

One-fifth of the country's population resides in the Helsinki capital region (including Helsinki, Espoo, Vantaa, and Kauniainen). The region is connected with commuter trains and bus routes. The 3 district courts with jurisdiction over the Helsinki capital region were combined. One-fifth of the offenders in the primary offense file were convicted in one of the three courts in the Helsinki capital region (N = 16,257).

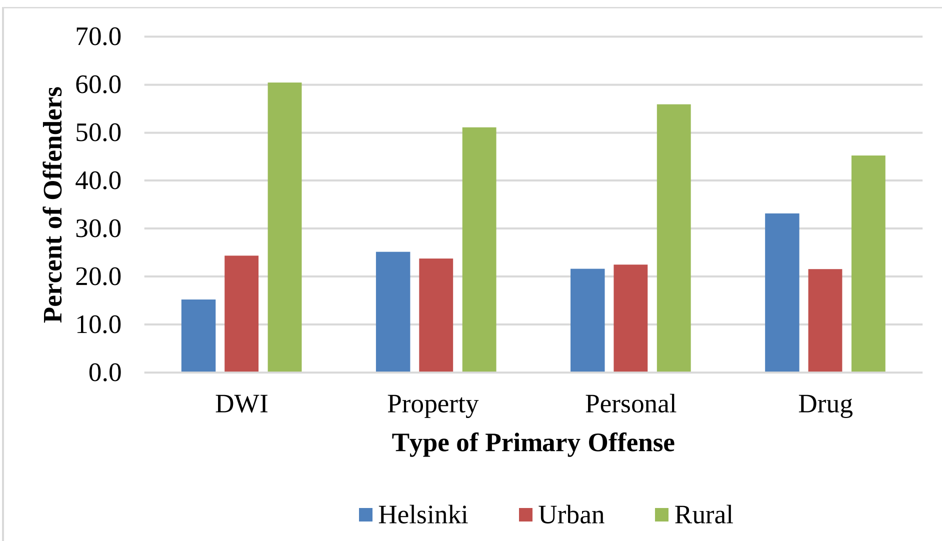
The second category, other urban, includes the greater Helsinki area, Tampere, and Turku. The greater Helsinki area includes the exurbs of Helsinki. Some individuals commute from the exurbs to work in Helsinki, though the public transportation connections are limited to longer commuter trains. The greater Helsinki region includes Hyvinkää, Järvenpää, Kerava, Kirkkonummi, Nurmijärvi, Sipoo, Tuusula, Mäntsälä, Pornainen, and Vihti provinces. Tampere and Turku are the two largest Finnish cities behind Helsinki. Over 300,000 people reside in each of these medium-sized urban areas.[74] Nearly a quarter of the offenders in the primary offense file were convicted in a district court located in one of these other urban provinces (N = 19,604).

I coded the remaining district courts as small urban\rural. About half of the population in Finland resides in rural areas. Another 10-15% of the population lives in small urban areas dispersed throughout the country. The district courts in these small urban\rural areas comprise a majority of the country's population. Almost 60% of the offenders in the primary offense file were convicted in a district court located in a small urban or rural area (N= 47,147).

[74] Tampere and Turku are labeled Medium-sized urban areas by the OECD.

Figure 4-8 shows the distribution of offenders by region for each of the four primary offense categories. The majority of offenders in each category were convicted in rural areas. The rate of property offending and personal offending was similar in urban areas (23.7% and 22.5%, respectively) and the Helsinki region (25.2% and 21.6%). Drug offenders were more likely to be convicted in the Helsinki region (33.2%) than other urban areas (21.6%). DWI offenders were more likely to be convicted in other urban areas (24.4%) than the Helsinki region (15.2%). The distribution of offenders between regions were statistically significant $\chi^2(6, N = 65{,}840) = 1.2e{+}03$, $p = .000$.

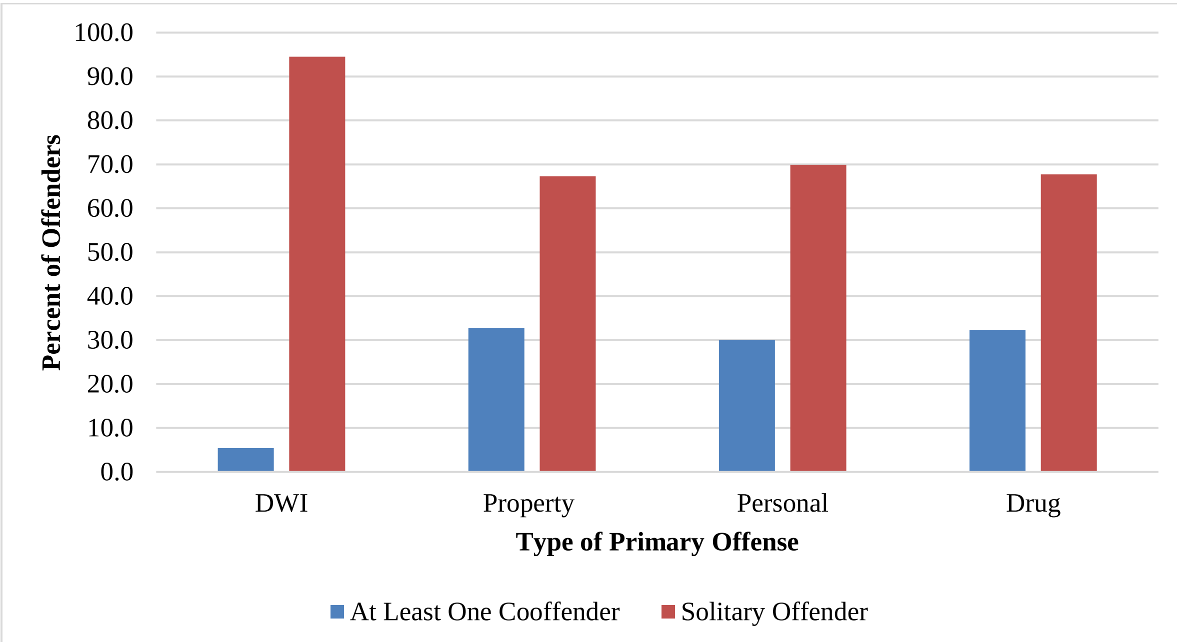
Figure 4-8. Distribution of Offenders by Region



<u>*Co-offending and Solo Offending*</u>

Register data includes a diary number for each offense. The diary is a unique indicator for the offenses and charges brought forth against an offender. These diary numbers are similar to docket numbers in the United States. If multiple offenders face charges for the same offense, they will share a diary number. As a result, co-offenders can be identified by matching offenders using diary numbers within a specific court. Using the district court ID and the diary number, I created a variable identifying whether the primary offense involved any co-offenders and, if so, how many. Overall, 79.77% of offenders were solitary offenders. Figure 4-9 shows the percent of solitary and non-solitary offenders by type of crime.

Figure 4-9. Percent of Solitary Offenders by Type of Crime



Given the nature of DWI offending, it is not surprising that DWI offenses are more likely than property, personal, or drug offenses to involve solitary offenders. Only 5.5% of DWI offenders shared a diary number with another offender. Most often, the diary number was linked to another offender who was charged with permitting an intoxicated person to drive their vehicle. Nearly a third of property (32.7%), personal (30.1%), and drug (32.3%) offenders committed their offense with at least one co-offender.

The number of co-offenders varied by type of crime. On average, non-solitary DWI offenders offended with only one other offender (mean = 1.22). Similarly, non-solitary personal offenders were also likely to offend with only one other offender (mean = 1.59). On average, non-solitary property offenders offended with 2-3 other offenders (mean = 2.52). Non-solitary drug offenders had the highest average number of co-offenders with an average of 3.03 co-offenders.

Multiple Charges

I received detailed data on the most serious primary offense for each offender, as well as detailed information for all co-offenses sentenced in the same judicial proceeding. Using these data, I constructed a binary measure to capture whether the offenders were convicted of a single charge or multiple charges. A majority of offenders were convicted of a single charge (64.18%).

The percent of offenders convicted of multiple charges varied by type of crime. Personal offenders were least likely to face multiple convictions (34.0%) followed by drug offenders (36.2%) and property offenders (37.1%). DWI offenders were most likely to be convicted of multiple charges (41.4%). An overwhelming majority (93.1%, N = 11,396) of the DWI offenders convicted of multiple charges were convicted of at least one other traffic offense in addition to their DWI offense. The percent of offenders convicted of multiple charges were statistically significantly different across the types of crime $\chi^2(3, N = 65{,}840) = 267.01$, $p = .000$.

Criminal History

The data for this study included detailed information for prior convictions. Finland does not have classifications for "summary," "misdemeanor," and "felony" offenses. However, the Finnish criminal justice system does separate less serious and more serious offenses. More serious offenses (most similar to felonies in the United States) are processed through criminal courts and result in criminal convictions. Criminal convictions include all offenses that are eligible for imprisonment sentences. The finding of guilt and issuance of punishment for criminal convictions is made by a district court judge. Less serious offenses (most similar to misdemeanors in the United States) are sentenced to summary penal fines. While summary penal fines are technically convictions, they are more streamlined than court convictions. Summary penal fines are issued directly by prosecutors. The least serious offenses (most similar to summary offenses in the United States) are the most streamlined and are associated with fixed fines instead of summary penal fines. Fixed fines are administered by the police. Summary penal fines and fixed fines may be challenged in the district court if the offender disagrees with the decisions made by the prosecutor or the police.

Data from the Legal Register Center included criminal convictions beginning in 1999 and summary penal fines beginning in 2001. I used these data to create four criminal history measures: a measure of the total criminal history including criminal convictions and summary penal judgments, a measure of the total number of criminal convictions, a measure of the total number of summary penal judgments, and binary indicators for the type of prior offenses in an offender's overall criminal history.

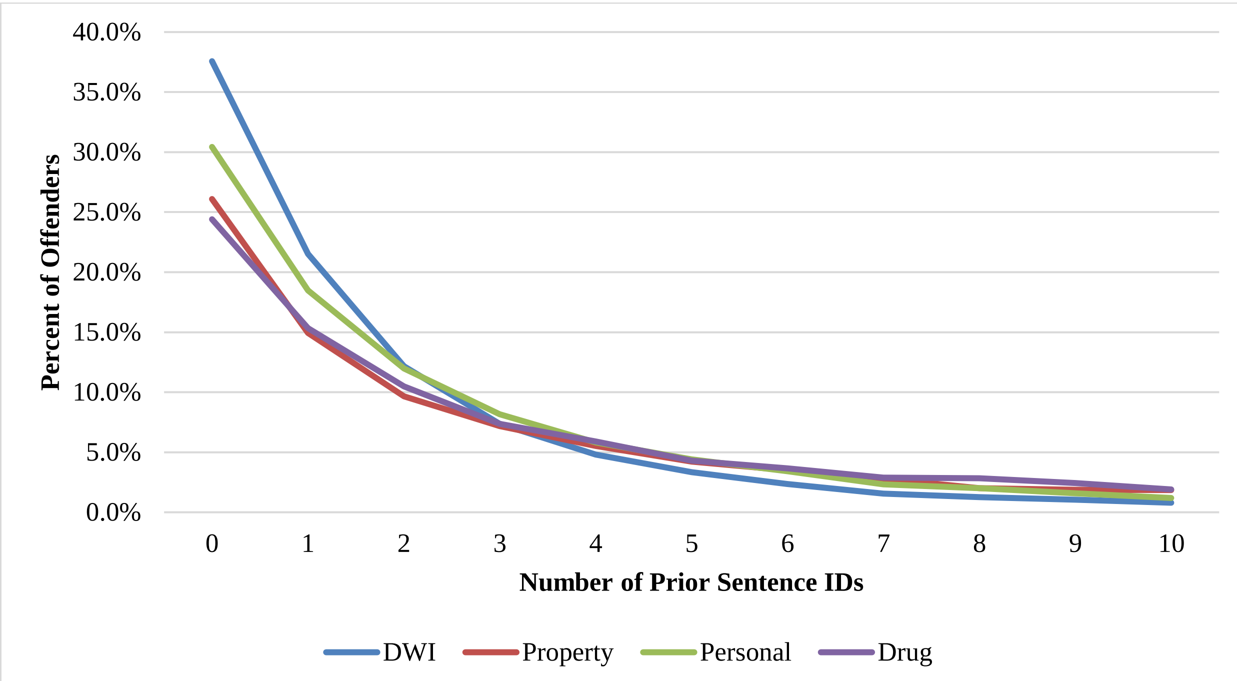
Quantitative Criminal History

The total number of prior sentence IDs (criminal convictions and summary penal fines) ranged from 0 to 543.[75] A third of all offenders (33.64%) had no prior sentence IDs. Another fifth of the data (19.17%) had only one prior sentence ID. The percent of offenders rapidly decreased with each additional prior sentence ID, with 89.74% of offenders having 10 or fewer prior sentence IDs. The general pattern of prior sentence IDs was consistent across all four crimes. However, DWI offenders were significantly less likely than other types of offenders to

[75] I manually checked several of the offenders who had extraordinarily large numbers of prior sentence IDs. There was nothing to suggest that these records were the result of any errors in the database. Instead, many of these offenders had a robust history of minor offenses, such as petty thefts. For example, one offender had multiple theft convictions on a monthly basis for several years.

have any prior sentence IDs. Figure 4-10 shows the percent of offenders with 0 to 10 prior sentence IDs for each of the four categories of offenders.

Figure 4-10. Total Prior Sentence IDs by Type of Crime

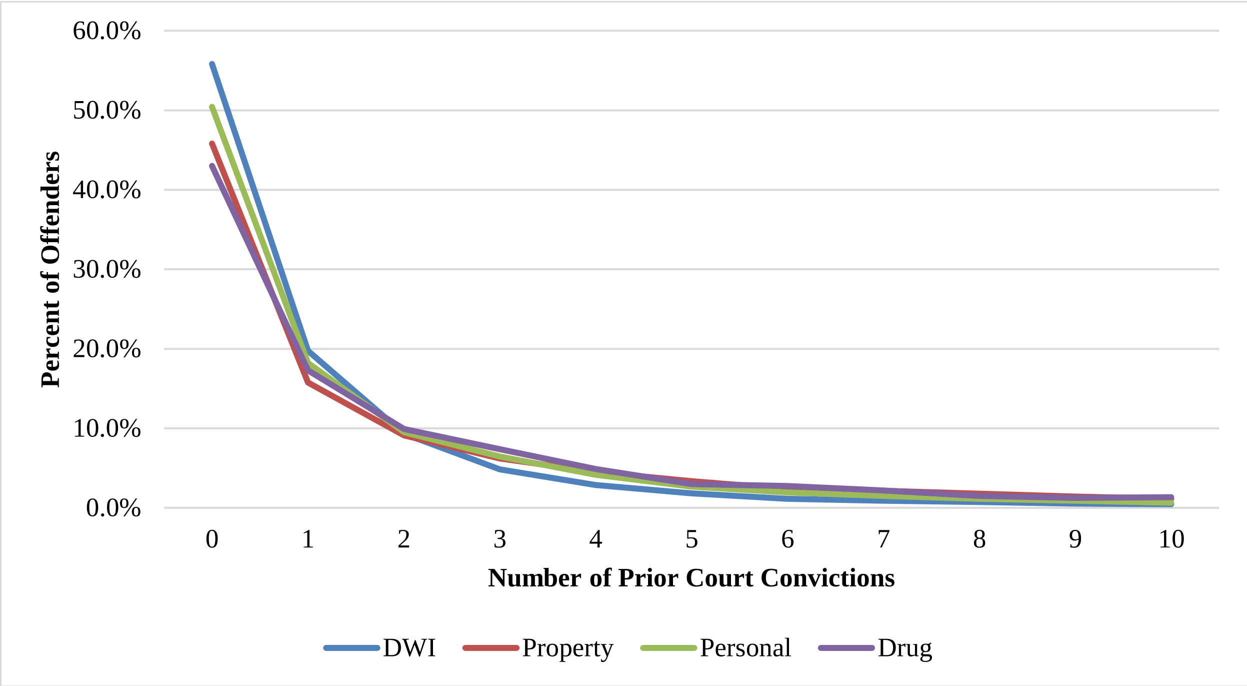


An ANOVA analysis indicated that average differences in prior sentence IDs were significantly different across the four crime types $F(3, 65836) = 817.04$, $p = 0.000$, post-hoc Tukey-Kramer test $p = 0.000$. On average, DWI offenders had the lowest number of prior sentence IDs (M = 2.97). Personal offenders had the second lowest number of prior sentence IDs (M = 4.33). Drug offenders had the third lowest number of prior sentence IDs (M = 6.72). Property offenders had the highest number of prior sentence IDs (M = 7.69). There were several outliers that likely drove up the average number of prior sentence IDs for this group as a whole (e.g., offenders with 177 – 543 prior sentence IDs). Many of these property offenders had lengthy records of petty thefts, rather than long records of more serious crimes.

As a sensitivity analysis, I recalculated the average number of prior sentence IDs after removing offenders with more than 10 prior arrests (about 10% of the data). The results of this additional analysis confirmed the strong effect of outliers for non-DWI offenders. The average number of prior sentence IDs was significantly lower for all offenses, but the reduction was largest for non-DWI offenders. After removing the top 10% of prior sentence IDs, the average number of sentence IDs was lowest for DWI offenders (1.67 IDs) followed by personal offenders (2.13 IDs), property offenders (2.40 IDs) and drug offenders (2.57 IDs). Interestingly, when the outliers are removed, drug offenders, rather than property offenders, have the highest average number of prior sentence IDs. Despite the increased similarity, an ANOVA analysis indicated the differences between means were still highly significant, across the four crime types $F(3, 58401) = 364.45$, $p = 0.000$, post-hoc Tukey-Kramer test $p = 0.000$.

Next, I divided the total prior sentencing IDs into the prior criminal convictions and prior summary penal fines to test for differences in the seriousness of prior offending. General patterns for prior criminal convictions were the same as the total criminal history measure (see Figure 4-11). However, the range of prior court convictions was more limited than prior sentence IDs (0 to 48). The majority of offenders (54.65%) had no prior court convictions. Virtually all of the offenders had 10 or fewer prior court convictions (96.99%). The amount of prior criminal convictions rapidly decreases with each additional conviction. These patterns were consistent across crime types and once again, DWI offenders were the least likely to have any prior criminal convictions. Property and drug offenders had the highest average number of prior court convictions.

Figure 4-11. Prior Court Convictions by Type of Crime

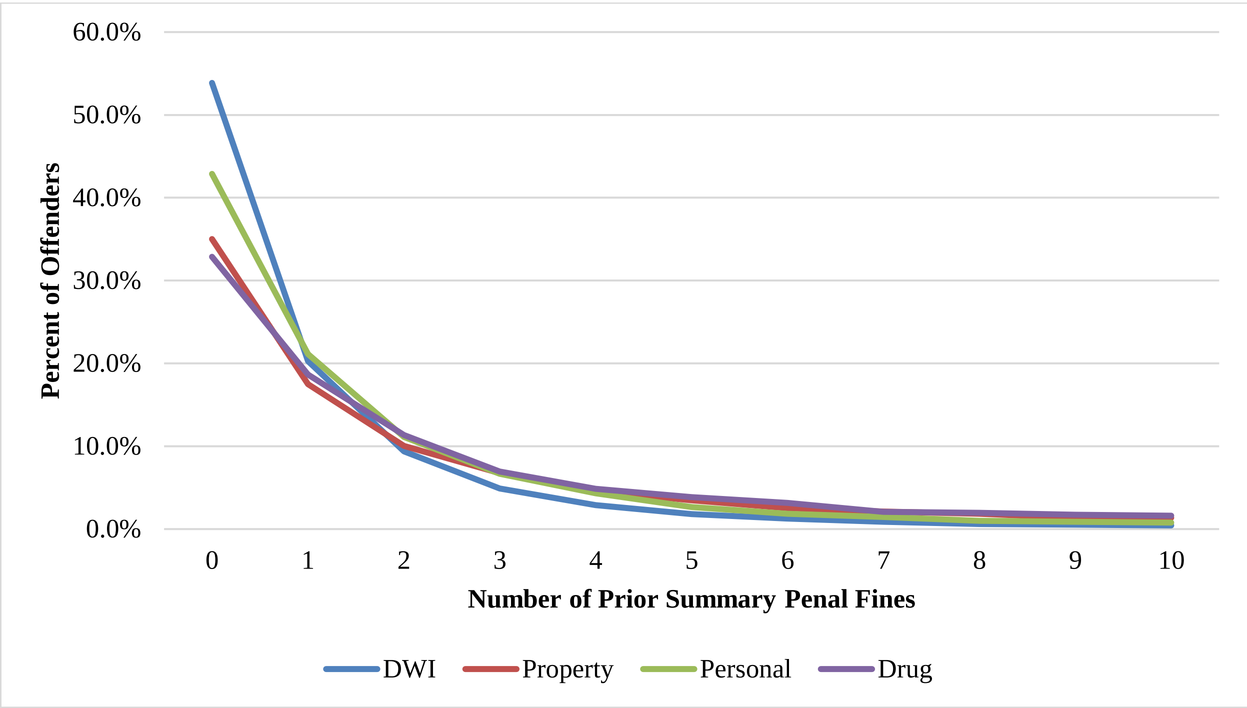


An ANOVA test indicated that the average number of prior court convictions were significantly different for the four types of crime, F(3, 65836) = 555.42, p = 0.000. A post-hoc Tukey-Kramer test indicated that the average prior court convictions for DWI (1.30), property (2.56), personal (1.69), and drug (2.47) were all significantly different from each other (p = 0.000) except for property and drug offenders (p = 0.440).

I performed the same analysis on the number of prior summary penal fines. The general trends for summary penal fines mirrored the trends for total sentence IDs and prior court convictions (see Figure 4-12). The substantial range for summary penal fines (0 to 510) explains the substantial range for total sentence IDs. This finding is consistent with the extensive criminal history for property offenders including a series of small thefts, which are processed using summary penal fines. The percent of offenders rapidly decreased with each additional summary penal fine. Almost all of offenders (94.03%) had 10 or fewer prior summary penal fines. DWI offenders were least likely to have any prior summary penal fines (53.87%). Property offenders

(65.0%) and drug offenders (67.1%) were the most likely to have at least one prior summary penal fine.

Figure 4-12. Prior Summary Penal Fines by Type of Crime



An ANOVA test confirmed that the average number of prior summary penal fines were significantly different for the four types of crime, $F(3, 65836) = 730.29$, $p = 0.000$. A post-hoc Tukey-Kramer test indicated that the average prior summary penal fines for DWI (1.67), personal (2.64), drug (4.25), and property (5.13) offenders were all significantly different from each other ($p = 0.000$). As a sensitivity analysis, I truncated this variable at 10 prior summary penal fines and again estimated the ANOVA analysis. The average number of summary penal fines decreased for all types of offenders, converging across the four groups (DWI = 1.05; property = 1.90; personal = 1.47; drug = 2.04) although differences were still statistically significant, F(3, 61512) = 652.86, $p = 0.000$. A post-hoc Tukey-Kramer test confirmed that the mean differences were statistically significant for each pair of offense types, $p \leq .001$.

Decomposing criminal history revealed a few important trends. First, the overall patterns in criminal history were similar for all types of crimes and all three measurements of criminal history – total sentence IDs, court convictions, and summary penal fines. However, differences in criminal history were greatest for less serious offenses as marked by differences in the percent of offenders with no prior summary penal fines. Overall, prior summary penal fines were more common than prior court convictions. The difference between prior court convictions and prior summary penal fines were greatest for non-DWI offenses.

Figure 4-13. Percent of Offenders with Any Criminal History

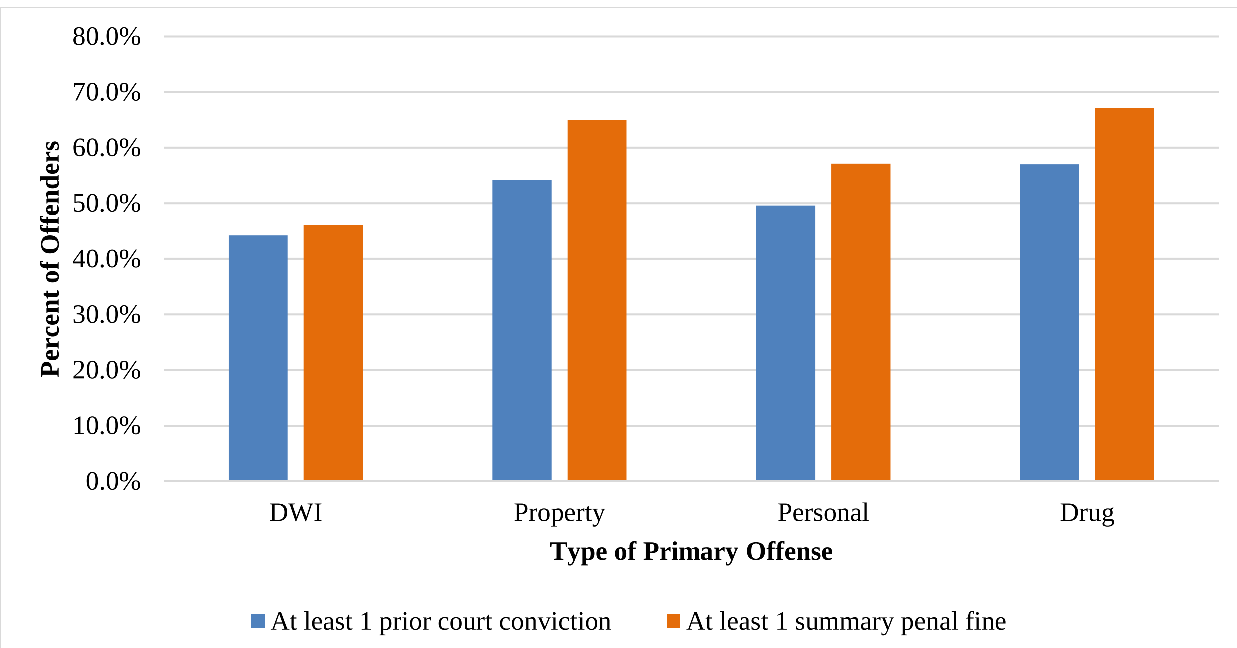


Figure 4-13 depicts the percent of offenders in each crime category with at least one prior court conviction or at least one prior summary penal fine. Less than half of DWI offenders had any prior court convictions (44.2%) or any prior summary penal fines (46.1%). Nearly half of all personal offenders at least one prior court conviction (49.6%), but more than half of all personal offenders had at least one prior summary penal fine (57.1%). Property and drug offenders were the most likely to have prior sentence IDs generally, and they also had the greatest differences in the types of criminal history. For property offenders, 54.2% of all offenders had at least one prior court conviction, but 65.0% had at least one prior summary penal fine. Similarly, 57.0% of all drug offenders had at least one prior court conviction, while 67.1% of all drug offenders had at least one prior summary penal fine.

Qualitative Criminal History

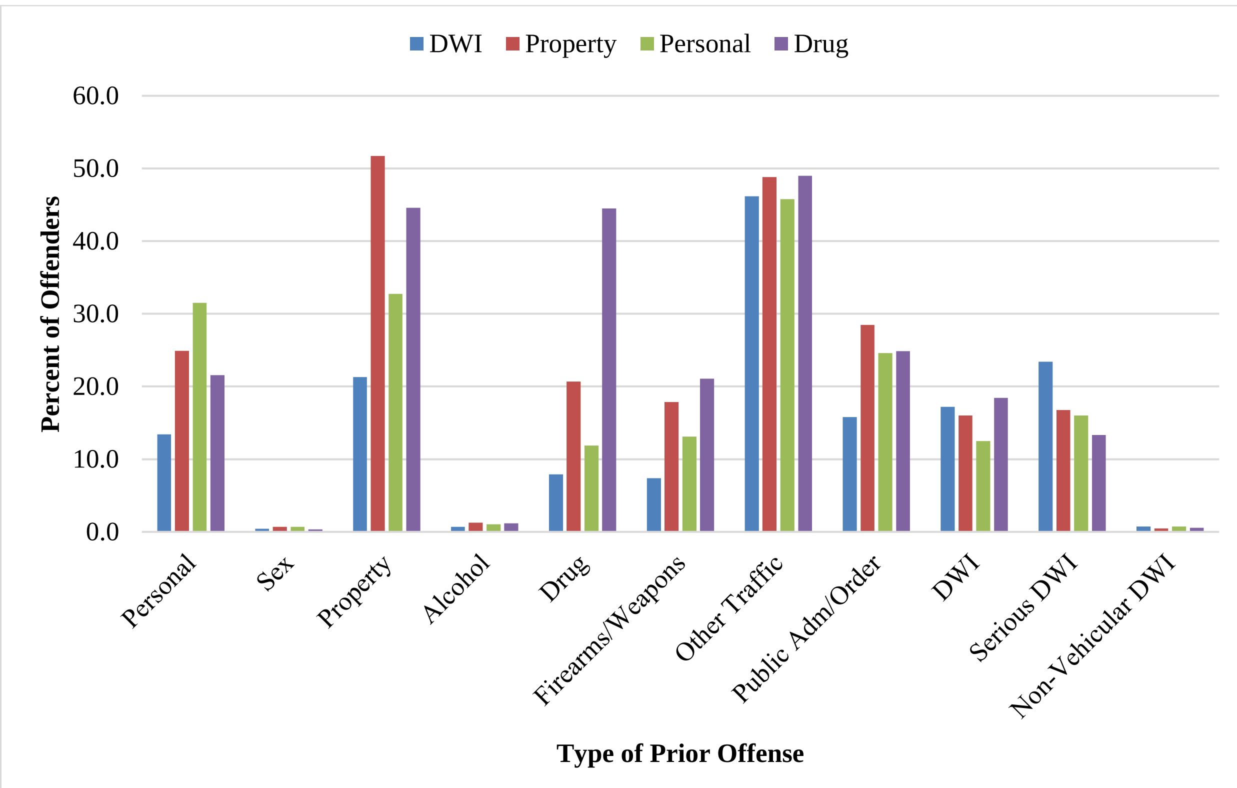
I also used data on prior court convictions and prior summary penal fines to create measures of the types of prior criminal behaviors. Specifically, I coded binary measures for criminal history for each of the 11 crimes types discussed previously where the value 1 indicated that the offender had at least one prior court conviction or summary penal fine for the particular prior crime type. These categories were not mutually exclusive. Thus, offenders may have a value of 1 for multiple different types of prior offending (e.g., personal, drug, and other traffic).

Each of the 11 prior crime types were significantly different for DWI and non-DWI offenders. Non-DWI offenders were significantly more likely than DWI offenders to have prior personal, sex, property, alcohol, drug, firearms/weapons, other traffic, and public administration/public order court convictions or summary penal fines (p = 0.000). However, DWI offenders were significantly more likely than non-DWI offenders to have prior DWI, serious DWI, and non-vehicular DWI court convictions or summary penal fines (p = 0.000; p = 0.000; p = 0.021, respectively).

Analyzing prior types of criminal history offers a second opportunity to evaluate the level of specialization present among offenders in Finland. I compared the four previously discussed crime categories (DWI, property, personal, and drug) for each of the 11 types of prior crimes.

Figure 414 shows the percent of offenders in each primary offense category who had at least one prior sentence for each of the 11 crime categories. Interestingly, the results do suggest some degree of specialization. Specifically, personal offenders were the most likely to have a sentence for a prior personal offense (31.5%). Property offenders were the most likely to have a sentence for a prior property offense (51.7%). Drug offenders were the most likely to have a sentence for a prior drug offense (44.5%). DWI offenders were the most likely to have a sentence for a prior DWI (17.2%) or serious DWI (23.4%).

Figure 4-14. Type of Prior Sentences by Type of Crime



DWI offenders were the least likely to have any type of non-DWI prior offense.[76] Differences between the rates of prior sex offenses, alcohol offenses, and non-vehicular DWI

[76] Sex offenses and other traffic offenses are the only exceptions, but the differences were not meaningful. Overall 0.41% of DWI offenders had a prior sex offense and 0.34% of drug offenders had a prior sex offense – a negligible

offenses were statistically significant across the four crime types, but these prior offenses were rare, and the differences between the four primary offense types was not meaningful. The largest difference between any two primary offenses for any of these three prior offenses was .5%.

Differences between the four primary offenses for other prior offense types varied. A few noticeable patterns emerged. Other traffic offenses were common for all offenders (ranging between 45.8% and 49.0%). Prior drug offenses were far less common for non-drug offenders (ranging from 7.9% to 20.7%) than for drug offenders (44.5%). Property offenders were the most likely or the second most likely to have any type of prior offense with the exception of normal DWIs. However, the difference in the percent of property, personal, and drug offenders with a prior DWI were small (16.0%, 12.5%, and 18.4%, respectively).

Overall, these findings suggest that qualitative variables capturing the type of prior offending may provide additional information about the current and future behavior of offenders. These findings provide another opportunity to reveal both generalization and specialization in offending. Each group of offenders was more likely than other groups of offenders to have previously committed the same type of offense as their current offense, and, this specialization was especially noticeable among DWI offenders.

Finally, I obtained information on prior incarcerations for offenders in the dataset. Prior incarcerations may be related to future offending because it serves as a proxy measure for the seriousness of prior offending. Alternatively, prior incarceration may have a direct criminogenic effect by embedding offenders in delinquent networks or may have an indirect criminogenic effect by isolating offenders from prosocial community networks. These processes suggest that

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difference. Similarly, 46.2% of DWI offenders had a prior other traffic offense and 45.8% of property offenders had a prior other traffic offense – a negligible difference.

incarceration may increase the probability of future offending. Overall, DWI offenders were the least likely to have a prior incarceration.

Criminal Justice Responses

The data include a measure for the type of sentence imposed for each judicial proceeding. These sentences include unconditional prison sentences, community service, conditional prison sentences, and fines. I coded these data into a categorical variable capturing the most serious type of sentence for each offender. I ordered seriousness of sentence as: unconditional imprisonment, community service, conditional imprisonment, and other sentence (mostly fines) whereby unconditional imprisonment is the most serious sentence and an "other" sentence was the least serious sentence.[77] Thus, if an offender received community service and a fine, they were placed into the community service group rather than the fines group.

[77] Conditional imprisonment sentences are suspended sentences. Consequently, if the offender does not recidivate, they are not required to actually complete the incarceration sentence. Suspended sentences are considered to be less serious than community service sentences.

Figure 4-15. Sentences by Type of Crime

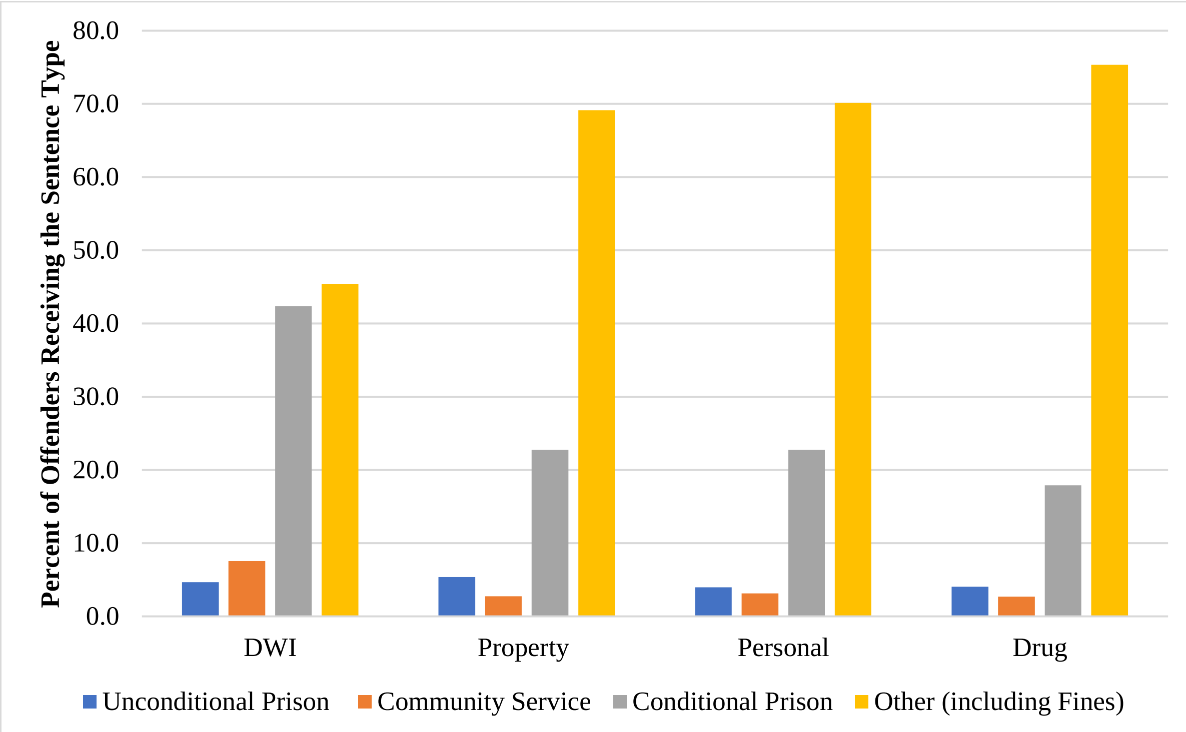


Figure 4-15 depicts the most serious type of offense for offenders by each of the four categories of crime. Overall, DWI offenders were more likely than non-DWI offenders to receive more harsh punishments. DWI offenders were the least likely to receive a fine as the most serious sentence. DWI offenders were the most likely to receive a prison sentence, either conditional or unconditional. In addition, DWI offenders were the most likely to be sentenced to community service. These findings suggest that DWI offenders are consistently treated more harshly than non-DWI offenders in the criminal justice system.

<u>Part 1: Review of Findings</u>

The comparisons in Part 1 provide an interesting look at the similarities and differences between DWI and non-DWI offenders. In general, overall patterns in the independent variables are consistent across all types of offenses. For example, males commit more offenses than females. Younger offenders commit more crimes than older offenders. The majority of offenders have no, or very little, criminal history.

Despite these similarities, there were statistically significant differences between DWI and non-DWI offenders for nearly all categories of all independent variables. It is not surprising to find so many significant differences given the large sample size of the data. Thus, it is important to not only consider whether these differences are statistically significant but also whether these differences are meaningful. The following is a review of the findings as they pertain to the individual hypotheses presented at the beginning of this chapter.

Gender

Hypothesis 1: (a) Males will be more likely than females to commit all offenses, however, (b) the gender gap will be narrower for DWI offending than for non-DWI offending. <u>Partially Supported</u>

Males were more likely than females to commit all offenses, but the gender gap was significantly larger for DWI offenses than for non-DWI offenses. In fact, DWI offenses had the smallest proportion of female offenders. Consistent with research showing that females are more likely to engage in small scale property offenses (Steffensmeier and Allan, 1996), the gender gap was narrowest for property offenses. The fact that the gender gap in DWI offending is large suggests that there may be strong gendered norms about drinking. Despite the promotion of gender equality in Finland, it is possible that traditional norms about women and excessive alcohol-use persist.

Alternatively, the increasing equality observed in patterns of drinking may not be unique to changing gender roles and the consumption of alcohol. Rather, the increasing equality in the consumption of alcohol may reflect more general increases in gender equality in Finland

(Mäkelä et al., 2012). In addition, the liberalization in drinking behaviors among women facilitated new relationships between women and individuals outside the family and has facilitated changes in institutions such as pubs and restaurants that were traditionally characterized as locations for male social gatherings (Mäkelä et al., 2012). These changes in social roles for women may also lead to an increase in women's participation in non-DWI offending. Additional research analyzing changes in the gender gap for multiple crime types across time is necessary to determine how increases in gender equality differentially impacted DWI and non-DWI crimes.

Age

Hypothesis 2: (a) On average, DWI offenders will be older than non-DWI offenders, and (b) the age of DWI offenders will peak later and decline more slowly than non-DWI offenders. <u>Supported</u>

The findings for age were consistent with prior research, such that all crimes peaked in early adulthood and declined through the life course. Supporting hypothesis 2a, DWI offenders had the oldest average age at date of sentence. The average age of DWI offenders was 10 years greater than the average age for drug offenders. Supporting hypothesis 2b, the age of DWI offenders showed a slower decline than the age of property, personal, and drug offenders. Consistent with other research on DUI offending in the US, Finnish DWI offenders showed a second peak in their age-crime curve with the rate of offending increasing between the ages of 40 and 50.

Surprisingly, personal offenders also exhibited a small second peak among middle-aged offenders (between 25 and 45). This similarity in the patterns of personal and DWI offending may have similar causes. Specifically, much of the personal and violent offending, such as aggravated assault and homicide, in Finland is associated with the consumption of alcohol. Therefore, the similarity in these age-crime curves may represent an overall increase in alcoholic consumption and related behaviors through the life course.

Although there were no original hypotheses about age of onset for criminal behaviors, it is interesting to note that DWI offenders were more likely to be late-onset offenders than property, personal, or drug offenders. However, these findings may be biased due to restrictions in the availability of criminal history data in Finland. Consequently, I do not draw any conclusions about the observed relationships for age at onset of offending.

Location

Hypothesis 3: (a) Non-DWI offenses will be more likely to occur in urban areas than in rural areas, but (b) DWI offenses will be more likely to occur in rural areas than in urban areas. Partially supported.

Drug offenses were the only type of offense that occurred more often in urban areas than rural areas. More than 50% of DWI, property, and personal offenses occurred in rural areas. These findings are likely due to the disproportionate concentration of the Finnish population in rural areas. The majority of theories which suggest crime is concentrated in urban areas were developed in the United States, where the population of the country is largely concentrated in urban areas. Consequently, the inconsistency in these overall findings with existing theories are likely representative of underlying differences between the United States and Finland.

Overall, DWI offenders were the most likely to be convicted in rural areas (60.4%) and the least likely to be convicted in the Helsinki region (15.2%). The difference in the percent of DWI offenders in the Helsinki region and DWI offenders in rural areas was larger than difference in the percent of non-DWI offenders in the Helsinki region and non-DWI offenders in rural areas. These findings do support the notion that DWI offenders are likely to be uniquely concentrated in rural areas compared to non-DWI offenders.

The Helsinki region has the most robust public transportation system, composed of buses, trams, and trains. In addition, taxis and Uber[78] are more common in the Helsinki region than in other urban or rural areas. Consequently, individuals who are drinking or doing drugs have better access to alternative forms of transportation, whereas individuals in rural areas likely have few alternatives to driving. Unlike property, personal, or drug crimes, where the opportunity to commit crime is greater in urban areas, there is greater opportunity for DWI offenses in rural areas.

Co-offending and Solo Offending

Hypothesis 4: DWI offenders will be more likely to be solo-offenders than non-DWI offenders. <u>Supported</u>

Consistent with hypothesis 4, DWI offenders were the least likely to have co-offenders for the primary offense. In instances when DWI offenders were linked with co-offenders, the co-offender was most commonly charged with permitting an intoxicated person to drive their vehicle. For all other offenses, nearly one-third of the offenders were associated with at least one co-offender.

Frequency of Prior Offending

Hypothesis 5: On average, DWI offenders will have fewer prior convictions than non-DWI offenders. <u>Supported</u>

[78] Uber is technically illegal. However, it is illegal only for drivers and not customers. Consequently, people still take advantage of this alternative taxi service in urban areas.

On average, DWI offenders had fewer prior sentences that non-DWI offenders. Unsurprisingly, property and drug offenders had the highest average number of prior sentences. These patterns held true for both prior court convictions (serious offenses) and summary penal judgments (less serious offenses). DWI offenders were also the most likely to be first-time offenders, with no prior court convictions or summary penal judgments.

While general patterns across all three measures of criminal history (total prior sentences, prior court convictions, and prior summary penal judgments) were consistent, the findings reveal that composite measures of total criminal history are driven largely by less serious offenses (summary penal fines). Consequently, these findings suggest that alternative considerations of criminal history, such as separating prior court convictions and summary penal fines may be important. In addition, these findings suggest that including only measures of prior court convictions significantly underestimates prior offending behaviors, particularly for property and drug offenders.

Types of Prior Offending and Specialization

Hypothesis 6: DWI offenders are more likely than non-DWI offenders to specialize in one particular type of offending. Partially Supported

Specialization was more common for DWI offenders than for most non-DWI offenders. Property offenders and Other Traffic offenders were more likely than DWI offenders to recidivate with a property, other traffic, or DWI offense, respectively. Recidivism with a DWI was significantly more likely with offenders whose primary offense was also a DWI than for offenders whose primary offense was a property, personal, or drug offense.

In addition, DWI offenders were the least likely to have any type of non-DWI prior offense. DWI offenders were the most likely to have a prior DWI or DWSI offense on their record. Taken together, these findings suggest that there is notable specialization among DWI offenders that is not as prevalent with property, personal, or drug offenders. Consistent with the criticism of the Marowitz typology of DWI offenders introduced in Chapter 2, it appears that there is both a group of DWI offenders who widely participate in other types of criminal or anti-social behaviors and a group of DWI offenders who commit only DWI offenses.

Types of Sentences

Hypothesis 7: DWI offenders will receive (a) fewer incarceration sentences than non-DWI offenders but (b) more intermediate punishments than non-DWI offenders. Partially Supported.

DWI offenders were more likely to receive harsh sanctions overall. DWI offenders were more likely than non-DWI offenders to receive an unconditional prison sentence, a community service sentence, or a conditional prison sentence. The largest differences were for intermediate punishments (community service and conditional prison sentences) providing support for hypothesis 7b. DWI offenders were overwhelmingly the least likely to be sentenced simply to economic sanctions or some lesser sanction. These findings likely reflect the Finnish criminal justice system's low tolerance for DWI behaviors. These findings provide support for the previously discussed cultural differences in how Finnish society views DWI offenses compared to more tolerant countries, such as the United States.

Recidivism

Hypothesis 8: DWI offenders will be less likely to recidivate than non-DWI offenders. Supported

Consistent with hypothesis 8, DWI offenders were less likely to recidivate than almost all non-DWI offenders. Sex offenders were less likely than DWI offenders to recidivate, but this may represent a lack of detection among sex offenders rather than a true difference in desistance from criminal behaviors. Recidivism rates for DWI were most similar to the recidivism rates for other traffic offenders, providing support for Marowitz's hypothesis that most DWI offenders are problem drinkers who drive, rather than serious criminals.

Part 2: Burgess Risk Instruments and DWI Offending

The second section of this chapter includes the analysis of DWI offenders and recidivism. This section uses the development of Burgess risk assessment instruments as a method of identifying characteristics related to recidivism among DWI offenders. In addition to identifying correlates of recidivism, Burgess risk assessment instruments establish a tool that may be used by practitioners to identify offenders who are most and least likely to recidivate.

This section proceeds in four parts. First, I describe the sample used to develop and validate Burgess risk assessment instruments. Second, I use the development sample to evaluate basic descriptive and bivariate statistics for DWI offending and recidivism. These analyses are performed for two separate dependent variables – general recidivism and DWI specific recidivism. Third, I conduct multivariate analyses to identify the variables that are statistically significantly related to recidivism. Significant variables are subsequently used to construct a Burgess risk assessment scale. Finally, I validate the Burgess risk assessment scale using the validation sample. This validation ensures that the scale does not overfit the data used in the development sample.

Sample Selection

The development of risk assessment instruments requires two independent samples: a development sample and a validation sample.[79] My starting sample included all offenders convicted of a DWI in Finland in 2008 or 2009. In order to create separate development and validation samples, I used SPSS to select a random sample of 50% of all offenders. The selection of a random sample minimizes the risk that the two samples will be systematically different from each other. In addition, neither sample should be systematically different from the overall sample.

The randomization process created a binary variable separating the two samples. I chose to select offenders receiving a “1” to be selected for the development sample. Offenders receiving a 0 were reserved for the validation sample. The selection process resulted in 14,901 offenders in the development sample and 14,981 offenders in the validation sample.[80] I compared the two samples using descriptive statistics to ensure that the randomization process avoided any systematic differences between the two samples, and there were none.

Any Reconvction

Coding Variables

Developing Burgess risk assessments instruments require additional considerations for coding the previously discussed independent variables. Specifically, Burgess risk assessment instruments require categorical variables to assign points for the calculation of a final risk score.

[79] Validation samples are sometimes referred to as test samples in risk assessment literature.
[80] I used SPSS random sampling procedures to split the sample into development and validation. In SPSS, you may specify an approximate, but not exact, percent of the observations to be selected. In this instance, I selected 50% of the sample, resulting in 49.9% of the sample in the “development” group and 50.1% of the sample in the “validation” group.

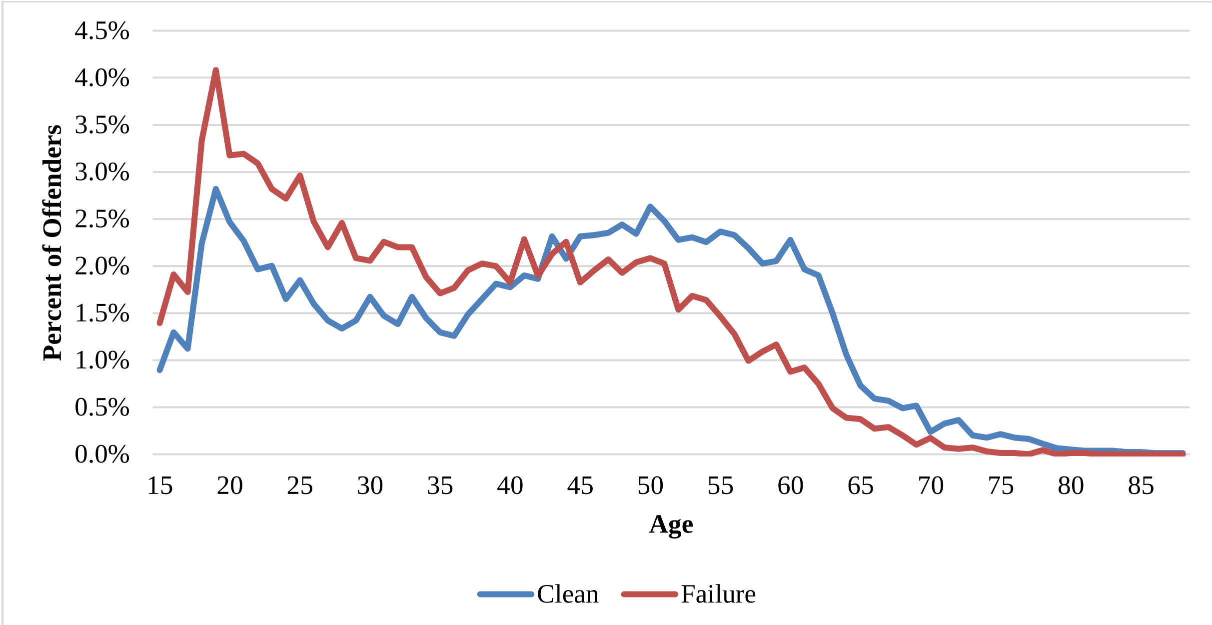
Consequently, I had to convert continuous variables such as age at sentence or number of prior sentences into categorical variables. Deciding how to categorize a continuous variable requires invokes questions of theory and statistics.

Age

My research questions concern crimes directly related to the consumption of alcohol. Thus, it was important to consider how age is related to access to alcohol in Finland. For example, at age 18, Finns can possess and purchase beer and alcohol with an alcohol by volume (ABV) percentage between 1.2% and 22%. Also at age 18, Finns are legally allowed to drink in bars, clubs, and restaurants. As a result, the risk of driving while intoxicated should significantly increase at age 18. However, at age 20, Finns can possess and purchase alcohol with an ABV of 23% and greater, further increasing the risk of serious intoxication. These social and structural features of Finnish society result in three unique risk groups: those under 18, those aged 18 and 19, and those over the age of 20.

Prior research on the age-crime curve indicates that offending general peaks in early adulthood and rapidly declines with age. However, the previous analysis suggests that the age-crime curve for DWI offenders is flatter, with the possibility of a second peak during middle-aged years. However, it is unclear how this varying age-crime curve may influence the relationship between age and recidivism for DWI offenders. I conducted bivariate analyses between age and recidivism to evaluate the relationship between age and my key independent variable – recidivism. Figure 4-16 shows a visual representation of the distribution of DWI offenders who recidivate and those who do not by their respective ages.

Figure 4-16. Age distribution and Recidivism for DWI Offenders



Bivariate analyses confirm the previously identified patterns. DWI offenders are most likely to recidivate in early ages. Rates of recidivism decline through the life course, but plateau temporarily during middle ages (roughly 35-50). Younger offenders are more likely to recidivate than not. Around age 45, the probability of recidivism reverses such that older offenders are more likely to desist from crime rather than recidivate. This pattern indicates that there are significant differences for the likelihood of recidivism by age. However, the best groupings of offenders by age are still unclear.

Table 4-5 provides an alternative look at the relationship between age and recidivism. This table presents the percent of DWI offenders who recidivate for each specific age. When transforming continuous variables into categorical variables, the goal is to identify similar groups in order to maintain the natural relationship between the continuous variable and the dependent variable, including any curvilinearity. Consequently, I looked for groups of offenders who were similar in their probability of recidivism across different ages.

Table 4-5. Probability of Recidivism by Age for DWI Offenders in the Development Sample. (N = 14,901)

		Clean		Failure		Total
		N	%	N	%	N
age	15	71	42.3%	97	57.7%	168
	16	103	43.6%	133	56.4%	236
	17	89	42.6%	120	57.4%	209
	18	178	43.4%	232	56.6%	410
	19	224	44.1%	284	55.9%	508
	20	196	47.0%	221	53.0%	417
	21	180	44.8%	222	55.2%	402
	22	156	42.0%	215	58.0%	371
	23	159	44.8%	196	55.2%	355
	24	131	40.9%	189	59.1%	320
	25	147	41.6%	206	58.4%	353
	26	127	42.5%	172	57.5%	299
	27	113	42.5%	153	57.5%	266
	28	106	38.3%	171	61.7%	277
	29	113	43.8%	145	56.2%	258
	30	133	48.2%	143	51.8%	276
	31	117	42.7%	157	57.3%	274
	32	110	41.8%	153	58.2%	263
	33	133	46.5%	153	53.5%	286
	34	115	46.7%	131	53.3%	246
	35	103	46.4%	119	53.6%	222
	36	100	44.8%	123	55.2%	223
	37	118	46.5%	136	53.5%	254
	38	131	48.2%	141	51.8%	272
	39	144	50.9%	139	49.1%	283
	40	141	52.6%	127	47.4%	268
	41	151	48.7%	159	51.3%	310
	42	148	52.9%	132	47.1%	280
	43	184	55.4%	148	44.6%	332
	44	165	51.2%	157	48.8%	322
	45	184	59.2%	127	40.8%	311
	46	185	57.6%	136	42.4%	321
	47	187	56.5%	144	43.5%	331
	48	194	59.1%	134	40.9%	328
	49	186	56.7%	142	43.3%	328
	50	209	59.0%	145	41.0%	354
	51	197	58.3%	141	41.7%	338
	52	181	62.8%	107	37.2%	288

53	183	61.0%	117	39.0%	300
54	179	61.1%	114	38.9%	293
55	188	64.8%	102	35.2%	290
56	185	67.5%	89	32.5%	274
57	174	71.6%	69	28.4%	243
58	161	67.9%	76	32.1%	237
59	163	66.8%	81	33.2%	244
60	181	74.8%	61	25.2%	242
61	156	70.9%	64	29.1%	220
62	151	74.4%	52	25.6%	203
63	119	77.8%	34	22.2%	153
64	84	75.7%	27	24.3%	111
65	58	69.0%	26	31.0%	84
66	47	71.2%	19	28.8%	66
67	45	69.2%	20	30.8%	65
68	39	73.6%	14	26.4%	53
69	41	85.4%	7	14.6%	48
70	19	61.3%	12	38.7%	31
71	26	83.9%	5	16.1%	31
72	29	87.9%	4	12.1%	33
73	16	76.2%	5	23.8%	21
74	14	87.5%	2	12.5%	16
75	17	94.4%	1	5.6%	18
76	14	93.3%	1	6.7%	15
77	13	100.0%	0	0.0%	13
78	9	75.0%	3	25.0%	12
79	5	100.0%	0	0.0%	5
80	4	80.0%	1	20.0%	5
81	3	75.0%	1	25.0%	4
82	3	100.0%	0	0.0%	3
83	3	100.0%	0	0.0%	3
84	2	100.0%	0	0.0%	2
85	2	100.0%	0	0.0%	2
86	1	100.0%	0	0.0%	1
91	1	100.0%	0	0.0%	1
91	1	100.0%	0	0.0%	1
Total	7,944		6,957		14,901

In addition, it is important to not overfit the model to the development data. Thus, making decisions based on the exact percentage of recidivism is problematic. Small changes in any given sample may alter those exact percentages, though more general trends should remain consistent.

Thus, I decided to use decade level categories, with the exception of the youngest offenders in order to account for different legal thresholds for access to alcohol in Finland. These groups are highlighted in different shades in Table 4-5.

Criminal history

Prior research on recidivism emphasizes the importance of criminal history operationalization. These concerns are especially important for research conducted outside of the United States, where criminal history may operate differently. Options for coding criminal history include the type of events included in criminal history analysis (e.g., arrests, convictions, or incarcerations) and the way criminal history is calculated (e.g., a binary measure or a multi-category nominal variable).

Coding criminal history requires consideration of practical constraints, theory, and methods. As noted in the data section, this dataset did not include complete information for arrests. In addition, the recidivism measure for this study is conviction. Using the same classification for independent and dependent variables (e.g., arrest v. conviction) minimizes the effect of error associated with the way that the variables are coded. This equalization should result in more accurate predictions. Therefore, using convictions for both the dependent and independent variables maximizes use of the data (since arrest data were not always available) while equalizing the measurement error in the independent and dependent variables.

There are two important dimensions to criminal history: quantity and quality. The frequency of prior offending may signal a greater commitment to criminal behaviors or greater access to criminal capital. In addition, different types of offenders (e.g., property or violent) may be more likely to continue their criminal behavior than others. For example, property offenders motivated by economic disadvantage may be more likely to continue offending than those who get into a bar fight because the conditions that motivate their offending (e.g., poverty) are more likely to persist throughout the life course. Thus, risk assessments must be able to capture both the frequency of prior offenses and the type of prior offenses. I include two types of criminal history measures in the initial analysis: number of prior convictions and type of prior convictions.

I coded the frequency of criminal history into a categorical variable using the same methods previously discussed for transforming age. Over a third of the sample (37.9%) had no prior convictions. Another fifth of the data (21.7%) had only one prior conviction. The remaining 40.4% of the sample ranged from 2 to 158 prior convictions. Bivariate analyses revealed clear differences in the rate of recidivism by number of prior convictions. I used this bivariate analysis to create categories of prior convictions that group similar recidivism rates while maintaining sufficient sample sizes in each category. Offenders with no prior convictions were least likely to recidivate (30.5%). Rate of recidivism increased by about 10% for each additional category. Chi-square tests confirmed that these categories of prior arrests were significantly different, $\chi^2(5, N = 14{,}901) = 2.0e{+}03$, $p = .000$.

Descriptive and Bivariate Statistics

I began my analyses by reviewing basic descriptive statistics for the development and validation samples. These analyses are largely redundant with the descriptive statistics presented in part one and will not be discussed at length. I also used these descriptive statistics to confirm that there were no systematic differences between the development and validation samples.

Next, I conducted bivariate analyses of the independent variables with recidivism. Table 4-6 presents the bivariate statistics for the development sample whereby “clean” offenders are those with no convictions during the four-year follow-up period and “failure” offenders are those with at least one conviction during the four-year follow-up period.

Table 4-6. Bivariate Statistics for DWI Development Sample (N = 14,901)

	Clean N	Failure N	Clean %	Failure %	Sig.
Gender					0.000
Male	6,669	6,220	84.0	89.4	
Female	1,275	737	16.0	10.6	
	7,944	6,957	100.0	100.0	
Age					0.000
< 18	441	582	5.6	8.4	
18-24	1,046	1,327	13.2	19.1	
24-29	606	847	7.6	12.2	
30-34	608	737	7.7	10.6	
35-40	596	658	7.5	9.5	
41-44	789	723	9.9	10.4	
45-49	936	683	11.8	9.8	
50-54	949	624	11.9	9.0	
55-59	871	417	11.0	6.0	
60+	1,102	359	13.9	5.2	
	7,944	6,957	100.0	100.0	
Mean	42.17	36.0			0.000
Location					0.000
Helsinki	1,135	1,142	14.3	16.4	
Urban	1,896	1,716	23.9	24.7	
Rural	4,913	4,099	61.8	58.9	
	7,944	6,957	100.0	100.0	
Cooffenders					0.000
Yes	342	482	4.3	6.9	
No	7,602	6,475	95.7	93.1	
	7,944	6,957	100.0	100.0	
Multiple charges					0.000
Yes	2,627	3,495	33.1	50.2	
No	5,317	3,462	66.9	49.8	
	7,944	6,957	100.0	100.0	
Total prior sentence Ids					0.000
0	3,924	1,725	49.4	24.8	
1	1,920	1,307	24.2	18.8	
2	903	917	11.4	13.2	
3	470	594	5.9	8.5	
4	240	473	3.0	6.8	
5	152	330	1.9	4.7	
6	100	231	1.3	3.3	
7	61	170	0.8	2.4	
8	48	143	0.6	2.1	
9	30	133	0.4	1.9	
10-14	54	350	0.7	5.0	
15-19	15	195	0.2	2.8	
20-24	7	121	0.1	1.7	
25-29	8	80	0.1	1.1	
30+	12	188	0.2	2.7	
	7,944	6,957	100.0	100.0	
Mean	1.29	4.88			0.000
Total Prior Court Convictions					0.000
0	5,364	3,005	67.5	43.2	
1	1,507	1,425	19.0	20.5	
2	569	801	7.2	11.5	
3	233	443	2.9	6.4	
4	125	308	1.6	4.4	
5	60	217	0.8	3.1	
6	27	146	0.3	2.1	
7	14	125	0.2	1.8	
8	12	91	0.2	1.3	
9	4	70	0.1	1.0	
10-14	20	203	0.3	2.9	
15-19	9	87	0.1	1.3	
20-24	0	26	0.0	0.4	
25-29	0	7	0.0	0.1	
30+	0	3	0.0	0.0	
	7,944	6,957	100.0	100.0	
Mean	0.62	2.07			0.000
Total Prior Summary Penal Fines					0.000
0	5,301	2,794	66.7	40.2	
1	1,558	1,473	19.6	21.2	
2	554	819	7.0	11.8	
3	244	463	3.1	6.7	
4	122	305	1.5	4.4	
5	55	193	0.7	2.8	
6	37	143	0.5	2.1	
7	17	105	0.2	1.5	
8	10	82	0.1	1.2	
9	4	76	0.1	1.1	
10-14	21	225	0.3	3.2	
15-19	12	106	0.2	1.5	
20-24	3	61	0.0	0.9	
25-29	4	40	0.1	0.6	
30-34	1	25	0.0	0.4	
35-39	1	14	0.0	0.2	
40+	0	33	0.0	0.5	
	7,944	6,957	100.0	100.0	
Mean	0.67	2.81			0.000

	Clean N	Failure N	Clean %	Failure %	Sig.
Current offense type (most serious)					0.000
DWI	3,744	2,851	47.3	41.0	
DWSI	4,170	4,106	52.7	59.0	
	7,914	6,957	100.0	100.0	
Age at first conviction					0.000
< 18	831	1,460	10.5	21.0	
18-24	1,083	1,311	13.6	18.8	
24-29	526	655	6.6	9.4	
30-34	609	641	7.7	9.2	
35-40	670	674	8.4	9.7	
41-44	840	641	10.6	9.2	
45-49	924	633	11.6	9.1	
50-54	888	444	11.2	6.4	
55-59	734	290	9.2	4.2	
60+	839	208	10.6	3.0	
	7,944	6,957	100.0	100.0	
Mean	39.83	32.2			0.000
Type of prior conviction(s)					
Prior personal conviction(s)					0.000
Yes	565	1,439	7.1	20.7	
No	7,379	5,518	92.9	79.3	
	7,944	6,957	100.0	100.0	
Prior sex conviction(s)					0.000
Yes	17	43	0.2	0.6	
No	7,927	6,914	99.8	99.4	
	7,944	6,957	100.0	100.0	
Prior property conviction(s)					0.000
Yes	841	2,279	10.6	32.7	
No	7,103	4,687	89.4	67.3	
	7,944	6,966	100.0	100.0	
Prior Alcohol conviction(s)					0.000
Yes	36	85	0.5	1.2	
No	7,918	6,872	99.7	98.8	
	7,954	6,957	100.1	100.0	
Prior drug conviction(s)					0.000
Yes	203	961	2.6	13.8	
No	7,741	5,996	97.4	86.2	
	7,944	6,957	100.0	100.0	
Prior firearms/weapons conviction(s)					0.000
Yes	247	855	3.1	12.3	
No	7,697	6,102	96.9	87.7	
	7,944	6,957	100.0	100.0	
Prior traffic conviction(s)					0.000
Yes	2,735	4,092	34.4	58.8	
No	5,209	2,865	65.6	41.2	
	7,944	6,957	100.0	100.0	
Prior Public Adm/Order conviction(s)					0.000
Yes	649	1,707	8.2	24.7	
No	7,295	5,205	91.8	75.3	
	7,944	6,912	100.0	100.0	
Prior DUI conviction(s)					0.000
Yes	874	1,632	11.0	23.5	
No	7,070	5,325	89.0	76.5	
	7,944	6,957	100.0	100.0	
Prior Serious DUI conviction(s)					0.000
Yes	1,371	2,123	17.3	30.5	
No	6,573	4,834	82.7	69.5	
	7,944	6,957	100.0	100.0	
Prior Non-Vehicular DUI conviction(s)					0.016
Yes	48	66	0.6	0.9	
No	7,896	6,891	99.4	99.1	
	7,944	6,957	100.0	100.0	
Prior Incarceration					0.000
Yes	410	1,083	5.2	15.6	
No	7,534	5,874	94.8	84.4	
	7,944	6,957	100.0	100.0	
Type of sentence (Most Serious)					0.000
Unconditional Prison	162	539	2.0	7.7	
Community Service	440	733	5.5	10.5	
Conditional Prison	3,435	2,821	43.2	40.5	
Other (including Fines)	3,907	2,864	49.2	41.2	
	7,944	6,957	100.0	100.0	
Average Length of Sentence					
Unconditional Prison	2.02	8.26			0.000
Community Service	4.90	9.33			0.000
Conditional Prison	26.19	25.48			0.218
Other (including Fines)	36.23	32.43			0.000

* p < .05 ** p < .01 *** p < .001 (Chi-square/ T-test for variable)

Overall, the findings are consistent with the general literature on the correlates of recidivism. Young offenders and male offenders were more likely to recidivate than older offenders and female offenders. Despite the prevalence of offending in rural areas, offenders in the Helsinki region were more likely to recidivate compared to offenders in other urban and rural areas. Similarly, despite the low frequency of DWI offenders sentenced with co-offenders, those who did have at least one co-offender were more likely to recidivate. Offenders sentenced for more serious offenses (DWSI) were more likely to recidivate. Offenders with fewer prior court convictions or summary penal fines were less likely to recidivate than offenders with more prior court convictions or summary penal fines. Offenders who began their offending behaviors at a younger age were more likely to recidivate than offenders who began offending at older ages. For each type of prior conviction, offenders who had committed a previous offense were more likely to recidivate than offenders who had not committed the same previous offense. Offenders with a history of incarceration were more likely to recidivate than those with no prior imprisonment. Offenders sentenced to more harsh punishments (e.g., unconditional imprisonment or community service) were more likely to recidivate than offenders sentenced to less harsh punishments (e.g., conditional imprisonment or fines).

Burgess Risk Scale Construction

While bivariate statistics can identify correlations between independent variables and recidivism, multivariate analyses are necessary to determine whether these relationships are significant when simultaneously considering other offender or offense characteristics. The dependent variable for these analyses is a binary indicator of recidivism where 1 represents a reconviction within four years and 0 represents no reconvictions during the follow-up period. Consequently, I used logistic regression for multivariate analyses.

Table 4-7 presents the results for the initial logistic regression model. As mentioned previously, all of the variables in the model are categorical or binary variables. Consequently, the odds ratio may be interpreted as 1 + the probability that X offender will recidivate compared to offenders in the reference group. For example, the model includes gender by using the variable for males in the model and the variable for females as the reference group. An odds ratio of 1.398 suggests males are 39.8% more likely to recidivate than females.

Gender, age, number of charges, type of current offense, number of prior sentences, prior property sentence, prior public administration or public order sentences, and prior drug sentences were all significantly predictive of recidivism among DWI offenders. When controlling for these characteristics, region and the remaining qualitative criminal history variables (personal/sex, other traffic, weapons, DWI, DWSI, and non-vehicular DWI) were not significantly predictive of recidivism. As expected, younger offenders were significantly more likely to recidivate than older offenders. In addition, more serious offenders (DWSI) were more likely to recidivate than less serious offenders. Similarly, offenders with more prior sentences were more likely to recidivate than offenders with fewer prior sentences. Having a prior property sentence, a prior public administration or public order sentence, and/or a prior drug sentence were all predictive of recidivism.

Table 4-7. Logistic Regression Risk Scale Development Sample (N = 14,901)

	Odds Ratio
Male	1.398***
Helsinki	1.058
Other Urban	1.069
Under 18	5.526***
Age 18-19	3.918***
Age 20-29	2.449***
Age 30-39	2.145***
Age 40-49	1.948***
Age 50-59	1.551***
Multiple Charges	1.249***
DWSI	1.176***
1 Prior Sentence	1.500***
2-3 Prior Sentences	2.157***
4-6 Prior Sentences	3.513***
7-9 Prior Sentences	4.405***
10+ Prior Sentences	10.250***
Prior Property Sentence	1.211**
Prior Personal/Sex Sentence	1.047
Prior Public Adm/Order Sentence	1.140*
Prior Other Traffic Sentence	1.027
Prior Drug Sentence	1.477***
Prior Weapon Sentence	1.012
Prior DWI Sentence	1.096
Prior DWSI Sentence	1.001
Prior Non-Vehicular DWI Sentence	1.144
_cons	0.132***
N	14,901
R-sq	0.1316
AIC	17934.3
BIC	18132.1

*p < .05 ** p < .01 *** p < .001

Reference categories: Black for race; rural for county; 60+ for age; DWI Type of DWI; 0 prior sentences for No. of Prior sentences.

Next, I used statistically significant variables to construct a discrete, unweighted Burgess risk scale.[81] For each factor (e.g., gender) the group that was more likely to recidivate received a point while the group less likely to recidivate received no points. For example, males were more likely to recidivate, so they received a point, while females received no points for gender.

In instances where the independent variable consists of a categorical variable, the process is slightly different. Zero points are assigned to the group that is least likely to recidivate. One point is added to each additional category that is statistically significantly more likely to recidivate than the prior category. In order to determine whether the groups in a category were significantly different from each other, I re-estimated the logistic regression rotating the reference group and testing for differences between each pair of groups in a given categorical variable. For example, Table 4-8 shows the rotations for the different age categories. All categories were statistically significant from each other except for the category of offenders between the ages of 30 and 39 and the category of offenders between the age of 40 and 49. Starting with the offenders least likely to recidivate, I assigned the following points: Age 60 and older – 0 points; age 50-59 – 1 point; age 30-49 – 2 points; age 20-29 – 3 points; age 18-19 – 4 points; age 17 and under – 5 points.

[81] Research comparing unweighted and weighted Burgess risk assessment instruments generally find that weighted models do not perform significantly better than unweighted models. In addition, weighted models run a greater risk of overfitting the scale to the development sample.

Table 4-8. Risk Assessment Development - Age Rotation, Decade Categories, Development Sample (N = 14,901)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
male	1.398***	1.398***	1.398***	1.398***	1.398***	1.398***	1.398***
Helsinki	1.058	1.058	1.058	1.058	1.058	1.058	1.058
Other Urban	1.069	1.069	1.069	1.069	1.069	1.069	1.069
Age							
<18	reference	1.411**	2.256***	2.576***	2.837***	3.563***	5.526***
18-19	0.709**	reference	1.599***	1.826***	2.012***	2.526***	3.918***
20-29	0.443***	0.625***	reference	1.142*	1.258***	1.579***	2.449***
30-39	0.388***	0.548***	0.876*	reference	1.101	1.383***	2.145***
40-49	0.352***	0.497***	0.795***	0.908	reference	1.256***	1.948***
50-59	0.281***	0.396***	0.633***	0.723***	0.796***	reference	1.551***
60+	0.181***	0.255***	0.408***	0.466***	0.513***	0.645***	reference
Multiple Charges	1.249***	1.249***	1.249***	1.249***	1.249***	1.249***	1.249***
Serious DUI	1.176***	1.176***	1.176***	1.176***	1.176***	1.176***	1.176***
Prior Sentence IDs							
1	1.500***	1.500***	1.500***	1.500***	1.500***	1.500***	1.500***
2-3	2.157***	2.157***	2.157***	2.157***	2.157***	2.157***	2.157***
4-6	3.513***	3.513***	3.513***	3.513***	3.513***	3.513***	3.513***
7-9	4.405***	4.405***	4.405***	4.405***	4.405***	4.405***	4.405***
10+	10.250***	10.250***	10.250***	10.250***	10.250***	10.250***	10.250***
Prior Property	1.211**	1.211**	1.211**	1.211**	1.211**	1.211**	1.211**
Prior Personal/Sex	1.047	1.047	1.047	1.047	1.047	1.047	1.047
Prior Padm/Order/A	1.140*	1.140*	1.140*	1.140*	1.140*	1.140*	1.140*
Prior Other Traffic	1.027	1.027	1.027	1.027	1.027	1.027	1.027
Prior Drug	1.477***	1.477***	1.477***	1.477***	1.477***	1.477***	1.477***
Prior Weapon	1.012	1.012	1.012	1.012	1.012	1.012	1.012
Prior DUI	1.096	1.096	1.096	1.096	1.096	1.096	1.096
Prior DWSI	1.001	1.001	1.001	1.001	1.001	1.001	1.001
Prior Non-Veh DUI	1.144	1.144	1.144	1.144	1.144	1.144	1.144
Constant	0.727**	0.516***	0.322***	0.282***	0.256***	0.204***	0.132***
N	14901	14901	14901	14901	14901	14901	14901
R-sq	0.1316	0.1316	0.1316	0.1316	0.1316	0.1316	0.1316
AIC	17934.3	17934.3	17934.3	17934.3	17934.3	17934.3	17934.3
BIC	18132.1	18132.1	18132.1	18132.1	18132.1	18132.1	18132.1

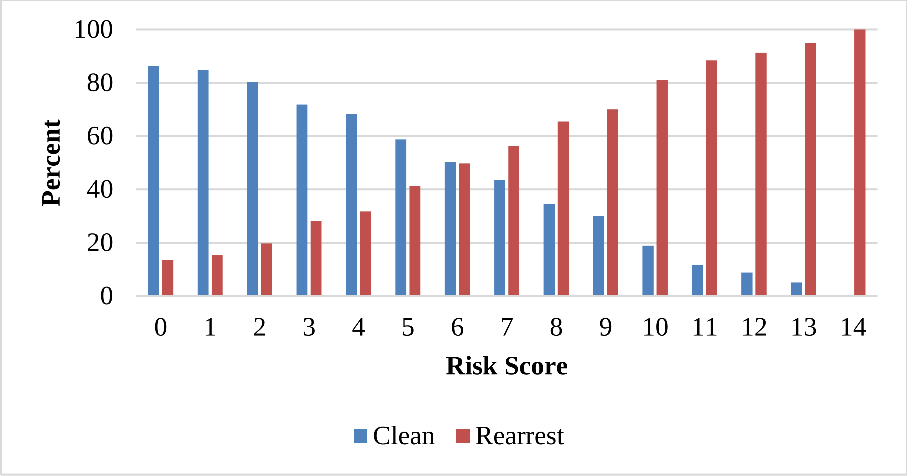
The final points for the final development Burgess scale are presented in Table 4-9. The table includes the total points for a given factor (e.g., 5 points possible for age) as well as the specific points assigned for each particular category within a factor.

Table 4-9. Risk Scale Predicting Any Reconviction 0-15, Development Sample (N=14,901)

Factor	Within Group Points	Total Factor Points	Factor	Within Group Points	Total Factor Points
Gender		**1**	**Prior Sentences**		**4**
Male	1		0	0	
Female	0		1	1	
Age		**5**	2-3	2	
<18	5		4-6	3	
18-19	4		7-9	3	
20-29	3		10+	4	
30-39	2		**Prior Property**		**1**
40-49	2		Yes	1	
50-59	1		No	0	
60+	0		**Prior Padm/Order/Alc**		**1**
Multiple Charges		**1**	Yes	1	
Yes	1		No	0	
No	0		**Prior Drug**		**1**
Type of DWI		**1**	Yes	1	
DWI	0		No	0	
DWSI	1				

I calculated the score for each offender and tested the overall relationship between the scale and recidivism. If the scale is properly constructed, then the probability of recidivism should increase for each additional point on the scale. That is, offenders with a higher risk score should be more likely to recidivate than offenders with a lower risk score. Figure 4-17 presents a graph of the probability of recidivism by risk score for the development sample.

Figure 4-17. Percent Reconvicted By Risk Score Development Sample (N = 14,901)



I validated my scale using the validation sample (N = 14,981) that was reserved in the initial sample selection process. Using receiver operating characteristics, I tested whether the scale predicted as well for the validation sample as it did for the development sample. These statistics are necessary to ensure that the scale was not over-fitted to specific aberrations in the development sample. A chi-square test of the area under the ROC curve confirmed that the scale predicts equally well for the development (AUC = 0.7258) and validation samples (AUC = 0.7224; $\chi^2(1) = 0.35$, p = .0.556).

It is difficult to determine what the "true" difference is between any two scores on the scale. In addition, it may be the case that two adjacent scores are not statistically significantly different. Consequently, risk assessments often include some sort of categorization of offenders into "low-risk" "medium-risk" and "high-risk," or something similar. I chose to follow the method established by the Pennsylvania Commission on Sentencing (PCS) to establish groups of offenders using the risk score. I confirmed the need for collapsing individual scores into larger scores by first calculating the confidence interval for probability estimates for each individual score. I calculated these confidence intervals using the combined development and validation samples (N = 29,882) in order to maximize the amount of statistical power for these analyses.

For the development scale, there were five instances of overlap in the confidence intervals for adjacent scores (0 and 1; 1 and 2; 11 and 12; 12 and 13; 13 and 14). The overlap was concentrated in the upper and lower tails of the distribution, likely caused by the smaller sample sizes for these scores.

Using the PCS method, I calculated the average risk score for all offenders in the data: 5.70. I then calculated one standard deviation (2.70) above and below the mean to create a group of “average” offenders. The lower limit for this group was 3.00 and the upper limit for the group was 8.40. Consequently, the group of “average offenders”, consists of those offenders with a risk score of 3 through 8. Offenders falling below one standard deviation below the mean (i.e., those with a risk score of 0 through 2) were categorized as “low-risk.” Offenders falling above one standard deviation above the mean (i.e., those offenders with a risk score of 9 through 15) were classified as “high-risk.” An analysis of the confidence intervals for these three collapsed groups indicated that each of the three groups were statistically significantly different.

I do not claim to make a judgment about the behavior of the offenders in the “average-risk” category. Overall, the probability of these offenders recidivating or not recidivating is nearly equal. However, the PCS method does claim that offenders in the “low-risk” category are significantly less likely to reoffend and offenders in the “high-risk” category are significantly more likely to reoffend than the “average” group. Using these standards, I calculated the percent of offenders correctly predicted by calculating the percent of low-risk offenders who did not recidivate and the percent of high-risk offenders who did recidivate. Overall, the scale correctly predicts the behavior of the individuals in these groups 80.77% of the time.

DWI Reconviction

Practitioners are often interested not only in who is likely to recidivate in general but also in who is likely to recidivate for a particular type of offense. Practitioners and activists often speak of the danger of repeat DWI offenders. In response to these concerns, I chose to develop a second risk assessment scale predicting the probability of recidivism by a second (or subsequent) DWI offense. This approach is similar to existing risk assessments that include one scale to predict any recidivism for general offenders and a second scale to predict recidivism by a personal offense (see PCS, 2018).

With general risk assessment instruments, the goal is to predict who is most likely or least likely to recidivate. Specialized risk assessments seek to predict not only who is likely to continue offending but also how those offenders are likely to offend in the future (e.g., violent offenses or DWI offenses). The ability to accurately predict specialized offending should be greater for groups of offenders who are more likely to engage in offense specialization. Given the relatively high degree of specialization among DWI offenders, it is possible that an accurate tool could be developed to identify potential repeat DWI offenders.

I used the same process to develop the general recidivism scale and the DWI recidivism scale. First, I completed new bivariate statistics with the development sample to assess basic correlations between independent variables and DWI recidivism.[82] Second, I used logistic regression to identify significant relationships between independent variables and DWI recidivism when simultaneously considering all offender and offense related characteristics. Third, I used the significant relationships to construct unweighted Burgess risk assessment

[82] I did not complete additional descriptive statistics since the development and validation samples for the DWI recidivism scale were the same as the development and validation samples for the general recidivism scale.

instruments and tested for subsequent predictive validity. Fourth, I validated the development scale on the validation population.

This section of analyses seeks to answer two questions: 1) What are the correlates of DWI recidivism and how do those differences compare to the correlates of general recidivism? 2) Can we effectively predict specific types of recidivism rather than general recidivism?

Descriptive and Bivariate Statistics

In the development sample (14,901 DWI offenders), 2,046 offenders recidivated with a DWI, representing 13.73% of all offenders in the development sample and 29.41% of the offenders who recidivated for any offense. There are two ways to compare offenders who recidivate by a DWI to other offenders. One could compare DWI recidivists to all other offenders (non-recidivists and offenders who recidivate by a non-DWI offense) or one could separately compare DWI recidivists to non-recidivists and offenders who recidivate by a non-DWI offense. I decided to conduct bivariate statistics using the latter method in order to identify how offenders who recidivate by a DWI offense are different from those who desist from offending and those who go on to commit other, non-DWI offenses. Table 4-10 presents the bivariate comparisons for each of the independent variables by the three recidivist groups (non-recidivists, non-DWI recidivists, and DWI recidivists).

Table 4-10. Bivariate Statistics for DWI Development Sample, DWI-Specific Recidivism (N = 14,901)

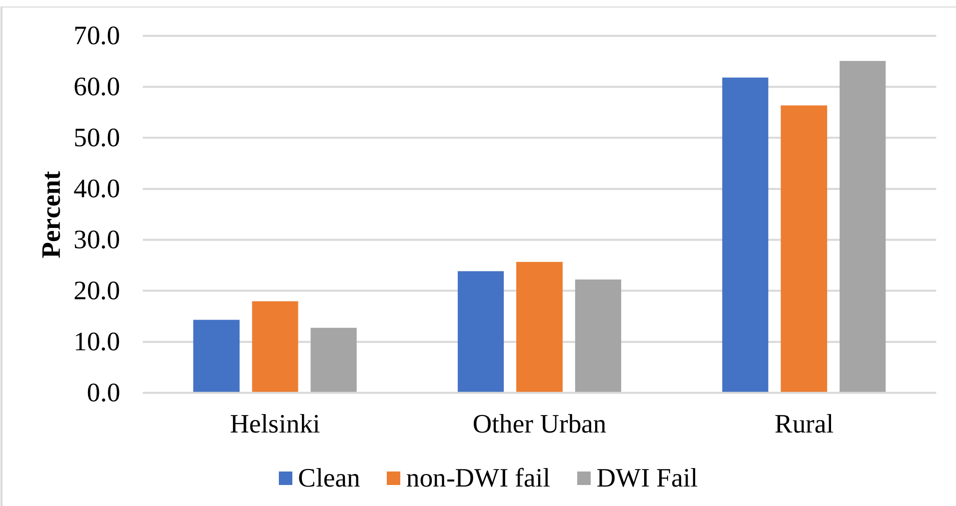
Table X. Bivariate statistics for DUI Development Sample DWI specific recidivism (N= 14,901)

	Clean	non-DWI fail	DWI Fail	Clean	non-DWI fail	DWI Fail	
	N	N	N	%	%	%	Sig.
Gender							0.000
Male	6,669	4,370	1,850	84.0	89.0	90.4	
Female	1,275	541	196	16.0	11.0	9.6	
	7,944	4,911	2,046	100.0	100.0	100.0	
Age							0.000
< 18	441	502	80	5.6	10.2	3.9	
18-24	1,046	1,104	223	13.2	22.5	10.9	
24-29	606	687	160	7.6	14.0	7.8	
30-34	608	568	169	7.7	11.6	8.3	
35-40	596	478	180	7.5	9.7	8.8	
41-44	789	466	257	9.9	9.5	12.6	
45-49	936	405	278	11.8	8.2	13.6	
50-54	949	317	307	11.9	6.5	15.0	
55-59	871	213	204	11.0	4.3	10.0	
60+	1,102	171	188	13.9	3.5	9.2	
	7,944	4,911	2,046	100.0	100.0	100.0	
Mean	42.17[a]	33.5	42.01[a]				0.000
Location							0.000
Helsinki	1,135	881	261	14.3	17.9	12.8	
Other Urban	1,896	1,262	454	23.9	25.7	22.2	
Rural	4,913	2,768	1,331	61.8	56.4	65.1	
	7,944	4,911	2,046	100.0	100.0	100.0	
Cooffenders							0.000
Yes	342	399	83	4.3	8.1	4.1	
No	7,602	4,512	1,963	95.7	91.9	95.9	
	7,944	4,911	2,046	100.0	100.0	100.0	
Multiple charges							0.000
Yes	2,627	2,612	883	33.1	53.2	43.2	
No	5,317	2,299	1,163	66.9	46.8	56.8	
	7,944	4,911	2,046	100.0	100.0	100.0	
Total prior sentence Ids							0.000
0	3,924	1,103	622	49.4	22.5	30.4	
1	1,920	849	458	24.2	17.3	22.4	
2	903	625	292	11.4	12.7	14.3	
3	470	422	172	5.9	8.6	8.4	
4	240	349	124	3.0	7.1	6.1	
5	152	239	91	1.9	4.9	4.4	
6	100	174	57	1.3	3.5	2.8	
7	61	130	40	0.8	2.6	2.0	
8	48	109	34	0.6	2.2	1.7	
9	30	107	26	0.4	2.2	1.3	
10-14	54	290	60	0.7	5.9	2.9	
15-19	15	172	23	0.2	3.5	1.1	
20-24	7	106	15	0.1	2.2	0.7	
25-29	8	70	10	0.1	1.4	0.5	
30+	12	166	22	0.2	3.4	1.1	
	7,944	4,911	2,046	100.0	100.0	100.0	
Mean	1.29	5.64	3.04				0.000
Total Prior Court Convictions							0.000
0	5,364	2,052	953	67.5	41.8	46.6	
1	1,507	971	454	19.0	19.8	22.2	
2	569	547	254	7.2	11.1	12.4	
3	233	311	132	2.9	6.3	6.5	
4	125	233	75	1.6	4.7	3.7	
5	60	170	47	0.8	3.5	2.3	
6	27	117	29	0.3	2.4	1.4	
7	14	98	27	0.2	2.0	1.3	
8	12	75	16	0.2	1.5	0.8	
9	4	57	13	0.1	1.2	0.6	
10-14	20	176	27	0.3	3.6	1.3	
15-19	9	72	15	0.1	1.5	0.7	
20-24	0	23	3	0.0	0.5	0.1	
25-29	0	6	1	0.0	0.1	0.0	
30+	0	3	0	0.0	0.1	0.0	
	7,944	4,911	2,046	100.0	100.0	100.0	
Mean	0.62	2.29	1.54				0.000
Total Prior Summary Penal Fines							0.000
0	5,301	1,735	1,059	66.7	35.3	51.8	
1	1,558	1,020	453	19.6	20.8	22.1	
2	554	600	219	7.0	12.2	10.7	
3	244	355	108	3.1	7.2	5.3	
4	122	260	45	1.5	5.3	2.2	
5	55	153	40	0.7	3.1	2.0	
6	37	112	31	0.5	2.3	1.5	
7	17	93	12	0.2	1.9	0.6	
8	10	70	12	0.1	1.4	0.6	
9	4	65	11	0.1	1.3	0.5	
10-14	21	199	26	0.3	4.1	1.3	
15-19	12	98	8	0.2	2.0	0.4	
20-24	3	53	8	0.0	1.1	0.4	
25-29	4	30	10	0.1	0.6	0.5	
30-34	1	24	1	0.0	0.5	0.0	
35-39	1	12	2	0.0	0.2	0.1	
40+	0	32	1	0.0	0.7	0.0	
	7,944	4,911	2,046	100.0	100.0	100.0	
Mean	0.67	3.35	1.51				0.000
Current offense type (most serious)							0.000
DWI	3,774	2,110	741	47.5	43.0	36.2	
DWSI	4,170	2,801	1,305	52.5	57.0	63.8	
	7,944	4,911	2,046	100.0	100.0	100.0	

	Clean	non-DWI fail	DWI Fail	Clean	non-DWI fail	DWI Fail	
	N	N	N	%	%	%	Sig.
Age at first conviction							0.000
< 18	831	1,247	213	10.5	25.4	10.4	
18-24	1,083	1,073	238	13.6	21.8	11.6	
24-29	526	496	159	6.6	10.1	7.8	
30-34	609	466	175	7.7	9.5	8.6	
35-40	670	458	216	8.4	9.3	10.6	
41-44	840	370	271	10.6	7.5	13.2	
45-49	924	371	262	11.6	7.6	12.8	
50-54	888	211	233	11.2	4.3	11.4	
55-59	734	127	163	9.2	2.6	8.0	
60+	839	92	116	10.6	1.9	5.7	
	7,944	4,911	2,046	100.0	100.0	100.0	
Mean	39.83	29.6	38.5				0.000
Type of prior conviction(s)							
Prior personal conviction(s)							0.000
Yes	565	1,169	270	7.1	23.8	13.2	
No	7,379	3,742	1,776	92.9	76.2	86.8	
	7,944	4,911	2,046	100.0	100.0	100.0	
Prior sex conviction(s)							0.000
Yes	17	29	14	0.2	0.6	0.7	
No	7,927	4,882	2,032	99.8	99.4	99.3	
	7,944	4,911	2,046	100.0	100.0	100.0	
Prior property conviction(s)							0.000
Yes	841	1,840	430	10.6	37.5	21.0	
No	7,103	3,071	1,616	89.4	62.5	79.0	
	7,944	4,911	2,046	100.0	100.0	100.0	
Prior Alcohol conviction(s)							0.000
Yes	26	71	14	0.3	1.4	0.7	
No	7,918	4,840	2,032	99.7	98.6	99.3	
	7,944	4,911	2,046	100.0	100.0	100.0	
Prior drug conviction(s)							0.000
Yes	203	827	134	2.6	16.8	6.5	
No	7,741	4,084	1,912	97.4	83.2	93.5	
	7,944	4,911	2,046	100.0	100.0	100.0	
Prior firearms/weapons conviction(s)							0.000
Yes	247	708	147	3.1	14.4	7.2	
No	7,697	4,203	1,899	96.9	85.6	92.8	
	7,944	4,911	2,046	100.0	100.0	100.0	
Prior traffic conviction(s)							0.000
Yes	2,735	3,021	1,071	34.4	61.5	52.3	
No	5,209	1,890	975	65.6	38.5	47.7	
	7,944	4,911	2,046	100.0	100.0	100.0	
Prior Public Adm/Order conviction(s)							0.000
Yes	649	1,335	372	8.2	27.2	18.2	
No	7,295	3,576	1,674	91.8	72.8	81.8	
	7,944	4,911	2,046	100.0	100.0	100.0	
Prior DUI conviction(s)							0.000
Yes	874	1,193	439	11.0	24.3	21.5	
No	7,070	3,718	1,607	89.0	75.7	78.5	
	7,944	4,911	2,046	100.0	100.0	100.0	
Prior Serious DUI conviction(s)							0.000
Yes	1,371	1,430	693	17.3	29.1	33.9	
No	6,573	3,481	1,353	82.7	70.9	66.1	
	7,944	4,911	2,046	100.0	100.0	100.0	
Prior Non-Vehicular DUI conviction(s)							0.001
Yes	48	37	29	0.6	0.8	1.4	
No	7,896	4,874	2,017	99.4	99.2	98.6	
	7,944	4,911	2,046	100.0	100.0	100.0	
Prior Incarceration							0.000
Yes	410	798	285	5.2	16.2	13.9	
No	7,534	4,113	1,761	94.8	83.8	86.1	
	7,944	4,911	2,046	100.0	100.0	100.0	
Type of sentence (Most Serious)							0.000
Unconditional Prisor	162	395	144	2.0	8.0	7.0	
Community Service	440	496	237	5.5	10.1	11.6	
Conditional Prison	3,435	1,898	923	43.2	38.6	45.1	
Other (including Fin	3,907	2,122	742	49.2	43.2	36.3	
	7,944	4,911	2,046	100.0	100.0	100.0	
Average Length of Sentence							
Unconditional Prisor	2.20	8.23[a]	8.34[a]				0.000
Community Service	4.90	8.88[a]	10.42[a]				0.000
Conditional Prison	26.19	24.20	29.53				0.000
Other (including Fin	36.23	32.74[a]	31.67[a]				0.000

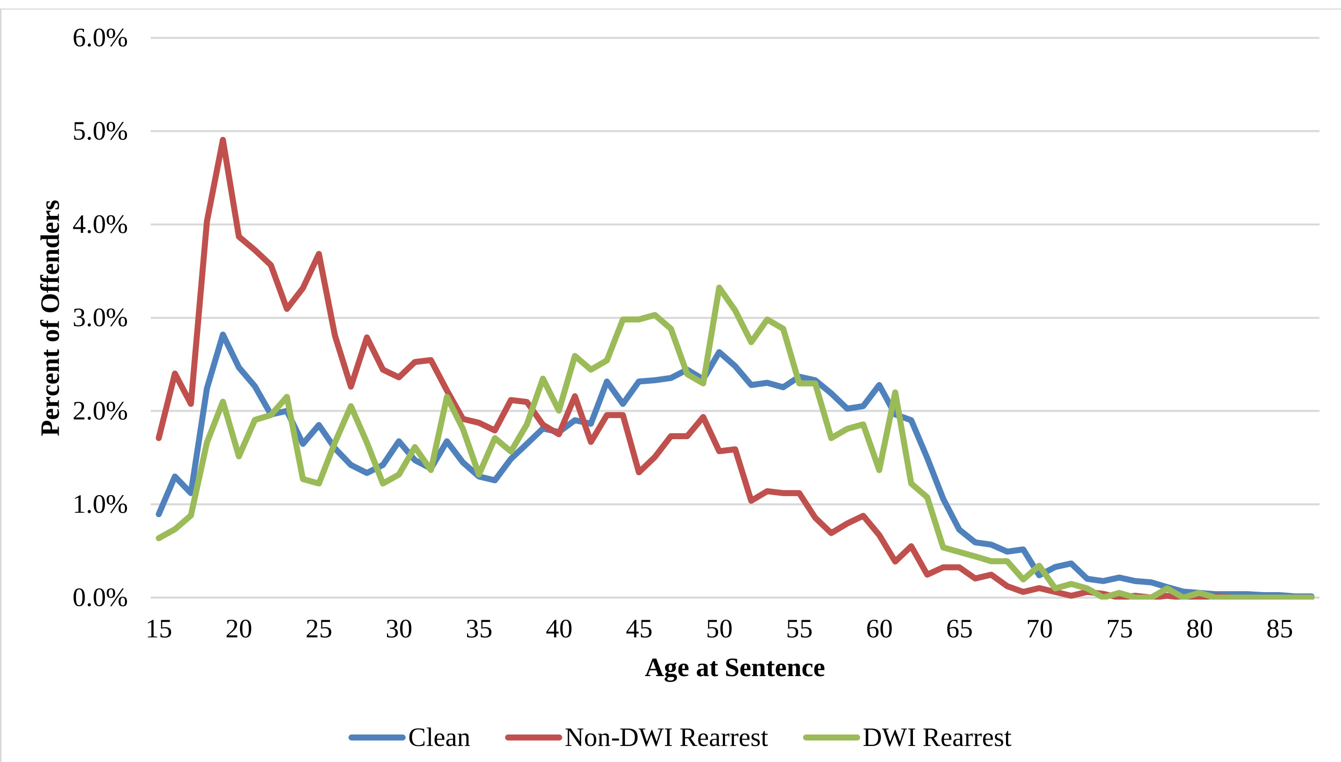
Offenders who recidivated by a DWI offense were overwhelmingly male (90.4%). The gender gap (percent male compared to percent female) for DWI recidivism was only slightly greater than the gender gap for non-DWI recidivism (89.0% male). The gender-gap was smallest for offenders who did not recidivate (84.0% male). The relationship between other demographic characteristics and DWI recidivists varied greatly from their relationships with general recidivists and non-recidivists. For example, offenders were more likely to recidivate in rural areas regardless of whether that recidivism was for a DWI or a non-DWI offense. As seen in figure 4-18. DWI recidivists were the least likely to live in the Helsinki region and the most likely to live in rural areas. Differences in recidivism by region were statistically significant $\chi^2(4, N = 14{,}901) = 67.97$, $p = .000$.

Figure 4-18. Recidivism by Region



The differences in the relationships between age and general recidivism and age and DWI recidivism were less subtle. Figure 4-19 shows the percent of offenders who were not reconvicted, reconvicted for a non-DWI offense and reconvicted for a DWI offense by age at their primary DWI conviction. The distribution of offenders with no reconvictions was generally flat with slight increases as age increased. These offenders were generally evenly distributed across different ages, with the percentage of offenders in each age category ranging between 1% and 2.5%. The age of offenders who recidivated with a DWI offense followed a similar pattern, although the percent of offenders in older ages was greater for DWI recidivists than non-recidivists. The age of offenders who recidivated with a non-DWI offense and offenders who recidivated with a DWI offense were inversely related such that younger offenders were significantly more likely to recidivate with a non-DWI offense and older offenders were significantly more likely to recidivate with a DWI offense. An ANOVA analysis indicated that the average age for non-recidivists (M = 42.17), non-DWI recidivists (M = 33.50), and DWI recidivists (42.01) were significantly different, $F(2, 14898) = 596.05$, $p = 0.000$. However, post-hoc Tukey-Kramer tests found that the average age for non-recidivists and DWI recidivists were not significantly different ($p = 0.897$).

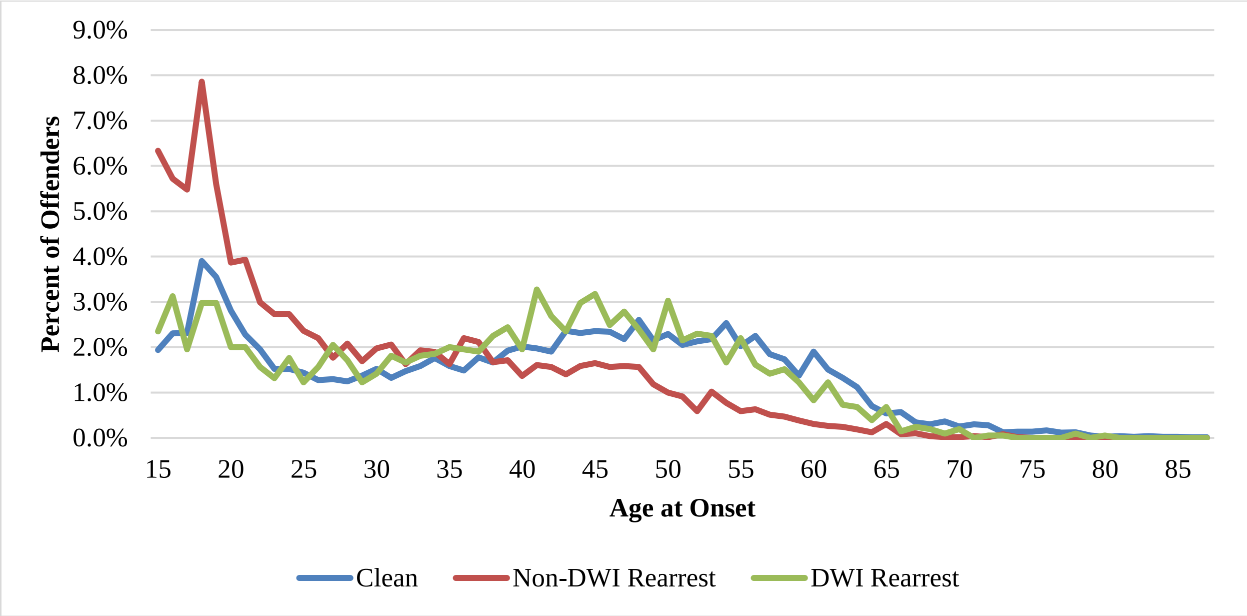
Figure 4-19. Age Distribution and Recidivism



Criminal History

The patterns for age at first conviction were similar to those for age at primary conviction (see Figure 4-20). Offenders reconvicted for a non-DWI offense were most likely to begin offending at younger ages. Age at onset of offending for offenders who recidivated with a non-DWI offense rapidly declined through the life-course. The average age at onset for offenders who recidivated with a non-DWI offense was 29.6. Age of onset for offenders who did not recidivate and for offenders who recidivated with a DWI were similar. The age of onset for these offenders varied greatly through the life course, resulting in a relatively flat distribution. The average age of onset was 39.84 for offenders who did not recidivate and 38.5 for offenders who recidivated with a DWI.

Figure 4-20. Age at Onset by Recidivism, DWI Development Sample



Offenders who did not recidivate were the least likely to have a criminal record. Half of all offenders (50.6%) who did not recidivate had at least one prior sentence ID before the primary DWI conviction. Two thirds (69.6%) of offenders who recidivated with a DWI had at least one prior sentence ID and about three quarters (77.5%) of offenders who recidivated with a non-DWI offense had at least one prior sentence ID. On average, offenders who did not recidivate had only 1.29 prior sentence IDs. Offenders who recidivated with a DWI offense had an average of 3.04 prior sentence IDs. Offenders who recidivated with a non-DWI offense had an average of 5.64 prior sentence IDs. An ANOVA analysis confirmed that the mean differences in prior sentence IDs were statistically significant $F(2, 14898) = 783.79$, $p = 0.000$. A post-hoc Tukey-Kramer test found significant differences for each pairwise comparison.

I found similar patterns for the decomposed quantitative criminal history measures. Only one third of offenders who did not recidivate had at least one prior court conviction (32.5%) or at least one prior summary penal fine (33.3%). Roughly half of all offenders who recidivated with a DWI offense had at least one prior court conviction (53.4%) or at least one prior summary penal fine (48.2%). For offenders who recidivated with a non-DWI offense, 58.2% had at least one prior court conviction and 64.7% had at least one prior summary penal fine. Unsurprisingly, these findings suggest that offenders who were less specialized (i.e., those who recidivated with a non-DWI offense) were the most likely to have involvement in prior criminal behaviors.

Qualitative criminal history measures were consistent with the quantitative criminal history measures. Offenders who did not recidivate were the least likely to have any conviction or summary penal fine in each of the specific crime groups. Offenders who recidivated with a non-DWI offense were the most likely to have a prior court conviction or summary penal fine for each of the crime types except for sex offenses and serious DWIs. The differences in the rate of prior sex offense convictions was negligible between the three groups (0.2% for non-recidivists; 0.6% for offenders who recidivate by a non-DWI offense; 0.7% for offenders who recidivate by a DWI offense). Prior DWIs present a more interesting story. Offenders who recidivated with a non-DWI offense were slightly more likely to have a prior DWI conviction (24.3%) than offenders who recidivated by a DWI offense (21.5%). However, offenders who recidivated with a DWI were slightly more likely to have a prior serious DWI (33.9%) or non-vehicular DWI (1.4%) than offenders who recidivated with a non-DWI offense (29.1% and 0.8%, respectively).

Finally, the percent of offenders with a prior record of incarceration suggest that offenders who recidivated with a non-DWI offense had more serious criminal records. In the development sample, 16.2% of offenders who recidivated with a non-DWI offense had at least one prior incarceration. Alternatively, 13.9% of offenders who recidivated with a DWI offense had at least one prior incarceration. Only 5.2% of non-recidivists had at least one prior incarceration.

Current Offense

DWI offenders were rarely sentenced with co-offenders. However, among DWI offenders, non-DWI recidivists were the most likely to have co-offenders (8.1%). The rate of DWI recidivists (4.1%) and non-recidivists (4.3%) who had at least one co-offender were nearly equal. Differences in co-offenders by type of recidivism were statistically significant $\chi^2(2, N = 14{,}901) = 94.60$, $p = .000$. Similarly, non-DWI recidivists were the most likely to have multiple charges (53.2%). Non-recidivists were the least likely to have multiple charges (33.1%). DWI recidivists fell in between these other two groups (43.2%). Differences in the percent of offenders with multiple charges by type of recidivism were also statistically significant $\chi^2(2, N = 14{,}901) = 511.65$, $p = .000$.

DWI recidivists were most likely to be sentenced for a DWSI (63.8%). Non-recidivists were least likely to be arrested for a DWSI (52.5%). Non-DWI recidivists were more likely than non-recidivists but less likely than DWI recidivists to be sentenced for a DWSI (57.0%).

Differences in the type of crime by type of recidivism were also statistically significant $\chi^2(2, N = 14{,}901) = 90.62$, $p = .000$.

Recidivists, both non-DWI (8.0%) and DWI (7.0%), were more likely than non-recidivists (2.0%) to have received an unconditional prison sentence. Recidivists were also more likely than non-recidivists to have received a community service sentence (5.5% of non-recidivists, 10.1% of non-DWI recidivists, and 11.6% of DWI recidivists). DWI recidivists were the least likely to have received an "other" sentence, such as a fine (25.3%). Differences in the most serious sentence by type of recidivism were statistically significant $\chi^2(6, N = 14{,}901) = 470.23$, $p = .000$.

Burgess Risk Scale Construction

The dependent variable for these analyses was a binary measure of DWI recidivism. Consequently, I used logistic regression models to account for the binary dependent variable. In order to be consistent with the Burgess instrument predicting any arrest, I used the same independent variables for the DWI recidivism instrument. In addition, I estimated the logistic regression using the previously identified development sample (N = 14,901). Table 4-11 shows the results for the logistic regression predicting DWI reconviction and compares the results to the logistic regression predicting any reconviction for the same sample. The logistic model explains very little of the variance in DWI recidivism. The R-squared value for the development model was 0.0319, less than one fourth of the R-squared value for the model predicting any recidivism.

Table 4-11. Logistic Regression Risk Scale Development, Development Sample (N = 14,901)

	Development Sample	
	Any Reconviction	DWI Reconviction
Male	1.398***	1.406***
Helsinki	1.058	0.799**
Other Urban	1.069	0.844**
Under 18	5.526***	0.690*
Age 18-19	3.918***	0.696*
Age 20-29	2.449***	0.787*
Age 30-39	2.145***	1.04
Age 40-49	1.948***	1.386***
Age 50-59	1.551***	1.443***
Multiple Charges	1.249***	1.056
DWSI	1.176***	1.316***
1 Prior Sentence	1.500***	1.047
2-3 Prior Sentences	2.157***	1.101
4-6 Prior Sentences	3.513***	1.143
7-9 Prior Sentences	4.405***	1.157
10+ Prior Sentences	10.250***	0.84
Prior Property Sentence	1.211**	0.956
Prior Personal/Sex Sentence	1.047	0.853
Prior Public Adm/Order Sentence	1.140*	1.06
Prior Other Traffic Sentence	1.027	1.145
Prior Drug Sentence	1.477***	0.902
Prior Weapon Sentence	1.012	0.898
Prior DWI Sentence	1.096	1.249**
Prior DWSI Sentence	1.001	1.427***
Prior Non-Vehicular DWI Sentence	1.144	1.628*
_cons	0.132***	0.078***
N	14901	14901
R-sq	0.1316	0.0316
AIC	17934.3	11597.4
BIC	18132.1	11795.3

*p < .05 ** p < .01 *** p < .001
Reference categories: Black for race; rural for county; 60+ for age; DWI for Type of DWI; 0 prior sentences for No. of Prior Sentences.

Only two findings were consistent between the any arrest logistic regression and the DWI logistic regression; males were significantly more likely than females to recidivate with a DWI (OR = 1.405) and offenders with a serious DWI were significantly more likely than offenders with a standard DWI to recidivate with a DWI (OR = 1.315).

Age and number of prior arrests were also significant, but the differences between the group classifications were different. The relationship with age and DWI arrests was curvilinear and older ages were significantly more likely to recidivate than younger ages. Table 4-12 shows the logistic regressions in which the reference category for age was rotated in order to identify significant differences between categories of age. The boxes indicate categories for which there were no significant differences. Offenders under the age of 18, between 18 and 19 and between 20 and 29 were equally likely to recidivate with a DWI. Offenders between the age of 40 and 49 and 50 and 59 were also equally likely to recidivate. Offenders between the age of 20 and 29 were more likely to recidivate than offenders under the age of 29 but less likely to recidivate than offenders between the age of 40 and 59. Offenders aged 60 and older were less likely to recidivate than offenders aged 40-59 but had an equal likelihood of recidivism with offenders aged 30-39. Ultimately, there were three distinct age categories: offenders under the age of 29, offenders aged 30-39 and offenders aged 60 and over, and offenders aged 40-59. By combining offenders aged 30-39 and offenders aged 60 and older, the categories more accurately reflect the increase in DWI offending that was previously identified for individuals between the age of 40 and 59.

Table 4-12. Risk Assessment Development - DWI Recidivism - Age Rotation, Decade Categories, Development Sample (N=14,901)

male	1.406***	1.406***	1.406***	1.406***	1.406***	1.406***	1.406***
Helsinki	0.799**	0.799**	0.799**	0.799**	0.799**	0.799**	0.799**
Other urban	0.844**	0.844**	0.844**	0.844**	0.844**	0.844**	0.844**
Under 18		0.991	0.878	0.664*	0.498***	0.479***	0.690*
Age 18-19	1.009		0.885	0.670**	0.502***	0.483***	0.696*
Age 20-29	1.139	1.129		0.756***	0.567***	0.545***	0.787*
Age 30-39	1.506*	1.493**	1.322***		0.750***	0.721***	1.04
Age 40-49	2.008***	1.991***	1.762***	1.333***		0.961	1.386***
Age 50-59	2.090***	2.071***	1.834***	1.387***	1.041		1.443***
Age 60+	1.448*	1.436*	1.271*	0.962	0.721***	0.693***	
Multiple Charges	1.056	1.056	1.056	1.056	1.056	1.056	1.056
DWSI	1.316***	1.316***	1.316***	1.316***	1.316***	1.316***	1.316***
1 Prior	1.047	1.047	1.047	1.047	1.047	1.047	1.047
2-3 Priors	1.101	1.101	1.101	1.101	1.101	1.101	1.101
4-6 Priors	1.143	1.143	1.143	1.143	1.143	1.143	1.143
7-9 Priors	1.157	1.157	1.157	1.157	1.157	1.157	1.157
10+ Priors	0.84	0.84	0.84	0.84	0.84	0.84	0.84
Prior Property	0.956	0.956	0.956	0.956	0.956	0.956	0.956
Prior Personal	0.853	0.853	0.853	0.853	0.853	0.853	0.853
Prior Pub Order/Adm	1.06	1.06	1.06	1.06	1.06	1.06	1.06
Prior Other Traffic	1.145	1.145	1.145	1.145	1.145	1.145	1.145
Prior Drug	0.902	0.902	0.902	0.902	0.902	0.902	0.902
Prior Weapon	0.898	0.898	0.898	0.898	0.898	0.898	0.898
Prior DWI	1.249**	1.249**	1.249**	1.249**	1.249**	1.249**	1.249**
Prior DWSI	1.427***	1.427***	1.427***	1.427***	1.427***	1.427***	1.427***
Prior Non-Veh DWI	1.628*	1.628*	1.628*	1.628*	1.628*	1.628*	1.628*
_cons	0.054***	0.054***	0.061***	0.081***	0.108***	0.113***	0.078***
N	14901	14901	14901	14901	14901	14901	14901
R-sq	0.0316	0.0316	0.0316	0.0316	0.0316	0.0316	0.0316
AIC	11597.4	11597.4	11597.4	11597.4	11597.4	11597.4	11597.4
BIC	11795.3	11795.3	11795.3	11795.3	11795.3	11795.3	11795.3

The quantitative measure of prior sentence IDs resulted in more complicated findings. From the initial logistic model, it appeared as though none of the prior sentence ID variables were significantly related to recidivism. Table 4-13 shows the rotations for the reference category in the prior sentence ID variables. The findings indicate that offenders with 10 or more prior arrests were significantly less likely to recidivate with a DWI than offenders with 4-9 prior sentence IDs. This finding may suggest that offenders with a longer criminal record are more likely to continue offending with more serious (non-DWI) offenses. However, a post-hoc likelihood ratio test found that the categorical variable for prior sentence IDs as a whole was not significant. Because of these findings, I did not include the number of prior sentences in the DWI scale.

Table 4-13. Risk Assessment Development - Prior Sentence Rotation DWI Reconviction, Development Sample (N=14,901)

male	1.406***	1.406***	1.406***	1.406***	1.406***	1.406***
Helsinki	0.799**	0.799**	0.799**	0.799**	0.799**	0.799**
Other urban	0.844**	0.844**	0.844**	0.844**	0.844**	0.844**
Under 18	0.690*	0.690*	0.690*	0.690*	0.690*	0.690*
Age 18-19	0.696*	0.696*	0.696*	0.696*	0.696*	0.696*
Age 20-29	0.787*	0.787*	0.787*	0.787*	0.787*	0.787*
Age 30-39	1.04	1.04	1.04	1.04	1.04	1.04
Age 40-49	1.386***	1.386***	1.386***	1.386***	1.386***	1.386***
Age 50-59	1.443***	1.443***	1.443***	1.443***	1.443***	1.443***
Multiple Charges	1.056	1.056	1.056	1.056	1.056	1.056
DWSI	1.316***	1.316***	1.316***	1.316***	1.316***	1.316***
No. of Priors						
0		0.955	0.909	0.875	0.864	1.19
1	1.047		0.952	0.916	0.905	1.246
2-3	1.101	1.051		0.963	0.951	1.309
4-6	1.143	1.091	1.038		0.988	1.360*
7-9	1.157	1.105	1.051	1.012		1.377*
10+	0.84	0.803	0.764	0.735*	0.726*	
Prior Property	0.956	0.956	0.956	0.956	0.956	0.956
Prior Personal	0.853	0.853	0.853	0.853	0.853	0.853
Prior Pub Order/Adm	1.06	1.06	1.06	1.06	1.06	1.06
Prior Other Traffic	1.145	1.145	1.145	1.145	1.145	1.145
Prior Drug	0.902	0.902	0.902	0.902	0.902	0.902
Prior Weapon	0.898	0.898	0.898	0.898	0.898	0.898
Prior DWI	1.249**	1.249**	1.249**	1.249**	1.249**	1.249**
Prior DWSI	1.427***	1.427***	1.427***	1.427***	1.427***	1.427***
Prior Non-Veh DWI	1.628*	1.628*	1.628*	1.628*	1.628*	1.628*
Constant	0.078***	0.082***	0.086***	0.089***	0.090***	0.066***
N	14901	14901	14901	14901	14901	14901
R-sq	0.0316	0.0316	0.0316	0.0316	0.0316	0.0316
AIC	11597.4	11597.4	11597.4	11597.4	11597.4	11597.4
BIC	11795.3	11795.3	11795.3	11795.3	11795.3	11795.3

Location was significantly predictive of DWI recidivism such that offenders in rural areas were more likely to recidivate than offenders in the Helsinki region or other urban areas. The odds of recidivism were not different for offenders in the Helsinki region or other urban areas. However, I chose not to use location-based variables in the final logistic Burgess scale due to ethical concerns arising from the statistical association between location-based variables and extra-legal characteristics, such as socioeconomic status. I did keep location in the final logistic equation to control for location-based differences in other variables, such as prior sentence IDs.

Prior DWIs, prior DWSIs, and prior non-vehicular DWIs were the only qualitative criminal history variables significantly related to DWI recidivism. Offenders with any type of prior DWI behavior were significantly more likely to recidivate with a DWI. This finding is consistent with descriptive and bivariate findings that suggest DWI offenders tend to have higher degrees of specialization in offending.

Burgess Risk Assessment Scale

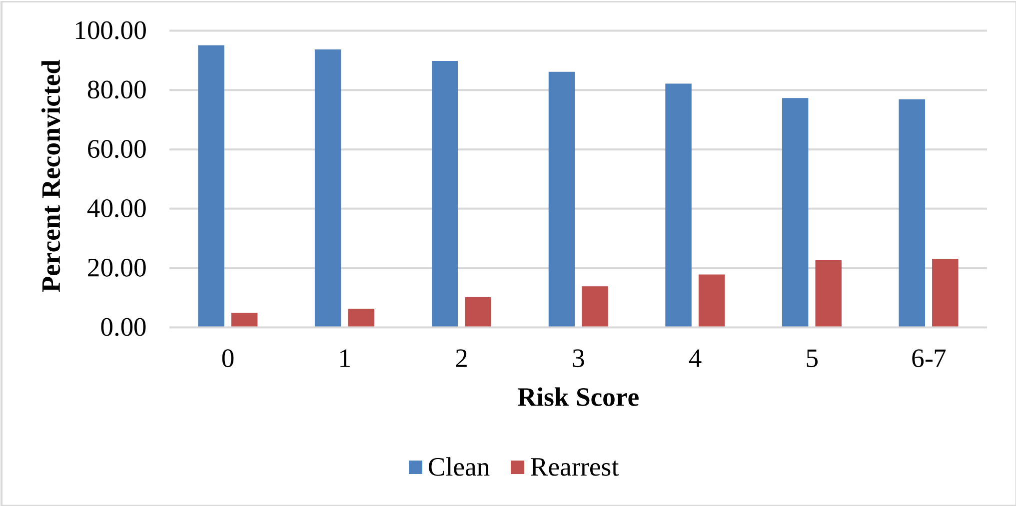
I used significant variables from the logistic regression to construct a risk instrument predicting the likelihood of recidivism with DWI. The final scale included points for gender, age, type of current offense, and three types of prior offenses (DWI, DWSI, and non-vehicular DWI). Each category received only one point except for age which received up to two points. The scale ranged from 0 to 7 points. The specific point values for each category are displayed in Table 4-14.

Table 4-14. Risk Scale 0-7 Predicting DWI Recidivism, Development Sample (N=14,901)

Factor	Within Category Points	Total Category points
Gender		1
Male	1	
Female	0	
Age		2
<18	0	
18-19	0	
20-29	0	
30-39	1	
40-49	2	
50-59	2	
60+	1	
Type of DWI		1
DWI	0	
DWSI	1	
Prior DWI		1
Yes	1	
No	0	
Prior DWSI		1
Yes	1	
No	0	
Prior Non-Vehicular DWI		1
Yes	1	
No	0	

The rate of DWI recidivism increased with each additional score on the Burgess risk scale. However, due to the rarity of DWI recidivism, the clear crisscrossing pattern of arrests and non-arrests is not present for the DWI risk scale. Figure 4-21 shows the percent of offenders who recidivated with a DWI and the percent of offenders who did not, by the risk score. Due to small sample sizes, I collapsed the offenders with a risk score of 6 and 7 into a single category.

Figure 4-21. Percent Reconvicted for DWI by Risk Score



I validated the DWI risk instrument using the validation sample (N = 14,981). A comparison of the ROC test for the development and validation samples confirmed that the scale predicts DWI recidivism equally well for each sample $\chi^2(1) = 0.09$, $p = .764$. The AUC for the validation sample (0.616) was slightly lower than the AUC for the development sample (0.619).

I calculated the confidence intervals and three risk classifications using the combined development and validation samples (N = 29,882). When each of the scores were considered individually, the confidence intervals for the probability of recidivism in each scale overlapped for two group combinations (5 and 6; 6 and 7). The average risk score was 2.91 with a standard deviation of 1.33. Consequently, the average group of offenders included those with a score between 2 and 4. Offenders with a score of 0 or 1 were classified as low-risk. Offenders with a score between 5 and 7 were classified as high-risk. The confidence intervals for the three collapsed groups did not overlap, indicating that the groups were statistically significantly different.

The scale predicting DWI recidivism performed substantially worse than the scale predicting any recidivism. For offenders in the low-risk and high-risk groups, the scale accurately predicted only 63.02% of the outcomes, compared to 80.77% accuracy for the any arrest scale. However, most the accuracy is derived from true negatives in the low-risk category. For low-risk offenders, the DWI scale correctly predicted the outcomes 93.81% of the time. For high-risk offenders, the DWI scale correctly predicted the outcomes only 23.14% of the time.

Part 2: Review of Findings

This section confirmed patterns of recidivism generally. Young, male offenders from urban areas with extensive criminal histories were most likely to recidivate. This section also identified interesting differences between offenders who recidivate with a subsequent DWI offense and offenders who recidivate with a non-DWI offense. Repeat DWI offenders were more likely to be from rural areas, to begin offending at an older age, and to have less serious criminal records.

This section also introduced the possibility of using actuarial risk assessments to model the likelihood of recidivism among DWI offenders in Finland. Given the large base rate of recidivism for any reconviction, risk assessment instruments were effective at predicting recidivism generally. However, the low base rate of DWI recidivism made it more difficult to predict DWI-specific recidivism. The following is a discussion of the findings from this section as they apply to hypotheses 9 through 11, presented at the beginning of the chapter.

General Recidivism

Hypothesis 9: DWI offenders who recidivate will be more likely than non-recidivists (a) to be males than females, (b) to be younger than older, and (c) to have more prior convictions. Supported.

Consistent with general criminological research, recidivists were more likely than non-recidivists to be males, younger, and to have more prior convictions. In addition, the analyses found that more serious offenders (those with a higher BAC) were more likely to recidivate. Among those with prior sentences, offenders were more likely to recidivate if they had a prior sentence for a property, public administration, public order, alcohol, or drug offense. These findings suggest that the general theories of recidivism are likely to apply to DWI offenders.

DWI Specific Recidivism

Hypothesis 10: DWI offenders who recidivate with a DWI will be more likely than non-recidivists and recidivists who recidivate with a non-DWI offense (a) to be younger than older, (b) to have fewer prior convictions, and (c) to have a prior DWI conviction. Partially Supported

Contrary to Hypothesis 10a, DWI recidivists were more likely than non-recidivists or non-DWI recidivists to be middle aged. Specifically, the highest rate of recidivism was among the previously identified second peak in the age-crime curve, between the ages of 40 and 60. In addition, the number of prior sentences was not predictive of DWI recidivism. However, DWI recidivists were more likely than non-recidivists and non-DWI recidivists to have a prior DWI, DWSI, or non-vehicular DWI. Although not originally hypothesized, males were more likely than females to recidivate with another DWI and offenders with a higher BAC were more likely than offenders with a lower BAC to recidivate with another DWI. These findings widely support the previous discussions about specialization among DWI offenders, particularly for those who offend at an older age.

Hypothesis 11: Risk assessment instruments will be able to predict general recidivism more accurately than DWI-specific recidivism. Supported.

As expected, the scale predicting DWI recidivism performed substantially worse than the scale predicting any recidivism. There are two factors that may explain the inability to accurately predict who will recidivate by a DWI. First, recidivism by a DWI is relatively rare (only 13.73% of the total sample). Second, it is important to remember that those scoring a 0 on the dependent variable for the logistic regression model are those who were not reconvicted *and* those who were reconvicted for a non-DWI offense. This combination likely contributes to the inability to identify only the offenders who will recidivate with a DWI offense. Unfortunately, there is no way to use an alternative statistical method such as a two-step regression model or a multinomial logistic regression to construct an additive Burgess risk assessment instrument.

Overall, it appears that Burgess risk assessment instruments are generally ineffective at predicting whether or not offenders will recidivate by a DWI, although the decomposition of the predictive validity did suggest that this tool could be used to effectively predict the offenders with the lowest risk of DWI recidivism. However, this scale must be used in combination with the any arrest scale due to the limitations in the dependent variable. Specifically, it is possible that an offender who is low-risk in the DWI recidivism scale could be high-risk for any reconviction. This combination would suggest that the particular offender is likely to recidivate, but that the recidivism is likely to be an offense other than a DWI. Alternatively, these scales could be used to identify offenders who are both low-risk for any reconviction and low-risk for a DWI reconviction. Identification of these true low-risk groups could help identify offenders who should be eligible for diversionary sentences, freeing up criminal justice resources for other offenders.

Part 3: Finland Specific Sensitivity Analyses

The development of risk assessment instruments is limited to data available to judges at the time of sentencing. The previous sections of this chapter relied on characteristics (offender- and offense-based) that are typically available to judges in courts both in the United States and

Finland. In Finland, information on offenders and offenses is more readily available than the United States. As a result, I was able to test whether the addition of new information could improve the accuracy of the risk assessment instruments.

If additional variables do improve predictions, this study would suggest that other courts should change their record keeping processes to collect more offender- and offense-based information. Given the digitization of records, altering record keeping processes to capture additional information (or to code information differently) should present minimal costs to courts. If additional information improves risk predictions, the benefits of reducing recidivism and targeting high-risk offenders would presumably outweigh the additional administrative costs.

Criminal History Specifications

As mentioned previously, Finland has a dual court system whereby some offenses qualify for a formal court conviction and some offenses qualify for a summary penal judgment. In the original analyses, criminal history is composed of both prior court convictions and prior summary penal judgments. However, it is possible that these components of criminal history should be considered separately. In addition, one could argue that the risk assessment should include only prior court convictions since the risk assessment instrument would be used only for sentencing at court convictions. I decided to test the effect of different specifications of prior criminal history.

I completed four additional analyses. First, I conducted new logistic regressions using only court convictions for both the quantitative and qualitative criminal history measures. I used the results from these logistic regressions to construct a new Burgess risk scale. Second, I conducted new logistic regressions using only summary penal judgments for both the quantitative and qualitative criminal history measures.[83] I used the results from these logistic regressions to construct a new Burgess risk scale. Third, I conducted new logistic regressions using separate indicators for court convictions and summary penal judgments on the quantitative criminal history variables and combined qualitative measures. Fourth, I compared the predictive accuracy of the new scales to the original scale which used both court convictions and summary penal judgments. The objective of this analysis is to determine which specification of criminal history best predicts recidivism for DWI offenders.

Table 4-15 presents the logistic regression results for the three new logistic regressions.[84] Model one includes separate variables for the quantitative measures of prior court convictions and prior summary penal judgments. Model two limits the quantitative and qualitative measures to prior court convictions. Model three limits the quantitative and qualitative measures to prior summary penal judgments. The results of the logistic regressions vary significantly. However, almost all of the differences are limited to the quantitative and qualitative criminal history measures. These analyses reveal the importance of considering the operationalization of criminal history measures. Overall, model one performed the best (R^2 = 0.131), model three performed second best (R^2 = 0.124), and model two performed the worst (R^2 = 0.111). The R^2 value for model one (R^2 = 0.131) was closest to the R^2 value of the original development scale (R^2 = 0.132).

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[83] There was one exception to this rule. Since all DWI, DWSI, and non-vehicular DWI offenses are court convictions, the qualitative measures for these offenses are not limited to summary penal judgments. While this is imperfect, it is the equivalent of including a measure for whether the offender is a first-time DWI offender or not. Given the broader research questions at hand, I felt it was appropriate to leave these court convictions in the model while testing the effectiveness of summary penal judgments more generally.

[84] I reviewed the bivariate statistics for prior court convictions and prior summary penal judgments to determine the best groups for the new categorical variables for the frequency of prior offending.

Table 4-15. Logistic Regression Risk Development, Testing Prior Record Coding, Development Sample (N = 14,901)

	Model 1 Odds Ratio	Model 2 Odds Ratio	Model 3 Odds Ratio
male	1.400***	1.472***	1.453***
Helsinki	1.049	1.125*	1.049
Other urban	1.068	1.100*	1.074
Under 18	5.441***	5.372***	5.260***
Age 18-19	3.906***	4.412***	3.941***
Age 20-29	2.426***	3.033***	2.648***
Age 30-39	2.141***	2.580***	2.293***
Age 40-49	1.950***	2.143***	2.032***
Age 50-59	1.556***	1.620***	1.588***
Multiple Charges	1.249***	1.332***	1.292***
DWSI	1.177***	1.137***	1.184***
1 Prior Court Conv	1.461***	1.643***	
2 Prior Court Conv	1.808***	2.195***	
3 Prior Court Conv	1.876***	2.566***	
4-5 Prior Court Conv	2.039***	3.216***	
6+ Prior Court Con	3.054***	6.848***	
1 Prior SPJ	1.392***		1.500***
2 Prior SPJs	1.744***		1.958***
3 Prior SPJs	1.962***		2.242***
4-6 Prior SPJs	2.597***		3.071***
7+ prior SPJs	5.050***		6.731***
Prior Property Sentence	1.212**	1.234**	1.291**
Prior Personal/Sex Sentence	1.051	1.029	1.376
Prior Public Adm/Order Sentence	1.137*	1.09	1.243**
Prior Other Traffic Sentence	1.082	1.095	0.996
Prior Drug Sentence	1.389***	1.622***	1.648***
Prior Weapon Sentence	0.984	1.097	1.045
Prior DWI Sentence	1.09	1.077	1.540***
Prior DWSI Sentence	1.014	0.938	1.547***
Prior Non-Vehicular DWI Sentence	1.182	1.143	1.529*
_cons	0.135***	0.139***	0.133***
N	14901	14901	14901
R-sq	0.1314	0.1113	0.124
AIC	17947.7	18350.9	18090.6
BIC	18183.6	18548.8	18288.4

*p < .05 ** p < .01 *** p < .001

Reference categories: Black for race; rural for county; 60+ for age; DWI for Type of DWI; 0 prior sentences for No. of Prior Sentences.

Table 4-16. shows the Burgess risk scales that would have been developed from each of the different criminal history specifications. For each of the logistic models, I rotated the reference category for age and the quantitative criminal history measures to determine how many points should be assigned to each of the separate categories. The variables in each of the scales vary, most significantly for the qualitative criminal history measures.

Table 4-16. Burgess Risk Scales Testing Prior Coding

Risk Scale 0-18, Testing Prior Record Coding: Model 1, Development Sample (N=14,901)

Factor	Within Group Points	Total Factor Points	Factor	Within Group Points	Total Factor Points
Gender		**1**	**Prior Court Convictions**		**3**
Male	1		0	0	
Female	0		1	1	
Age		**5**	2-5	2	
<18	5		6+	3	
18-19	4		**Prior Sum. Penal Judgments**		**4**
20-29	3		0	0	
30-39	2		1	1	
40-49	2		2-3	2	
50-59	1		4-6	3	
60+	0		7+	4	
			Prior Property		**1**
Multiple Charges		**1**	Yes	1	
Yes	1		No	0	
No	0		**Prior Padm/Order/Alc**		**1**
			Yes	1	
Type of DWI		**1**	No	0	
DWI	0		**Prior Drug**		**1**
DWSI	1		Yes	1	
			No	0	

Risk Scale 0-14, Testing Prior Record Coding: Model 2, Development Sample (N=14,901)

Factor	Within Group Points	Total Factor Points	Factor	Within Group Points	Total Factor Points
Gender		**1**	**Prior Court Convictions**		**4**
Male	1		0	0	
Female	0		1	1	
Age		**5**	2-3	2	
<18	5		4-5	3	
18-19	5		6+	4	
20-29	4				
30-39	3		**Prior Property Court Conviction**		**1**
40-49	2		Yes	1	
50-59	1		No	0	
60+	0		**Prior Drug Court Conviction**		**1**
Multiple Charges		**1**	Yes	1	
Yes	1		No	0	
No	0				
Type of DWI		**1**			
DWI	0				
DWSI	1				

Risk Scale 0-19, Testing Prior Record Coding: Model 3, Development Sample (N=14,901)

Factor	Within Group Points	Total Factor Points	Factor	Within Group Points	Total Factor Points
Gender		**1**	**Prior Summary Penal Judgments**		**4**
Male	1		0	0	
Female	0		1	1	
			2-3	2	
Age		**6**	4-6	3	
<18	6		7+	4	
18-19	5		**Prior Property**		**1**
20-29	4		Yes	1	
30-39	3		No	0	
40-49	2		**Prior Padm/Order/Alc**		**1**
50-59	1		Yes	1	
60+	0		No	0	
			Prior Drug		**1**
Multiple Charges		**1**	Yes	1	
Yes	1		No	0	
No	0		**Prior DWI**		**1**
			Yes	1	
Type of DWI		**1**	No	0	
DWI	0		**Prior DWSI**		**1**
DWSI	1		Yes	1	
			No	0	
			Prior Non-Veh DWI		**1**
			Yes	1	
			No	0	

Each of the scales were validated using the validation sample. None of the comparisons were significant, indicating that the final scales predicted equally well for the development and validation samples. The AUC values for the three new scales were similar. For model one, the AUC was 0.727. For model two, the AUC was 0.704. For model three, the AUC was 0.716.

I tested the differences in the predictive accuracy of the original scale and the three new scales using a chi square test for the AUC of each scale. The original scale (AUC = 0.726) performed significantly better than the scales including only court convictions (Model 2, AUC = 0.704) or only summary penal judgments (Model 3, AUC = 0.716), $p = 0.000$. However, the scale including separate quantitative measures for prior court convictions and prior summary penal judgments (Model 1, AUC = 0.727) performed significantly better than the original model (AUC = 0.726), $p = 0.000$. Model one performed significantly better than model two or model three, $p = 0.000$.

These findings seem to suggest that the expanded model including separate quantitative measures for prior court convictions and prior summary penal judgments is a better model than the more condensed, original model. However, the differences in the AUC were minor, and there was significant overlap in the 95% confidence interval of the AUC estimates for the two models. Consequently, it is unclear how much benefit is gained from the more complicated model.

I decided to compare the accuracy in predictions for the low- and high-risk groups in the original model and the model containing to expanded quantitative history variables. The original Burgess scale correctly predicted 80.77% of the outcomes for offenders in the low- and high-risk groups. The expanded Burgess scale correctly predicted 82.17% of the outcomes for offenders in the low- and high-risk groups. However, the number of offenders who fell into the low- or high-risk group was smaller for the expanded scale (7999 offenders in the original scale; 7459 in the expanded scale).

Deciding which scale is “better” requires several considerations. From a purely statistical standpoint, the expanded model predicts more accurately than the original scale, as indicated by tests in the AUC and the overall predictions in the low- and high-risk groups. However, the increases in predictive accuracy were minimal (0.001 increase in AUC; 1.40% increase in accurate low- and high-risk predictions) and the scale was derived from a logistic regression model that explained less variance than the original logistic regression models (R^2 for expanded model = 0.131; R^2 for original model = 0.132). The original model is more parsimonious and requires less specific information to be used. With the original scale, judges need information only on the number of prior guilty sentences. In the expanded scale, judges need to know precisely how each of the prior sentences were processed (as court convictions or summary penal judgments). In addition, the expanded scale significantly increases the influence of criminal history variables on the final risk score. In the original model, 6 out of 15 points on the scale are related to criminal history (46.67%). However, on the expanded scale, 10 out of 18 points on the scale are related to criminal history (55.56%). Policy makers must decide how much of an influence prior criminal history should play at sentencing and whether they would prefer a less parsimonious model in order to gain a 1% increase in predictive accuracy.

Expanded Risk Scales: Any Reconviction

Finnish district courts have systematic access to additional criminal justice characteristics that may be predictive of recidivism. To test these effects, I developed expanded scales by replicating the original development processes with models that include a measure for co-offenders and prior incarcerations. Both variables were coded as binary measures. For the co-offender measure, a value of 1 was assigned to all offenders who had at least one co-offender for the primary offense. For the prior incarceration measure, a value of 1 was assigned to offenders who had at least one prior incarceration sentence.

I expected both measures to significantly contribute to the ability to predict who would recidivate. First, having at least one co-offender could serve as an indicator of embeddedness in criminal networks. Association would criminal peers should increase the probability that an offender will continue offending in the future. In addition, the presence of co-offenders may be helpful in predicting the type of recidivism an offender will engage in. Specifically, I expected solo offenders to be more likely than group offenders to recidivate by DWI. Second, prior incarceration should serve as a proxy for the seriousness of an offender's criminal history. The quantitative variables capture frequency of offending and the qualitative variables capture the broad types of offending. However, prior incarceration captures the seriousness of an offender's criminal history, particularly in a country with low incarceration rates like Finland.

First, I estimated a logistic regression predicting any recidivism with the original independent variables and the two additional independent variables. Table 4-17 shows the original and expanded logistic regression coefficients. All of the coefficients that were previously significant were also significant in the expanded model. Additional rotations for age and prior arrest categories indicated that the within group differences for larger categorical variables were also the same. The binary measure for number of co-offenders was not significant. However, the measure for prior incarceration was significant, $p < .05$.

Adding the two additional variables only slightly increased the explained variance in the dependent variable. The R^2 value increased by 0.0003, a less than 1% increase in the total value. Although the prior incarceration variable was statistically significant, it is unclear whether the addition of that variable would significantly increase the predictive ability of a Burgess risk assessment instrument.

Table 4-17. Original and Expanded Logistic Regression, Any Reconviction, Development Sample (N = 14,901)

	Original Odds Ratio	Expanded Odds Ratio
Male	1.398***	1.387***
Helsinki	1.058	1.055
Other Urban	1.069	1.068
Under 18	5.526***	5.632***
Age 18-19	3.918***	3.994***
Age 20-29	2.449***	2.500***
Age 30-39	2.145***	2.154***
Age 40-49	1.948***	1.943***
Age 50-59	1.551***	1.543***
Multiple Charges	1.249***	1.249***
DWSI	1.176***	1.176***
1 Prior Sentence	1.500***	1.507***
2-3 Prior Sentences	2.157***	2.167***
4-6 Prior Sentences	3.513***	3.493***
7-9 Prior Sentences	4.405***	4.353***
10+ Prior Sentences	10.250***	9.788***
Prior Property Sentence	1.211**	1.201**
Prior Personal/Sex Sentence	1.047	1.041
Prior Public Adm/Order Sentence	1.140*	1.130*
Prior Other Traffic Sentence	1.027	1.022
Prior Drug Sentence	1.477***	1.465***
Prior Weapon Sentence	1.012	1.001
Prior DWI Sentence	1.096	1.096
Prior DWSI Sentence	1.001	0.984
Prior Non-Vehicular DWI Sentence	1.144	1.151
At Least 1 Co-offender		0.894
Prior Incarceration		1.192*
_cons	0.132***	0.132***
N	14,901	14,901
R-sq	0.1316	0.1319
AIC	17934.3	17931.2
BIC	18132.1	18144.3

I reconstructed the Burgess risk assessment instrument, adding a point for offenders who had at least one prior incarceration. The range of the expanded scale was 0 to 16. However, no offender reached a score of 15 or 16 in the development sample. ROC analyses indicated that the AUC for the expanded scale was 0.727. The AUC for the original scale (AUC 0.726) was lower than the AUC for the expanded scale, but the differences were negligible. I validated the expanded scale on the validation sample (N = 14,981) and the Burgess risk scale performed equally well for the development sample (AUC = 0.727) and the validation sample (AUC = 0.724), $\chi^2(1) = 0.26$, $p = .613$.

The mean score for the full sample increased slightly from 5.70 to 5.80. The standard deviation of the mean also increased slightly to 2.82. The changes in the mean and standard deviation did not change the classification of risk categories. Consequently, offenders who scored between 0 and 2 were classified as low-risk, offenders who scored between 3 and 8 were classified as average-risk, and offenders who scored above 9 were classified as high-risk. By adding a point without changing the risk score groups, offenders could only move up from the low-risk to the average-risk group or up from the average-risk to the high-risk group. In total, 32 offenders moved from low-risk to average-risk and 307 offenders moved from average-risk to high-risk. Overall, 81.02% of predictions in the low- and high-risk categories were accurate, a minor increase from the 80.77% accuracy in the original scale.

Gottfredson and Gottfredson note that variables should be included in the Burgess risk scale if they are significantly related to recidivism *and* they significantly increase the predictive ability of the scale. Consequently, I compared the ROC curve for the original and expanded scales to test whether the expanded scale was significantly better at predicting recidivism than the original scale. The expanded scale did not perform significantly better than the original scale,

$\chi^2(1) = 3.28$, $p = .0.070$. Despite the significant relationship between prior incarceration and recidivism, adding a point for prior incarcerations does not increase the ability to predict recidivism. In addition, the expanded scale increased the percent of offenders in the average- and high-risk categories. Consequently, prior incarceration should not be included as a risk factor in the final Burgess risk instrument.

Expanded Scales: DWI Reconviction

I followed the same replication processes to establish an expanded scale predicting recidivism by a DWI. Table 4-18 shows the comparison of the original and expanded logistic regressions predicting recidivism by a DWI. All of the variables that were previously significant were also significant in the expanded model. I rotated the reference categories for age and prior sentence IDs to check for stability across within group differences. For age, the findings were generally similar. However, offenders aged 60 and older were no longer significantly different from offenders aged under 18. Despite this difference, I decided to maintain the original scale point categories for age for two reasons. First, the magnitude of the difference in the odds for the youngest and oldest groups were similar in each model. Second, theoretically, there is reason to believe that the youngest offenders really are different than the oldest offenders when considering patterns of behavior. Rotations for prior sentence IDs revealed similar patterns in significant differences. However, a likelihood ratio test confirmed that prior sentence IDs as a whole were not significant, and I did not include prior sentence IDs in the expanded Burgess scale.

Table 4-18. Logistic Regression Risk Scale Development, Development Sample (N = 14,901)

	DWI Recidivism	
	Original	Expanded
Male	1.406***	1.387***
Helsinki	0.799**	0.794**
Other Urban	0.844**	0.842**
Under 18	0.690*	0.72
Age 18-19	0.696*	0.725*
Age 20-29	0.787*	0.815*
Age 30-39	1.04	1.048
Age 40-49	1.386***	1.384***
Age 50-59	1.443***	1.436***
Multiple Charges	1.056	1.062
DWSI	1.316***	1.320***
1 Prior Sentence	1.047	1.05
2-3 Prior Sentences	1.101	1.103
4-6 Prior Sentences	1.143	1.131
7-9 Prior Sentences	1.157	1.139
10+ Prior Sentences	0.84	0.802
Prior Property Sentence	0.956	0.951
Prior Personal/Sex Sentence	0.853	0.853
Prior Public Adm/Order Sentence	1.06	1.049
Prior Other Traffic Sentence	1.145	1.14
Prior Drug Sentence	0.902	0.897
Prior Weapon Sentence	0.898	0.89
Prior DWI Sentence	1.249**	1.251**
Prior DWSI Sentence	1.427***	1.403***
Prior Non-Vehicular DWI Sentence	1.628*	1.648*
At Least 1 Cooffender		0.724**
Prior Incarceration		1.188*
_cons	0.078***	0.079***
N	14901	14901
R-sq	0.0316	0.0325
AIC	11597.4	11590.3

The variable capturing co-offenders was significant ($p < .01$) such that offenders with at least one co-offender were less likely to recidivate with a DWI than solo offenders (OR = 0.724).

The variable capturing prior incarcerations was also significant ($p < .05$) such that offenders with at least one prior incarceration were more likely to recidivate than offenders with no prior incarcerations (OR = 1.188).

Expanding the model to include the two additional variables slightly increased the explained variance in DWI recidivism. The R^2 value increased by 0.0009, a 3% increase in the total R^2 value of the original model. Once again, it is unclear whether the addition of these variables would significantly contribute to the predictive ability of the Burgess risk scale.

I constructed a new Burgess risk assessment instrument predicting recidivism by a DWI, adding one point for solo offenders and one point for offenders with at least one prior incarceration. The range of the expanded scale was 0 to 9. ROC analyses indicated that the AUC for the expanded scale was 0.620. I validated the expanded scale on the validation sample (N = 14,981) and the Burgess risk scale performed equally well for the development sample (AUC = 0.620) and the validation sample (AUC = 0.615), $\chi^2(1) = 0.24$, $p = .625$.

The mean score on the expanded scale for the full sample was 3.95 and the standard deviation of the mean was 1.47. Offenders with a score between 0 and 2 were classified as low-risk. Offenders with a score between 3 and 5 were classified as average-risk. Offenders with a score between 6 and 9 were classified as high-risk. These cut-points were different than the cut-points in the original scale. As a result, offenders may have shifted into higher or lower risk categories on the new expanded scale. Comparison of these two groups indicated that 31 offenders moved from low-risk to average-risk and 839 offenders moved from average-risk to high-risk. On the other hand, 419 offenders moved down from average-risk to low-risk, and 77 offenders moved from high-risk to average-risk. Overall, 60.45% of the predictions in the low-and high-risk categories were accurate, a decrease from the 63.02% accuracy in the original scale.

Despite the statistically significant relationship between co-offenders and prior incarcerations and DWI recidivism, these analyses indicate that the expanded scale does not perform better than the original scale. In addition to the decreased accuracy in the predictions for low- and high-risk offenders, ROC analyses indicated that the expanded scale (AUC = 0.620) did not perform significantly better than the original scale (AUC = 0.619), $\chi^2(1) = 0.14$, $p = 0.708$. These findings suggest that indicators of co-offenders and prior incarcerations should not be included in the final Burgess risk scale.

Part 3: Review of Findings

Finland Specific Risk Assessment Variables

Hypothesis 12: Alternative specifications of criminal history that are specific to the Finnish Criminal Justice System will significantly increase the predictive ability of the risk assessment instrument. Not Supported.

Models developed using only prior court convictions or only prior summary penal judgements did not perform as well as the models that included all prior criminal offending. Alternative specifications of an offender’s complete criminal history provided a minimal increase to the AUC and the overall predictions in the low- and high-risk groups. However, the overall model used to develop the risk instrument explained less variance and did not result in a meaningful increase in predictive accuracy.

Hypothesis 13: Adding independent variables for prior incarceration and co-offending will significantly increase the predictive ability of the risk assessment instrument. Not Supported.

The expanded scale, developed from a model including prior incarcerations and the presence of co-offenders, did not significantly increase the predictive ability of the general or the DWI specific risk assessment instruments. Given Gottfredson and Gottfredson's (1994) guidance for developing risk assessment instruments, the original scale should be preferred over the expanded scale. In addition, these findings challenge the notion that additional information can result in significantly more accurate predictions.

Discussion

The dangers of driving while impaired by drugs or alcohol can be found across the globe. Despite the international prevalence of drinking and driving, much of what we know about DWI offenders comes from studies conducted on offenders in the United States and United Kingdom. This study fills several gaps in the literature. First, the study expanded our knowledge of DWI offenders generally by conducting a comprehensive analysis of DWI offenders and recidivism in a country outside of the United States and the United Kingdom. Second, the study expanded our understanding of the similarities and differences between DWI and non-DWI offenders by directly comparing different types of offenders in a comprehensive, nationwide criminal database. Third, the study expanded our knowledge of risk assessment instruments by developing and validating risk assessment instruments in a different cultural and structural context.

The findings from this research also indicate that DWI offenders are both similar to and different from to non-DWI offenders. Rather than treating DWI offenders as completely "unique," these findings suggest that many of the characteristics of DWI offenders are highly similar to non-DWI offenders. To the degree that DWI offenders are similar to non-DWI offenders, existing criminological theories should be able to explain DWI offending. However, there were also some important differences between DWI offenders and non-DWI offenders, particularly with regard to age and offense specialization. Future research should focus on these differences in order to expand existing theories or develop new theories that can explain DWI offending and how/why it differs from non-DWI offending.

In general, it appears that many of the theories of criminal behaviors may help explain DWI offending. Even in instances where the correlates of behavior were different for DWI and non-DWI offenders, there were still underlying trends that remained the same. For example, both DWI and non-DWI offending peaked in early adulthood, consistent with theories which suggest that most offenders quickly mature out of delinquency. However, the number of offenders arrested for a DWI decreased more slowly across age than the number of offenders arrested for non-DWI offenses.

In addition, the results from this chapter confirm that the general findings in recidivism literature are applicable to DWI offenders. Specifically, young, male offenders with extensive criminal history are the most likely to reoffend. On average, DWI offenders tend to be less serious offenders who are likely to specialize in DWI offending. Consistent with the typology established in Chapter 2 of this dissertation, there were many first-time DWI offenders with no criminal history and who did not recidivate, there were other DWI offenders who recidivated with a DWI offense and who had little to no record of non-DWI offending, and there were DWI offenders with extensive, general criminal histories who recidivated with a range of non-DWI offenses.

Interestingly, the similarities between DWI offenders and non-DWI offenders were strongest for offenders convicted of a person crime. These findings are likely explained by the relationship between alcohol and person crimes such as simple assault. In Finland, even the majority of serious assaults and homicides are committed by persons under the influence of alcohol. These findings suggest that theories focused on the relationship between alcohol and crime may be sufficient to explain a broad range of offending behaviors, including crimes against a person and DWI offenses. Additional research analyzing the use of alcohol and the commission of a broad range of offenses including offenses against a person, offenses against property, and DWI offenses is necessary to further develop our understanding of the alcohol-crime association.

The findings from this chapter suggest that risk assessment instruments may be used in Finland to accurately predict the likelihood of recidivism among DWI offenders. However, it is more difficult to identify which DWI offenders will recidivate specifically by committing a second or subsequent DWI. The findings indicate that risk assessment instruments may successfully identify offenders who have the lowest risk of recidivating by a DWI, which may be helpful for policy decisions regarding the allocation of specific criminal justice resources. In a country that does not currently offer diversionary sentences for DWI offenders, practitioners may consider implementing risk assessment instruments to identify low-risk offenders who should be diverted from costly incarceration sentences. Future research and consideration of differential policy contexts is necessary to determine the best method for implementing risk assessments in unique criminal justice settings.

Chapter 5 : An International Comparison: Finland and the United States

International and cross-jurisdictional research allow for the comparison of relationships in different structural and cultural contexts. This chapter discusses the differences and similarities in the findings from the Pennsylvania and Finland studies. This chapter addresses two specific questions about specialized risk assessment instruments for DUI[85] offenders: (1) Do risk assessment instruments perform equally well on a local and foreign population of offenders?, and (2) How does the accuracy of risk assessment instruments vary across different contexts? This chapter also addresses two broader questions about DUI offenders: (1) Are there consistencies in the differences between DUI and non-DUI offenders in Finland and Pennsylvania? That is, are DUI offenders always a unique group of offenders?, and (2) Is the likelihood of recidivism among DUI offenders invariant across different structural and cultural contexts? Throughout this chapter, I position the findings from the studies conducted in Pennsylvania and Finland into a larger theoretical context and suggest multiple areas of future research.

This chapter applies the scale developed in Finland to the population of DUI offenders in Pennsylvania. After applying the Finnish scale to Pennsylvania offenders, I test whether the scale performs as well, or better than, the scale developed using the Pennsylvania offenders. This analysis serves as a test of the applicability of risk assessment instruments beyond the population on which the scale was developed.

Following the assessment of the applicability of risk scales on two different populations, this chapter moves into a theoretical explanation of the similarities and differences between DUI

[85] For this chapter, I return to the language of DUI rather than DWI. Much of the prior literature on impaired-driving refers to DUI offenses rather than DWI offenses. Because this chapter positions the overall findings from the dissertation in the broader literature, I chose to use DUI rather than DWI.

offenders in Pennsylvania and Finland. Due to restrictions on the use of criminal justice data, it was not possible to conduct direct empirical comparisons between the offenders in each jurisdiction. However, this chapter does compare the overall findings in Chapter 2 and Chapter 4 and explores different structural and cultural contexts in Finland and Pennsylvania that may explain the similarities and differences identified in the independent analyses.

Testing Cross-Application of Scales

Some risk assessment instruments are developed locally on populations of offenders in the same jurisdiction in which the risk assessment would ultimately be used (e.g., Pennsylvania and Virginia). Alternatively, some jurisdictions have adopted risk assessment instruments developed on populations of offenders in a different jurisdiction (e.g., the Northpointe COMPASS instrument). Despite the differing opinions, there is no research that compares two different scales developed using the same methods but populations from different jurisdictions. In order to test the cross-applicability of risk assessment instruments between jurisdictions, I applied the Finnish DUI risk assessment scale to my sample of DUI offenders in Pennsylvania. This section discusses the practical issues with applying a scale to a new jurisdiction and compares the accuracy between the local (PA) scale and the foreign scale (Finland) on predictions for the offenders in Pennsylvania.

I hypothesize that the scale developed using a sample of offenders in Pennsylvania will predict recidivism among DUI offenders in Pennsylvania better than the scale developed using a sample of offenders in Finland. Monahan and Skeem (2013) emphasize that the factors that predict recidivism in one jurisdiction may not predict recidivism in a different jurisdiction. Some of the cross-jurisdictional differences may be related to the types of resources available in a particular jurisdiction and the relationship between those resources and factors measured in a risk instrument. Alternatively, cross-jurisdictional differences may be related to demographic differences in the offending population. That is, if the base rate for a given risk factor is disproportionately high in a jurisdiction, it may not provide any use to a risk instrument attempting to discern low- and high- risk offenders.

In order to test this hypothesis, I used the final dataset from the study discussed in Chapter 2. Prior to conducting any analyses, I recoded several variables in the dataset to conform with the risk factors used in the Finnish scale. After applying the scale to the Pennsylvania offenders, I conducted several tests for accuracy comparing the Pennsylvania and Finnish risk assessment instruments predicting general recidivism and the Pennsylvania and Finnish risk assessment instruments predicting DUI-specific recidivism.

Assigning Points

Although the Finland scale included the same general risk factors as the Pennsylvania scale (e.g., age, number of priors, type of DUI), the way that the risk factors were coded varied between the two jurisdictions. Table 5-1 shows the risk factors and the categories for each factor used in the Finnish risk scale predicting general recidivism and Table 5-2 shows the risk factors and the categories for each factor used in the Finnish risk scale predicting DUI-specific recidivism. In order to apply the risk instrument to the Pennsylvania data, I first had to recode age, type of DUI, and number of prior convictions.

Table 5-1. Risk Scale Predicting Any Reconviction 0-15, Development Sample (N=14,901)

Factor	Within Group Points	Total Factor Points	Factor	Within Group Points	Total Factor Points
Gender		**1**	**Prior Sentences**		**4**
Male	1		0	0	
Female	0		1	1	
Age		**5**	2-3	2	
<18	5		4-6	3	
18-19	4		7-9	3	
20-29	3		10+	4	
30-39	2		**Prior Property**		**1**
40-49	2		Yes	1	
50-59	1		No	0	
60+	0		**Prior Padm/Order/Alc**		**1**
Multiple Charges		**1**	Yes	1	
Yes	1		No	0	
No	0		**Prior Drug**		**1**
Type of DWI		**1**	Yes	1	
DWI	0		No	0	
DWSI	1				

Table 5-2. Risk Scale 0-7 Predicting DWI Recidivism, Development Sample (N=14,901)

Factor	Within Category Points	Total Category points
Gender		1
Male	1	
Female	0	
Age		2
<18	0	
18-19	0	
20-29	0	
30-39	1	
40-49	2	
50-59	2	
60+	1	
Type of DWI		1
DWI	0	
DWSI	1	
Prior DWI		1
Yes	1	
No	0	
Prior DWSI		1
Yes	1	
No	0	
Prior Non-Vehicular DWI		1
Yes	1	
No	0	

In Chapter 2, I imputed values for the age categories because age was missing for 703 offenders. The Finnish scale did not use the same categories for age, and it was not possible to recode the imputed values into the categories used in the Finnish risk scale. Consequently, I chose to re-impute age using a new categorical variable for age for which the categories were consistent with the categories used in the Finnish risk scale. The age categories were the same for the scale predicting general recidivism and the scale predicting DUI-specific recidivism.

I used chained imputation methods and imputed 11 datasets, consistent with the imputation techniques used in Chapter 2. I used all available demographic (e.g., age, gender, county), offense (e.g., type of DUI, multiple conviction charges), and criminal history (e.g., number of priors and types of priors) to predict age in the imputation model.

The coding of prior convictions was relatively straight forward. All offenders had a count measure for the number of prior convictions. I created a new categorical variable for the number of prior convictions consistent with the classifications used in the Finnish risk instrument predicting general recidivism. The number of prior convictions was not relevant for the scale predicting DUI-specific recidivism.

There were some differences in the types of prior offenses. In the Pennsylvania data, prior DUI offenses were not coded separately by BAC. The Pennsylvania sentencing guidelines for DUI offenders counts each prior DUI offense, regardless of the BAC level. Consequently, for the DUI-specific recidivism scale, offenders in Pennsylvania could receive a maximum of one point for the types of priors rather than the three possible points identified in the scale.

Type of DUI presented a unique challenge for applying the Finnish instrument to Pennsylvania data. The statutes in Finland and Pennsylvania include differing classifications of DUI offenses based on BAC level. In Finland, there are only two types of alcohol-impaired DUI offenses: those with a BAC of .05% to .11% and those with a BAC of .12% or greater. Similarly, there are two types of drug-impaired DUI offenses: driving while impaired by drugs and driving while seriously impaired by drugs. Pennsylvania DUI offender data did not include an indicator for the driver's level of intoxication. Instead, I previously classified DUI offenders based on the range of BAC associated with different DUI statutes in Pennsylvania. Unfortunately, the classifications of BAC in Pennsylvania statutes (<.08%, .08-.09%, .10-.15%, and .16%+) were not consistent with the .12% threshold in Finnish statutes. Furthermore, the Pennsylvania statutes do not make distinctions among drug-impaired DUI offenses based on the *level* of intoxication.

I coded a binary measure for the type of DUI offense. The first group included alcohol-impaired DUI offenders with a BAC of .09% or less and all drug-impaired DUI offenders. The second group (driving while seriously impaired) included alcohol-impaired DUI offenders with a BAC of .10% or greater. Using this binary coding, offenders with a BAC of .10% or .11% are technically misclassified on the Finnish risk scale. The alternative classification (grouping offenders with a BAC of .10% - .15% in the lower category) would have misclassified offenders with a BAC of .12%, .13%, .14%, and .15%. Absent a measure distinguishing the types of drug-impaired DUI offenders in Pennsylvania, I defaulted all offenders to the less serious DUI classification.[86] I used this binary classification for the general recidivism scale and the DUI-specific recidivism scale.

The final scale predicting any reconviction within 5 years of release for the primary offense ranged from 0 to 13. As per the Finnish risk classifications, offenders with a score of 0 to 2 were classified as low-risk, offenders with a score of 3 to 8 were classified as average-risk, and offenders with a score of 9 to 13 were classified as high-risk.

The final scale predicting DUI-specific recidivism within 5 years of release for the primary offense ranged from 0 to 5. As per the Finnish DUI risk classifications, offenders with a score of 0 or 1 were classified as low-risk, offenders with a score of 2 to 4 were classified as average-risk, and offenders with a score of 5 were classified as high-risk.

[86] My sample of DUI offenders in Pennsylvania included only the offenders for whom the DUI offense was the most serious offense. It may be likely that DUI offenders who are seriously impaired by drugs may be more likely to also be charged with possession of drugs or drug paraphernalia, both offenses which are more serious than a drug-impaired DUI offense.

Any Reconviction - Evaluating Accuracy

Table 5-3 shows the distribution of offenders across the three risk classifications. About 8.0% of offenders were classified as high-risk and low-risk. This is a stark difference from the distribution we would expect given the methods used to construct the risk classifications. When developed, the cut-points for risk classifications were established using the mean plus/minus one standard deviation. The intention of this method is to identify roughly the 16% of offenders who are higher-than-average risk and the 16% of offenders who are lower-than-average risk.[87] Regardless of the accuracy in the predictions for offenders classified as high- and low-risk, this scale fails to accurately identify meaningful amounts of offenders who exhibit atypical risk profiles.

Table 5-3. Risk Classification - Finnish Any Reconviction Scale, Pennsylvania DUI Offender Imputed Samples, (N = 510,598)

	N	%
Low-Risk	21,241	4.16
Average-Risk	468,546	91.76
High-Risk	20,811	4.08

Overall, the scale performed better than chance. An ROC test found that the AUC for the Finland scale on the Pennsylvania data was 0.618. The AUC for this scale fell within a similar range to the other scales discussed in Chapter 2 and Chapter 4. However, an ROC comparison of the Finland and Pennsylvania scales found that the Pennsylvania scale performed significantly better for the sample of Pennsylvania DUI offenders (Finland scale AUC = 0.618 and Pennsylvania scale AUC = 0.655, χ^2 (1) = 2502.03, p < 0.000).

[87] Assuming the data are normally distributed across the risk scale, 68% of offenders should fall within one standard deviation above and below the mean.

In addition to the ROC comparisons, it is important to evaluate which scale performs best for the low- and high-risk classifications. Table 5-4 shows the distribution of offenders in low- and high-risk categories as well as the accuracy of the predictions for low- and high-risk offenders for the Finland and Pennsylvania scales applied to the Pennsylvania sample of DUI offenders.

Table 5-4. Accuracy for High- and Low-Risk - Any Reconviction

	Finland Scale		Pennsylvania Scale	
	N	% Accurate	N	% Accurate
High- and Low-Risk	42,052	68.8%	186,583	59.7%
High-Risk	20,811	49.5%	109,097	38.6%
Low-Risk	21,241	87.7%	77,486	89.3%

The Finnish scale performed better than the Pennsylvania scale for the combined high- and low-risk classifications (68.8% accurate vs. 59.7% accurate). The accuracy of predictions for low-risk offenders were similar between the two scales (87.7% for the Finnish scale and 89.3% for the Pennsylvania scale). The Finnish scale performed better than the Pennsylvania scale for high-risk classifications (49.5% vs. 38.6%, respectively).

It appears that the improved accuracy for the Finnish risk instrument is driven by the smaller number of offenders classified as low- or high-risk. As mentioned previously, only 8% of offenders were classified as high-risk under the Finnish risk instrument. In contrast, the Pennsylvania risk instrument classified 21.37% of offenders as high-risk. On the other hand, both scales performed equally well for predicting low-risk offenders, even though the Pennsylvania scale classified 4.44 times as many offenders as low- or high-risk.

DUI Recidivism – Evaluating Accuracy

Table 5-5 shows the distribution of offenders across the risk classifications for DUI-specific recidivism. Similar to the findings for the any recidivism scale, the Finnish risk instrument over-classified offenders as average-risk (74.1%) and under-classified offenders as high-risk (3.34%). Unlike the any recidivism scale, the DUI instrument over-classified offenders as low-risk (22.56%).

Table 5-5. Risk Classification - Finnish DUI Reconviction Scale, Pennsylvania DUI Offender Imputed Samples, (N = 510,598)

	N	%
Low-Risk	115,195	22.56
Average-Risk	378,361	74.10
High-Risk	17,042	3.34

Analysis of the ROC curve for the Finnish DUI risk instrument indicated that the scale did not perform better than chance (AUC = 0.488). As a result, the Finnish DUI risk instrument performed significantly worse than the Pennsylvania DUI risk instrument (Finland scale AUC = 0.488 and Pennsylvania scale AUC = 0.547, χ^2 (1) = 905.06, $p < 0.000$). These findings suggest that the Finnish DUI risk instrument would not validate on a population of DUI offenders in Pennsylvania.

Disaggregation of the predictive accuracy for low- and high-risk offenders confirmed the superiority of the Pennsylvania DUI scale. Table 5-6 shows the number of offenders classified as low- and high-risk of DUI recidivism as well as the accuracy of predictions for low- and high-risk classifications.

Table 5-6. Accuracy for High and Low Risk - DUI Reconviction

	Finland Scale		Pennsylvania Scale	
	N	% Accurate	N	% Accurate
High- and Low-Risk	132,237	78.7%	189,894	51.5%
High-Risk	17,042	11.2%	98,665	14.3%
Low-Risk	115,195	88.7%	91,229	91.8%

Although the Finnish scale had higher accuracy rates for the high- and low-risk classifications combined (78.7% vs. 51.5%), the Pennsylvania scale had higher rates of accuracy for high-risk classifications (14.3% for the Pennsylvania scale vs. 11.2% for the Finnish Scale) and for low-risk classifications (91.8% for the Pennsylvania scale vs. 88.7% for the Finnish Scale). The higher rate of combined low- and high-risk accuracy for the Finnish scale was driven by a smaller sample of high-risk offenders on the Finnish scale.

Neither the Pennsylvania or the Finnish scale exhibited high rates of accuracy for predicting DUI recidivism. As discussed in Chapter 2, the low base rate of DUI recidivism among DUI offenders in Pennsylvania makes it difficult to accurately predict DUI-specific recidivism. Regardless of this base rate problem, the Pennsylvania scale once again classified more offenders as having an atypical DUI recidivism profile and may be more useful for practitioners overall.

Summary of Findings

The analyses in this section support the initial hypothesis, that the scale developed using a sample of offenders in Pennsylvania will predict recidivism among DUI offenders in Pennsylvania better than the scale developed using a sample of offenders in Finland. This study provides initial empirical support for the idea that risk assessment instruments in the criminal justice system should be developed on local populations of offenders.

Even just the coding of variables alone introduced complications that may arise from using risk assessment instruments in new jurisdictions. Differences in local statutes or the availability of data may undermine the ability to accurately classify offenders on a particular scale. By developing scales locally, practitioners can account for structural differences based in the law or based in the availability of certain types of information. In my study, all of the factors were available in the Pennsylvania dataset, but the variables lacked enough detail to accurately classify all offenders. In other cases, it may be that entire factors are not available to practitioners. By omitting some or all of the classifications for risk factors in a scale, the accuracy of predictions is likely to decrease. It is possible that the accuracy of the Finnish scale for DUI offenders in Pennsylvania could be improved with additional data on the types of DUI offenses committed by offenders and the types of prior DUI convictions in offenders' criminal histories.

The Finnish scale predicting general recidivism did predict risk better than chance (AUC = 0.618). In addition, the accuracy of the predictions for low- and high-risk offenders was similar to the accuracy from the Pennsylvania scale. Despite these similarities, the Finnish scale classified far fewer offenders as low- or high- risk. With only 4.16% of offenders classified as low-risk and 4.08% of offenders classified as high-risk, the Finnish scale would rarely provide additional information to criminal justice officials.

These findings provide further support for the local development of risk instruments. Monahan and Skeem (2013) note that most risk assessment instruments will reach a similar level of overall predictive accuracy because the same general factors are significant predictors across scales (e.g., age and criminal history) and because there appears to be a "ceiling" for the overall accuracy level of any given risk instrument. However, scales developed in non-local jurisdictions are still dependent upon the distribution of risk factors present in a particular population. By applying the scale to a different population with a different distribution of factors included in the scale, the instrument is less efficient at identifying populations with different levels of risk.

The Finnish scale predicting DUI-specific recidivism did not perform better than chance (AUC = 0.488). Although the accuracy for the predictions for low-risk and high-risk offenders was similar to the accuracy for the predictions made by the Pennsylvania scale, the Finnish scale classified fewer offenders as high-risk. The main use of the DUI-specific recidivism scale lies in the classification of high-risk offenders, since offenders who are low-risk for DUI recidivism may not recidivate or may recidivate with a non-DUI offense. The Pennsylvania risk scale classified 5.79 times more offenders as high-risk than the Finnish scale and had a higher rate of predictive accuracy for high-risk offenders (11.2% for the Finnish scale vs. 14.3% for the Pennsylvania scale).[88]

The Pennsylvania risk instrument predicting general recidivism would be more useful than the Finnish risk instrument predicting general recidivism for identifying atypical DUI offenders in Pennsylvania. However, by increasing the number of offenders who would be classified as high- or low-risk, the Pennsylvania risk instrument increased the number of false-positives (i.e., offenders classified as high-risk but who did not recidivate). If the goal is to identify a meaningful population of offenders who are higher- or lower-than-average risk of recidivism, the Pennsylvania scale is clearly preferable. If the goal is to create a risk scale with the greatest predictive accuracy overall, the Pennsylvania scale is clearly preferable. If the goal is

[88] As discussed in Chapter 2, there are additional theoretical and methodological concerns with using the DUI-specific recidivism scale developed on the full sample of offenders. While the Pennsylvania scale does perform better than the Finnish scale, there is reason to believe that neither scale should ultimately be used to predict the recidivism behaviors of DUI offenders in Pennsylvania.

to create a predictive instrument while minimizing false-positives, the Finnish scale is likely preferable.

The deficiencies in the Finnish general recidivism scale were especially evident for low-risk offenders. The Pennsylvania scale classified 6.25 times as many offenders as low-risk without decreasing the accuracy of predictions for low-risk offenders. Although the Pennsylvania scale included more false-positives, the Finnish risk scale over-estimated the risk classification for a significant population of DUI offenders. As discussed in Chapter 2, one possible use of sentencing risk instruments for DUI offenders could be to identify low-risk offenders who should be eligible for diversionary sentences. The Pennsylvania risk instrument is clearly superior for identifying a significant portion of offenders who are low-risk.

Regardless of the ultimate policy goal, these analyses emphasize the complexity of applying risk instruments to a new population of offenders. Although skeptical of using non-local risk instruments, Monahan and Skeem (2013) indicate that scales should at least be validated on a local population before deciding to implement a new risk scale. The authors do not suggest what types of validation are sufficient for determining whether a risk instrument is predictive in a particular jurisdiction. While the Finnish scale appears to validate on the Pennsylvania data when analyzing ROC curves, disaggregation of the risk classifications and subsequent accuracy indicate that the Finnish scale would be relatively useless if applied to offenders in Pennsylvania.

DUI Offenders in Finland and Pennsylvania: Similarities and Differences

Answering the call for comparative criminology (Adler, 1996; Farrington, 1999), this dissertation presents two similar studies conducted in different cultural and structural contexts. The findings from the studies presented in Chapter 2 and Chapter 4 revealed many similarities and differences in the correlates of DUI offending and recidivism. In addition, these studies show how the development of risk assessment instruments may provide benefits to different criminal justice contexts, albeit in different ways. Similarities identified in two dissimilar contexts lay a stronger foundation for establishing generalizable theories to explain offending behaviors (Kohn, 1987). Moreover, differences identified in two dissimilar contexts allow for a better understanding of the need for contextual explanations for criminal offending and can reveal how current theories are constrained by the social, cultural, and political structures under which they were developed (Bennett, 2009).

While this study advances our knowledge through the use of comparative criminological approaches, both studies take place in WEIRD (Western, Educated, Industrialized, Rich, and Democratic) societies, limiting the overall generalizability. Recent criticisms in the field of psychology indicate that citizens of WEIRD societies make up only 12% of the world's total population (Henrich, Heine, and Norenzayan, 2010a). Psychologists note that there are important differences in analytical thinking and subsequent decision-making processes in non-Western and Western countries. Specifically, Henrich et al. (2010a) note, "anthropologists have long suggested: that people from Western, educated, industrialized, rich and democratic (WEIRD) societies – and particularly American undergraduates – are some of the most psychologically unusual people on Earth."

Heinrich et al. (2010b) find that Western societies rely more heavily on analytical reasoning while non-Westerners rely more heavily on holistic reasoning. Analytical reasoning relies on formal rules structures to explain decision-making and to predict behavior, whereas holistic reasoning relies on a broader consideration of the context to explain decision-making and to predict behaviors. Given that much of our research in criminology involves an understanding of individual decision-making (e.g., the decision to commit crimes, the decision to punish), it is important to consider that this dissertation, which relies on samples of offenders from two Western counties, may not be generalizable to non-Western or non-Industrialized societies.

Despite these limitations, this dissertation is still a significant expansion beyond the current literature base. Although critical of the reliance on WEIRD populations generally, Heinrich et al. (2010b) are particularly critical of the dominance of American samples in academic research. The authors note that Americans are different from other WEIRD populations in that, "Americans are, on average, the most individualistic people in the world." (p. 74). Individualism is a characteristic ingrained in American culture, from the time that children are born.[89] Individualism is a core pillar of American culture which helps explain why the United States, compared to other large Western counties has, "the highest crime rate, the longest working hours, the highest divorce rate, the highest rate of volunteerism, the highest percentage of citizens with a post-secondary education, the highest productivity rate, the highest GDP, the highest poverty rate, and the highest income-inequality rate; and Americans were the least supportive of various governmental interventions." (Heinrich et al., 2010b: p. 75). Unlike other countries, American society tends to promote a distinct separation between individuals and the state.

While Finland is a WEIRD population, it differs structurally and culturally from the United States. As a welfare country, Finnish culture emphasizes the concept of "society" and the relationship between the broader society and social cohesion (Kettunen, 2012). In fact, Finland, like many other Nordic-countries, often uses the term "society" to refer to the "state,"

[89] Heinrich et al. (2010b) note that Americans were the only persons in a survey of 100 societies who lay their baby to sleep in a separate room, highlighting the independence and individualism promoted immediately after children are born.

emphasizing the communitarian norms which view civil society as a part of the state, not distinct from the state (Kettunen, 2012). With a state that emphasizes equality and a culture that emphasizes social cohesion, Finland has been recognized as being the safest country, the third least corrupt country, and the happiest country in the world. It has the fourth lowest poverty rate among OECD (Organization for Economic Cooperation and Development) countries and the fifth lowest income differences in OECD countries (see Statistics Finland, 2018). Furthermore, Finnish education and health care systems have been recognized as some of the best in the world (see Statistics Finland, 2018).

Given that Finland and Pennsylvania are both WEIRD societies, the exhibit several similarities. Consistent with the findings that WEIRD societies rely on formal systems of rules, both Finland and Pennsylvania have well developed criminal justice systems that strictly govern illegal behavior, such as DUI offending. In general, these criminal justice systems establish explicit expectations for citizens (e.g., that they will not drive with a BAC above the legal limit) and impose sanctions (e.g., probation or incarceration) for individuals who violate these formal rules. To the extent that individuals in WEIRD societies rely on analytical reasoning, well established systems of law should act as a deterrent to criminal behavior (Beccaria, 1764/1963).

Despite these broad similarities, differences in the relationship between individuals and the state are likely to cause variation in criminal offending and the effectiveness of criminal sanctions. In America, where individuals are perceived as separate from the state, there is likely to be a greater reliance on formal social control institutions for addressing criminal behavior. In Finland, where society and the state are viewed as one in the same, there is likely to be a greater emphasis on informal social control and a stronger relationship between formal and informal control structures. The implications of the interdependent relationship between formal and informal control for DUI offending and punishment is discussed later in this chapter.

This dissertation explored two important areas of criminological research: DUI offending and the development and use of risk assessment instruments. The following sections discuss the results from Chapter 2 and Chapter 4 as they pertain to DUI offending, DUI recidivism, and the development and use of DUI risk assessment instruments. The discussion positions the findings of this dissertation in a more general theoretical context while expanding upon the review of the cultural and structural contexts which help explain the convergence and divergence of findings across the two studies.

DUI Offending and Recidivism

DUI offenders in Finland and Pennsylvania were similar in many ways. First, the findings from both studies provide support for a tripartite typology of DUI offenders that I proposed in Chapter 2. Second, the age distribution for DUI offenders differed from the age distribution for non-DUI offenders such that DUI offending remained steady through the life course. Third, DUI offenses were concentrated in rural areas.

Despite these similarities, there were also notable differences in the DUI offending populations in Finland and Pennsylvania. First, DUI offenders in Finland were more likely than DUI offenders in Pennsylvania to have a prior criminal record. Second, DUI offenders in Finland were more likely than DUI offenders in Pennsylvania to recidivate with any offense, particularly with a non-DUI offense.

The General Profile of DUI Offenders

Prior approaches to classifying DUI offenders based on their level of alcohol and/or drug use (DeMichele, Payne, and Lowe, 2013) or their history of problematic driving behaviors

(Marowitz, 1998) are insufficient to explain DUI offending. The persistent exclusion of DUI offenders from criminological research and the overwhelming emphasis on DUI offenders as addicts (DeJong and Hingson, 1998; Nochajski and Stasiewicz 2006; Maenhout et al, 2014) has prevented a more holistic understanding of both DUI offending and recidivism.

Both studies in this dissertation identified the three general populations of DUI offenders that I had hypothesized: those with no criminal history and no recidivism, those with DUI or other alcohol-related criminal history and DUI recidivism, and those with more general criminal histories who recidivated with a range of DUI and non-DUI offenses. The consistency in this typology across the two study sites suggests that there are broad classifications of DUI offenders that are generalizable to different structural and social contexts. Importantly, the behavior of each of these sub-groups may be explained by different criminological theories that focus on different inherent or structural characteristics and their associations with criminal offending.

The general consistency in the findings in this dissertation and the support for a tripartite typology of DUI offenders may be explained by the four previously established alcohol-crime link explanations: (1) direct cause explanations, (2) situational characteristics explanations, (3) common-cause, or spurious explanations, and (4) cultural explanations. Much of the prior research on the alcohol-crime association focuses on explanations for violent offending (Wild, Graham, and Rehm, 1998; Graham and West, 2001; Martin, 2001; Gruenewald et al., 2006). However, these explanations are helpful for understanding non-violent alcohol-related criminal offending, such as DUI. Consistent with Martin (2001), the heterogeneity in the typology I established indicates that an integrative approach combining some elements from all four of the alcohol-crime links is likely best to explain DUI offending.

The consumption of alcohol has the same intoxicating effects for individuals in all countries. Consistent with the direct cause explanation of the alcohol-crime link (Gustafson, 1994), intoxication has pharmacological effects on the brain that can affect decision-making and impulse control. Even rational actors with high levels of self-control may commit crimes while under the influence of drugs or alcohol. For some individuals, DUI offending may be no more than the result of a night of heavy drinking.

Individuals who are not highly intoxicated may also be influenced by situational characteristics (Steele and Josephs, 1990). If an individual is drinking at a bar in a rural area with no public transportation or taxi services, they may be more likely to drive home after consuming too many drinks at the bar. These situational characteristics may interact with direct-cause explanations, such that situational factors may have less influence on decision-making as intoxication increases and rational thinking decreases.

Alternatively, the alcohol-crime relationship may be related to alcohol use. Alcohol and drug use is also a global phenomenon. Increasing alcohol consumption and heavy drinking in Finland have caused a range of public health concerns including high rates of DUI offending (Karlsson et al., 2010). Similarly, a World Health Organization (2014) report on alcohol use ranked the United States a 4 out of 5 on the alcohol-attributable "years of life lost" scale.

There are two possible explanations for the relationship between problematic alcohol use and crime. First, the relationship may be spurious (Jessor and Jessor, 1977). That is, individuals may have an underlying likelihood to engage in problem behaviors in general, resulting in high rates of alcohol consumption and a broad range of criminal behaviors. This explanation is consistent with general theories of criminal offending, such as self-control theory, which suggest that there are some individuals who are more likely to engage in many different types of antisocial or criminal behaviors, including DUI (Keane et al., 1993).

However, the necessary condition of intoxication for DUI offending suggests that criminological theories of self-control (Gottfredson and Hirschi, 1990) are not sufficient for explaining DUI offending among populations who drink. As noted previously, intoxication is likely to impair general decision-making abilities and inhibit an individual's self-control. Subsequently, self-control theories are not sufficient to explain why some people drink and drive and others drink and do not drive. However, theories of self-control may be able to explain differences in drinking patterns that may result in different likelihoods of DUI offending. Additional research on a broader population sample (i.e., a sample not limited to offenders) is necessary to test how differential selection into excessive drinking may help explain the correlates of DUI offending.

Second, increasing alcohol use may be a response to social stress (Linsky et al., 1985; Staff et al., 2014, and subsequent criminal offending (e.g., DUI) may simply be the result of intoxication, situational factors, and cultural norms (Martin, 2001). Some theories of criminal offending posit that alcohol and drug use may be a way to cope with negative reactions resulting from societal strain (Agnew and White, 1992). Original writings on strain theory directly associate societal strain with the intersection of culture and structure (Merton, 1938). Individuals who would not engage in crime normally may turn to alcohol or drugs and associated criminal behaviors as a way to cope with life events (e.g., unemployment, divorce) that foster negative emotions. In some ways, alcohol-use and subsequent alcohol-related offending may be a "normal" reaction when individuals feel as though they are failing to achieve cultural goals (e.g., stable employment or maintaining a happy, healthy family) (Merton, 1938).

In order to fully assess how these theoretical explanations may be related to the typology of DUI offenders established in this dissertation, future research should use data that includes both criminal history characteristics and measures of alcohol and drug use. As discussed in Chapter 2, prior studies have relied on datasets that do not include any comprehensive measures of criminal history. On the other hand, this dissertation did not include any measures of alcohol or drug use. As such, all discussions of substance use as a possible explanation for any of the findings are purely speculative. The next step in developing a general theory of DUI offending is to conduct a comprehensive study that is able to assess trends in general criminal offending and trends in alcohol or drug use.

DUI Offending and Age

Prior research on the age-crime curve finds that offending tends to peak early and decline rapidly with age (Greenberg, 1985; Laub and Sampson, 2003). In both Finland and Pennsylvania, DUI offending peaked in early adulthood, rapidly declined initially thereafter, but plateaued through middle age. In both samples, a sort of "second peak" appeared for offenders between the ages of 35-55. This unique trend in age suggests that traditional theories positing that offenders "mature out" of crime are not sufficient to explain DUI offending (Greenberg, 1985).

There are four possible explanations for the unique age-crime curve for DUI offending. First, the second peak in offending may be driven by older offenders who engage in alcohol or drug use as a response to social stresses (e.g., unemployment or divorce) (Linsky et al., 1985; Staff et al., 2014). Second, the second peak in DUI offending may reflect changes in social roles as young children age and parental responsibilities decrease (Staff et al., 2014). Increases in unstructured leisure time and a greater social acceptability for drinking may lead to increases in alcohol consumption, resulting in DUI behaviors.

Third, the second peak may be driven by more serious offenders who mature out of general offending, but who continue to engage in antisocial behaviors such as illicit drug use or binge drinking. This explanation is consistent with some prior research on samples of serious offenders (Laub and Sampson, 2003). While this explanation is able to explain persistence in offending through the life course, it does not explain DUI behaviors for older offenders who do not have a prior record.

Finally, the second peak may represent cohort differences in the acceptance of heavy drinking and drinking and driving. It is possible that older cohorts came of age during a time when there was less stigma around heavy drinking and fewer regulations on drinking and driving and that liberal views of alcohol consumption persist through the lifecourse. Supporting this hypothesis, recent studies on alcohol consumption has found more significant increases in alcohol consumption for older cohorts than for younger cohorts (Dawson et al., 2015). However, the Pennsylvania Commission on Crime and Delinquency reports that the rate of DUI in Pennsylvania was almost the exact same in 2015 (368.5 per 100,000) as it was in 1990 (367.7 per 100,000), indicating very little change in the overall rate of offending as cohorts have aged (PCCD, 2015). If cohort-based differences were sufficient for explaining the second peak, I would expect to see changes in offending patterns with cohort replacement over time. Additionally, older offenders were more likely to come of age during the rise of community organizations (e.g., MADD) aimed at educating the public about the dangers of DUI offending and lobbying for increased punishments for DUI offenders (Fell and Voas, 2006). Thus, I would expect that older cohorts may actually have more conservative views of drinking and driving.

The second peak was also present in the age distribution for DWI offenders in Finland. It is possible that there are cohort-period effects present in both Finland and the U.S. data. However, social drinking used to be heavily stigmatized in Finland. Older cohorts came of age when casual drinking (e.g., with lunch or dinner) was discouraged. Younger cohorts in Finland came of age during the liberalization of formal and informal regulations on alcohol (Mäkelä et al., 2012). Access to alcohol steadily increased following broad reforms beginning in the mid-1990s. As the frequency of consumption increases, one would expect that younger cohorts would actually exhibit higher rates of DUI than older cohorts. Consequently, cohort-based effects are unlikely to explain the second peak in the unique DUI age-crime curve.

My dissertation was unable to determine what drives the differences in DUI offending with age. Additional research is needed on DUI offenders to disaggregate the age-crime curve and to determine what factors contribute to the more gradual decline in rates of offending through the life course. Ideally, future research would be able to identify age, period, and cohort effects by analyzing DUI offenders from multiple birth cohorts over time (Keyes et al., 2012; Dawson et al., 2015).

DUI Offending and Location

Many theories of criminal offending focus on the behaviors of individuals in dense urban areas (e.g., Sampson and Groves, 1989). Some theories suggest that crime is more likely to occur in urban areas than rural areas due to increased opportunity and decreased networks of informal social control (Stark, 1987; Sampson and Groves, 1989). The studies in this dissertation suggest that DUI offenses may not follow the same patterns.

In both Finland and Pennsylvania, the majority of DUI offenses occurred outside of dense urban areas. While the opportunity for property or person crimes increases as the population increases (e.g., there is more property to steal or more persons to assault), the opportunity for DUI crimes may increase as the population decreases. Rural neighborhoods are less likely to have robust public transportation networks such as buses, trams, subways, or taxis (Velaga et al., 2012). As such, it is more likely that individuals will consume alcohol or drugs and have no access to any form of transportation other than driving their own cars. These structural conditions are likely to result in a higher prevalence of DUI offending.

The prevalence of DUI offending in rural areas may also be the result of social differences between rural and urban communities. Some research suggests that individuals in rural areas are more likely to have an alcohol use disorder (Borders and Booth, 2007). Access to drug or alcohol treatment programs may also be limited in rural areas. One small study of 118 DUI offenders in a rural setting found that rural DUI offenders had high rates of alcohol use and faced limited access to substance use or mental health treatment (Dickson, Wasarhaley, and Webster, 2013).

Future research should focus on the differences between DUI offenders in rural, suburban, and urban areas to better understand the geographic differences in DUI offending and recidivism. Additional research should analyze differences in the availability of treatment for DUI offenders as well as the different types of criminal justice responses (such as the use of DUI courts) in urban and rural jurisdictions.

DUI Offenders and Criminal History

DUI offenders in Pennsylvania were less likely to have a prior criminal record than DUI offenders in Finland. In Pennsylvania, three-quarters of all offenders had no prior criminal record. In Finland, only one-third of all offenders had no prior criminal record.

The differences in the findings between Finland and Pennsylvania may be driven largely by both a different composition of the types of DUI offenders and a differential response to DUI offenders in each jurisdiction. Prior research on offenders in the United States finds that DUI offenders are more likely to have prosocial bonds such as marriage or employment (DeMichele, Payne, and Lowe, 2013). Prior research on offenders in Finland suggests that DUI offenders most often come from socially disadvantaged backgrounds (Karjalainen et al., 2011). Insofar as social disadvantage and substance use are associated with higher rates of criminal offending, it follows that the DUI population in Finland would be more likely to have a criminal record. While DUI offending in Pennsylvania tends to be associated with non-criminal, one-time offenders, DUI offending in Finland tends to be associated with general offenders who more frequently participate in a range of criminal behaviors. In this way, the proportion of offenders in each of the three groups in the DUI offender typology is different in Finland and Pennsylvania.

The prevalence of criminal records among DUI offenders in Finland may be associated with strict policing and sanctions for DUI offenders. The absence of a significant population of one-time, non-criminal DUI offenders in Finland may result from strict institutions of formal social control and the stigma associated with a criminal label. Alternatively, the absence of strong informal social control mechanisms in the United States results in a large population of one-time DUI offenders who are deterred from future offending by formal social control mechanisms that are often lenient for first-time DUI offenders. The same types of structural and cultural characteristics that impact criminal history also influence recidivism. A more robust discussion of these differences follows in the next section.

DUI Offenders and Recidivism

In the criminal justice system in the United States, DUI offenders are generally considered to be less serious offenders. In some states, 14% of the driving population have a DUI record (Ross, 1992). This estimate does not include individuals who had a DUI expunged from their official record. In addition, most states have diversion laws that allow first-time DUI offenders to have their records expunged if they do not recidivate during a specified time period (typically six months to one year).[90] While some politicians have spoken out against the "immorality" of drunk driving, advocates for harsher punishments of DUI offenders tend to focus on non-incarceration sentences, such as mandatory ignition interlock policies (see Alisa's Law of 2015).

The criminal justice system in Finland generally treats DUI offenders more harshly. In Finland, there are no diversion policies for first-time offenders, and all DUI offenders are eligible for incarceration. DUI offenders face a minimum of day-fines and maximum of six months imprisonment. Serious DUI offenders (determined by BAC level) face a minimum of a day-fine for 60 days and a maximum of two years imprisonment. These punishments are similar to the punishments for narcotic drug offenses in Finland.

The findings from my dissertation imply there may be a unique benefit of using rehabilitative criminal justice policies for DUI offenders. In Pennsylvania, DUI offenders receive more rehabilitative and reintegrative sanctions. Roughly half of all first-time DUI offenders receive a diversionary disposition, avoiding a permanent criminal label (Knoth, 2015). Sanctions

[90] Full expungement of a criminal record may not occur for a longer time period. For example, in Pennsylvania, individuals who successfully complete a diversionary probation period of 6 months to one year may have the DUI arrest and conviction removed from their criminal history report (e.g., the report commonly made available in background checks). However, Pennsylvania courts retain a record of the DUI for 10 years. If an offender commits another DUI offense after completing diversion but prior to the 10-year lapse period, then the offender is not eligible for diversion for the subsequent DUI offense. If the offender commits a DUI after the 10-year lapse period, the offender would be processed as a first-time DUI offender and would be eligible for a diversionary sentence.

for DUI offenders often include no incarceration. When incarceration is ordered, the mandatory minimums often require no more than 72 hours of incarceration (see Chapter 2). These structural responses result in relatively low recidivism rates, both for DUI-specific and general criminal recidivism.

In Finland, a country that generally emphasizes rehabilitative approaches to criminal sanctions (Lappi-Seppälä, 2009), DUI offenders are often an exception to lenient sentencing policies. DUI offenders are often incarcerated and there are no diversionary sanctions. Offenders who are not sentenced to incarceration often receive orders to serve significant periods of community service and to pay economic sanctions. These structural responses result in relatively high recidivism rates, both for DUI-specific and general criminal recidivism.

While readers might expect that a dissertation comparing Finland and the United States would conclude that the United States could learn from the rehabilitative structures in Finland, it appears that Finland could actually learn from the United States. More lenient, reintegrative sanctions appear to be correlated with lower levels of recidivism. These findings are consistent with single-jurisdiction analyses that compare the recidivism rates between diverted and non-diverted DUI offenders (Taxman and Piquero, 1998; Knoth, 2015)

The higher rate of recidivism for DUI offenders in Finland also reflects social differences from the United States more broadly. The total adult per capita consumption of alcohol is higher in Finland (12.52 litres of pure alcohol per person) than the United States (9.44 litres of pure alcohol per person). However, surveys indicate that Finns are far less approving or forgiving of DUI offenses than are Americans. Americans are four times more likely than Finns to rate DUI as personally acceptable (Achermann Stürmer, 2016; AAAFTS, 2017). Furthermore, while only 1% of Finns indicate that they have driven a vehicle while over the legal limit in the last 12 months, 12.7% of Americans report that they have driven a vehicle while intoxicated in the last 12 months.

These findings are contrary to prior research analyzing the relationship between macro-level drinking norms and social control. Linsky and colleagues (1986) suggested that communities that are less tolerant of drinking will engage of stricter policing of drinking-related behaviors while communities that are more tolerant of drinking may be more forgiving of alcohol-related behaviors. As such, they hypothesize that differences in DUI offending are explained by the structures of formal and informal social control resulting from differences in general alcohol culture. In contrast to the Linsky et al. (1986) hypothesis, Finland is more tolerant of drinking and is known for their culture of binge-drinking (Rehm et al., 2003), but they also engage in more strict policing of alcohol-related behaviors such as DUI. Additional aggregate level research directly comparing social tolerance of alcohol consumption and rates of alcohol-related crime is necessary to better understand the relationship between informal social control and DUI offending.

Cultural differences between Finland and the United States that inform systems of formal and informal social control are likely a better explanation for these findings. The separation between society and the state in the United States fosters a reliance on formal social control institutions to respond to instances of DUI offending. In contrast, the close relationship between the state and society in Finland suggests that formal and informal social control institutions are directly related. Despite some appeals to the immorality of DUI offending, Americans are more likely than Finns to rate DUI offending as personally acceptable and to have personally engaged in DUI offending in the last year (Achermann Stürmer, 2016; AAAFTS, 2017).

Consistent with the age-graded informal social control theory (Laub and Sampson, 1993), informal social control should have an influence on individual behaviors. That is, prosocial bonds should function as a deterrent to antisocial behavior. This theory also posits that types of formal social control may negatively affect social bonds and weaken informal social control. In the US, it appears that there are relatively few social consequences associated with arrest and conviction for a DUI. This is particularly true when the DUI offender is processed using diversionary sanctions and does not obtain a permanent criminal record. However, in Finland, extreme social disapproval of DUI behaviors has fostered a negative social stigma associated with DUI offenders. DUI offenders face strict disapproval and strict punishments from both formal and informal social control institutions.

Prior research indicates that DUI offenders in Finland are more likely than other offenders to face negative social consequences following their arrest. Arrest for a DUI in Finland has been associated with short-term and long-term increases in unemployment, debt, divorce, and other forms of social disadvantage (Oksanen et al., 2015). It is possible that the social stigma associated with a criminal record for DUI offending serves as a negative turning point for offenders in Finland, leading to additional criminal offending. This hypothesis is further supported by the differences in the types of recidivism by DUI offenders in Finland and the US. While half of the DUI offenders in Pennsylvania who recidivated did so with a DUI, only one-third of the DUI offenders in Finland who recidivated did so with a DUI. Recidivism, particularly for non-DUI offenses, in Finland may be driven by a “downward spiral” following the arrest and conviction for a DUI (Oksanen et al., 2015). Thus, consistent with a labeling theory explanation, Finland’s punitive response to DUI appears to have a negative impact on the lives of many DUI offenders.

The Development and Use of DUI Risk Assessment Instruments

The use of risk assessment instruments is expanding across different jurisdictions and different aspects of the criminal justice system. But prior to this dissertation, risk assessment instruments focusing on criminal characteristics had not yet been used for DUI offenders. In two projects, I was able to test the development of risk assessment instruments for DUI offenders both in a state that has developed other sentencing risk assessment instruments for non-DUI offenders and in a country that had not developed sentencing risk assessment instruments for any offenders. My studies have several important implications for the future development and use of risk assessment instruments generally, and they reveal much needed areas for future research.

The development of similar instruments in different structural and cultural contexts revealed four interesting similarities and differences. First, the recidivism patterns of DUI offenders could accurately be modeled in both jurisdictions using the same static correlates of criminal offending and Burgess risk assessment methodology. Second, risk assessment instruments were less effective at predicting DUI-specific recidivism than general recidivism in both jurisdictions. Third, prior DUI convictions were predictive of DUI recidivism in Finland but not in Pennsylvania. Finally, the benefits gained from developing risk assessment instruments for DUI offenders differed between the two jurisdictions.

Risk Assessment Instruments for DUI Offenders

Although several states have implemented sentencing risk assessments in order to reduce incarceration and to more effectively allocate limited criminal justice resources (Silver and Miller, 2002; Taxman, 2006; Kleiman, 2012), there has been no prior work on DUI offenders, even though DUI offenses make up the largest number of arrests in the United States. Nor, to my knowledge, are there any current sentencing risk assessments analyzing the likelihood of reoffending for DUI offenders. In further evidence of this gap regarding DUI, there is little literature discussing the development and use of risk assessment instruments outside of the United States.

Given the general concentration of prior DUI studies in the fields of addiction, psychology, and mental health, there has been little focus on the criminal characteristics of DUI offenders. Current assessments for DUI offenders[91] rely heavily on measures of drug or alcohol use and the goal of these assessments is to determine the risk level for impaired driving and the need for alcohol or drug treatment (Dill and Wells-Parker, 2006; Robertson, Wood, and Holmes, 2014). Studies evaluating the effectiveness of current assessments for DUI offenders often rely solely on measures of repeated DUI offending or future alcohol use (Dill and Wells-Parker, 2006). Inherent in this limitation is an assumption that DUI offenders are most likely to recidivate with a repeat DUI offense rather than general criminal behaviors. Further, the ability to determine the validity of these assessments is complicated by a reliance on self-reported characteristics (e.g., offender reported alcohol consumption) and a reliance on official measures of DUI recidivism (i.e., outcome measures that underestimate recidivism since most DUI incidents do not result in arrest) (Dill and Wells-Parker, 2006).

Consistent with contemporary attention to dynamic characteristics (e.g., alcohol and drug use), many of the current assessments for DUI offenders are better classified as risk and needs assessments. These types of third- and fourth-generation risk assessments are useful for identifying the appropriate types of treatment that may be able to target dynamic characteristics (Andrews, Bonta, and Wormith, 2006, Andrews and Bonta, 2010). While these types of

[91] Some examples of current assessments used for DUI offenders include: Alcohol Dependence Scale, Adult Substance Use and Driving Survey, Alcohol Severity index, Alcohol Use Disorders Identification Test, Inventory Drug-Taking Situations, Drug Abuse Screening Test, Michigan Alcoholism Screening Test, Substance Abuse Subtle Screening inventory, and Research Institute on Addiction Self Inventory (Robertson, Wood, and Holmes, 2014).

assessments may be relevant for other stages in the criminal justice system, sentencing risk assessments are different in that they are intended to identify the likelihood of recidivism, not to reduce recidivism (Monahan and Skeem, 2013). Sentencing risk assessments focused on static criminal characteristics serve a distinct purpose and should be considered as an additional tool that may help practitioners effectively distribute resources for DUI offenders.

Chapter 2 and Chapter 4 illustrated the ability to use criminal characteristics, including criminal history and offense seriousness, to predict general recidivism patterns for DUI offenders. Both studies successfully developed actuarial risk assessment instruments that predict recidivism within an acceptable overall range of accuracy (as measured by the AUC). These assessments may provide more reliable estimates of likelihood of recidivism because they rely on official data rather than offenders' self-reported behaviors.[92] In addition, these instruments focus on predicting general criminal behaviors rather than focusing solely on repeat DUI offending. The findings from these studies indicate that DUI offenders are at least equally as likely to recidivate with non-DUI offenses as they are to recidivate with DUI offenses. By focusing only on repeat DUI offending, practitioners are likely to underestimate the likelihood of recidivism for DUI offender populations.

Consistent with the general research on risk assessment instruments (Gendreau et al., 1996; Monahan and Skeem, 2013; Scurich and Monahan, 2015), age and prior criminal history were the two most significant predictors of recidivism in both Finland and Pennsylvania. The relationships between age and recidivism and between criminal history and recidivism were

[92] I recognize that there are also limitations to official data sources. For example, not all offending behaviors result in arrests that are recorded in an individual's criminal history. This limitation is especially prevalent when the data are limited to convictions. Offenders may have some charges dropped or reduced through plea bargains, resulting in an underestimate of true criminal history. Even with these limitations, official data is still likely to be more accurate than self-reported behaviors disclosed in a court mandated evaluation (Dill and Wells-Parker, 2006).

consistent with similar relationships identified in risk assessment instruments for non-DUI offenders (see PCS, 2013, 2018). These studies indicate that, although there may be some differences between DUI offenders and the general offending population, risk assessments that rely on static characteristics of offending are also effective for predicting recidivism for DUI offenders. Additional research should directly test whether DUI offenders actually need a separate risk assessment instrument, or if DUI offenders can be effectively integrated into more general risk assessment instruments.[93]

Predicting General vs. DUI-Specific Recidivism

Predicting human behavior is difficult. Predicting *rare* human behavior is even more challenging. Both the study in Finland and the study in Pennsylvania had to deal with low base rates for DUI-specific recidivism. As a result of the base rate problem, both studies had difficulties predicting the likelihood of reoffending with a DUI offense.

Risk assessment instruments predicting particular types of reoffending exist for a variety of outcomes, including violence, sex offenses, and homicide. There is increasing interest in being able to identify offenders who are likely to be repeat DUI offenders (Jones and Lacey, 2000; DeMichele, Payne, and Lowe, 2013). Both the samples of offenders in this dissertation exhibited some degree of specialization among DUI offenders; one-third of recidivists in Finland recidivated with a subsequent DUI offense while half of the recidivists in Pennsylvania recidivated with a subsequent DUI offense. Risk assessment instruments may be useful in identifying the high-risk populations who are likely to recidivate with a DUI. However, given the

[93] In Pennsylvania, DUI offenders were excluded from the general risk assessment instrument and the Commission on Sentencing indicated they would evaluate them separately (PCS, 2011). However, the Commission did not complete any empirical analysis to consider whether including DUI offenders would significantly change the outcomes of the risk assessment instruments.

low base rate issue, risk assessments for DUI offenders may be more useful (and accurate) for identifying low-risk populations who could be eligible for reduced or alternative sanctions.

In order to develop better models predicting DUI-specific recidivism, future research should integrate measures of drug and alcohol use as predictors in the risk scale. Courts could also choose to synthesize current DUI assessments and Burgess risk instruments by integrating criminal characteristics into existing drug and alcohol assessments. For example, in Pennsylvania, DUI offenders must undergo a CRN evaluation which includes measures of drug and alcohol use, prior DUI convictions, and BAC at time of arrest. Sentencing risk assessment instruments could incorporate the components of the CRN evaluation that are not already accounted for. Alternatively, the CRN evaluation could be redeveloped to focus solely on substance use characteristics (e.g., drug and alcohol use) and could include the Burgess risk score, which focuses on criminal characteristics, as an additional component of the evaluation.

Research must consider the practical constraints faced by criminal justice practitioners (Ulmer and Johnson, 2004). One of the most significant considerations for developing risk assessment instruments is the limited availability of data. Sentencing risk assessments may include only the information that is available to developers of risk instruments and to judges at the time of sentencing. In Pennsylvania, the Commission on Sentencing is the agency responsible for developing at the state level, both sentencing risk assessment instruments and the computer modules used by courts to complete risk assessments prior to sentencing. In contrast, individual courts are responsible for conducting CRN evaluations and maintaining the data from individual evaluations. Because of this split responsibility, there are significant structural barriers to integrating current DUI offender evaluations and sentencing risk assessment instruments.

Jurisdictions like Pennsylvania should consider whether the benefits associated with creating comprehensive databases that store all offender information (including official court data, criminal history data, and drug and alcohol assessment data) outweigh the costs associated with implementing a comprehensive, statewide data-sharing system. Creating integrated data systems would significantly improve the ability to develop risk prediction instruments. In addition, a comprehensive database of DUI offender information would expand the possibilities for research that could be used to pursue other evidence-based policies for the sentencing and treatment of DUI offenders.[94]

Courts could also decide to use risk assessment instruments to predict the DUI offenders who are likely to recidivate with a non-DUI offense. As discussed in Chapter 2, this alternative approach may not require the inclusion of drug or alcohol use characteristics. By predicting the likelihood of recidivism for a non-DUI offense, risk assessment instruments would provide information to judges that is not already available through current DUI offender assessments. As noted previously, non-DUI recidivism may pose a greater threat to the general public than DUI recidivism. The Pennsylvania study in Chapter 2 indicates that non-DUI recidivism instruments may still be affected by the low base rate problem, but predictions for high-risk offenders on the non-DUI recidivism scale were still more accurate than predictions for high-risk offenders on the DUI recidivism scale. In addition, non-DUI recidivism scales may be more useful in jurisdictions where the DUI offending population consists of more general offenders. The development of non-DUI recidivism scales for DUI offending populations should be replicated in other jurisdictions with different base rates of DUI and non-DUI recidivism.

[94] For an example of a study that uses data from multiple sources to evaluate policies related to DUI offenders, see Barnoski, 2007.

Prior DUI and Recidivism

Prior DUI offenses were strong predictors of DUI recidivism in Finland, while prior DUI offenses were not predictive of DUI recidivism in Pennsylvania. This finding may be explained by a higher rate of substance use among DUI offenders in Finland. One-fifth of first-time prisoners in Finland are diagnosed as alcoholics and the most common offenses among substance abusing offenders are violent crimes, property crimes, and drunk-driving (Joukamaa, 1995). Given the high rate of substance use among the offending population in Finland, it follows that DUI offenders in Finland may be more likely to repeat their behaviors if the underlying substance use disorder goes untreated. In Pennsylvania, it appears that the majority of offenders were first-time offenders who did not recidivate. It is unlikely that these offenders have a persistent substance use disorder that would lead to chronic DUI offending.[95]

It was interesting and a bit puzzling that prior DUI convictions were not predictive of DUI recidivism in Pennsylvania, and that offenders who had a prior DUI conviction were actually less likely to recidivate than offenders without a prior DUI conviction. Additional models analyzing recidivists found only that offenders with a prior DUI conviction were more likely to recidivate with a DUI offense than a non-DUI offense. The findings indicating a negative relationship between prior DUIs and recidivism were likely driven by the extremely low base-rate of recidivism for DUI offenders (see discussion in Chapter 2, Part II) and the confounding of selection effects in the Pennsylvania model.

In Finland, the base rate of recidivism is much higher, and evidence suggests that DUI offenders are more serious offenders than non-DUI offenders. In Pennsylvania, 11.6% of the

[95] Alternatively, these findings in Pennsylvania could suggest that treatment programs are effective at treating underlying drug and alcohol use disorders, resulting in a lower likelihood of recidivism. Future research should assess the use and effectiveness of treatment for first-time DUI offenders.

offenders who had a prior DUI recidivated with a subsequent DUI. In Finland, 21.2% of the offenders who had a prior DUI recidivated with a subsequent DUI. Similarly, in Pennsylvania, 14.7% of the offenders who recidivated with a DUI had a prior DUI conviction and 14.0% of the offenders who did not recidivate with a DUI had a prior DUI conviction. In Finland, 21.5% of the offenders who recidivated with a DUI had a prior DUI conviction while 16.1% of the offenders who did not recidivate with a DUI had a prior DUI conviction. These findings reflect the higher rates of recidivism among DUI offenders in Finland compared to Pennsylvania, but also suggest that there may be more specialization or more repeat-DUI offenders in Finland.

Future research should focus on the use and effectiveness of different drug and alcohol treatment programs for different types of DUI offenders. Once again, research would benefit greatly from comprehensive datasets that include both robust measures of criminal characteristics and information related to court-mandated treatment programs. Studies analyzing the use and effectiveness of drug and alcohol treatment programs could partition samples of DUI offenders into the three categories of offenders established in this dissertation: one-time, non-criminal DUI offenders, repeat DUI offenders with underlying substance use disorders, and general offenders who engage in a range of criminal offenses including DUI. While program evaluations may find that treatment programs are generally effective at reducing recidivism for DUI offenders, it is possible that these programs have null effects for general offenders who are not motivated by an underlying substance use disorder.

In addition, research analyzing the sentencing of DUI offenders should evaluate differential assignment to treatment for first-time and repeat DUI offenders. It is possible that judges are less likely to assign first-time DUI offenders to treatment programs than they are to assign repeat DUI offenders to treatment programs. In fact, in Pennsylvania, the evaluation that determines the need for treatment explicitly considers whether an offender has a history of DUI behaviors. If DUI offenders are not mandated to complete treatment programs until their second or subsequent DUI offense, it is possible that first-time DUI offenders would be more likely than repeat DUI offenders to recidivate.

Benefits of Risk Assessment Instruments

Current approaches to sentencing for DUI offenders vary between Pennsylvania and Finland. In the Pennsylvania, punishments for DUI offending are less severe and courts are primarily focused on identifying underlying drug or alcohol use disorders. In Finland, punishments for DUI offending are harsh, with little focus on treatment or reintegration. Given these differences, risk assessment instruments in the two jurisdictions may serve different purposes to achieve different policy goals.

Chapter 2 explained the current processes for processing DUI offenders in Pennsylvania. Rather than using risk assessments to assist in the identification of offenders who are likely to recidivate with a subsequent DUI offense, courts would likely benefit more from a risk assessment instrument identifying offenders who are likely to recidivate with a non-DUI offense. Current court evaluations are likely to identify the offenders who do not engage in criminal offending generally, but who may commit a subsequent DUI due to an underlying substance use disorder. Risk assessment instruments may be able to identify the offenders who do not have an underlying substance use disorder but who are likely to engage in a range of criminal behaviors. As such, the benefits of risk assessment instruments in Pennsylvania may be largest when identifying high-risk offenders.

On the other hand, Finland already uses harsh punishments for all DUI offenders. Finland currently does not have a diversion alternative for DUI offenders. Recently, some researchers have called for an increase in treatment programs for DUI offenders and the adoption of alternative punishment options for DUI offenders (Karjalainen et al., 2014). Risk assessment instruments may be useful for implementing a diversion program or for identifying candidates for alternative sanctions. Similar to the risk assessments currently used in Virginia, Finland could benefit from using the Burgess risk assessment instrument developed in Chapter 4 solely to identify low-risk offenders who are unlikely to recidivate.

Using the same methods for predicting risk of recidivism, Pennsylvania and Finland could both implement risk assessment instruments to achieve different outcomes. This comparison highlights the need to consider local court contexts and overall policy goals when developing and implementing risk assessment instruments (Monahan and Skeem, 2013). Many critics of risk assessments fear that implementation of these scales will result in an increase in severity of punishment for high-risk offenders (Hannah-Moffat, 2013). There is little empirical evidence to support these claims and initial research suggests that risk assessments are actually likely to decrease judicial perceptions of offender risk (Ruback et al., 2016). In addition, Chapter 4 emphasizes how risk assessments could be used in overly punitive systems to explicitly reduce the severity of punishments for offenders. Rather than questioning whether risk assessments ought be used at all (Hannah-Moffat, 2013), research should focus on different ways of using risk assessment instruments to responsibly achieve policy goals.

As discussed in the beginning of this chapter, this dissertation provides additional support for the local development of risk assessment instruments. Chapter 2 and Chapter 4 illustrated how small changes to the development or presentation of a particular risk scale can cause major changes in the way the risk instrument is interpreted or used by practitioners. The comparisons in Chapter 5 indicate that, although risk assessments may achieve acceptable levels of accuracy in different jurisdictions, scales developed on local populations of offenders outperform scales developed on non-local populations of offenders. Increases in accuracy, and therefore justice, and the possibility of customization to achieve particular policy goals suggest that jurisdictions should spend the resources to develop their own risk assessment instruments rather than relying on general scales developed by other courts or private companies on non-local populations.

Limitations

There were several limitations to the research in this dissertation. First, both studies in the dissertation relied on official criminal justice data on arrests and convictions. Second, neither study included measures of alcohol or drug use. Third, the studies were limited to demographic and criminal justice characteristics. Finally, I was unable to make direct comparisons between the data in Pennsylvania and Finland. The following is a discussion of these limitations and the need for additional research.

This dissertation relied on official police, courts, and corrections data to identify DUI offenders and to gather information related to criminal history and recidivism. There is increasing concern that official data do not reflect actual offending behavior (Thornburg and Krohn, 2003) and that official data are biased by disparities in the likelihood of arrest (Baumer, 2013). Research on risk assessments has extended these criticisms to suggest that measures of prior arrest and recidivism are discriminatory measures that capture differences in policing rather than offending (Starr, 2014). In response to these criticisms, I used measures of convictions rather than arrests; my data did not include arrests that did not result in conviction, potentially reducing the bias associated with disparate police practices. However, the studies in my dissertation are still unable to escape any inherent bias that may result from differential probabilities of being convicted conditioned on the differential probabilities of first being arrested.

The use of official data may be uniquely problematic for DUI offending. As noted previously, the likelihood of arrest for a DUI is extremely low. It is possible that some of the offenders who did not recidivate actually did continue driving under the influence following their index event but were not identified or apprehended by police. Self-report data would be useful for answering theoretical questions about DUI offenders and recidivism. More accurate measures of reoffending would also be useful for analyzing whether treatment programs are effective at modifying behavior.

Self-report data would be less useful for developing actuarial risk assessment instruments at sentencing. Even if models could be developed using self-report data, the instruments would likely be implemented using official court data. It is unlikely that judges would rely on an offender's self-disclosed offending behaviors as a measure of criminal history. A full discussion on the ethics of risk assessment instruments and the data and factors used to predict risk was beyond the scope of this dissertation. Future research should continue to consider the ethics and possible disparate outcomes associated with risk assessment instruments and the factors used to predict recidivism.

This dissertation analyzed DUI offenders as criminals rather than as problematic substance users. The studies in this dissertation did not include measures of substance use or indicators of substance use disorders. Consequently, I was unable to directly test hypotheses related to substance use. For example, the typology of offenders established in Chapter 2 suggests that there may be a population of DUI offenders who have underlying substance use disorders which motivate their DUI-specific offending. However, I was unable to test whether or not the population of repeat DUI offenders actually did have higher rates of substance use disorders than the offenders who did not recidivate or the offenders who recidivated with a non-DUI offense. All of the conclusions about differences in substance use or substance use disorders was purely speculative. Future research should be conducted on comprehensive datasets that include both measures of criminal justice involvement and measures of substance use.

Third, the studies in this dissertation relied solely on administrative data containing information about demographics and criminal justice contacts. As such, the data did not include any measures of informal social control (e.g., marriage, employment) or social stress (e.g., sudden unemployment, loss of a loved one, divorce). Throughout this dissertation, I speculate that the findings may be driven by changes in social networks, social control, or social stress, but I was unable to directly test these explanations. Additional research on DUI offenders which combines administrative criminal justice data with measures of socioeconomic status (SES) and social networks and that can track changes in SES and social networks over time would significantly improve our understanding of the motivations for DUI offending and recidivism.

Finally, I was unable to make direct comparisons between DUI offenders in Finland and DUI offenders in Pennsylvania. I was prohibited from transporting either dataset to a foreign location for analysis as per various data-sharing agreements. Direct comparisons are becoming increasingly difficult as jurisdictions continue to increase their security protocols for official data. Specifically, the European Union recently passed new privacy laws (see the General Data Protection Regulation) banning the export of personal data outside of the EU. While there are some research exceptions in the regulation, it is still unclear whether existing administrative data will be accessible to researchers outside of the EU member states. Similarly, statutes governing the use of criminal history data in Pennsylvania prevented me from taking data from the PCS to another jurisdiction. These restrictions on administrative data in the U.S. make it difficult to engage in cross-jurisdiction comparisons.

In the absence of direct comparisons of data, my conclusions about the similarities and differences between offenders in Finland and Pennsylvania are speculative. These limitations hinder the ability to engage in precise hypothesis testing. Future research should combine data from multiple jurisdictions in order to provide reliable statistical tests of the similarities and differences in DUI offending behaviors. Cross-national comparisons would provide the most extreme test of the generalizability of criminological theories. However, there are still benefits that would be gained from engaging in cross-state comparisons. If possible, researchers in the U.S. should combine administrative data from multiple states to test the effectiveness of different policies for DUI offenders and to further test the advantages to developing localized risk assessment instruments.

Conclusion

Across the globe, it is illegal to drive under the influence of drugs or alcohol. Despite the widespread prohibition on impaired-driving, DUI offenders are largely considered addicts first and offenders second. This dissertation reverses existing approaches to DUI offenders by focusing on the criminal correlates of DUI offending and recidivism. I sought to answer three important questions about DUI offenders: (1) How do DUI offenders differ from the general offending population? (2) What factors influence the commission of DUI offenses and are those factors different from those that influence general and DUI-specific recidivism? and (3) how do the correlates of DUI offending and recidivism vary across different geographic and cultural contexts. In addition, I sought to explore how risk assessment instruments could be used to predict future offending for DUI offenders and whether the development and use of DUI risk assessments varied across different structural and cultural contexts.

This dissertation answered these important questions by conducting a statewide evaluation of DUI offenders in Pennsylvania and a nationwide evaluation of DUI offenders in Finland. In each study, I created comprehensive datasets on the criminal characteristics of DUI offenders by combining data from multiple sources. The final datasets represent two of the largest, most extensive databases on DUI offenders in the world. The datasets were used to make direct comparisons between DUI offenders and non-DUI offenders, to assess general correlates of DUI offending and recidivism, and to test the development of actuarial risk assessment instruments predicting the likelihood of general and DUI-specific recidivism for DUI offenders.

DUI offenders are not a homogenous group. Rather, this dissertation proposed and found support for a tripartite typology of DUI offenders. First-time, non-criminal DUI offenders differed significantly from the general offending population. Repeat DUI offenders who are unlikely to engage in non-DUI offending were both similar to and different from the general offending population. Diverse offenders, who engaged in a range of DUI and non-DUI behaviors, mirrored the characteristics that are common in studies of the general offending population.

This dissertation represents the first use of Burgess risk assessment instruments to predict the likelihood of recidivism among DUI offenders. In addition, this dissertation conducted the first international comparison of the development and use of risk assessment instruments. The studies in this dissertation found that static risk assessments with an acceptable level of accuracy could be developed to predict the likelihood of future offending for DUI offenders. In addition, this dissertation proposed new methods for the development and use of risk assessment instruments. Finally, the dissertation found support for the localized development of risk instruments instead of relying on general risk instruments developed in a single jurisdiction or by a private company.

Answering the call for comparative criminology, this cross-national dissertation has several important implications for theory and policy. By analyzing DUI populations as offenders rather than addicts, this dissertation lays the foundation for applying general criminological theories to explain the behavior of DUI offenders. This dissertation suggests ways in which existing theories may be expanded or modified to explain DUI offending and recidivism. In addition, the cross-national comparison of risk assessments identified important questions about the development and use of risk instruments. It is clear that DUI risk assessment instruments focused on static factors and criminal characteristics could assist practitioners to more effectively allocate criminal justice resources.

While this dissertation lays the foundation for applying general criminological theories to explain DUI offending, future research should directly test existing theories about criminal characteristics on diverse populations of DUI offenders. Additional research should expand upon the policy questions posed in this dissertation by testing ways to integrate static risk assessment instruments based on criminal characteristics with existing DUI offender assessments that focus on drug and alcohol use, and particularly substance use disorders. Furthermore, policy makers should support research that analyzes the effectiveness of use and effectiveness of current punishments (both punitive and rehabilitative) for different types of DUI offenders.

There is much still to be known about DUI offenders. Given the prevalence of impaired driving, both in the United States and around the globe, the field of criminology should do more to advance our understanding of DUI offending. While some DUI offenders may have a substance use disorder, they are all criminals. It is my hope that the studies presented in this dissertation begin the movement toward a more comprehensive understanding of DUI offending and recidivism and toward additional empirical research that supports evidence-based policies that may reduce the global prevalence of impaired driving.

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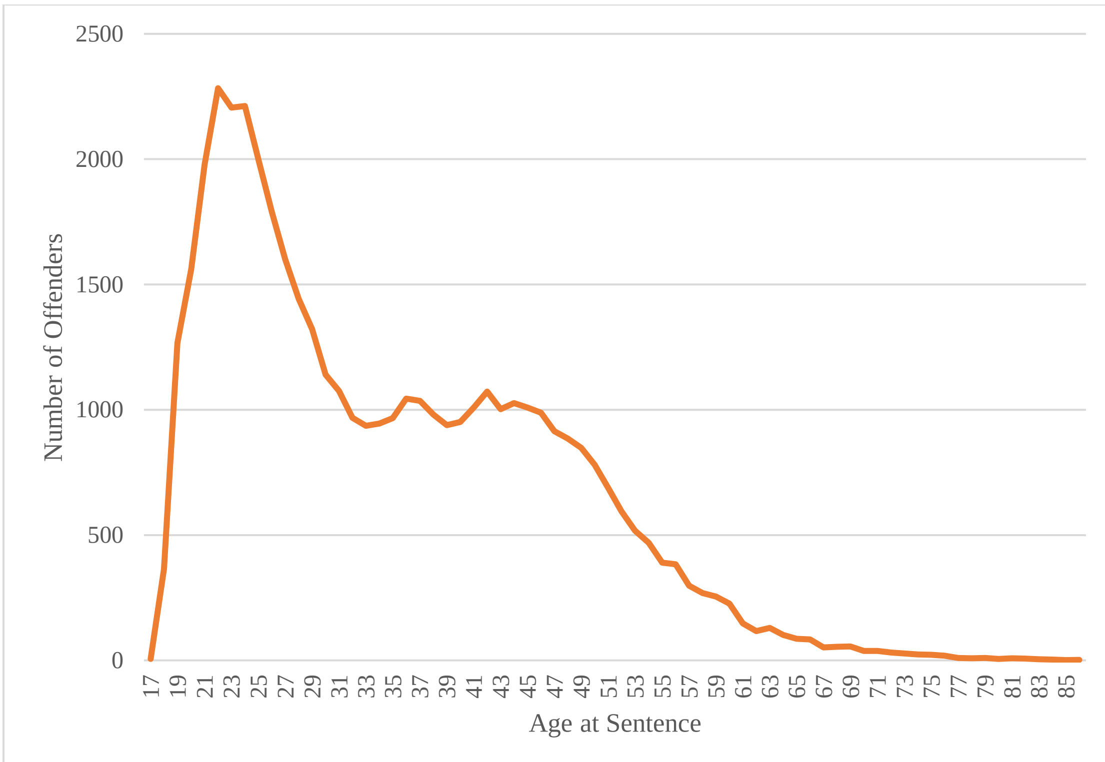
Appendix A. Description of DUI charges in Pennsylvania Statutes (75 Pa.C.S.A. 3802) and Statutory Minimum Sentences (75 Pa.C.S.A. 3804) by subsection

Subsection	**Offense Description**	**Statutory Minimum Incarceration length (Days)**			
		1st DUI	2nd DUI	3rd DUI	4th+ DUI
A1	General impairment - incapable of driving	0	5	10	10
A2	General impairment - BAC .08% - <.10%	0	5	10	10
B	High Rate of Alcohol - BAC .10% - <.16%	2	30	90	365
C	Highest Rate of Alcohol - BAC .16% or greater	3	90	365	365
D1	Controlled Substances	3	90	365	365
D1i	Controlled Substances - Schedule 1	3	90	365	365
D1ii	Controlled Substances - Schedule II	3	90	365	365
D1iii	Controlled Substances - Metabolite	3	90	365	365
D2	Polydrug impairment	3	90	365	365
D3	Alcohol and Drug impairment	3	90	365	365
D4	Solvent or Noxious Substance	3	90	365	365
E	Minor (<21) BAC .02% +	2	30	90	365
F1i	Commercial Vehicle (non school vehicle) BAC .04%+	2	30	90	365
F1ii	School Bus or School Vehicle BAC .02% +	2	30	90	365
F3	Commercial Vehicle (including School Vehicle) Alcohol General impairment	2	30	90	365
F4	Commercial Vehicle (including School Vehicle) Drug General impairment	2	30	90	365

Appendix B. Age of DUI offenders in Pennsylvania. Full sample, when age was not missing, N = 45,715



Appendix C. Variables in original datasets

Primary Offenses File

Variable Name	Variable Description
id	Personal ID from PIN
sentence_id	Reference sentence ID
birth_date	DOB from PIN
PIN	PIN
age	Age calculated from DOB and district court date
crime_code	Crime code (rikoskoodi)
dc_diary_number	Diary number - same for all cooffenders
dc_id	District court ID
date_of_offence	Date of primary offense
date_of_district_court_sentence	Date of district court sentence for primary offense
date_of_court_of_appeals_sentence	Date of appeals court sentence for primary offense (if applicable)
suspended_sentence	Number of suspended prison sentence days for whole sentence ID
community_service	Number of community service days in sentence for whole sentence ID
prison_sentence	Number of prison days in sentence for whole sentence ID
fine	Number of day fines in sentence for whole sentence ID

Co-Offenses File

Variable Name	Variable Description
id	Numeric identifier for each offense
person_id	Personal ID from PIN (same as primary offense)
ref_sentence_id	Reference sentence ID+B23:C25
crime_code	Crime code (rikoskoodi)
ms_offence	Indicator for the most serious offense

Criminal Background (Convictions and Summary Penal Fines) File

Variable Name	Variable Description
id	Numeric indentifier for each offense in criminal background
person_id	Personal ID from PIN (same as primary offense)
ref_sentence_id	Reference sentence ID
sentence_id	RST sentence id for the sentence that includes the offense in this observation
doo	Date of offense
convicted_after	Indicator for offenses commited before the primary offense, but sentenced before the primary offense sentencing date
conviction_type	Type of conviction - court conviction or summary penal fine
crime_code	Crime code (rikoskoodi)

Appendix C. Variables in Original Datasets (Continued)

Prior Incarcerations File

Variable Name	Variable Description
id	Numeric identifier for each imprisonment sentence
person_id	Personal ID from PIN (same as primary offense)
ref_sentence_id	Reference sentence ID
date_of_sentence	First date of imprisonment
date_of_release	Date of release from incarceration
type_of_sentence	Type of prison sentence

Recidivism File 1 (2008 - June 2013)

Variable Name	Variable Description
id	Numeric identifier for each sentence
person_id	Personal ID from PIN (same as primary offense)
ref_sentence_id	Reference sentence ID
sentence_id	RST sentence ID for recidivism offense
mso	Indicator for most serious offense in sentence ID
priority	RST priority code for seriousness
doo	Date of offense
crime_code	Crime code (rikoskoodi)
conviction_type	Type of conviction - court conviction or summary penal fine
first_conviction_date	District court sentencing date
last_conviction_date	Final sentence date (appeals court date, if applicable)

Recidivism File 2 (June 2013 - December 2013)

Variable Name	Variable Description
id	Numeric identifier for each sentence ID
person_id	Personal ID from PIN (same as primary offense)
ref_sentence_id	Reference sentence ID
sentence_id	RST sentence ID for recidivism case
doo	Date of offense
crime_code	Crime code (rikoskoodi)
conviction_type	Type of conviction - court conviction or summary penal fine
dui_coof	Indicator for whether or not there was a DUI co-offense
adui_coof	Indicator for whether or not there was an aggravated DUI co-offense
first_conviction_date	District court sentencing date
last_conviction_date	Final sentence date (appeals court date, if applicable)

Appendix D. Descriptive Statistics for the Full Sample by DWI offenders (N = 29,882) and Non-DWI Offenders (N = 53,126)

	DWI	Non DWI	DWI	Non DWI	
	N	N	%	%	Sig.
Gender					0.000
Male	25,880	44,279	86.6	83.3	
Female	4,002	8,847	13.4	16.7	
	29,882	53,126	100.0	100.0	
Age					0.000
< 18	2,125	5,079	7.1	9.6	
18-24	4,685	12,056	15.7	22.7	
24-29	3,052	7,754	10.2	14.6	
30-34	2,619	5,896	8.8	11.1	
35-40	2,493	4,798	8.3	9.0	
41-44	3,065	5,054	10.3	9.5	
45-49	3,269	4,189	10.9	7.9	
50-54	3,082	3,107	10.3	5.8	
55-59	2,638	2,378	8.8	4.5	
60+	2,854	2,815	9.6	5.3	
	29,882	53,126	100.0	100.0	
Mean	39.19	34.0			0.000
Location					0.000
Helsinki	4,548	11,709	15.2	22.0	
Urban	7,282	12,322	24.4	23.2	
Rural	18,052	29,095	60.4	54.8	
	29,882	53,126	100.0	100.0	

	DWI	Non DWI	DWI	Non DWI	
	N	N	%	%	Sig.
Cooffenders					0.000
Yes	1,630	15,166	5.5	28.5	
No	28,252	37,960	94.5	71.5	
	29,882	53,126	100.0	100.0	
Multiple charges					0.000
Yes	12,376	17,355	41.4	32.7	
No	17,506	35,771	58.6	67.3	
	29,882	53,126	100.0	100.0	
Current offense type (most serious)					0.000
Property	-	15,571	0.0	29.3	
Personal	-	16,548	0.0	31.1	
Sex Crimes	-	686	0.0	1.3	
Public Adm/Order	-	6,221	0.0	11.7	
Other Traffic	-	7,969	0.0	15.0	
Alcohol	-	154	0.0	0.3	
Drug	-	3,839	0.0	7.2	
Weapons	-	1,353	0.0	2.5	
DWI	13,263	-	44.4	0.0	
DWSI	16,619	-	55.6	0.0	
Non-Vehicular DWI	-	785	0.0	1.5	
	29,882	53,126	100.0	100.0	

Appendix D. Descriptive statistics for the Full Sample by DWI Offenders (N= 29,882) and Non DWI Offenders (N = 53,126), continued

	DWI	Non DWI	DWI	Non DWI	
	N	N	%	%	Sig.
Total prior sentence Ids					0.000
0	11,228	16,693	37.6	31.4	
1	6,429	9,483	21.5	17.9	
2	3,638	5,913	12.2	11.1	
3	2,202	4,017	7.4	7.6	
4	1,434	2,853	4.8	5.4	
5	999	2,112	3.3	4.0	
6	701	1,670	2.3	3.1	
7	465	1,221	1.6	2.3	
8	375	961	1.3	1.8	
9	314	853	1.1	1.6	
10-14	842	2,507	2.8	4.7	
15-19	438	1,483	1.5	2.8	
20-24	256	895	0.9	1.7	
25-29	165	653	0.6	1.2	
30+	396	1,812	1.3	3.4	
	29,882	53,126	100.0	100.0	
Mean	3.0	5.1			0.000
Total Prior Court Convictions					0.000
0	16,680	28,686	55.8	54.0	
1	5,895	8,675	19.7	16.3	
2	2,779	4,459	9.3	8.4	
3	1,441	2,899	4.8	5.5	
4	853	1,896	2.9	3.6	
5	548	1,295	1.8	2.4	
6	337	979	1.1	1.8	
7	272	796	0.9	1.5	
8	214	607	0.7	1.1	
9	156	500	0.5	0.9	
10-14	457	1,446	1.5	2.7	
15-19	175	554	0.6	1.0	
20-24	54	215	0.2	0.4	
25-29	18	77	0.1	0.1	
30+	3	42	0.0	0.1	
	29,882	53,126	100.0	100.0	
Mean	1.3	1.79			0.000
Total Prior Summary Penal Fines					0.000
0	16,096	21,894	53.9	41.2	
1	6,063	10,533	20.3	19.8	
2	2,805	5,747	9.4	10.8	
3	146	348	0.5	0.7	
4	865	2,288	2.9	4.3	
5	541	1,536	1.8	2.9	
6	373	1,122	1.2	2.1	
7	260	836	0.9	1.6	
8	186	667	0.6	1.3	
9	154	529	0.5	1.0	
10-14	498	1,757	1.7	3.3	
15-19	225	943	0.8	1.8	
20-24	135	549	0.5	1.0	
25-29	82	349	0.3	0.7	
30-34	46	248	0.2	0.5	
35-39	27	148	0.1	0.3	
40+	66	500	0.2	0.9	
	29,882	53,126	100.0	100.0	
Mean	1.67	3.3			0.000
Recidivism					
Four Year					0.000
Yes	13,949	27,803	46.7	52.3	
No	15,933	25,323	53.3	47.7	
	29,882	53,126	100.0	100.0	
DWI reconviction					0.000
Yes	4,052	2,791	13.6	5.3	
No	25,830	50,335	86.4	94.7	
	29,882	53,126	100.0	100.0	

	DWI	Non DWI	DWI	Non DWI	
	N	N	%	%	Sig.
Age at first conviction					0.000
< 18	4706	12591	15.7	23.7	
18-24	4732	11714	15.8	22.0	
24-29	2466	5586	8.3	10.5	
30-34	2417	4823	8.1	9.1	
35-40	2675	4518	9.0	8.5	
41-44	3034	4166	10.2	7.8	
45-49	3097	3280	10.4	6.2	
50-54	2665	2574	8.9	4.8	
55-59	2035	1793	6.8	3.4	
60+	2055	2081	6.9	3.9	
	29882	53126	100.0	100.0	
Mean	36.17	30.63			0.000
Type of prior arrest(s)					
Prior personal arrest(s)					0.000
Yes	4003	12219	13.4	23.0	
No	25879	40907	86.6	77.0	
	29882	53126	100.0	100.0	
Prior sex arrest(s)					0.000
Yes	122	341	0.4	0.6	
No	29760	52785	99.6	99.4	
	29882	53126	100.0	100.0	
Prior property arrest(s)					0.000
Yes	6370	18515	21.3	34.9	
No	23512	34611	78.7	65.1	
	29882	53126	100.0	100.0	
Prior Alcohol arrest(s)					0.000
Yes	206	537	0.7	1.0	
No	29676	52589	99.3	99.0	
	29882	53126	100.0	100.0	
Prior drug arrest(s)					0.000
Yes	2370	8020	7.9	15.1	
No	27512	45106	92.1	84.9	
	29882	53126	100.0	100.0	
Prior firearms/weapons arrest(s)					0.000
Yes	2202	7025	7.4	13.2	
No	27680	46101	92.6	86.8	
	29882	53126	100.0	100.0	
Prior traffic arrest(s)					0.000
Yes	13792	25552	46.2	48.1	
No	16090	27574	53.8	51.9	
	29882	53126	100.0	100.0	
Prior Public Adm/Order arrest(s)					0.196
Yes	4725	12127	15.8	22.8	
No	25157	40999	84.2	77.2	
	29882	53126	100.0	100.0	
Prior DWI arrest(s)					0.000
Yes	16371	23549	54.8	44.3	
No	13511	29577	45.2	55.7	
	29882	53126	100.0	100.0	
Prior Serious DWI arrest(s)					0.000
Yes	5143	6856	17.2	12.9	
No	24739	46270	82.8	87.1	
	29882	53126	100.0	100.0	
Prior Non-Vehicular DWI arrest(s)					0.021
Yes	222	323	0.7	0.6	
No	29660	52803	99.3	99.4	
	29882	53126	100.0	100.0	
Prior Incarceration					0.000
Yes	2970	17355	9.9	32.7	
No	26912	35771	90.1	67.3	
	29882	53126	100.0	100.0	
Type of sentence (Most Serious)					0.000
Unconditional Prison	1395	1989	4.7	3.7	
Community Service	2256	1225	7.5	2.3	
Conditional Prison	12662	9802	42.4	18.5	
Other (including Fines)	13569	40110	45.4	75.5	
	29882	53126	100.0	100.0	
Average Length of Sentence					
Unconditional Prison	4.87	5.72			0.001
Community Service	6.59	2.34			0.000
Conditional Prison	26.19	28.98			0.000
Other (including Fines)	34.59	26.54			0.000

Appendix E. Most Common Crimes by Crime Category

Property

	N	%	Cum %
Theft	2,975	19.11	19.11
Fraud	2,185	14.03	33.14
Criminal damage	1,834	11.78	44.92
Petty theft	806	5.18	50.09
Forgery	726	4.66	54.76
Petty criminal damage	726	4.66	59.42
Means of payment fraud	544	3.49	62.91
Stealing of a Motor Vehicle for temporary use	515	3.31	66.22
Petty fraud	507	3.26	69.48
Embezzlement	387	2.49	71.96

Personal

	N	%	Cum %
Assault	12,447	75.22	75.22
Menace	1,095	6.62	81.83
Petty assault	608	3.67	85.51
Aggravated assault	483	2.92	88.43
Invasion of domestic premises	392	2.37	90.8
Negligent bodily injury	372	2.25	93.04
Robbery	300	1.81	94.86
Negligent homicide	140	0.85	95.7
Attempted assault	111	0.67	96.37
Aggravated invasion of domestic premises	99	0.6	96.97

Sex Offenses

	N	%	Cum %
Sexual abuse of a child	378	55.1	55.1
Sexual abuse	106	15.45	70.55
Rape	41	5.98	76.53
minor rape	26	3.79	80.32
Abuse of a victim of prostitution	25	3.64	83.97
Coercion into a sexual act	22	3.21	87.17
attempted rape	19	2.77	89.94
Attempted sexual abuse of a child	16	2.33	92.27
Aggravated sexual abuse of a child	15	2.19	94.46
Pandering	9	1.31	95.77

Public Adm/Public Order

	N	%	Cum %
Relinquishing a vehicle to an intoxicated person	1,207	19.4	19.4
Defamation	414	6.65	26.06
Work safety offence	343	5.51	31.57
Resistance to a person maintaining public order	335	5.38	36.96
Registration offence	333	5.35	42.31
Violent resistance to a public official	288	4.63	46.94
Violation of a restraining order	283	4.55	51.49
Desertion	236	3.79	55.28
Aggravated dishonesty by a debtor	193	3.1	58.38
Resistance to a public official	190	3.05	61.44

Other Traffic

	N	%	Cum %
Causing a serious traffic hazard	4,525	56.78	56.78
Causing a traffic hazard	3,077	38.61	95.39
Operation of a vehicle without a license	345	4.33	99.72
Flight from the scene of a traffic accident	22	0.28	100

Alcohol

	N	%	Cum %
Unauthorized distribution of alcohol	48	31.17	31.17
Unauthorized professional distribution of alcohol	23	14.94	46.1
Unauthorized professional manufacturing of alcoholic substance	20	12.99	59.09
Unauthorized distribution of alcohol - attempted minor offence	17	11.04	70.13
illegal possession of an alcoholic beverage - minor offence	12	7.79	77.92
illegal possession of an alcoholic beverage	9	5.84	83.77
smuggling of alcoholic substance - mitigating circumstances	8	5.19	88.96
Minor alcohol offence (1143/1994)	7	4.55	93.51
illegal possession of spirits	3	1.95	95.45
Aggravated alcohol offence	2	1.3	96.75

Drug

	N	%	Cum %
Narcotics offence	2,751	71.66	71.66
Unlawful use of narcotics	451	11.75	83.41
Medicine offence	322	8.39	91.79
Doping offence	144	3.75	95.55
Aggravated narcotics offence	134	3.49	99.04

Preparation of a narcotics offence	16	0.42	99.45
Aggravated doping offence	11	0.29	99.74
Abetting a narcotics offence	5	0.13	99.87
Petty doping offence	5	0.13	100

Weapons

	N	%	Cum %
Firearms offence	659	48.71	48.71
Possession of a dangerous object	154	11.38	60.09
Firearms infraction (1/1998)	113	8.35	68.44
Possession of an object or substance suitable for injuring another person	107	7.91	76.35
Careless handling	95	7.02	83.37
Petty firearms offence	66	4.88	88.25
Violation of regulations on dangerous objects	62	4.58	92.83
Explosives offence	58	4.29	97.12
Violation of regulations on objects suitable for injuring another person	29	2.14	99.26
aggravated firearms offence	5	0.37	99.63

DWI Categories

	N	%	Cum %
Driving while Intoxicated	13,263	100	100
Driving while Seriously Intoxicated	16,619	100	100

Non-Vehicular DWI

	N	%	Cum %
Waterway Traffic Intoxication	777	98.98	98.98
Non-motor powered Traffic Intoxication	5	0.64	99.62
Air Traffic Intoxication	2	0.25	99.87
Rail Traffic Intoxication	1	0.13	100

Lauren Kay Knoth
Condensed Vita
211 Oswald Tower
University Park, PA 16802
LKK140@psu.edu / Lauren.knoth@gmail.com

Education

Ph.D., Criminology, The Pennsylvania State University	2018
Graduate Certificate in Quantitative Methods	
M.A., Criminology, The Pennsylvania State University	2015
B.S., Criminal Justice (Summa Cum Laude), Washburn University	2012
B.A., Sociology (Summa Cum Laude), Washburn University	2012

Peer Reviewed Publications

Knoth, L.K. & Ruback, R.B. (2016). Victim, Offender, Advisor Triad Networks and Reporting to the Police. *Journal of Interpersonal Violence*. Published online first.

Ruback, R. B., Kempinen, C. A., Tinik, L. A., & **Knoth, L.K.** (2016). Communicating Risk Information at Criminal Sentencing: An Experimental Analysis. *Federal Probation* 80(2):47-56.

Ruback, R.B., **Knoth, L.K.**, Gladfelter, A.S., Lantz, B. (2018). Restitution Payment and Recidivism: An Experimental Analysis. *Criminology & Public Policy*. Forthcoming.

Government Reports

Hester, R., **Knoth, L.,** Ruback, B.R., Tinik, L., and Zvonkovich, J. (May, 2018). The Development and Validation of the Proposed Risk Assessment Scales. Risk Assessment Project Phase III. Pennsylvania Commission on Sentencing: State College, PA. *Authors listed alphabetically.*

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Teaching Experience

2015	CRIM 100; Introduction to Criminal Justice
2015-2016	Guest Lectures: CRIM 430 - American Correctional System and Crime; CRIM 012 – Introduction to Sociology; SOC 001 – Introduction to Sociology; SOC 591 – Teaching Seminar; CRIM 451 – Race, Crime, and Justice.

Funded Research and Awards

2017	Best Published Paper, Criminology Graduate Student Paper Competition, Pennsylvania State University. “Victim, Offender, Advisor Triad Networks and Reporting to the Police.”
2016-2017	United States Fulbright-CIMO Grantee to conduct research at the Institute of Criminology and Legal Policy at the University of Helsinki in Helsinki, Finland. (9-month full support grant ~ $16,000)
2015	Center for Life Course and Longitudinal Studies (C2LS) Summer Supplement Award, for “Juvenile Arrests and Substance Abuse: The Short and Long Term Labeling Effects of Juvenile Arrest” ($1,500)