

EVALUATING THE RELIABILITY AND VALIDITY OF THE CORRECTIONAL
OFFENDER MANAGEMENT PROFILING FOR ALTERNATIVE SANCTIONS
(COMPAS) TOOL: IMPLICATIONS FOR COMMUNITY CORRECTIONS POLICY

By

Bryn A. Herrschaft

A Dissertation submitted to the
Graduate School-Newark
Rutgers, The State University of New Jersey
in partial fulfillment of requirements
for the degree of
Doctor of Philosophy
Graduate Program in Criminal Justice
written under the direction of
Bonita Veysey, Ph.D.
and approved by

Newark, New Jersey

January 2014

© 2014

Bryn A. Herrschaft

ALL RIGHTS RESERVED

ABSTRACT

Evaluating the Reliability and Validity of the Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) Tool: Implications for Community Corrections Policy

By Bryn A. Herrschaft

Dissertation Director:
Bonita Veysey, Ph.D.

Dissertation Committee:
Johnna Christian, Ph.D.
Joel Caplan, Ph.D.
Zachary Hamilton, Ph.D.

With an increasing number of offenders released to the community from prisons each year, prisoner reentry has become an important area of focus for criminal justice practitioners and policymakers. Parole supervision was originally established as a means of offender reintegration, but high rates of re-offending present a challenge to discretionary release to parole supervision. As a result, the most important function of parole supervision has shifted to the protection of public safety, leading to the development of risk prediction instruments used to identify offender risk to the community. While early forms of risk assessment used limited practices of professional judgment to predict offender risk, more contemporary risk assessment instruments use individual factors known to affect recidivism to determine offenders who pose the greatest risk to society once they are released from prison.

The present study examined the reliability and validity of one such instrument, the Correctional Offender Management for Profiling Alternative Sanctions (COMPAS) tool,

using a diverse sample of male offenders released to parole supervision in New York City. Specifically, this study assessed the psychometric properties of the COMPAS using correlations and internal consistency estimates to assess reliability. The predictive validity of the COMPAS composite risk scores on several recidivism outcomes was assessed using AUC and RIOC analyses. Additionally, this dissertation study compared the predictive validity of the two composite COMPAS risk scores with the predictive validity of risk scores calculating using several static factors from each offender's computerized case history (CCH) known as the DCJS any risk and risk for violence scores on a re-arrest for any crime and a re-arrest for a violent crime.

Results from this study indicate that the COMPAS is a reliable risk/needs instrument with this sample. While the COMPAS composite recidivism risk and history of noncompliance scores achieve moderate predictive validity on their corresponding outcomes, the COMPAS composite violent recidivism risk score does not. When the COMPAS composite recidivism risk score is compared to the DCJS any risk score on validity in predicting re-arrest, the DCJS risk score, based solely on static variables, outperforms the COMPAS. The implications of this research for parole practice and policy, both locally in the State of New York and more broadly, as well as directions for future research, are also discussed.

ACKNOWLEDGEMENTS

It has been a long journey to completing this dissertation and degree. I would like to take this opportunity to thank all of the people I have met on this rollercoaster ride as each of them has provided me with something vital in the process of closing this chapter in my life, and starting a new journey.

First, I would like to thank my dissertation committee chair, Dr. Bonita Veysey, for your patient devotion to providing me support and guidance on my journey. I entered graduate school with little direction in what I was truly passionate about, and without your mentorship, the door to countless opportunities to make a real difference in the field of criminal justice would never have opened. During my time in graduate school, you provided me with not only mentorship, but friendship, encouraging me with research opportunities to broaden my knowledge, develop my critical thinking skills, and grow as a scholar and researcher. And without your encouragement and motivation, I would not have been able to finish this dissertation and complete my journey. I could never fully express my thanks to you in words for being involved in the entirety of my graduate career.

Additionally, I would like to thank the other members of my dissertation committee for their help and support throughout the years. Many thanks to Dr. Johnna Christian for always answering my questions, sharing your wisdom and knowledge, and involving me in research projects that would pique my interest. For these reasons, and your inspiration in researching offender reentry and community corrections, I am incredibly thankful to have known you. I owe thanks to Dr. Joel Caplan and Dr. Zachary Hamilton, for being true role models of young scholars with incredible resumes of

applied experience. You both have always inspired me to pursue scholarship in a unique way, thinking about the practical application of my research to policy and practice in the real world. I am also forever grateful that Dr. Hamilton was involved in hiring me for my first real research job at the Center for Court Innovation from which this dissertation was born.

This dissertation would not have been possible without the commitment of the New York State Division of Criminal Justice Services (DCJS) to share data with independent researchers and the time dedicated to producing the dataset used in this study. This author, however, is solely responsible for the methodology and results obtained using the DCJS data.

Similarly, this dissertation would not have been possible without the Harlem Community Justice Center and the Center for Court Innovation. To Mike Rempel, the Director of Research for the Center for Court Innovation, I would like to extend my gratitude for your generosity in supporting this research, your trust in me as a researcher, and your constant ability to find challenging opportunities for me to further develop my knowledge and skills during my employment with CCI. To Chris Watler, the Director of the Harlem Community Justice Center, I would like to extend my heartfelt thanks for your leadership, your welcoming personality, and your trust in me as a researcher during my tenure there. And to all my former colleagues, especially Lama Hassoun Ayoub, Jennifer Bryan, Suvi Hynynen-Lambson, Rachel Swaner, and Aaron Arnold, I would like to extend my appreciation for all the laughs and memories we shared, and your contributions to my development as a researcher and scholar.

I must also recognize the outstanding colleagues, peers and friends I was privileged to meet and get to know during my time in graduate school. It would be impossible to name all of the great people with promising futures that I have met along the way, but a special thanks to Estee Marchi, Aunshul Rege, Brian Smith, Mike Jenkins, Heather Tubman-Carbone and Michael Ostermann. Whether it was chatting about life, working on research projects together, offering much needed advice, or motivating me to finish this dissertation, each of you was responsible for making my time in graduate school an enjoyable and fulfilling experience. A very special thanks to Laura Salerno, who has been a true friend throughout our time in graduate school, and in recent months, has answered my countless questions and offered me endless advice as she preceded me in completing her journey.

Without the unconditional love and support of my family, friends, and siblings, I never would have made it this far. These individuals have all inspired me with their friendship and supported me through so many chapters in my life. I am so happy to share this milestone, which has been a long time coming, with them. To my very best friends, Kimberly Walsh and Samita Das, I am so grateful for your friendship and the countless times you have offered a listening ear to me in times of need. And to my parents, Peter and Karinne, thank you for your unrelenting belief in me, your constant devotion to my journey through life, and your teachings about dreaming big and working hard to accomplish my goals. I love and appreciate you both more than you will ever realize.

And last, but certainly not least, I would like to thank my love, Steve, who has been with me throughout the most taxing years of this process. Your support for me has been unwavering – not an easy feat given the amount of time it has taken me to get to this

point in the process. Your love and encouragement have been my strongest sources of motivation to finish this work. Thank you for always telling me how proud you were of me for getting so much done, even after I had only written a page or two on any given day, and never complaining when I came up to bed late because I was trying to finish a thought. Though we may not have started this journey together, I am so thankful that I can celebrate this accomplishment with you and the boys by my side, and look forward to continuing on my journey in life with you.

TABLE OF CONTENTS

CHAPTER 1 - Introduction	1
CHAPTER 2 – The Development of Evidence-Based Practice in Community Corrections	4
Shifts in Sentencing and Corrections Policy	4
The Impact on Corrections and Incarceration	6
Increasing Needs & Offender Reentry.....	9
Education and employment.....	10
Housing.....	13
Physical Health.	13
Mental Health.....	15
Substance Abuse.....	16
Family and Parenting Concerns.....	18
Risk-Needs-Responsivity (RNR) Theory and Offender Risk.....	19
Risk Principle.....	20
Need Principle.....	21
Responsivity Principle	22
The Evidence-Based Practice Movement	23
The Principles of Effective Intervention in Community Corrections	25
Principles of Assessment and Intervention	26
Principles of Offender Change.....	27
Principles of Outcome and Quality Improvement	29
Summary.....	30
CHAPTER 3 – Evolution of Risk Assessment.....	31
First-Generation Risk Assessment.....	31
Second-Generation Risk Assessment	33
Third-Generation Risk Assessment	35
Wisconsin Risk & Needs Assessment (WRN).	36
Community Risk-Needs Management Scale.....	36
Level of Service Inventory Revised (LSI-R).....	37
Fourth-Generation Risk Assessment.....	39
Ohio Risk Assessment System (ORAS).	40
Correctional Assessment and Intervention System (CAIS).....	41
Level of Service/Case Management Inventory (LS/CMI).....	42
Correctional Offender Management Profiling for Alternative Sanctions (COMPAS).	44
Theoretical Foundations of the COMPAS.....	44
The COMPAS Composite Risk Scores.....	46
Criminogenic Risk/Needs Profile.	47
Explanatory Typology.	52
Response Bias Scales.....	54
Understanding COMPAS Scores.....	54
Using COMPAS Scores.....	55
COMPAS Validity & Reliability	56
Validity with Parole Samples.....	59

Issues in Predicting Risk.....	60
Base Rates and Sample Size.	60
False Positives and False Negatives.	61
Cut-off Scores.	63
Selection of Predictor Variables.	64
Instrument Length and Resource Utilization.	65
Summary.	65
CHAPTER 4 - Background.....	67
Overview of Parole Supervision in New York State	67
Profile of the Parolee Population in New York State.	68
Re-arrest and Revocation in New York State & New York City	68
Risk Assessment in New York State.	69
Overview of the Harlem Parole Reentry Court.....	71
Profile of Parolees in the Reentry Court Catchment Area.	72
Utilization of the COMPAS Tool.	73
CHAPTER 5 - Problem Statement & Research Questions.....	75
Research Question #1: Is the COMPAS tool a reliable recidivism prediction instrument for a diverse parolee sample in New York?.....	77
<i>Hypothesis 1A</i>	78
<i>Hypothesis 1B</i>	78
Research Question #2: Is the COMPAS tool a valid recidivism prediction instrument for a diverse parolee sample in New York?.....	78
<i>Hypothesis 2A</i>	78
<i>Hypothesis 2B</i>	79
<i>Hypothesis 2C</i>	79
Research Question #3: What sub-scales of the COMPAS tool will best predict recidivism for a diverse parolee sample in New York?.....	79
<i>Hypothesis 3</i>	79
Research Question #4: Is the COMPAS tool a better predictor of recidivism than a DCJS risk score developed solely based on static factors from an offender's computerized case history (CCH)?	79
<i>Hypothesis 4A</i>	80
<i>Hypothesis 4B</i>	80
CHAPTER 6 - Methodological Plan	81
Participants.....	81
Data Sources and Data Collection	82
Risk Measures.....	84
COMPAS Composite Risk Scores.....	85
COMPAS Risk/Need Sub-scales.	85
DCJS Risk.....	86
Outcome Measures.....	86
CHAPTER 7 - Results	89
Descriptive Statistics.....	89
Research Question #1: Evaluating the Reliability of the COMPAS.....	93
Research Question #2: Evaluating the Validity of the COMPAS	94
Regression Analyses.	96

AUC and RIOC Analysis.....	97
<i>Composite Risk Score and Prediction of Re-arrest.</i>	98
<i>Composite Violence Risk Score and Re-arrest for Violent Crime.</i>	100
<i>History of Non-Compliance Subscale and Revocation.</i>	101
Survival Analyses.	103
Research Question #3: Subscale Predictors of Re-arrest for Any Crime	108
Regression Analyses	112
AUC and RIOC Analyses.	113
<i>Any Risk Score</i>	113
<i>Violent Risk Score and Prediction of Re-arrest for Violent Crime.</i>	115
CHAPTER 8 - Discussion.....	117
Research Question #1	117
Research Question #2	118
Research Question #3	120
Research Question #4	123
Summary.	124
CHAPTER 9 - Limitations and Suggestions for Future Research.....	125
Limitations	125
Sample Size and Composition.	125
Sampling Method.....	126
Secondary Data Analysis.	128
Official Arrest Records and Outcome Measures.	128
Generalizability and Suggestions for Future Research	132
CHAPTER 10 - Implications for Community Corrections Policy and Practice.....	134
Implications for Scholarship	134
Implications for Community Corrections Practice and Policy.	135
Local-Level Implications for Parole.	136
Broader Implications for Parole and Risk Assessment.	137
APPENDIX A – Sample COMPAS Assessment	142
APPENDIX B – IRB Approval Letter	155
WORKS CITED.....	156
CURRICULUM VITAE.....	179

TABLES

Table 1. Sample Descriptives

Table 2. Descriptive Statistics and Inter-Correlations for Sub-Scale and Composite COMPAS Scores

Table 3. Logistic Regression Analysis of COMPAS Risk Measures and Outcomes

Table 4. Cox Regression Analysis of COMPAS Risk and Outcomes Measures

Table 5. Cox Regression Analysis of Composite Risk and Covariates on Re-arrest for Any Crime

Table 6. Correlation of COMPAS Subscales and Re-arrest for Any Crime

Table 7. COMPAS Subscale and Composite Risk Scores by Recidivism Group (N=202)

Table 8. Cox Regression Analysis of COMPAS Subscales on Re-arrest for Any Crime

Table 9. Logistic Regression Analysis of DCJS Risk Measures and Outcomes

Table 10. Chi-Square Results for Differences in Recidivism for Traditional Parole and Reentry Court Parolees

Table 11. T-test for Differences between Mean Survival Time for Traditional Parole and Reentry Court Parolees

FIGURES

- Figure 1. Criminal Typology Descriptions
- Figure 2. ROC Curve for COMPAS Composite Risk Score
- Figure 3. Observed Correct Predictions of Re-arrest Using the Composite Risk Score
- Figure 4. Random Correct Predictions of Re-arrest Using the Composite Risk Score
- Figure 5. ROC Curve for COMPAS Composite Violent Risk Score
- Figure 6. ROC Curve for History of Non-Compliance Subscale and Revocation for Technical Violation
- Figure 7. Observed Correct Predictions of Revocation for TV Using History of Noncompliance Score
- Figure 8. Random Correct Predictions of Revocation for TV Using History of Noncompliance Score
- Figure 9. Kaplan-Meier Survival Curve of Parolees (N=202) Re-arrested within One Year of Release
- Figure 10. Kaplan-Meier Survival Curve of Parolees (N=202) Re-arrested within One Year of Release by COMPAS Risk Group
- Figure 11. Kaplan-Meier Survival Curve of Parolees (N=202) Revoked within One Year of Release
- Figure 12. Kaplan-Meier Survival Curve of Parolees (N=202) Revoked within One Year of Release by COMPAS Risk Group
- Figure 13. ROC Curve for DCJS Any Risk Score Compared to COMPAS Composite Risk Score
- Figure 14. Observed Correct Predictions of Re-arrest Using the DCJS Any Risk Score
- Figure 15. Random Correct Predictions of Re-arrest Using the DCJS Any Risk Score
- Figure 16. ROC Curve for DCJS Violent Risk Score Compared to COMPAS Composite Violent Risk Score

CHAPTER 1 - Introduction

Over the last 20 years, prison populations in the United States have experienced unprecedented growth, with over 1.6 million prisoners housed in state and federal correctional facilities as of June 2009 (West, 2010), translating to 1 out of every 100 American adults serving time behind bars (Pew Center on the States, 2008). Of those who are incarcerated, about 700,000 will leave state and federal prisons to return to their communities each year (Sobol, Minton, & Harrison, 2007). Those leaving prison contribute to an even greater number of offenders, approximately 4.8 million individuals or one out of every 50 adults, under community supervision including parole (Maruschak & Bonczar, 2013). Though the number of adults under community supervision has declined from 5 million in 2009 (Glaze & Bonczar 2010), a decrease in the number of probationers is responsible for 95% of the reduction in the community supervision population while the parole population has remained relatively stable over time (Maruschak & Bonczar, 2013).

Despite the fact that probation and parole agencies supervise more than twice the number of offenders as prison institutions, only 12% of correctional budgets are allocated to the operation of community corrections agencies (Pew Center on the States, 2009). Considerable numbers of offenders, and limited resources, have placed increased pressures on parole boards to exercise good judgment in offenders granted discretionary release and parole agencies to effectively manage their caseloads and prevent re-offending. Though the rate of return to prison for parolees has been slowly declining, 25% of parolees in 2012 were re-incarcerated as a result of a new felony conviction or a

technical violation and 13% had another unsuccessful outcome, like absconding (Maruschak & Bonczar, 2013).

As a result of significant numbers of offenders under parole supervision and significant recidivism rates, scholarly interest in community corrections and offender reentry has peaked in recent years. Research has been dedicated to developing new tools and strategies to address parolee needs and reduce recidivism. Overall, it has been found that reductions in recidivism and successful community reintegration can be achieved by targeting risk and criminogenic needs with selected interventions and directing more intensive services to higher risk parolees (Andrews & Bonta, 1998; Lowenkamp & Latessa, 2004). One of the promising strategies to address parolee needs and reduce recidivism, is the development of actuarial assessments of risk and need which can be utilized by parole officers to make important supervision and treatment-related decisions (Lowenkamp & Latessa, 2004; Lowenkamp, Latessa, & Holsinger, 2006).

The present study examined the reliability and validity of one such instrument, the Correctional Offender Management for Profiling Alternative Sanctions (COMPAS) tool, using a diverse sample of male offenders released to parole supervision in New York City. To-date, the wealth of reliability and validity knowledge available for earlier tools, like the LSI-R, has not yet accumulated for this instrument. Though there are several reliability and validity studies of the COMPAS, many were conducted by the tool's proprietor, Northpointe Institute of Public Management, Inc., and a very limited body of independent research currently exists due to the proprietary nature of the tool.

This dissertation will contribute to the existing research on the COMPAS instrument and its effectiveness in measuring offender risk and need with a diverse

sample of parolees in New York City. In recent years, the higher-cost, dynamic-based COMPAS tool replaced a low-cost, static-based risk score for all offenders leaving prison. At a general level, contributing to the development and accumulation of this body of knowledge on the COMPAS is very important given the fact that offender risk assessment results are used in decision-making that can have profound effects on parolees. At a more specific level, the results of this study could have direct implications for community corrections policy in the City of New York and the State as a whole.

The following chapters of this study present a review of the literature and background information on parole in New York; a methodological plan, results and discussion of study analyses; and implications for future research and community corrections policy and practice. Chapter 2 discusses the evidence-based practice movement in corrections and the theoretical underpinnings of offender risk assessment. Chapter 3 traces the evolution of offender risk assessment instruments, with a detailed focus on the COMPAS tool. The importance of this study, its research questions, and its hypotheses are presented in Chapter 4. Chapter 5 gives local-level background information on parole in New York. In Chapter 6, the study's methodology is described, with results of all statistical analyses reported in Chapter 7 and a discussion of those results appears in Chapter 8. Chapter 9 details the limitations of this study and directions for future research while Chapter 10 discusses the implications of this research for community corrections and parole practice and policy.

CHAPTER 2 – The Development of Evidence-Based Practice in Community Corrections

Effectively identifying and addressing offender needs has been difficult in corrections due to budgetary constraints, lack of programming options, and changing political and ideological environments that modify the focus and goals of correctional practice. Prior to the 1970's, indeterminate sentencing and an emphasis on the rehabilitation of offenders were the prevailing practices in the criminal justice system. Recommendations to transform the justice system made by a panel appointed by President Lyndon B. Johnson emphasized rehabilitation, provision of services, and community reintegration (Mackenzie, 2001). Special attention was given to community treatment, diversion programs, offender reintegration, and education and employment programs. With this focus, parole supervision was considered to be a second chance and an opportunity to reform after release from prison.

Shifts in Sentencing and Corrections Policy

In 1974, Robert Martinson published an article based on a meta-analysis of offender programs that concluded that most treatment programs were not effective in their rehabilitative goals and corrections should focus their resources elsewhere (Lipton, Martinson, & Wilks, 1975). Criticisms of the study were widespread indicating that Martinson's study had significant methodological limitations and included programs in the meta-analysis that were very poorly implemented (Mackenzie, 2001). After the release of the report, other scholars produced research that disagreed with Martinson's claim (Palmer, 1975) and in 1979, Martinson also published an article stating that some programs did in fact work, despite his earlier claims. However, the results of the Martinson analysis were widely accepted despite these limitations and opposing research

evidence (Mackenzie, 2001). A common phrase, “nothing works” became widely used to describe offender rehabilitation and treatment programs.

A political and social climate ripe for shifts in sentencing and corrections practice was created by issues that came to the forefront at a similar time as the Martinson report. Inequalities in sentencing practices and protests over prison conditions and release decisions were made public, yielding the belief that subjective discretion created significant inequities in the justice system, particularly for minority offenders. An escalating crime rate between 1965 and 1975 contributed to increases in public fear of crime and the belief that rehabilitation was too “soft” on offenders and that discretion posed a threat to public safety by facilitating the release of dangerous criminals to the community. An escalation in drug use in the 1970s, and the subsequent ‘war on drugs’, had significant influence on increasing sanctions for the punishment of drug use and distribution.

These political and social issues influenced a shift from indeterminate sentencing and a focus on rehabilitation to significantly more punitive, determinate sentencing and corrections policies. Determinate sentencing is the practice of weighing the severity of the crime and the offender’s criminal history as the only factors in the determination of punishment. Determinate sentencing limits judicial discretion in issuing a sentence at conviction and the ability of the parole board to make decisions about when to release an offender to parole since sentence length was relatively fixed (Serill, 1977). The intention of determinate sentencing was to address the perceived inequalities created by discretion and create a more uniform, standardized process resulting in increased levels of fairness.

The crime control model was also incorporated into sentencing policy and practices (Mackenzie, 2001). In crime control, the focus is on incapacitation and deterrence as the main methods of preventing crime. Incapacitation is the notion that crime prevention is successful when offenders are incarcerated and as a result, cannot commit crimes in the community, and this strategy is widely accepted by the public for this reason (Zimring & Hawkins, 1995). Mandatory minimum sentences and other 'get tough' policies further limit the discretion of judges and correctional officials. 'Three strikes' policies and 'truth-in-sentencing' practices have resulted in an increase in the average number of months individuals spend in prison (Hughes, Wilson, & Beck, 2001).

The Impact on Corrections and Incarceration

Shifts in sentencing policy and practice have resulted in significant impacts for corrections and offender reentry. Over the last 40 years, as a result of more punitive sentencing practices, the United States has experienced a 500% increase in the number of people incarcerated in prisons or jails (The Sentencing Project, 2012). The 'war on drugs' has led to a ten-fold increase in the number of drug offenders for every 100,000 adults, making up the majority of the growth in state and federal prisons between 1980 and 1996 (Blumstein & Beck, 1999). Not surprisingly, prison overcrowding has become a serious issue as a result of the immense growth in the number of individuals in prison. In fact, state prisons were operating at between 13% and 22% above capacity while Federal prisons were operating at 27% above capacity in 1998 (Beck & Mumola, 1999).

While the prison population has increased exponentially overall, recently it has started to show signs of slowing down. However, the percentage of offenders being released has significantly decreased; a statistic that continues to contribute to issues with

prison overcrowding. Between 1993 and 1998, the average number of months an offender spent in prison increased from 21 to 28 months (Lynch & Sabol, 2001). More punitive policies have resulted in more offenders serving lengthier sentences in prison and limited ability to use early release options like good-time reductions and parole release to manage prison overpopulation. Under the new policies and practices, parole boards are severely limited in their ability to use discretion to release offenders to parole supervision. Some states have eliminated early release by the decision of a parole board entirely, while other states have significantly restricted the ability of the parole board to release certain types of offenders. In fact, parole board discretion has been almost entirely eliminated. In 1997, most release decisions were mandatory, rather than discretionary, as a result of determinate sentence expiration and good-time provisions (Ditton & Wilson, 1999).

Increases in prison populations also have had a profound effect on the availability of treatment programs and interventions in prison. Prison overcrowding has placed significant strain on correctional budgets and prisons have struggled to cut costs. When making budget cuts, prisons often cut programming first, yielding a shortage in available programs to address normal prison populations, and even less to address burgeoning ones. For example, in 2009, as California was struggling with budget deficits due to soaring correctional populations, correctional officials cut 40% of the budgeted funding for rehabilitation services in prison (Rothfeld, 2009). In New Jersey, in 1995, only 1 to 2.5% of the correctional budget was set aside for educational programming and services, and most of the money was meant targeted toward juveniles (Travis, Keegan, & Cadora, 2003).

The limited availability of monetary resources to spend on prison programming resulted in prisons facing the problem of increasing offender needs and a decline in the availability of prison programming to address those needs. From 1991 to 1997, the percentage of offenders who were participating in prison programming decreased (Lynch & Sabol, 2001). Only 35% of offenders were participating in education programs and 10% in substance abuse programs in 1997 compared to 42% and 25% respectively, six years prior. One study revealed that 20% of offenders in prison in Illinois, Ohio, and Texas had not even been offered an opportunity to participate in educational and employment programs while incarcerated (Visser, Debus, & Yahner, 2008).

Parole supervision has been increasingly utilized to manage offenders returning from prison with a focus on supervision, deterrence, and the improvement of public safety. Of the individuals released from prisons each year, almost 80% are released to parole supervision (Glaze & Bonczar, 2006; Harrison & Beck, 2006). However, it is often overlooked that increased reliance on parole supervision to manage offenders can also contribute to prison overcrowding. In 2009, about 33% of all new admissions to prison were for parole violations (West & Sabol, 2011) and only slightly more than half of parolees would complete parole successfully in 2011 (Maruschak & Bonczar, 2013). With increased reliance on parole to ease prison overcrowding and facilitate successful reintegration, more successful reentry management of offender needs has become an important focus for corrections policy and practice in recent years.

Increasing Needs & Offender Reentry.

The majority of offenders who are currently incarcerated will be released to the community at some point in time. Increased stays in prison, paired with lack of prison programming and services, present significant challenges for public safety and offender reentry. The release of offenders to the community must balance the goals of protecting the safety of the public with the goal of facilitating a successful transition to productive citizenship for the offender (Travis, Solomon, & Waul, 2001). As a result of the shortage of resources and programs, offenders are leaving prison with significantly less preparation and higher levels of unaddressed needs than ever before. In fact, offenders often leave prison with the same issues that lead them to prison in the first place, placing additional burden on community corrections and parole agencies to address offender needs (Petersilia, 2000; Travis, 2000).

Statistics on offenders have shown a high prevalence of a variety of needs including education, employment, housing, substance abuse, health issues, and family concerns. Each of these needs independently can present a unique barrier to successful transition from prison. However, offenders are not often single issue people – they have a complex array of needs that when combined, significantly increase the difficulties associated with reentering society following incarceration (O'Brien, 2002; Visser, Winterfield, & Coggeshall, 2005). Therefore, it is not only important to understand the role of each of these needs in the reentry process, but also the complex interaction between needs and successful ways to address offender needs (La Vigne, Davies, Palmer, & Halberstadt, 2008). With this understanding, parole agencies have a better chance of achieving more successful outcomes with returning offenders under their supervision.

Education and employment. Two of the most important factors in ensuring a successful transition from prison back to the community are education and employment. Inmates often arrive in prison with minimal education, limited employment skills, and a minimal work history. Education and employment are two areas of offender need that are often directly connected to one another. While nine in 10 state prisons and all federal prisons offer educational programs for inmates (Harlow, 2003), employment training programs appear to be more limited (Justice Policy Center, 2006). Increases in the number of offenders in prison with educational and employment needs and no change in the number of program spots available has limited access to these programs for an even greater number of inmates (Harlow, 2003). Due to limited availability of in-prison education and employment programs, and the limitations in finding and maintaining legitimate employment upon release, offenders face daunting challenges in their reentry following incarceration.

About 41% of the nation's incarcerated population had not completed high school or a GED program compared to 18% of the general population (Harlow, 2003). Though the percentage of inmates who had not completed high school remained stable between 1991 and 1997, the number of prison inmates without a high school education increased. In 2001, a study showed that 19% of inmates in state prisons were completely illiterate and an additional 40% were functionally illiterate (Rubinstein, 2001). Though more than half of inmates report participating in education programming in prison (Harlow, 2003), the most popular programs are those that may not provide the greatest benefit in employability upon release, like high school or GED preparation classes.

Offenders are more likely than the general population to have experienced recent unemployment, particularly in the months before incarceration. In 1997, less than 70% of offenders reported that they had been employed in the month before their arrest (Government Accounting Office, 2000). Offenders often have unstable employment histories since many resort to illegitimate sources of income, and lack the education necessary to obtain stable, well-paying employment. Also, most offenders come from low-income, predominantly minority communities with few jobs available, some level of labor market discrimination, and limited access to networks of people in legitimate work environments (Holzer, Raphael, & Stoll, 2003). Job-training programs for offenders have increased in availability in recent years, but due to increasing numbers of incarcerated offenders, participation in those programs continues to be limited. Also, job-training programs often focus specifically on teaching offenders the specific work-related skills they will need to find employment, but ignore teaching cognitive and life skills, like work ethic, which are needed to succeed in a legitimate occupation (Bushway & Reuter, 2002; Travis, Solomon, & Waul, 2001).

Most offenders do recognize that finding a stable job is an important factor in staying out of prison after their release (Justice Policy Center, 2006), yet there are significant barriers to employment that offenders will experience. Many offenders experience issues with the stigma of being formerly incarcerated, which not only creates issues in employment, but also leads to a “wage penalty” associated with incarceration (Western & Pettit, 2000). Being formerly incarcerated may also limit the types of jobs that an offender is able to have, and some states ban ex-offenders from any type of public employment (Petersilia, 1999). Incarceration also creates a significant gap in an

offender's work history, especially if they were legitimately employed prior to their incarceration, and may eliminate professional connections and social contacts that could assist the offender in securing employment upon release (Western, Kling, & Weiman, 2001).

Parolees who fail to obtain minimum-wage employment following release are more likely to recidivate and those who do not maintain stable employment over an extended period of time may be more likely to commit future crimes (Sampson & Laub, 1993; Visher, Debus, & Yahner, 2008). A study of prisoners released in Indiana showed that post-release employment and education were two of the greatest predictors of recidivism for all offenders. Offenders who were not employed for at least three months following release were more likely to recidivate than those who had obtained employment (Nally, Lockwood, Ho, & Knutson, 2012). Additionally, offenders with a high school diploma or GED were almost 10% less likely to recidivate and those with at least two years of post-secondary education were almost 25% less likely to recidivate when compared to offenders with no high school diploma or GED.

There is some current evidence that correctional education and job-training programs in prison can significantly reduce recidivism for offenders following their release (Bushway & Reuter, 1997; Cronin, 2011; Davis, Bozick, Steele, Saunders, & Miles, 2013; Travis, 2005). It is important for community corrections agencies and those supporting the reentry of offenders to consider education and employment programs that improve job skills and job readiness to increase employability of offenders, and as a result, reduce recidivism among parolees released from incarceration.

Housing. The most immediate challenge for offenders returning from prison is securing stable housing (Justice Policy Center, 2006). Many returning offenders live with family members or intimate partners following release, but some evidence suggests that arrangements with family members are often short-lived (Travis, Solomon, & Waul, 2001). There are also many offenders who return without stable housing plans and face a significant number of obstacles and barriers, including a limited number of affordable housing options, financial and legal barriers, and strict eligibility requirements for federal housing. Shelters are only temporary solutions, if space is even available, and many offenders end up homeless as a result of the lack of affordable housing options.

However, offender needs related to housing can sometimes be overlooked by policymakers, practitioners, and researchers. Offenders believe that finding a stable place to live is very important to their success after prison and most believe that they will need significant assistance in securing stable housing. Studies have shown that offenders without stable housing arrangements are more likely to be returned to prison after release (Fontaine, 2013; Metraux & Culhane, 2004). The period immediately following release from prison is the most critical for success and aiding individuals in finding housing may be an important factor in reducing recidivism (Travis, Solomon, & Waul, 2001).

Physical Health. Offenders suffer at much higher rates of chronic disease than the general population (Hammett, Roberts, & Kennedy, 2001; NCCHC, 2002). About 39% of federal inmates and 43% of state inmates report at least one chronic medical condition (Wilper, et al., 2009) while 37% of jail inmates have at least one chronic medical condition and 15% report having more than two chronic diseases (Maruschak, 2006). When considering specific chronic conditions, federal and state prisoners are

almost twice as likely to suffer from diabetes, slightly more likely to suffer from hypertension or persistent asthma, and almost twice as likely to have suffered a previous heart attack, than the general population (Wilper, et al., 2009). Despite higher prevalence rates of many chronic diseases, many inmates have not received sufficient care for these conditions due to poverty, lack of access, and lack of health insurance until they become incarcerated (Travis, Solomon, & Waul, 2001).

Specific policies like the ‘war on drugs’, which have resulted in the increased use of incarceration for those with substance abuse and dependency, have contributed to a rise in higher rates of infectious diseases than the general population. About 25% of all state and federal inmates have histories of intravenous drug use, putting them at much higher risk for infectious diseases like HIV/AIDS and hepatitis C (CASA, 1998). About 3.4% of all inmates in state and federal prisons are HIV positive or have confirmed AIDS (Maruschak, 2009) while one-third of all inmates have been diagnosed with hepatitis C compared to about 1.5% in the general population (Beck & Maruschak, 2004).

Many physical health conditions require significant community-based care following release from incarceration to maintain physical well-being. However, many corrections agencies are not equipped to prepare offenders to address their physical healthcare needs or connect them directly to services following release and this is a major concern for offenders leaving prison (Justice Policy Center, 2006). Continuity of care is particularly important for those with infectious diseases like HIV and tuberculosis, but less than one-third of correctional facilities report making follow-up appointments in the community for released offenders (Hammett, Roberts, & Kennedy, 2000). To facilitate a successful release from prison with care for physical health needs, prisons and

community corrections agencies must work together to establish a continuum of care and address barriers to sufficient care including enrollment in benefits programs and assistance in identifying community-based treatment providers.

Mental Health. Prison and jail inmates also suffer from significantly higher rates of mental illness than the general population. In 2005, more than half of all prison and jail inmates suffered from a mental health issue with much higher rates in state prison and local jails. Mental illness rates among incarcerated populations are much higher than the general population, almost 6 times higher in the most recent comparison (James & Glaze, 2006). Estimating the lifetime prevalence of particular mental illness is difficult in prison populations, but the most common conditions among prison inmates are major depression (13.1 to 18.6%), anxiety (18.2-30.1%), and post-traumatic stress disorder (4.9-11.7%) (NCCHC, 2002).

Trauma appears to also have an effect on offenders and issues of mental health. Though female offenders have been the focus of much of the research on trauma prevalence rates and their impact (Cook, Smith, Tusher, & Raiford, 2005; Messina & Grella, 2006), recent studies have found that male prisoners also suffer significant and persistent traumatic experiences in their lives that represent complex challenges for treatment and offender reentry (Miller & Najavits, 2012; Wolff, Huening, Shi, & Frueh, 2013). Substance abuse, for instance, is often a means of self-medication for mental health conditions that manifest from traumatic experiences and therefore, substance use is a symptom of a more complex issue, rather than the problem (Boles, Joshi, Grella, & Wellish, 2005; Fellitti, 2004).

Mentally ill offenders present significant challenges for successful reentry upon release. They are more likely to have more complex risk and needs including lengthier criminal histories, higher rates of unemployment, substance abuse, homelessness, and trauma history, and lengthier stays in prison than other offenders (Ditton, 1999). In addition, offenders with mental illness are more likely to have been arrested for a violent offense and are more likely to commit a new violent offense upon release. The majority of mentally ill offenders receive mental health treatment of some kind, including medication, during incarceration. However, successful reentry for these offenders will be almost impossible without significant community-based treatment upon release. Parole agencies are often unequipped to address the special needs of mentally ill parolees and compliance with medications and treatment in the community is more difficult to detect and enforce resulting in significant future contact with the criminal justice system (Lurigio, 2001; Monahan, 1996).

Substance Abuse. In the most recent survey of state and federal prisoners, 80% of state prisoners report a history of drug or alcohol use (Petersilia, 2003) and over half of all state prisoners and 45% of all federal prisoners meet the criteria for substance dependence or abuse (Mumola & Karberg, 2006). About one-third of both state and federal offenders were under the influence of drugs at the time of the offense and over half had used drugs in the month prior to the offense. Substance abuse appears to be linked to mental illness in incarcerated populations – in 2005, 74% of state prison inmates with a mental illness also met the criteria for substance dependence or abuse, compared to 56% of state prison inmates without mental illness (James & Glaze, 2006). Dual-diagnosis offenders are at much higher risk for relapse and recidivism upon release

when compared to those with a mental illness or substance abuse or dependency issue, and require a complex array of services to address their specific needs (Baillargeon, et al., 2010).

Offenders recognize that drug use is one of the main causes of their past and current issues, including criminal behavior (Justice Policy Center, 2006). However, studies have shown that most offenders with these issues do not receive treatment during their incarceration. Of the offenders meeting the criteria for drug dependence or abuse, only 15% participated in an actual drug treatment program administered by treatment professionals (Mumola, 1999; Mumola & Karberg, 2006). The majority of offenders reporting program participation attended a self-help group, peer counseling, or a drug education program.

Without effective treatment, relapse rates for offenders with substance abuse issues are extremely high (Wexler, Lipton, & Johnson, 1998). A meta-analysis of drug treatment programs indicated that individuals who received drug treatment were 15% less likely to relapse and 6% less likely to recidivate than individuals who did not receive drug treatment (Prendergast, Podus, Chang, & Urada, 2002). An additional meta-analysis of incarceration-based drug treatment programs produced similar results – those who participated in drug treatment in prison were 7% less likely to recidivate than those who did not (Mitchell, Wilson, & Mackenzie, 2006).

Drug treatment programs during incarceration, like cognitive-behavioral interventions and in-prison therapeutic communities show effectiveness in reducing substance abuse and preventing recidivism (Gaes, Flanagan, Motiuk, & Stewart, 1999). In-prison treatment programs are most effective when paired with community-based

aftercare and participation following release from incarceration (Mears, Winterfield, Hunsaker, Moore, & White, 2003; Moore & Mears, 2003). Therefore, offenders who are nearing the end of their prison term are prime targets for drug treatment programs with in-prison and community-based components that provide a continuum of care which can reduce recidivism and drug use.

Family and Parenting Concerns. Over 50% of prisoners in the United States are parents to minor children under the age of 18 (Glaze & Maruschak, 2008). By the middle of 2007, approximately 2% of children had at least one incarcerated parent and this statistic jumps to 10% of all children when considering parents in jail, on probation or on parole (Mumola, 2000). As a result of parental incarceration, families often experience significant disruptions in relationships, living arrangements, and financial support and parents experience significant challenges in maintaining contact with their children during their incarceration. The location of prisons in a state's rural areas when the majority of offenders come from the state's urban centers is a significant issue for maintaining contact with children and families (Justice Policy Center, 2006; Kates, Ransford, & Cardozo, 2005).

Female offenders are more likely to experience significant concern over family and children. Compared to their male counterparts, women are more likely to have primary custody of their children prior to incarceration (Enos, 2001). Women also tend to be the primary caretakers of their children, about 40% were living in a single-parent household the month before their arrest (Glaze & Maruschak, 2008) and their removal disrupts the financial welfare and stability of their children during their incarceration (Mumola, 2000). While 90% of male prisoners are likely to have their children in the care

of the other parent during their incarceration, women are far less likely to have the same luxury (Enos, 1998). As a result, women are more likely to risk losing parental rights to their children due to the *Adoption and Safe Families Act of 1997* and prison environments make it impossible for women to satisfy all of the requirements to maintain these rights (Day, 2005; Halperin & Harris, 2004; Hayward & DePanfilis, 2007).

Positive family relationships and support, prior to, during, and following incarceration can significantly improve outcomes, including reductions in recidivism (Hairston, 1988, 2002; La Vigne, Visher, & Castro, 2004; Sullivan, Mino, Nelson, & Pope, 2002). Positive familial support not only limits the stresses of returning from prison, but family may also provide shelter, financial support, and assistance in locating employment which can contribute to lower rates of recidivism (Nelson, Dees, & Allen, 1999). Many offenders express the belief that family support will be an important support in keeping them out of prison after they are released (Justice Policy Center, 2006). For these reasons, it is important that community corrections agencies focus on positive engagement with family and children to support the reentry process and achieve more successful outcomes.

Risk-Needs-Responsivity (RNR) Theory and Offender Risk

The Risk-Needs-Responsivity model and theory was first formalized by Andrews, Bonta, and Hoge (1990) with the goal of improving the effectiveness of services through matching interventions to offender risk and needs, like those mentioned above, known to affect outcomes. The theory was later expanded to include the theory of the psychology of criminal conduct (PCC) by Andrews and Bonta (1998, 2006). Over time, the Risk-Needs-Responsivity model has been enhanced to continually support the evidence-based

practice movement. The tools based upon these theories assist justice professionals in determining the level, targets, and type of intervention programs based on an individual's risk of recidivism, criminogenic needs, and learning style. The three core principles of the theory are the principles of risk, need, and responsivity.

Risk Principle. The risk principle is summarized by Andrews, Bonta, & Hoge (1990) as higher levels of services for offenders who represent a higher risk and less intensive services for offenders who represent lower risk. There are two aspects of the risk principle, prediction of re-offense and matching to treatment. The prediction component of the risk principle involves a formalized assessment of an offender's risk of future criminal behavior to determine how likely that offender is to commit a new crime. It is important to ensure that whatever method of risk assessment is used is reliable and can be trusted to differentiate between low and high risk offenders. Matching offenders to levels of treatment based on risk to achieve the greatest treatment effect is the second component of the risk principle. Based on this principle, higher risk offenders experience a reduction in recidivism if they are given more intensive services than lower risk offenders (Andrews & Bonta, 1998).

Many empirical studies have examined the concept of matching treatment levels to offender risk level, finding reduction in recidivism for higher risk offenders who received intensive services (Lowenkamp & Latessa, 2004; Lowenkamp, Pealer, Smith, & Latessa, 2006). Further, some of these studies have also showed that providing those same intensive services to lower risk offenders will actually produce a negative effect and lead to higher rates of recidivism (Andrews & Kiessling, 1980; Bonta, Wallace-Capretta, & Rooney, 2000). As a result, attention to the risk level of an offender is an important

decision-making tool in selecting not just the types of treatment, but the intensity of treatment.

Need Principle. The needs principle can be summarized as the matching the types of interventions delivered to offenders' particular criminogenic needs. Offenders may have many needs that need should be addressed upon their release from prisons, but the best outcomes will be achieved when the needs that contribute to criminal behavior are specifically targeted with treatment. Needs that contribute to criminal behavior, or criminogenic needs, are a subset of risk factors and are dynamic characteristics of offenders and their environment that yield reductions in recidivism when they are targeted and changed (Andrews, Bonta, & Hoge, 1990; Latessa & Lowenkamp, 2005). In order to effectively incorporate the needs principle, assessment instruments must be able to determine the specific criminogenic needs and dynamic risk factors of each offender.

The Risk-Needs-Responsivity literature has identified seven major criminogenic needs that would be promising to assess and target: antisocial personality pattern, procriminal attitudes, social supports for crime, substance abuse, family/marital relationships, school/work, and prosocial recreational activities. Criminal history is also very important, but is a static risk factor that cannot be changed. Five of these original criminogenic risks and needs, social supports for crime (criminal associates/peers), antisocial personality pattern (criminal personality), procriminal attitudes (criminal thinking), criminal history (criminal involvement), and school/work (vocation/education), have been identified as the "big five" risk factors or the most important risk/needs factors in predicting recidivism from empirical research (Gendreau, Little, & Goggins, 1996).

Responsivity Principle. The responsivity principle can be summarized as matching the styles and methods of treatment services to the strengths and learning styles of the offender. The development of this principle results from reviews of the literature on service effectiveness with offender sub-samples, and literature on the interactions of groups of offenders with the style of treatment (Andrews, Bonta, & Hoge, 1990). The effectiveness of certain modes of treatment appears to be related to individual offender characteristics as well as program delivery and staff (Andrews & Kiessling, 1980). It has been argued that the principle of responsivity is just as important as the risk and needs principles, but is not given the attention it needs to contribute to improving correctional interventions (Kennedy, 2000).

There are two types of responsivity, general and specific. General responsivity involves the fact that cognitive social learning interventions are the most effective way to change people's behavior, regardless of the type (Andrews & Bonta, 2006; Bonta & Andrews, 2007). Cognitive social learning interventions, like cognitive behavioral therapy, are structured, goal-oriented interventions designed to address dysfunctional emotions and maladaptive cognitive thought processes that lead to criminal attitudes and thinking. Empirical studies have shown that cognitive social learning interventions are highly successful and are part of evidence-based practice in offender treatment (Clark, 2011; Landenberger & Lipsey, 2005; Milkman & Wanberg, 2007).

Specific responsivity involves considering an offender's specific strengths and personality factors when considering treatment options. Offenders have different learning styles that either facilitate or inhibit their ability to learn, including important differences between auditory and visual learners. Offenders, treatment settings, and treatment staff

are not all alike and therefore, certain treatment environments might work for some offenders and not others. For example, offenders with mental health issues may need treatment before they will be responsive to other types of group-oriented, collaborative programs (Bonta & Andrews, 2007). Specific responsivity also involves the consideration of other important offender-specific characteristics including language, gender, and culture (Cullen, 2002). Cultural and gender differences in offenders can lead to different individual barriers that can limit program participation and completion and identifying these barriers is critical to success (Kane, Bechtel, Revicki, McLaughlin, & McCall, 2011).

Best practices in specific responsivity start with assessments that will measure the learning styles and personality factors of an offender to match to appropriate treatments (Kennedy, 2000). Some current third- and fourth-generation assessments identify specific offender characteristics and make recommendations to treatment programs based on some responsivity characteristics. However, these assessments do not reach the full potential of incorporating the responsivity principle and future instruments will more fully assess responsivity and contribute to designing more effective treatment services for offenders.

The Evidence-Based Practice Movement

With increases in prison populations, increased reliance on parole supervision, and lack of resources to address offender needs during incarceration, offender reentry has come to represent a massive threat to public safety. Over two-thirds of prisoners will be re-arrested for a new crime within three years of release and more than half will be returned to prison for a new crime or parole violation (Langan & Levin, 2002). One study

also estimates that offenders released from prison account for about 20% of all arrests, a statistic likely much higher when considering that most crimes are not detected by police (Rosenfeld, Wallman, & Fornango, 2005). A conscious effort to find out what works to reduce offender recidivism following release has resulted in the adoption of evidence-based practice and policy in corrections.

Evidence-based practice (EBP) in corrections evolved from the use of EBP in the field of medicine, where physicians use the most empirically supported treatment options to make clinical decisions (Guevara & Solomon, 2009). Though used interchangeably with terms like best practices and ‘what works’, evidence-based practice in any field has a distinct meaning in requiring a definable outcome that is measurable and based on practical application of the practice in the real world. Based on this definition, evidence-based practice is best applied in fields with an emphasis on outcomes, including criminal justice fields like corrections.

In corrections, evidence-based policy and practice focuses on risk reduction resulting in decreases in crime and improvements in public safety. Practices can involve empirically supported principles that inform treatment selection or specific interventions that have been empirically tested and shown to produce positive outcomes. Implementation of these principles or interventions is based on finding good evidence that they are effective and achieve acceptable outcomes. Interventions are considered to be effective if they reduce offender risk, reduce recidivism, and make long-term improvements to public safety (Guevara & Solomon, 2009). The best outcomes in corrections can be achieved with knowledge of empirically supported causes of crime and implementation of programs and interventions that have been shown to be effective

(Latessa, Cullen, & Gendreau, 2002). Evidence-based practice also involves a commitment to quality improvement and continuous evolution based on an ever growing body of research. New evidence may emerge that indicates that old strategies have ceased to be effective and/or that newer strategies show better outcomes and should be integrated into policy and practice.

Implementing and sustaining evidence-based practice in corrections also requires two other components for system reform, organizational development and collaboration, and the three concepts together are known as the Integrated Model (Guevara & Solomon, 2009). Once an agency has committed to evidence-based practice, a shift from traditional supervision requires the modifications of values and beliefs, the transformation of organizational culture, and the construction of new infrastructure to support the changes. Collaboration with external stakeholders can support the organizational shift and creates the buy-in necessary to maintain the change over time. Effective collaboration with stakeholders can also improve organizational outcomes, initiate changes in the larger system to further the proliferation of evidence-based practice as a systemic change, and lead to more informed policymakers and better decision-making at the macro level.

The Principles of Effective Intervention in Community Corrections

The Crime and Justice Institute (2004), in collaboration with the National Institute of Corrections (NIC) developed a coherent framework of guiding principles of effective intervention in community corrections based on the tenets of evidence-based practice and the Integrated Model. This framework emphasizes evidence-based practices, organizational change, and integrating the current systems with best practices to create

lasting change. There are eight evidence-based principles of effective interventions in this integrated model that are all highly interdependent.

Principles of Assessment and Intervention. The dominant principles of effective intervention were developed as a result of the importance of Risk-Needs-Responsivity theory in evidence-based practice. The first principle, assessing offender risk/needs, involves the development and maintenance of a valid and reliable method of assessing offender risk. Preferred methods should be validated with similar populations, focus on dynamic and static risk factors, and criminogenic needs, and involve training for staff on the standard procedures for implementation that influence the effectiveness of the tool (Austin, et al., 2003; Flores, et al., 2006; Lowenkamp & Latessa, 2000). Informal offender assessments, which often take place over the course of interaction with an offender, should be used to reinforce the results of formalized assessments.

The other main principle of effective intervention, targeting interventions, involves all three of the major principles of RNR theory. For review, the risk principle in effective interventions will involve the prioritization of supervision and treatment resources for high-risk offenders to achieve the greatest reductions in risk. Effective interventions also address the need principle, focusing resources on the most critical criminogenic needs. Considering individual characteristics when matching offenders to treatment services, or the responsivity principle, is also an integral component of effective interventions.

The principle of targeting interventions also involves two additional concepts - dosage and treatment. Dosage involves the strategic application of the treatment and supervision services with an offender based on their risk level. Most offenders, including

those with both low and high risk, appear to do best with shorter, more intensive services. Studies have shown that outcomes are most successful with about 100 contact hours over the course of 3-9 months (Bourgon & Armstrong, 2005; Latimer, Dowden, Morton-Bourgon, Edgar, & Bania, 2003; Lipsey, 1995). These same studies have shown that offenders with either high levels of risk or complex needs may need extended services, about 200 contact hours, and offenders with both high levels of risk and complex needs may need 300 contact hours to achieve significant reductions in recidivism. The treatment principle involves the delivery of targeted and timely treatment interventions and the integration of treatment services with the requirements of sanctions and supervision to achieve the greatest success in reducing recidivism. Selected treatment interventions should be evidence-based and provide the highest level of benefit to the offender (Palmer, 1995).

Principles of Offender Change. Four of the principles of effective intervention, enhancing intrinsic motivation, skill training with directed practice, increasing positive reinforcement, and engaging on-going support in natural communities, involve an emphasis on behavioral change and pro-social support systems needed to reinforce offender change. Behavioral change is often difficult and motivation to change can be enhanced by supportive, sensitive interactions with correctional staff and motivational interviewing techniques that assist people in overcoming ambivalence about changing their behavior (Harper & Hardy, 2000; Miller & Rollnick, 2001; Ryan & Deci, 2000).

Strategies to enable change must be employed once an offender has become motivated to engage in changing behavior. Cognitive-behavioral strategies focus on eliminating disruptive thought processes and replacing them with problem-solving skills

and must be delivered by well-trained staff who understand anti-social thinking and social learning. Cognitive-behavioral therapy (CBT) teaches pro-social attitudes and behaviors through role-playing and modeling strategies and is an evidence-based intervention shown to reduce recidivism (Bourgon & Guitierrez, 2012; Bush, Glick, & Taymans, 2011; Clark, 2011; Landenberg & Lipsey, 2005; Lipsey, Chapman, & Landenberger, 2001; Lowenkamp, Hubbard, Makarios, & Latessa, 2009; Wilson, Bouffard, & Mackenzie, 2005).

Once an offender has begun the change process, sustaining that change over time becomes very important. Positive reinforcement, also known as contingency management (CM), has been shown to be highly effective in helping offenders sustain their behavior change over a long period of time (Higgins, Heil, & Lussier, 2004; Petry & Bohn, 2003; Stitzer, Petry, & Peirce, 2010; Petry & Simcic, 2002). Behaviorists also recommend the application of swift negative reinforcement for unacceptable behavior with graduated consequences that emphasize accountability and personal responsibility for bad decisions. Together, both positive and negative reinforcement can be useful for sustaining behavior changes in offenders in criminal justice settings (Carey 2009; Rudes, et al., 2012).

Another principle of sustaining change over time is the engagement of pro-social support in an offender's immediate environment or community. Family members and other supportive people in an offender's life can be very successful in providing external positive reinforcement for behavior change. Studies have shown the effectiveness of this approach, also known as the Community Reinforcement Approach (CRA) in supporting sustained behavior change and improving outcomes in a variety of offenders including drug-addicted populations (Hochstetler, DeLisi, & Pratt, 2010; Kirby, Marlow, Festinger,

Garvey, & La Monaca, 1999; Meyers, Miller, Smith, & Tonnigan, 2002; Myers, Villanueva, & Smith, 2005; Roozen, et al., 2004). Other supplemental initiatives involving the community, like restorative justice, can also help improve bonds to and increase pro-social relationships with the community (Prashaw, 2001).

Principles of Outcome and Quality Improvement. Two of the principles of effective intervention, measuring relevant practices/processes and providing measurement feedback, involve the documentation and quality improvement process of effective interventions. Measuring practices/processes involves two components: documenting offender change and staff performance. Documenting offender change measures the effectiveness of the provided services while documenting staff performance promotes staff commitment to treatment delivery and implementation fidelity (Durlak, 1998; Henggeler, Melton, Brondino, Scherer, & Hanley, 1997; Mihalic, 2004; Mihalic & Irwin, 2003).

Following the documentation process, the information collected regularly by measurement processes should serve two purposes in providing feedback – improving outcomes and improving the quality of the intervention. Informing offenders of their progress can enhance motivation, build accountability, and improve outcomes (Agostinelli, Brown, & Miller, 1995). Similarly, accountability for, integrity to, and focus on the goals of the program can be enhanced through performance reviews with staff (Alvero, Bucklin, & Austin, 2001). When outcomes are not up to expectations, information collected by staff can be used to make modifications to the program and improve the quality and fidelity of the intervention to yield more success in achieving outcomes.

Summary. Though the documentation of the principles of effective intervention focuses specifically on community corrections, the model is broad enough to be applicable to all components of the criminal justice system. Systems that can implement and maintain the principles of effective intervention in supervision and treatment have the greatest likelihood of reducing recidivism and conforming to the standards of the evidence-based practice movement.

CHAPTER 3 – Evolution of Risk Assessment

Offender risk assessment strategies have evolved out of the principles of the Risk-Need Responsivity (RNR) model. Focusing on reducing recidivism through matching treatment services to an offender's risk for re-offending and focusing treatment on criminogenic needs are the main tenets of offender risk assessment instruments. With increased reliance on evidence-based practice, offender risk assessment is one of the chief principles of effective intervention in community corrections and a critical component of decision-making (Crime & Justice Institute, 2004). Offender risk assessment results are used to make a variety of very important decisions that can have profound effects on offenders, including classification and service provision during incarceration, discretionary release to parole, and supervision and services received on parole. As a result of this increased reliance, it is imperative that risk assessment instruments demonstrate reliability and validity.

Historically, methods of offender risk assessment have changed based on shifts in corrections practice and policy and transform with improvements in measurement and technology. For example, more contemporary methods of risk assessment have used the development of new treatment strategies and focus on evidence-based practice to incorporate the responsivity principle. Many current methods of risk assessment measure the individuals' abilities, strengths, and personality to maximize offenders' responsiveness to treatment. The evolution of risk assessment, described within the four generations of risk assessment tools, document the modifications and improvements to risk assessment instruments over time.

First-Generation Risk Assessment

First generation risk assessment was based on unstructured clinical judgments where correctional staff and clinical professionals used training and experience to make predictions about which offenders needed enhanced security and supervision (Bonta & Andrews, 2007). Subjective judgments of risk are often prone to human error and bias, and clinicians issuing judgments about risk are not often provided with opportunities to change or improve risk assessment through feedback on predictive accuracy (Grove, et al., 2000). This form of subjective risk assessment was widely accepted as a valuable method until studies found that clinical judgments were inferior to actuarial risk predictions and suffered from limitations that significantly affected the scientific validity of the method (Bonta, Law, & Hanson, 1998; Grove, et al., 2000; Grove & Meehl, 1996).

Despite these limitations, remnants of first-generation concepts of subjective judgment still exist today, specifically in the form of the professional override. Professional override involves the recognition that justice professionals have special knowledge of an offender's particular patterns and circumstances that cause a disagreement with the results of an individual's assessed risk (Andrews, Bonta, & Hoge, 1990). The professional chooses to incorporate these other factors into the decision-making process, overriding the risk score in a sense. Some researchers support the use of the professional override and warn against the exclusive use of risk assessment tools that are only moderately more accurate in predicting recidivism than chance (Sreenivasan, Weinberger, Frances, & Cusworth-Walker, 2010). However, other researchers have conducted empirical analysis demonstrating that professional overrides actually reduce

the predictive validity of the assessment tool, and tended to over-classify individuals as a higher risk (Wormith, Hogg, & Guzzo, 2012).

Second-Generation Risk Assessment

Recognition of the necessity for objective, actuarial, scientifically-based assessment tools began to grow in the 1970s, leading to a shift away from first generation subjective clinical judgments (Bonta & Andrews, 2007). Second generation risk tools utilize variables known to influence risk of reoffending and assign each item response a numerical score. Those numerical scores for variables in the assessment are then summed to produce a risk score where increasing risk values are equivalent to a higher risk of re-offense.

One example of a second-generation risk assessment tool is the Salient Factor Score (SFS), developed to assist with Federal parole selection until its abolition in 1984 (Hoffman & Beck, 1974). The SFS consists of seven predictors of reoffending including age at first commitment, number of convictions, and number of incarcerations. Items are weighted in a way where higher SFS scores indicate a lower likelihood that the offender will be at risk to re-offender. Criminal history variables, like the number of convictions, are negatively weighted most heavily and the tool focuses mainly on static risk predictors that do not change over time (Hoffman, 1994).

Another example of a second-generational actuarial risk assessment tool is the General Statistical Information on Recidivism Scale created by the Correctional Service of Canada (Nuffield, 1982). This scale was developed to assist the National Parole Board with making release decisions. The GSIR contains 15 weighted variables with a significant relationship to recidivism and sums them to produce a risk score where higher

scores indicate a higher risk for recidivism. Since its initial development, the tool has undergone several revisions to improve face validity and reflect changes in legislation, and its newest version, the Statistical Information on Recidivism – Revised 1 Scale (SIR-R1) continues to be used by the Correctional Service of Canada (Barnum & Gobeil, 2012).

Following the initial implementations of actuarial risk assessment tools for risk prediction, empirical research indicated that second-generation tools were much more accurate in their prediction of recidivism than subjective clinical judgments (Andrews, Bonta, & Wormith, 2006; Grove, et al., 2000). Some tools, like the SFS also demonstrated consistent predictive accuracy between samples of offenders released ten years apart (Hoffman, 1994). Correctional agencies began to adopt these tools as a direct result of their improved accuracy in differentiating between low- and high-risk offenders.

However, like their predecessors, second-generation tools also suffered from several shortcomings in predicting offender risk. A major limitation is the utilization of only static, immutable risk factors that cannot be changed to mitigate an offender's risk (Andrews & Bonta, 1998; Bonta, 1996). Risk scores either remain the same or increase over time as an offender accumulates a greater criminal history, and there is no ability to decrease risk, a main goal of community corrections. Another limitation is the use of information that correctional systems already collect and share, which can limit the breadth of factors theoretically relevant and known to be associated with recidivism (Bonta & Andrews, 2007). Despite these limitations, evidence has shown that there are advantages to using second-generation instruments over newer assessments including

increased predictive accuracy, increased objectivity, and decreases in time required to administer the assessment (Barnoski & Drake, 2007).

Third-Generation Risk Assessment

To address the limitations of second-generation risk tools, third-generation risk assessments were developed that were sensitive to changes in an offender's situation and environment. Though some static items remained important components of the third-generation risk calculation, the majority of items used in the determination of risk were dynamic risk factors, or factors that can change and be targeted by an intervention to manage and mitigate offender risk (Bonta & Andrews, 2007). These tools produce a more comprehensive profile of an offender's risk and specific needs using factors that are theoretically and empirically linked to recidivism which results in these instruments being referred to as "risk-need" instruments (Andrews & Bonta, 1995, 1998).

Targeting offender risks is, based on theory, expected to affect offender risk, and as a result, affect recidivism. There is significant empirical evidence that changes in scores on some third-generation risk instruments are connected to changes in recidivism (Andrews & Robinson, 1984; Motiuk, Bonta, & Andrews 1990; Raynor, 2007; Raynor, Kynch, Roberts, & Merrington, 2000). Reducing risk and reducing recidivism are important goals of many correctional programs and interventions, and third-generation risk tools allow quantifiable measurement of the effectiveness of programs in targeting the risk factors that will reduce recidivism (Bonta, 2002). It is for these reasons that third-generation risk assessment tools are considered to be vast improvements over previous risk assessment instruments in accurately predicting offender risk. There are several

prominent risk-need instruments that are currently used to predict offender risk based on static and dynamic risk factors.

Wisconsin Risk & Needs Assessment (WRN). The Wisconsin Risk & Needs Assessment is a third-generation risk instrument that includes a risk scale, a needs scale, and a client management classification (CMC) tool. The CMC produces a recommendation for specific types of treatment based on an offender's needs. Some overlap can occur between the risk and needs scales when assigning an individual to a supervision level, but the three components are not calculated using the same variables.

Predictive validity studies have largely focused only on the risk scale, but evidence shows that this tool has good predictive validity (Baird, 1981, 1991; Bonta, Parkinson, Pang, Barkwell, & Wallace-Capretta, 1994; Yacus, 1998). However, other research studies have shown that the accuracy of the risk scale is minimal at best (Wright, Clear, & Dickson, 1984) and that the needs scale does not explain significant variance in or demonstrate reasonable correlation with recidivism (Bonta, Parkinson, Pang, Barkwell, & Wallace-Capretta, 1994; Henderson & Miller, 2011). Similarly, mixed evidence of a relationship between CMC score and recidivism following release has been found (Harris, 1994).

Community Risk-Needs Management Scale. The Community Risk-Needs Management Scale was developed by the Correctional Service of Canada to be used in parole supervision and measures both offender risks and needs (Motiuk, 1993; Motiuk & Porporino, 1989). This tool combines the risk scale of the Statistical Information on Recidivism (SIR) tool with twelve offender needs in its assessment and is designed specifically to be used in making decisions, an important departure from the Wisconsin

scale. However, only the highest score on either the risk or needs scale is utilized in the classification decision (Andrews & Bonta, 1998) and some of the needs were not predictive of recidivism (Motiuk & Poporino, 1989).

Level of Service Inventory Revised (LSI-R). The Level of Service Inventory-Revised was developed as a third-generation approach to offender risk assessment in Canada and is one of the most well-known and well-studied risk assessment instruments. It is designed to assess an offender's static and dynamic risk and needs factors and can be used to determine overall risk for recidivism, predicted parole success, and amenability to treatment for risk reduction (Andrews & Bonta, 1995). The LSI-R is comprised of 54 individually scored items measuring static and dynamic risk and needs in ten major areas: criminal history, education/employment, financial, family/marital, accommodation, leisure/recreation, companions, alcohol/drug problems, emotional/personal, and attitudes/orientation.

Each item is scored dichotomously and an overall composite risk score is generated up to 54 risk points. Scores on each of the ten individual areas of risk and needs can also be generated. Increases in an individual's composite risk score indicate increases in the individual's risk level. Low scores indicate low risk/needs offenders who may warrant minimal supervision upon release from prison while high scores indicate high risk/needs offenders who require intensive supervision upon release. Cut-off scores, encouraged to be developed based on the offender population being measured, divide offenders into grouped risk levels for caseload assignment and supervision/treatment decisions (Andrews & Bonta, 2003).

A main goal of risk prediction instruments is to exhibit predictive validity with all offenders. Overall, the LSI-R has received significant empirical attention and support in demonstrating its ability to accurately predict recidivism with offenders in all types of criminal justice settings including prisons and community corrections (Flores, Lowenkamp, Smith, & Latessa, 2006; Gendreau, Little, & Goggin, 1996; Holsinger, Lowenkamp, & Latessa, 2003; Lowenkamp, Lovins, & Latessa, 2009; Vose, Cullen, & Smith, 2008). Empirical research has also demonstrated that the LSI-R shows predictive validity with a variety of different populations including male and female offenders (Ostermann & Herrschaft, 2013; Rettinger, 1998), prison and community corrections samples (Flores, et al., 2006b; Girard & Wormith, 2004; Lowenkamp & Bechtel, 2007; Schlager, 2005; Vose, 2008), offenders with mental illness (Ferguson, James, & Ogloff, 2009), offenders with drug histories (Kelly & Walsh, 2008), violent offenders (Campbell, French, & Gendreau, 2009), and general recidivism for sex offenders (Ragusa-Salerno, Ostermann, & Thomas, 2013).

Despite evidence of overall predictive validity with a variety of populations, the LSI-R suffers from several limitations. Other validation studies have indicated that the LSI-R does not predict recidivism sufficiently above chance (0.50) for halfway house residence or racial minorities (Dowdy, Lacy, & Unnithan, 2002; Holsinger, Lowenkamp, & Latessa, 2006; Schlager & Simourd, 2007), and despite some predictive validity evidence, some studies have shown weaker predictive validity with female offenders (Barnoski & Aos, 2003; Van Voorhis, Wright, Salisbury, & Bauman, 2010). An additional criticism of the LSI-R, is that African-American offenders are significantly

more likely to be overclassified as high risk when compared to White and Hispanic offenders (Fass, Heilbrun, DeMatteo, & Fretz, 2008).

Additional limitations to the instrument and its validity also exist, including low base rates and insufficient follow-up times (Andrews, Bonta, & Wormith, 2006). Some of the studies cited above show smaller effect sizes in predictive validity than studies conducted by the tool's developers. This may be caused by a phenomenon known as the allegiance effect. The allegiance effect was first demonstrated when comparing studies on the efficacy of psychosocial treatments and the study's results related to the therapeutic allegiance of the investigators. The most effective treatment in each study was often the therapy to which the authors were most loyal (Luborsky, et al., 1999). In a study of three well-validated risk assessment tools, it was shown that predictive validity studies of assessment tools may also fall victim to the allegiance effect. A tool's developers tend to obtain stronger predictive validity results than independent research because their allegiance and loyalty is for their own tool (Blair, Marcus, & Boccacini, 2008). However, proponents of the LSI-R contend that differences in training and administration of the tool affect the ability of the instrument to accurately predict recidivism (Flores, Lowenkamp, Holsinger, & Latessa, 2006; Lowenkamp, Latessa, & Holsinger, 2004) and that greater effect sizes are a result of the integrity of implementation (Andrews, et al., 2011).

Fourth-Generation Risk Assessment

To address the limitations that have emerged from empirical research of third-generation assessment tools, development of more comprehensive fourth-generation risk assessment tools has begun in recent years. Fourth-generation risk tools both profile static

and dynamic risks and needs and develop comprehensive management and intervention recommendations based on the offender profile. The major goal of fourth-generation instruments is to adhere to the principles of effective treatment and to achieve the correctional goal of enhancing public safety through recidivism reduction (Andrews, Bonta, & Wormith, 2006). Other important differences between third-generation and fourth-generation assessment approaches include consideration of a broader array of criminological theories, inclusion of the strengths perspective of offender rehabilitation, utilization of advanced statistical modeling, and increased reliance on web-based assessment technology (Brennan, Dieterich, & Ehret, 2009).

There are several fourth-generation tools, that have received substantial attention, including the Ohio Risk Assessment System [ORAS] (Latessa, et al., 2010), the Correctional Assessment and Intervention System [CAIS] (Ore & Baird, 2014), the Level of Service/Case Management Inventory [LS/CMI] (Andrews, Bonta, & Wormith, 2006), and the Correctional Offender Management Profiling for Alternative Sanctions [COMPAS] (Brennan, Dieterich, & Ehret, 2009).

Ohio Risk Assessment System (ORAS). The Ohio Risk Assessment System was developed as a statewide assessment tool used to evaluate offender risk and needs that could predict recidivism at various points in the criminal justice system and be shared between multiple criminal justice agencies (Latessa, et al., 2010). The ORAS is comprised of four assessment instruments to be administered at various stages in an offender's justice system involvement including pre-trial, community supervision, institutional intake, and reentry. The Ohio Department of Rehabilitation and Correction (ODRC) uses the ORAS to measure risk, identify criminogenic needs, identify barriers to

programming, and to direct supervision and treatment-related decision-making for offenders that reduce recidivism.

The implementation of the ORAS statewide in Ohio has allowed consistency in risk measurement across the state and its automated format allows items from individual assessment to auto-populate into future instruments, improving the ability to share offender risk information from agency to agency. The instrument has been shown to have promising relationships to recidivism for both female and male offenders, but the reported correlations are sensitive to base rates and generalizability to all offenders in Ohio and other samples of offenders in other states is limited (Latessa, et al., 2009).

Correctional Assessment and Intervention System (CAIS). The Correctional Assessment and Intervention System was developed by the National Council on Crime and Delinquency (Ore & Baird, 2014). The CAIS is an automated, web-based instrument that utilizes the Wisconsin Risk/Needs Scale (WRN) and the Case Management Classification (CMC) instrument. The WRN and CMC are administered using a structured interview, and the responses are entered into the web-based system (CAIS) that produces a comprehensive assessment report.

The comprehensive assessment report includes not only a thorough profile of actuarial risk and offender needs, but information about the extent to which those needs drive a particular offender's criminal behavior. The tool produces a recommendation for supervision strategies and programs that will address the needs that are likely to have the greatest effect on that individual's criminal behavior and is designed to assist supervising staff in creating the most effective case plan possible for each offender to facilitate successful rehabilitation.

Since the tool is comprised of the WRN and the CMC, validation studies do not exist on the CAIS, but rather, empirical research focuses on the predictive validity of the instruments that comprise the tool. Empirical research of the predictive validity of the tool is limited when compared to other tools like the LSI-R. As discussed previously, some studies have demonstrated that the WRN has good predictive validity in assessing risk (Yacus, 1998), but other studies have shown that the instrument is only minimally predictive over chance (Connelly, 2003; Harris, 1994).

As a response to empirical research indicating the poor performance of the WRN, the Wisconsin Department of Corrections commissioned research to examine the utility of the current scales and suggest potential changes to the instrument that would increase its effectiveness (Eisenberg, et al., 2009). The original scoring on the WRN was shown to over-classify offenders as high risk, and researchers recommended improvements to the instrument including reweighting. The predictive accuracy of the tool, as measured by the Area Under the Curve (AUC) with ROC curve analysis, increased from 0.61 to 0.66 with the recommended changes. However, Henderson & Miller (2013) argue that the improvements were only minimal at best and that existing evidence indicates that the WRN should be replaced with more predictive risk/need instruments.

Level of Service/Case Management Inventory (LS/CMI). The Level of Service/Case Management Inventory functions both as an offender risk/needs assessment and a case management tool (Andrews, Bonta, & Wormith, 2004). It combines revised items from the third-generation Level of Service Inventory-Revised with new sections dedicated to addressing the concepts of offender management. The tool is designed to assist in every aspect of risk management and risk reduction through treatment planning

for criminal justice agencies. Like the LSI-R, extensive training is necessary for agency staff to successfully administer and score the instrument, and interpret the results to make case management and treatment planning decisions.

Similar to the LSI-R, the LS/CMI has been the focus of substantial research to test its predictive accuracy. Since the LS/CMI utilizes a revised version of the LSI-R in its risk assessment, all of the aforementioned LSI-R validation studies and their results support the validity of the LS/CMI instrument for risk assessment. However, validation studies have been conducted using the LS/CMI as an independent instrument as well.

Overall, the LS/CMI tool is correlated with recidivism and demonstrates predictive validity (Andrews, Bonta, & Wormith, 2004). As a fourth-generation risk assessment tool, the LS/CMI, like the third-generation LSI-R, aims to exhibit predictive validity in a variety of contexts and with a variety of different offender populations. The LS/CMI has been shown to demonstrate predictive validity, often times above the strong predictive validity AUC of 0.70, with female offenders (Andrews, Bonta, & Wormith, 2008; Andrews, et al., 2012; Rettinger & Andrews, 2010) and sex offenders (Wormith, Hogg, & Guzzo, 2012).

offenders with mental health issues (Bonta, Blais, & Wilson, 2013),

Like its predecessor, the LS/CMI suffers from similar limitations that affect the predictive accuracy of the tool including low base rates, insufficient follow-up times, and inconsistencies in tool implementation and administration that affect overall accuracy. Additionally, many of the validation studies of the LS/CMI have been conducted using samples of Canadian offenders. While a main goal of this instrument is to effectively

predict risk regardless of person or place, validity results may not be generalizable to all populations, including offenders in the United States.

Correctional Offender Management Profiling for Alternative Sanctions

(COMPAS). The Correctional Offender Management Profiling for Alternative Sanctions tool was developed by the Northpointe Institute for Public Management, Inc. to assess crucial static and dynamic risk and needs factors and to provide support in decisions around placement, supervision, and case management (Northpointe Institute for Public Management, 2012). The COMPAS tool is a web-based instrument that can be administered using offender self-report, or scripted or structured interviews using paper or a computer. Data is entered into a web-based, automated scoring tool that produces a comprehensive offender profile of risk and needs that can be used to inform case management decisions.

The COMPAS Core assessment is considered gender-neutral and is designed to be used with individuals at any point during their involvement with the criminal justice system. The COMPAS is also available in several specialized, standardized adaptations of the COMPAS Core including the Youth COMPAS, for juvenile offenders, the COMPAS Women, for female offenders, and the COMPAS Reentry for offenders on post-prison supervision. These adaptations include a pre-selected number of risk and need subscales specific to the specialized version and can include any other COMPAS Core scales that agencies want to include to assess their population of interest.

Theoretical Foundations of the COMPAS. The COMPAS was developed using a foundation of theory-based assessment approaches and incorporates scales developed from theoretical explanations of crime and criminal behavior (Northpointe, 2012). The

COMPAS utilizes common explanatory theories in the development of risk assessment tools including social learning theory, sub-culture theory, control/restraint theory, criminal opportunity theory, antisocial and criminal personality theories, and general theories of crime. Like most third-generation and fourth-generation risk assessment tools, the COMPAS also incorporates the important principles of Risk-Needs-Responsivity (RNR) in its assessment model and the principles of evidence-based practice and effective intervention in corrections in its case planning and management component.

Unique to the COMPAS, the instrument has incorporated one of the ideas empirically validated in the principles of effective intervention literature, the recognition and management of changes in risk level over time (Andrews, Bonta, & Hoge, 1990; Bonta, Rugge, Scott, Bourgon, & Yessine, 2008). Reassessing risk scores over time can be an important component of responsivity and the effective management of increases or decreases in risk level with modifications to supervision and treatment plans (Healey 1999; Schlager & Pacheco, 2011). In response to this important concept, the COMPAS Core comes with an optional, built-in reassessment tool known as the Case Supervision Review that can be used to re-assess an individual's risk and needs over time. This tool allows supervision staff to respond effectively to increases in risk level with more intensive supervision and treatment, or decreases in risk level with appropriate modifications to lower the intensity of supervision and treatment.

The COMPAS also recognizes the role that offender strengths and protective factors, emphasized by the "good lives" model of offender rehabilitation, play in mitigating and managing risk (Fortune & Ward, 2013; Fortune, Ward, & Willis, 2012; Ward & Maruna, 2007). Areas identified by the COMPAS as low needs, such as

vocation/employment (if the offender has a reasonable education and employment history) or residential instability (indicating a stable housing situation upon release) can be used in case planning to support risk management. However, there has been recent contention between scholars that support Risk-Needs-Responsivity theory and those scholars that support the “good lives” model of offender rehabilitation. Risk-Needs-Responsivity supporters argue that the “good lives” model encourages weak assessment approaches through unstructured professional judgment (Andrews, Bonta, & Wormith, 2011), while “good lives” model supporters argue that RNR theory does not appropriately consider the importance of incorporating an offender’s strengths in the plan for rehabilitation and risk reduction (Ward & Maruna, 2007). Others also contend that RNR scholars do not fully understand the application of the “good lives” model to offender reentry practices (Ward, Yates, & Willis, 2013).

The COMPAS Composite Risk Scores. The COMPAS Core profile includes three composite risk scores structured around three outcomes – failure to appear, violent recidivism, and general recidivism and a subscale that also functions as a measure of risk for non-compliance (Northpointe, 2012). The composite scores aggregate responses from the selected subscales to provide a predictive measure of a more complex construct involving the interaction of multiple risk and needs factors. The subscales incorporated into the linear equation for general recidivism risk and into the scores for violent recidivism, failure to appear, and history of noncompliance, were chosen based on theoretical and empirical evidence of their relationship to the risk of interest.

The composite failure to appear score is designed to predict the risk of an offender failing to appear in court or experience a new felony arrest during pretrial release. The

composite general recidivism risk score is designed to predict the risk of an offender experiencing a new misdemeanor or felony offense within two years of COMPAS administration and can be used in a variety of contexts, including parole supervision. The last composite risk score, for violent recidivism, is designed to predict the risk of an offender being arrested for a new violent misdemeanor or felony offense within two years of COMPAS administration. Additionally, the history of noncompliance subscale also functions as a composite risk score, aggregating information from the subscales about prior community supervision compliance. This score is designed to predict the risk of technical violations on community supervision.

Criminogenic Risk/Needs Profile. Forty other possible subscales are available to measure the probability of the presence of different types of both static and dynamic criminogenic risk and needs factors (Northpointe, 2012). Some of these risk/needs scales are similar to previous tools (e.g. the LSI-R), but other scales add depth and breadth to the COMPAS in comparison to other risk assessment instruments. Agencies using the COMPAS Core, or another standardized version, can choose particular subscales or groups of subscales that are appropriate for their population of interest at the various stages of criminal justice involvement. The COMPAS Core generally includes a standard set of nineteen subscales, including the history of noncompliance scale, and measure criminogenic risk and needs that can be utilized for case planning and case management. The risk and needs factors that are dynamic can be targeted by supervision and treatment strategies to reduce overall risk.

There are two different kinds of criminogenic risk/needs subscales in the COMPAS instrument – basic scales and higher order scales. Basic scales provide

measures of simple constructs or basic needs factors. Higher order scales involve groupings of basic subscales and are designed to measure more complex constructs or complex needs factors. They can also include items from other scales that crosscut several domains. Higher order subscales on the COMPAS are the cognitive behavioral scale, the criminal opportunity scale, the history of noncompliance scale, the social adjustment scale, the socialization failure scale, and the vocation/education scale. All of the other subscales are classified as basic scales.

Five of the COMPAS subscales are designed to measure the “big five” risk and needs factors for criminal behavior (Gendreau, Little, & Goggin, 1996). These subscales are the criminal associates/peers scale, the criminal involvement scale, the criminal personality scale, the criminal thinking scale, and the vocation/education scale (Northpointe, 2012). The criminal associate/peers scale measures the degree to which an individual is involved with a network of delinquent friends and associates, including gang affiliation. The criminal involvement scale measures the degree to which an individual is involved in the criminal justice system, including the extensiveness of the individual’s criminal history – the most important major risk factor in predicting criminal behavior. The criminal personality scale measures the various personality dimensions that are related to repeated criminal behavior (i.e. factors/symptoms related to antisocial personality). These dimensions include impulsivity, risk-taking, restlessness/boredom, absence of guilt, selfishness/narcissism, tendency to dominate others, violent temper, and exploitation of others (Hare, 1991).

Somewhat related to an individual’s criminal personality is the criminal thinking self-report scale that measures the degree to which an offender holds antisocial attitudes

and beliefs (Northpointe, 2012). This scale combines items that involve cognitions used to justify, support, or rationalize the criminal behavior (Bandura, Barbaranelli, Caprara, & Pastorelli, 1996). These dimensions include moral justification, refusal to accept responsibility, victim blaming, and excuses that minimize the seriousness of and damage done by the crime. The final “big five” risk factor of social achievement is measured by the COMPAS vocation/education scale. This scale is a higher order scale that combines the results of the basic vocation and education scales to assess the degree of an individual’s successes or failures in the areas of work and education. The scale essentially represents the probability of a lack of educational or vocational resources (Northpointe, 2012).

Directly related to some of the “big five” risk factors, the cognitive-behavioral scale, another higher order scale, includes the concepts from the criminal associates, criminal opportunity, criminal thinking, socialization failure, and social adjustment scales. The cognitive-behavioral score represents the probability of the individual having needs related to dysfunctional emotions and behaviors, anti-social beliefs, and criminal thinking that contributes to criminal behavior. These areas of need can be addressed with cognitive restructuring activities commonly found in evidence-based therapeutic approaches like cognitive-behavioral therapy (CBT).

The criminal opportunity scale, another higher order scale, assesses the construct of criminal opportunity resulting from lack of pro-social bonds, activities, and controls which results in criminal behavior based on routine activity theory (Cohen & Felson, 1979) and social control theory (Hirschi, 1969). The items included in the criminal opportunity scale represent an environment with criminal activity, affiliation with

criminal associates/peers, an absence of pro-social activities and relationships, and high boredom and restlessness (Northpointe, 2012). Similar to the criminal opportunity scale, the family criminality scale focuses on lack of pro-social role models as a result of parental and sibling criminal behavior and drug use history (Northpointe, 2012). Based on social learning theory, participation in criminal behavior can result from modeling the behavior of family members and research has shown that criminal behavior in adulthood can be linked to parental criminality for several reasons including social learning, transmission of anti-social values, and genetic influences (Lykken, 1995).

Two basic scales measure violent behavior, the current violence scale and the history of violence scale (Northpointe, 2012). The current violence scale assesses the degree of violence in the instant offense. While the current violence scale is not a good indicator of future crime or violence, it is included in the risk/needs profile as good practice in identifying an individual's propensity towards violence. The history of violence scale assesses the seriousness of violence in an individual's criminal history, including the frequency of violent felony offenses, the use of weapons, and the severity of injuries to the victims. History of violence is one of the most powerful predictors of future violent behavior (Farrington, 1991).

Three of the subscales are related to measuring an offender's social environment (Northpointe, 2012). The financial problems scale measures the degree to which an offender has experienced an impoverished environment and financial problems, including trouble paying bills and conflicts with family members over money. Financial issues are also linked to other issues in social environment including lower social class, poor housing, and community disorganization. The residential instability scale measures the

degree to which an individual has established long-term ties to a community, assessed by considering the offender's access to a stable and verifiable address, local telephone number, and long term community ties. Residential instability and financial problems can contribute directly to the four other scales measuring connection to pro-social institutions. The social environment scale measures the amount of crime, disorder, and potential to be victimized in the neighborhood in which an offender lives. The disorder of the neighborhood can be indicated by a gang presence, an open drug market, likelihood of victimization, presence of weapons, and inadequate housing.

Four of the subscales measure the degree of success in creating relationships with main pro-social institutions and activities. The social adjustment scale, a higher order scale, measures the degree to which an individual has problematic relationships with pro-social institutions including employment, school, and family (Northpointe, 2012). Individuals who score high on this scale have often been fired from employment, had significant problems in school, had conflict with family members and possible family violence, and experienced financial problems. The social isolation scale measures the degree to which an offender has a positive social support network and is in touch with members of that network. Positive social support can act as a protective factor for offenders even in the presence of negative social environments and other issues (Estroff & Zimmer, 1994). High scores on this scale represent the absence of a support network which can contribute to feelings of social isolation and loneliness and can result in anger and violent behavior.

The leisure/boredom scale assesses the degree to which an offender experiences boredom and restlessness, and an inability to maintain a connection to pro-social

activities of interest (Northpointe, 2012). Aimlessness and boredom are related to criminal behavior in both social control theory (Hirschi, 1969) and the general theory of crime (Gottfredson & Hirschi, 1990). These issues are not related to a person's community or environment, but rather, related to an individual's valuation of pro-social activities and relationships. Last, the socialization failure scale, a higher order scale, measures the breakdown of socialization through assessing juvenile delinquency, problem behavior in school, family criminality, and early drug use. The scale focuses on an offender's upbringing and factors that might have contributed to a negative world-view and the formation of anti-social attitudes and behaviors. These attitudes may be indicated by the early onset of delinquent behavior, problems in school, and family issues (Northpointe, 2012).

The last subscale to discuss, the substance abuse scale, is a significant risk factor in both general criminal behavior and violent behavior (Gendreau, Little, & Goggin, 1996) and is related to many of the other criminogenic subscales. This scale is only a general indicator of substance abuse problems, where high scores indicate an individual with significant drug and alcohol problems that may require substance abuse interventions (Northpointe, 2012). Inability to manage a drug or alcohol problem can cause significant issues on parole supervision, including technical violations and arrest for new crimes. The cutpoints on this scale are much lower than the other scores, indicating that all offenders scoring above a 3 should at the very least, be evaluated further for a substance abuse issue.

Explanatory Typology. One component of the COMPAS offender profile that is unique to this risk assessment instrument is the explanatory typology which is designed

to incorporate the responsivity component of RNR theory in the instrument. The explanatory typology is chosen from eight prototypical treatment-relevant typologies of offender behavior, based on general theories of delinquency and developing using advanced pattern recognition and cross-validation procedures (Brennan & Breitenbach, 2009; Northpointe, 2009). The typologies represent the eight common offending and behavior patterns shown to appear in criminal justice populations and were designed to provide an explanatory profile of an individual that would guide supervision and treatment decisions (Figure 1). They were developed to provide the “closest” fit to an individual and are not meant as absolute statements about the type of individual being assessed. There are individuals not assigned a typology category who either fall on the boundary of multiple typologies or who are hybrids of multiple typologies.

Figure 1. Criminal Typology Descriptions

Category 1 – Low risk, older, mostly non-violent drug offenders with some social exclusion, chronic criminal and drug histories, and **low** propensity for anti-social behavior.

Category 2 – Low risk, “situational” offenders with no clear explanation for criminal justice involvement, shorter criminal histories, social stability, and **low** propensity for anti-social behavior. Some individuals in this category do become involved in serious violence created by an accidental or situational trigger.

Category 3 – Low risk, older, “late-starter” offenders with shorter criminal histories, fairly stable social backgrounds, issues with chronic alcohol use, and **low** propensity for anti-social behavior

Category 4 – Low risk, Older, socially marginalized, habitual offenders with lengthy criminal histories, impoverished and poorly education, and **low** propensity for anti-social behavior.

Category 5 – High risk, young, criminally versatile, socially marginalized offenders with frequent gang affiliation and **high** propensity for anti-social behavior.

Category 6 – High risk, older, socially marginalized, long-term drug offenders with histories of repeated non-compliance, and **high** propensity for anti-social behavior.

Category 7 – High risk, criminally versatile, socially marginalized offenders with lengthy, dangerous criminal histories and **high** propensity for anti-social behavior.

Category 8 – Similar to category 2: Low risk, “situational” offenders with no clear explanation for criminal justice involvement, shorter criminal histories, social stability, and **low** propensity for anti-social behavior. However, a small proportion of this category may be “faking good” indicated by the internal check for lying.

Response Bias Scales. In addition to the composite risk scores, needs subscales, and explanatory typology, two response bias scales are also calculated for each offender (Northpointe, 2012). The random responding bias scale allows practitioners to determine if an offender has simply filled in random response during a self-report or answered haphazardly during an interview. The lying scale allows practitioners to determine if an offender is employing deception in responses to the assessment.

Understanding COMPAS Scores. Northpointe has collected normative data from the profile results of 30,000 COMPAS assessments administered to prison and jail inmates, probationers, and parolees from sites across the United States (Northpointe, 2012). This normative data allows a comparison of each individual offender and a representative comparison population in an agency’s sample. Agencies using the COMPAS instrument can select the default norm group or a more specific subgroup of individuals that more accurately represent their assessment population of interest. The default norm group includes a gender-specific national composite reference group for comparison, sampled from the comprehensive normative dataset. A more specific subgroup of individuals, including prison inmates, jail inmates, and probationers can be selected from the default norm group if more appropriate.

Raw scores for both the composite risk measures and the subscales are converted into deciles, or increments of ten points. These deciles are determined using the reference group by ranking the scale scores and then dividing the scores into ten equal groups,

ranging from lowest (1) to highest (10). When the COMPAS is scored for an individual in a particular COMPAS user agency, his or her score is located in relation to the scale scores of the selected reference group. For example, an individual with a composite recidivism risk score of six indicates that 40% of the reference population looks more risky than that individual, and 50% of the reference population looks less risky.

The default norm group has standardized cut-points of low (1-4), moderate (5-7), and high (8-10) risk groups. However, these cut-points are not always applicable to the population of interest as deciles can be interpreted only in a relative sense and are always directly connected to the reference group. If the norm group happens to be comprised mainly of lower risk individuals, than an individual assessed by the agency to have a high risk score may not be high risk, but rather, falls on the higher end of the distribution. It is important, then, for agencies utilizing the COMPAS to consider the most appropriate reference group for comparison to their planned assessment target group.

Using COMPAS Scores. A key purpose of the COMPAS instrument is the utilization of the offender profile to inform case planning and management, including the selection of supervision and treatment options for an individual. Though the COMPAS is designed as an easy to use, user-friendly tool, Northpointe provides a standard two-day training program for line staff that covers use of the tool, interpretation of the results, and strategies for using the results for case planning and management.

The composite failure to appear (FTA) score can be used to make decisions about the appropriateness of pretrial release for an offender and allow the selection of appropriate conditions of pretrial release to manage an offender's risk level. The composite general recidivism risk score and the violent recidivism risk score have

significant versatility in their utilization for community corrections populations specifically. The composite risk scores can be used to guide discretionary release decisions, assignment to levels of supervision on parole, formulations of special conditions for risk management on parole, and parole supervision and treatment planning.

However, these composite risk scores do not give a complete, holistic, picture of any individual offender. It is possible, for example, that an offender can be considered low risk, but have high levels of need – if those needs are not addressed, the individual may be at greater risk to recidivate than the COMPAS initially predicted. For this reason, it is important that the risk/needs profile generated from the subscales and the explanatory typology be considered in guiding supervision and treatment planning on parole release. In fact, it is recommended by Northpointe that all three elements, the risk prediction scales, the risk and needs profile, and the explanatory profile, be used collectively to select supervision levels and treatment planning that best fit an offender's individual situation (Northpointe, 2009). To provide additional assistance with using the risk/needs profile for case planning, the COMPAS Field Guide for Practitioners (2013) contains examples of goals and tasks that might be developed in a case plan to address each of the areas in which an offender is determined to have a level of need.

COMPAS Validity & Reliability. In line with best practices in risk assessment, the COMPAS is designed to distinguish between the prediction of recidivism through risk scales and the measurement of needs to target with case management through needs scales (Northpointe, 2013). Northpointe has conducted extensive internal analyses of the reliability and validity of the COMPAS tool and has expressed a commitment to testing, evaluating, and improving its instrument.

To ensure the reliability and validity of the COMPAS tool, Northpointe conducts pilot testing, when possible, in new jurisdictions prior to the implementation of the COMPAS. So far, assessments have been conducted with the Michigan Department of Corrections [MDOC] (Brennan & Dieterich, 2008; Dieterich, Oliver, & Brennan, 2011; Dieterich, Brennan, & Oliver, 2011), the New York State Division of Parole [NYSP] (Brennan, Dieterich, & Breitanbach, 2008); the New York State Division of Probation and Correctional Alternatives [NYPCA] (Brennan & Dieterich, 2009), and the California Department of Corrections and Rehabilitation [CDCR] (Farabee, et al., 2010). Data from these pilot studies are used for a variety of purposes, including testing the reliability and validity of the COMPAS instrument.

Internal consistency reliability and test-retest reliability of the COMPAS have been examined. Internal consistency of the criminogenic scales was analyzed using smaller samples of the offenders from the CDCR pilot study and a separate study of probationers in San Bernardino County (SBC), California. The average internal consistency, measured by Cronbach's alpha, was 0.70 for the CDCR sample (Brennan, Dieterich, & Oliver, 2005) and 0.73 for the SBC sample (Brennan, Dieterich, & Oliver, 2006). In an analysis of a combined sample of CDCR and MDOC offenders, Cronbach's alpha values for the criminogenic needs subscales ranged from 0.56 to 0.86 with the criminal peers, criminal attitudes, leisure/recreation, social isolation, and social environment scales showing internal consistency above a Cronbach's alpha of 0.80. The criminogenic needs scales also show very high test-retest reliability, ranging from near perfect to perfect correlations (0.70 to 1.00), and the average test-retest correlation coefficient is 0.88 (Farabee, et al., 2010).

Using data from published studies on the internal consistency and test-retest reliability of the LSI for comparison, it appears that the COMPAS outperforms the LSI scales on these measures. Farabee, et al.. (2010) administered both the COMPAS and the LSI-R to a sample of inmates in California and the COMPAS had a much higher test-retest correlation coefficient (0.88) when compared to the LSI-R (0.64). However, the conclusion about internal consistency superiority was predicated on inaccurate reporting of the average internal consistency of the LSI-R in the referenced study. The field guide reports that Simourd (2004) found that the average internal consistency of the LSI-R was only 0.39 with a sample of prisoners in Canada. However, the reported average internal consistency in that study was actually a Cronbach's alpha of 0.82. Other studies of the LSI-R have found moderate acceptable mean internal consistency between 0.70 and 0.80 (Hanson & Wallace-Capretta, 2000a) or strong mean internal consistency between 0.80 and 0.90 (Hanson & Wallace-Capretta, 2000b; Simourd, 2006).

All of the aforementioned pilot studies have included analyses to test the predictive validity of the COMPAS composite recidivism risk score and several measures of recidivism. The Area Under the Curve (AUC) analyses for composite recidivism score and any re-arrest in the pilot studies produced ROC statistics ranging from 0.68 to 0.73, indicating moderate to strong ranges of predictive accuracy with different populations (Northpointe, 2012). The ROC statistics for the composite violent recidivism score and re-arrest for a person offense ranged from 0.65 to 0.74, indicating a similarly moderate to strong range of predictive accuracy. Additionally, other studies conducted by Northpointe researchers with presentence and probation samples found ROC statistics as high as 0.80

for the COMPAS risk scales and recidivism outcomes, with most of the ROC statistics exceeding 0.70 (Brennan & Oliver, 2000; Brennan, Dieterich, & Ehret, 2009).

A number of studies on the LSI-R risk score and re-arrest for any crime has found ROC statistics on the lower end of the COMPAS ranges, generally between 0.63 and 0.66 (Barnoski & Aos, 2003; Lowenkamp & Bechtel, 2007; Ostermann & Herrschaft, 2013). Similarly, ROC statistics for the LSI-R score and violent recidivism are in a similar range of 0.64 to 0.66 (Barnoski & Aos, 2003; Dahle, 2006). Based on these statistics, it is reasonable to conclude that the COMPAS risk scales are slightly more accurate, in certain populations, than the LSI-R risk scores in predicting both general and violent recidivism.

Validity with Parole Samples. However, the strong ranges of predictive accuracy of the COMPAS risk models on re-arrest for any crime are weakened when considering parole and reentry samples. The lowest ROCs in the pilot studies (0.68 and 0.70) were obtained with parole and reentry samples in New York and California, indicating that the COMPAS may only demonstrate moderate predictive accuracy with this population. The highest ROC statistics, including those in the Breitenbach, Dieterich, and Ehret (2009) analysis, were generally produced in samples of probationers. The studies mentioned thus far measuring the predictive accuracy of the COMPAS have all been conducted by researchers from Northpointe, the proprietor of the COMPAS tool. Research has suggested that greater effect sizes found by a tool's developing agency are the result of a phenomenon known as the allegiance effect (Blair, Marcus, and Boccaccini, 2008).

A number of independent studies of the COMPAS risk scales and re-arrest measures with parolees have found more moderate ROC statistics for the composite risk and composite violent risk scores. Studies of the COMPAS composite risk score and re-

arrest for any crime produced ROC statistics of 0.53 to 0.70, much lower than the strong predictive accuracy ROC statistics of 0.70 to 0.80 reported by Northpointe researchers (Farabee, et al., 2010; Fass, Heilbrun, Dematteo, & Fretz, 2008; Zhang, Roberts, & Farabee, 2011). Similarly, some of these studies also analyzed the predictive accuracy of the COMPAS violent risk score and re-arrest for a violent offense and found ROC statistics to be 0.65, much lower than many of the ROC statistics reported for the violent recidivism scale in the pilot studies. As a result of mixed findings, more independent empirical research would seek to add a deeper understanding to the reliability and validity of the COMPAS tool when compared to more static measures of recidivism risk.

Issues in Predicting Risk

There are several critical challenges and critiques of the use of actuarial methods of risk assessment in clinical contexts, including the justice system, even with improved validity. Some of these issues are base rates and sample size; false positives and false negatives; cut-off score decisions, individual-level predictions based on group-level statistics; selection of predictor variables; and instrument length and resource utilization.

Base Rates and Sample Size. Base rates and sample size in a given study of risk prediction have a reciprocal relationship in affecting the predictive accuracy of an instrument. Base rates are the frequency of the occurrence of the outcome of interest in a population, or recidivism in most cases of offender risk prediction (Gottfredson & Moriarty, 2006). If half the offenders in a study sample experience a re-arrest on parole supervision following release from prison, the base rate of recidivism in that sample, as defined by re-arrest, is 50%.

Low base rates of the outcome of interest influence the type of error committed by the prediction tool, including the rates of false positives and false negatives (Farrington & Tarling, 1985; Gottfredson, 1978). Certain sub-types of offenders have very low base rates of the outcome of interest. For example, sex offenders tend to have very low base rates of sexual recidivism, making risk prediction potentially problematic with frequent prediction errors (Hart, Michie, & Cooke, 2007; Ragusa-Salerno, Ostermann, & Thomas, 2013).

Base rates which affect the accuracy of a prediction tool, causing prediction errors, are directly influenced by the representativeness of the study sample. Non-representative samples may have a low base rate of recidivism and as a result, the instrument will produce higher rates of false positives. It is recommended that samples be representative of the population on which the instrument is normed and large enough to yield acceptable base rates, about 500 or more offenders (Jones, 1996). Additionally, it is recommended that base rates be determined for the outcomes of interest in order to minimize the problems associated with false positives and false negatives (Gottfredson, 1978).

False Positives and False Negatives. When making predictions of risk, some predictions will be accurate while others will not be accurate (Auerhahn, 2006). There are two main types of prediction errors common to all risk prediction instruments. In the context of recidivism, a false positive is the prediction that an offender is at high risk to recidivate when in fact they never re-offend. A false negative is the opposite, a prediction that an offender is at low risk to recidivate when in fact that offender does re-offend. The accuracy in predicting risk is influenced by selection ratios and base rates. Risk

prediction instruments show much more predictive validity with outcomes with high base rates, or base rates that are close to fifty percent in dichotomous outcomes, and more prediction error in outcomes with low base rates (Craig, Browne, Stringer & Beech, 2004; Ho, 2013).

False positives and false negatives have different impacts on the offender and society as a whole. False negatives can present a significant risk to public safety when an offender is assessed as low risk, but in reality, poses a high risk of re-offending (Auerhahn, 2006; Clear, 1988). False negatives could result in higher risk offenders receiving lesser sentences or in higher risk offenders being released to parole supervision when in fact, they pose a significant danger to society. These prediction errors, then, are highly visible and highly criticized as they often result in new crimes committed by the offender (Schlager, 2005). Therefore, risk prediction instruments would rather reduce the rate of false negatives, even if the trade-off is an increase in the rate of false positives.

False positives are often unrecognizable and the public does not even know that they occur regularly. False positive predictions lead to more issues for an offender, in terms of the fairness and equity in the system, rather than a threat to public safety. Many of the issues resulting from false positives not only represent significant cost to the offender, but also to the taxpayers who must shoulder the burden of rising correctional costs (VanVoorhis & Brown, 1996).

False positive predictions can lead an offender to be sentenced to a harsher punishment if risk prediction is used in sentencing decisions, resulting in issues of fairness and equity (Auerhahn, 2006). If risk prediction is used in the parole release process, false positives can cause an offender to be denied parole release and force them

to serve additional time in prison when they pose little threat to the public. While parole is considered a privilege rather than a right, making parole release decisions based on inaccurate assessment still introduces issues of fairness and justice. Additionally, false positives in parole supervision can lead to a low-risk offender participating in intensive supervision and treatment, which is against the basic tenets of Risk-Needs-Responsivity theory and can lead to worse outcomes for low-risk offenders (Andrews & Kiessling, 1980; Bonta, Wallace-Capretta, & Rooney, 2000).

Cut-off Scores. Cut-off scores should consider the base rate of the outcome of interest in the sample and be assigned following an analysis of the frequencies of the outcome of interest. However, setting cut-off scores should also consider other factors, like availability of resources and the purpose of the risk prediction score, prior to classifying offenders into risk categories (Baird, 2009). Cut-off scores that are too low will classify the majority of the sample as high-risk while cut-off scores that are too high will classify the majority of the sample as low-risk.

Each of these scenarios carry a consequence. High-risk offenders require high intensity supervision and resources to conform to the principles of RNR theory. Too many offenders labeled as high risk, when in fact they all may not be high risk, can cause unnecessary strain on supervision and treatment resources, and correctional budgets. Conversely, too many offenders labeled as low risk, when in fact some of them may be higher risk, can yield an insufficient provision of resources to those offenders and consequently, a significant threat to public safety.

Individual Level Predictions and Group Statistics. One of the main criticisms of actuarial risk assessment tools generally, and in the criminal justice system, is the

application of aggregated group statistics to individual behavior which introduces significant amounts of error (Grove & Meehl, 1996; Hart, Michie, & Cooke, 2007; Silver & Miller, 2002). The risk of an offender is never an absolute, but rather a relative risk prediction. It is whether one offender is more or less likely to recidivate than others rather than a definite prediction of individual behavior (Auerhahn, 2006). Some studies have shown that margins of error in predicting individual-level outcomes are so high that the results of the assessment are useless in practice (Hart, Michie, & Cooke, 2007). Improving the accuracy of risk assessments in predicting individual-level outcomes has remained a challenge for even the most recent generations of risk assessment (Andrews, Bonta, & Wormith, 2006).

Selection of Predictor Variables. Research has suggested that a wide array of risk/needs measures can be used in the prediction of risk for offenders in the criminal justice system. However, the availability of a lengthy list of possible predictors of outcomes does not warrant the inclusion of all variables in an instrument designed to predict offender risk (Baird, 2009). Some instruments, like the LSI-R, include predictor variables that research has shown have little correlation with recidivism outcomes, like re-arrest (Austin, Coleman, Peyton, & Johnson, 2003; Baird, Flores, Travis, & Latessa, 2004; Baird, et al., 2013). Empirical research on the validity of prediction tools often does not involve individual item analysis, but experts have suggested that removing variables with little to no relationship to the outcome of interest can actually improve the validity of the instrument (Baird, 2009; Flores, Travis, & Latessa, 2004). Validity, therefore, can be maximized if unnecessary predictor variables are removed from the risk

prediction instrument, which can directly affect an instrument's length and resource utilization.

Instrument Length and Resource Utilization. Including an extended list of questions to ascertain a large number of risk/needs predictor variables can also make a risk assessment instrument rather lengthy. Longer instruments are more difficult to administer and require more staff time and resources, contributing to issues with cost and efficiency. For example, the COMPAS instrument in its core form is approximately 135 questions, of which the first 28 involve the staff responsible for administering the tool to go through the offender's criminal history. These initial questions may require staff to do a hard count of the data in areas where electronic databases do not provide real-time aggregated statistics on criminal history variables, yielding a significant number of hours devoted to completing this section alone on top of the time required to administer the remaining questions to an offender.

Research has suggested that shorter risk prediction tools can actually achieve greater predictive accuracy than their lengthier counterparts (Onifade, et al., 2008; Wagner, 2008). If savings in cost, staff time, and efficiency can be made by administering shorter risk assessment tools, this factor only strengthens the argument that risk prediction instruments should only contain the limited set of risk/needs variables directly correlated with outcomes of interest.

Summary. With the weight given to the results of an individual's risk assessment in important decisions, it is important that the drive to innovation does not take priority over the performance of risk assessment tools. Supervision and treatment resources are allocated to offenders during incarceration and community corrections supervision based

on some form of assessment of offender risk and need. As a result of the aforementioned issues, many assessment tools fall short of the threshold of vast improvements in prediction above random chance ($AUC = 0.70$). Inaccuracies in risk assessment can have a profound impact on the lives of offenders and hold real consequences for society as a whole (Andrews & Bonta, 2004).

Baird and colleagues (2012) even suggest that third- and fourth-generation risk instruments, including both risk prediction and assessment of criminogenic need, have coupled two principles that might be better suited for separate assessments. Combining assessments of risk and need have created lengthy assessment tools that result in utilization of monetary and staff resources in agencies. Additionally, though the criminogenic needs of an offender should be addressed, many of these variables have little relationship to recidivism and may decrease the ability of the instrument to accurately predict offender risk.

CHAPTER 4 - Background

Overview of Parole Supervision in New York State

Historically, the New York State Division of Parole managed the community supervision of all parolees in New York City and New York State. As of 2011, the Division of Parole merged with the Department of Correctional Services to create the New York State Department of Corrections and Community Supervision (DOCCS), now responsible for the supervision of all individuals in the state both in prison and under parole supervision. The merger was designed to streamline departmental functions and enhance public safety and reduce cost by achieving better outcomes. The mission of the merged agency was to create a more extensive continuum of care for offenders by meeting their needs during incarceration followed by supportive services under community supervision (“DOCCS Fact Sheet”, 2011).

Over the last decade, an average of 24,000 individuals annually have been released to parole supervision from a New York State Prison, but recently over the past several years, the number of parole releases has fallen to about 22,000 individuals (Department of Corrections & Community Supervision, 2014). In addition to the new releases each year, DOCCS continues to supervise those whose parole supervision is ongoing. The average active parolee population over the last several years was over 36,500 individuals. However, the number of active parolees in New York State has been steadily declining at a similar rate to the declining number of incarcerated individuals – both the prison and parolee populations have experienced between an 8 and 9% decrease since 2011 (Department of Corrections and Community Supervision, 2014).

Profile of the Parolee Population in New York State. The majority of the parolee population in New York State is male (94%) and relatively young, with a median age of only 37 years old (Department of Corrections & Community Supervision, 2014). Parolees in New York are largely minority – almost half of parolees are African-American and almost a quarter are Hispanic. Compared to 2008 in which 46% of parolees were under supervision as a result of drug convictions, most parolees in New York State in 2013 were under supervision for violent offenses (51%), followed by drug offenses (23%), and property offenses (11%).

Similar to parolees all over the country, New York State parolees have an overwhelming need for services upon their release to the community. Despite the lower percentage of drug conviction offenses among parolees, 63% of New York State parolees have a drug abuse history and 47% have a history of alcohol abuse. Slightly over one-third of parolees have no high school diploma or GED and almost two-thirds of parolees are unemployed.

Re-arrest and Revocation in New York State & New York City. In its annual report on parolees in New York State, DOCCS does not include any measure of re-arrest in its aggregated statistics to provide a baseline for re-arrest within one year of release from incarceration. However, a report on recidivism in New York City using local level data indicated that 23% of parolees released between 2001 and 2008 were re-arrested within one year of release (Herrschaft & Hamilton, 2011).

In New York, a violation of the conditions of parole does not necessarily mean that the parolee will be automatically returned to prison upon revocation of parole. Parolees can be returned to prison as a possible outcome, but they can also be placed in

an alternative program or restored to the community. Though these alternatives to re-incarceration do exist in New York, they are under-utilized when compared with revocations that result in return to prison which account for about 64% of all parolees with violations of parole conditions (Department of Corrections & Community Supervision, 2014). Parole revocations for violation of parole conditions account for 3 out of every 4 returns to prison in New York (The Editorial Board, 2014). At the local level, in New York City, about 15% of parolees released from incarceration between 2001 and 2008 experienced a revocation of their parole for a technical violation. Only about 1% experienced a revocation of their parole for a new felony conviction.

As Stated previously, prison and parolee populations have been declining over the last several years in New York. However, though these populations have been decreasing in number, the number of parolees returned to prison, either for a rule violation or a new felony conviction, has remained relatively stable. This represents an increase in the proportion of parolees being returned to prison each year. In 2004, for example, 18.5% of all active parolees that year were returned to prison for rule violations or new convictions compared to 20.5% of all active parolees in 2013. Additionally, the percentage of parolees returning to prison for rule violations has increased from 2004 to 2013 by about 3% while the percentage of parolees returned for new convictions in that same period has declined slightly. Despite a promising reduction in the prison and parolee populations, recidivism during parole supervision remains an increasing concern for criminal justice practitioners and policy makers in the State of New York.

Risk Assessment in New York State. In response to growing concerns about prisoner reentry, community reintegration, and evidence-based practice on the national

level, DOCCS implemented the COMPAS assessment with all individuals exiting DOCCS custody in New York State in January of 2012. Prior to 2012, the New York State Division of Criminal Justice Service (DCJS) utilized an offender's criminal history to calculate a risk score that was then forwarded to DOCCS and used to determine risk levels to guide community supervision decisions. Though the basis of the risk score was rooted in empirical research, the risk score only accounted for static factors and did not account for dynamic criminogenic factors known to influence recidivism risk in evidence-based practice. As a result, all parolees exited incarceration to the same level of supervision and parole conditions until a parole officer could make more individualized decisions based on their first-hand experience with the parolee.

In an effort to foster evidence-based practice throughout the system, Parole Board members receive a copy of the COMPAS assessment. The Parole Board is meant, by legislative statute, to review the assessment and incorporate an individual's risks and needs into their determination of parole eligibility for discretionary releases. According to a New York State Senator, the goal of the COMPAS in discretionary release decisions is to provide Parole Board members with an objective measure that directs focus away from the parolee's original crimes and the misconceptions about offenders who commit those crimes that create bias in Parole Board decision-making (Caher, 2007).

Following release, the risk levels produced by the COMPAS assessment are then used to assign parolees to one of four risk categories to aid in caseload assignment and distribution among parole officers in each bureau based on risk level (Department of Corrections & Community Supervision, 2014). Parole officers supervising the highest risk offenders (Level I) have a caseload of only 25 parolees while officers supervising the

lowest risk offenders (Level 4) have a caseload of about 160 parolees). Sex offenders and those with mental health conditions are all supervised at Level I. In 2013, fifty-two percent of parolees were supervised at the less intensive levels (3 and 4) while 46% of parolees were supervised at the more intensive levels (1 and 2).

Overview of the Harlem Parole Reentry Court

The Harlem Parole Reentry Court began operation in 2001 as a pilot demonstration project and collaboration between the non-profit think-tank, the Center for Court Innovation, the New York State Division of Criminal Justice Services, and the New York State Division of Parole (now the Department of Corrections and Community Supervision). The demonstration project was developed in East Harlem as a response to statistics indicating that approximately ten percent of the entire parolee population of New York City was returning to four of the eight police districts of Harlem (Farole, 2003).

The Reentry Court draws on the problem-solving court model to provide supervision, judicial oversight, and case management services to parolees for six months following their release from state prison. It was one of the first nine reentry court programs in the country to be funded by the United States Department of Justice. The goal of the program is to enhance public safety and reduce recidivism in East and Central Harlem by stabilizing parolees upon their return to community and enhancing their reintegration by targeting important factors that influence recidivism including employment, housing, substance abuse, and family responsibilities (Hamilton, 2010). The early years of the Court's operation produced many accomplishments, but also experienced many barriers and obstacles in the implementation of a very new model of

parole supervision (Farole 2003). However, despite these barriers, the Reentry Court continued to make changes to its model to achieve better outcomes for parolees in East and Central Harlem.

The increasing need for a Reentry Court in these areas was confirmed in a study done by the Justice Mapping Center in 2007. Based on the results, a one mile corridor in East Harlem was shown to be home to the highest concentration of formerly incarcerated males, 1 in every 20 men, in all of New York City (Moore, 2007). In addition to this dense population of formerly incarcerated individuals, these neighborhoods suffer from increased rates of crime, poverty, educational failure, and unemployment that compound existing difficulties for parolees of staying out of prison once released (Upper Manhattan Reentry Task Force, 2008).

Profile of Parolees in the Reentry Court Catchment Area. Out of the population of parolees released from New York State prisons each year, slightly more than half return to a neighborhood in New York City. Out of those returning to the borough of Manhattan, over 50% are assigned to parole supervision in Upper Manhattan, an area including the catchment area of the Reentry Court in East and Central Harlem.

In an analysis of parolees supervised in Manhattan in 2008, individuals supervised in Upper Manhattan exhibited characteristics indicating they have a deeper involvement and longer history with the criminal justice system (Upper Manhattan Reentry Task Force, 2008). When compared to parolees in the rest of Manhattan, Upper Manhattan parolees were slightly older, slightly more violent in terms of original offense, and more likely to have been returned to prison on a prior parole term. They also exhibited differences in important dynamic risk factors including a higher likelihood of

unemployment, less involvement in supportive programming, and significantly less engagement with mental health programs.

Utilization of the COMPAS Tool. Interest in prisoner reentry on the national scale began to increase and the Harlem Parole Reentry Court was one of the first recipients of Second Chance Act funding in 2009. Drawing from the results of a preliminary evaluation conducted by the Center for Court Innovation, the Reentry Court used this new funding to implement new evidence-based practices (Hamilton, 2010). One of the additions to the program was the utilization of an evidence-based risk assessment tool, the Correctional Offender Management Profiling for Alternative Sanctions tool, or COMPAS.

The COMPAS tool is administered to parolees accepted into the Harlem Parole Reentry Court and functions as an evidence-based component of pre-release planning. In order to maximize pre-release case planning, the goal of COMPAS administration is to administer the tool prior to a parolee's release from incarceration, but due to unique issues with location and procedures at New York State Prisons, this was not always possible. Many of the participant parolees arrive at a pre-release facility in very close proximity to the Harlem Parole Reentry Court and agreements with the New York State Department of Corrections and Community Supervision allow Reentry Court case managers to contact and administer the assessment prior to their release to parole supervision.

The results of the COMPAS assessment provide important information to parole officers and case managers about the parolees. Risk levels of parolees are utilized as a supervision intensity-related factor as well as a contributing factor to the matrix of the

pilot graduated sanctions protocol in use by the Reentry Court team. Decisions about incentives for parole compliance and decisions as punishment for non-compliance in the graduated sanctions matrix are based on the offender's risk level. The results of the assessment also provide staff with important information about the parolee's criminogenic needs that must be targeted to reduce overall recidivism risk. Criminogenic needs offer an opportunity to create tailor-made, individualized case plans involving parole conditions and treatment referrals as an effective strategy for successful parolee reintegration

CHAPTER 5 - Problem Statement & Research Questions

While there is innumerable scholarship on the validity of risk assessment tools like the LSI-R, existing scholarship around the Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) tool is limited. Much of the reliability and validity research on the COMPAS tool has been conducted internally during its development by Northpointe Institute for Public Management, Inc, the proprietor of the COMPAS tool. However, these studies are subject to the biases of research that can occur due to the allegiance effect, or the findings of greater effect sizes in validation studies by a tool's developers. This dissertation serves to advance the literature as an initial step into the exploration of the utility of the COMPAS tool in a non-subjective, independent environment.

Though limited, existing peer-reviewed scholarship on the validity of the COMPAS tool has produced mixed results. The majority of the current studies on the validity of the COMPAS have been conducted with probationers – a group considered to generally be less risky than parolees since probation is used as an alternative punishment to jail or prison. A common criticism of risk assessment tools has also been the tendency to over-classify different populations of offenders, including women and racial minorities (Barnoski & Aos 2003; Whiteacre, 2006). The COMPAS tool has been shown to have limitations, including lower and inconsistent validity with parolees of different ethnicities/races (Fass, Heilbrun, DeMatteo, & Fretz, 2008). Though this study cannot address limitations of prior research with regard to female offenders and parolees, it will add to the existing scholarship on the utility of the COMPAS tool with different

populations by testing the tool's validity with a racially diverse parolee sample returning to a high-risk neighborhood of Harlem in New York City.

In addition, most current analyses of the COMPAS tool have focused solely on the predictive validity of its 3 composite risk scores of recidivism risk, recidivism risk for violence, and risk of failure to appear. Most independent studies did not test the reliability of the COMPAS tool or focus on the risk and needs profile (subscales) of offenders in their analyses. The present study will contribute to the literature through a more in-depth analysis of the reliability of the COMPAS tool with a parolee sample including the risk/needs profile (subscales).

Some research has also compared the predictive validity of the COMPAS to other dynamic tools like the LSI-R or to static risk factors garnered from the CCH. As a fourth-generation risk assessment tool using recent technical breakthroughs, the COMPAS tool should have better predictive validity than other previous generation tools, including risk prediction based on static CCH (computerized criminal history) factors alone. This dataset included a unique measure to New York City and New York State, the Division of Criminal Justice Services (DCJS) risk score, used prior to the implementation of the COMPAS. The DCJS score was calculated solely based on static risk factors in an individual's CCH data that was already collected at minimal cost to the Department of Corrections and Community Supervision (DOCCS). However, like most contemporary risk assessment tools, the implementation and usage of the COMPAS tool represents a new, additional cost to the State and City of New York including training costs, annual per user licensing fees, and annual software maintenance fees. Empirical research has indicated that the COMPAS does not greatly improve upon the predictive validity of

other tools, including several static measures that can be collected from an individual's CCH rather inexpensively (Zhang, et al., 2011). This dissertation will contribute to the existing literature in this area with a comparison of the predictive validity of the COMPAS to the predictive validity of the static, CCH-derived, DCJS risk score.

This research is based on the assumption that risk assessment can be a useful tool in recidivism prediction by informing the parole decision-making process and the development of case management plans for offenders returning to parole supervision in both New York City and New York State. Errors in risk assessment often have profound implications for both individual offenders and society as a whole. The results of this scholarship will contribute to a more broad conversation about the implications of risk assessment in community corrections policy and practice, with a focus on the debate in the literature around the fundamental differences between the goals of risk prediction and risk reduction and management and the best assessment tools to accomplish those goals. Since the COMPAS is now the sole method for assessing offender risk for the Department of Corrections and Community Supervision in New York State, an examination of its reliability, validity, and utility is necessary including a comparison to the predictive validity of the static-based actuarial DCJS risk scores.

Research Question #1: *Is the COMPAS tool a reliable recidivism prediction instrument for a diverse parolee sample in New York?*

For the purposes of testing whether the good internal consistency of the COMPAS tool holds up with the particular parolee sample in this study, the first analysis will explore the reliability of the COMPAS. COMPAS composite risk scores and sub-scale scores were evaluated with analyses including descriptive statistics, correlations, and

internal consistency estimates (Chronbach Alpha). None of the current independent peer-reviewed studies of the COMPAS have focused on reliability, but results were compared to the results of aggregated internal reliability studies conducted by Northpointe.

Hypothesis 1A

- The composite risk scores of the COMPAS of a diverse parolee sample in New York will be reliable at a scientifically approved alpha level.

Hypothesis 1B

- The sub-scale scores of the COMPAS of a diverse parolee sample in New York will be reliable at a scientifically approved alpha level.

Research Question #2: *Is the COMPAS tool a valid recidivism prediction instrument for a diverse parolee sample in New York?*

This component of the study evaluated the validity of the COMPAS with a diverse parolee sample in New York. Specifically, the study looked at the predictive validity or the ability of the tool to predict the likelihood that an offender recidivated over what is expected by chance (50%). Two of the COMPAS composite risk scores (recidivism and violent recidivism) and one specific sub-scale score (history of non-compliance) were matched to specific outcome criteria including re-arrest for any crime, re-arrest for a violent crime, and revocation of parole for a technical violation.

Descriptive statistics are provided while logistic regression, AUC/ROC, and RIOC analyses are explored to test the validity of the COMPAS in predicting recidivism. Time to failure was measured using survival analysis. Results were compared to the results of aggregated predictive validity based on internal studies conducted by Northpointe.

Hypothesis 2A

- The COMPAS composite risk for recidivism score will predict recidivism, defined as a parolee who was re-arrested within one year of release for any crime, greater than 50% of the time.

Hypothesis 2B

- The COMPAS composite risk for violence score will predict recidivism, defined as a parolee who was re-arrested within one year of release for a violent crime, greater than 50% of the time.

Hypothesis 2C

- The COMPAS sub-scale for history of non-compliance score will predict non-compliance, defined as a revocation of parole for a technical violation within one year of release, greater than 50% of the time.

Research Question #3: *What sub-scales of the COMPAS tool will best predict recidivism for a diverse parolee sample in New York?*

This phase of research examined the COMPAS sub-scales that could best distinguish parolees who recidivate from parolees who will not. Re-arrest for any crime was used as the criterion variable. Descriptive statistics and point bi-serial correlations with recidivism were analyzed for each sub-scale. A Wilcoxon-Mann-Whitney rank-sum test will analyze for differences between recidivists and non-recidivists on sub-scale scores. Binary logistic regression will be used to determine the significant predictors of re-arrest considering all of the sub-scales as covariates. The hypothesis was formulated based on the results of meta-analysis of the “big five” risk factors that predict criminal behavior and recidivism (Gendreau, Little, & Goggin, 1996).

Hypothesis 3

- The criminal associates, criminal involvement, criminal personality, criminal thinking, and vocation/education sub-scales of the COMPAS will be the most significant predictors of recidivism for parolees in New York.

Research Question #4: *Is the COMPAS tool a better predictor of recidivism than a DCJS risk score developed solely based on static factors from an offender’s computerized case history (CCH)?*

This facet of the study was developed based on similar research in California that discovered that static factors from an individual’s CCH was just as accurate as the

COMPAS tool in predicting recidivism above chance (Zhang, et al., 2011). The same AUC/RIOC analyses performed to measure the predictive validity of the COMPAS tool were repeated for the DCJS risk score, a score generated based solely on static factors from an individual's CCH. The two composite DCJS risk scores, one for recidivism and one for violent recidivism, were correlated to specific outcome criteria including re-arrest for any crime and re-arrest for a violent crime. The ability of the DCJS risk score to predict recidivism above chance (50%) was then compared to the ability of the COMPAS composite risk and risk for violence to predict recidivism above chance, based on the methods used by Zhang, et al. (2014) to compare the COMPAS to the static criminal history variables of a parolee.

Hypothesis 4A

- The COMPAS composite risk for recidivism score will demonstrate stronger predictive validity for recidivism prediction, defined as parolee who was re-arrested within one year of release for any crime, than the DCJS any risk score.

Hypothesis 4B

- The COMPAS composite risk for violence score will demonstrate stronger predictive validity for violent recidivism prediction, defined as parolee who was re-arrested within one year of release for a violent crime, than the DCJS violent risk score.

CHAPTER 6 - Methodological Plan

The proposed study includes secondary data analysis of two administrative datasets that include demographic, risk assessment, criminal history, and recidivism information for a sample of adult male parolees released to supervision in New York State between 2010 and 2011. This chapter will provide a detailed description of sample selection and data collection procedures as well as an overview of data analysis procedures.

Participants

As part of Second Chance Act funding, the Harlem Parole Reentry Court implemented a randomized control trial to evaluate the effectiveness of the program in reducing recidivism for returning parolees. The randomized control trial was implemented with a standard procedure for randomly selecting participants for the Reentry Court from a list of parolees returning to the eligible catchment area. Each week, a list of potential parolees returning to a pre-release correctional facility was received and randomized. Those randomized into the Parole Reentry Court group would be administered the COMPAS at the facility prior to release, when possible. Those who were randomized into the control group would report to traditional parole supervision as assigned and would not receive a COMPAS assessment.

Participation in the Reentry Court was not voluntary – all participants randomized who returned to the parole catchment area were required to report to the Reentry Court once assigned there. However, there were some caveats not originally anticipated in the randomization process that caused some eligible participants to receive a COMPAS assessment, but never report to the Reentry Court. These reasons included an address

change that placed them out of the catchment area or failure of the case to be transferred and assigned to the Reentry Court program. Participants who did not report for the Reentry Court were included in the sample due to the different objectives of this proposed study and the original randomized control trial.

Data Sources and Data Collection

As part of its regular operations, the Parole Reentry Court collected COMPAS data on all individuals set to be released who had been selected to participate in the Reentry Court. Case managers worked with parole officers to collect as much of the preliminary current charge, criminal history, and non-compliance data. Case managers then traveled to the pre-release facility to administer the remaining sections of the tool to participants prior to their release. Due to lack of access to internet in the pre-release facility, the tool was administered on paper and the case managers would enter the responses into the COMPAS web-based scoring tool upon their return to the Court's offices. The web-based tool delivers a score report for each parolee once all data has been entered. This score report was utilized in case conferencing with parole officers to develop an individualized supervision and case management plan. COMPAS data for all participants is stored in a secure, online database that can be downloaded to a hard file at any point in time. The COMPAS database includes demographic information collected for each participant and all risk profile information provided in the score report.

The New York State Division of Criminal Justice Services (DCJS) is a part of the Executive Branch of the New York State Government, serving an all-purpose role for criminal justice issues, including a number of policy- and grant-making functions. DCJS also acts as the official designated Statistical Analysis Center (SAC) for New York State.

As the State SAC, DJCS collects data from multiple primary sources, including police, probation, corrections, and parole agencies, as well as the court system. DCJS organizes all of this information for both its own internal reporting and research purposes, and information sharing with outside researchers and research organizations.

The standard DCJS dataset includes all data from an individual's computerized criminal history (CCH) file, the central repository for criminal history information for an individual in New York State. The CCH is comprised of information on all points of contact with the justice system, making it an especially rich dataset. The DCJS dataset includes important demographic variables as well as a summary count of all prior arrests and convictions for an individual. Data also includes descriptive information and dates for all fingerprintable arrests, charges filed, court actions, dispositions, and sentencing. Post-conviction agencies submit all relevant data on the individual including parole release dates, technical violations, parole revocations, and parole end dates. Overall, recidivism measures can be created for the follow-up period desired using all the records following the reference release date.

The COMPAS dataset was submitted to DCJS to be matched with the CCH files for each parolee. The New York State Identification Number (NYSID), included in the COMPAS dataset, is a unique identifier assigned to each parolee and was used to match the study participants with the administrative data collected by DCJS. CCH files from DCJS report on all criminal justice involvement for an individual in New York State including arrests, acquittals, convictions, sentences, parole release information, and parole violations (PVs). Once the CCH data was collected, the NYSID was replaced in the COMPAS dataset with a placeholder that matched the unique ID assigned to the

parolee in the CCH dataset. The complex CCH data was flattened and cleaned to yield the particular outcome measures of interest for this proposed study.

The proposed study then aggregated the COMPAS data with the CCH data to create a composite dataset including individuals' demographic, risk assessment, criminal history, and recidivism information for this proposed study. Since the CCH file measures all of an individual's justice system involvement from their first arrest through present day, recidivism information was identified between the date of release for the current parole term and December 31, 2012. However, the follow-up time period for recidivism was standardized to 365 days (1 year) following release to ensure all participants had an equal time at risk.

Risk Measures

The COMPAS tool uses all criminal history and self-reported response data to create a comprehensive risk profile for each individual. The risk profile contains three composite risk scores and eighteen sub-scales measuring specific criminogenic risks and needs. All twenty-one scores are calculated using deciles based on actuarial models and rated on a scale of one to ten. The deciles are derived from the selected norm group of offenders (prison, jail, probation) that have been studied by Northpointe, and represent cut points or the percentage of the population that looks both more and less risky than the individual (Northpointe, 2013). These cut points may differ based on the norm group chosen by the agency based on their COMPAS implementation plans. However, the Reentry Court's utilization of COMPAS was a pilot program and used the general cut points set by Northpointe to assess level of risk and need for the sample of parolees included in this study.

COMPAS Composite Risk Scores. Composite risk scores are designed to provide high-level aggregated risk information for each parolee. All composite risk scores are designed to report on the level of risk of an individual for a particular event on a scale of one to ten. Normal cutting points range from low (1-4), to medium (5-7), to high risk (8-10). The risk for recidivism composite provides the risk level for any recidivism event, originally constructed using any arrest within a two year follow-up period. The risk for violence composite provides the risk level for any recidivism event involving violence. The risk for failure to appear composite provides a risk level for failure to appear in court or commit a new crime while an individual is on pretrial release. This composite score was not relevant to the current study, and therefore, was not utilized in any analyses.

COMPAS Risk/Need Sub-scales. In addition to composite scores of risk level, risk profile information includes the scores on eighteen sub-scales of criminogenic risk and need. Sub-scales are divided into three types that specify the cutting points used to determine the level of risk or need. The criminal involvement, history of violence, current violence, and history of non-compliance sub-scales measure criminogenic risk and are treated similarly to composite risk. These sub-scales have cut points of low risk (1-4), medium risk (5-7), and high risk (8-10). The remaining sub-scales focus on criminogenic needs and are designed to report on the likelihood of those needs being present, from unlikely to probable to highly probable. Almost all criminogenic need sub-scales are designed as unlikely (1-5), probable (6-7), and highly probable (8-10). However, substance abuse and criminal associates/peers sub-scales are treated with slightly different cutting points. Substance abuse is designated as unlikely (1-2), probable (3-4),

and highly probable (5-10) while criminal associates/peers is classified as unlikely (1-4), probable (5-7), and highly probable (8-10).

DCJS Risk. Since the statewide implementation of the COMPAS tool in New York State, the DCJS risk score was discontinued on July 1, 2013 and is no longer utilized for caseload assignment. However, until 2013, DCJS used known static risk predictors including age, gender, and important criminal history variables taken from an individual's computerized criminal history (CCH) to calculate a risk for recidivism and risk for violence score (Division of Criminal Justice Services, 2011). These risk scores were calculated within four months of release from correctional supervision. The DCJS risk score was calculated on a scale of one to ten and cut points were low (1-3), medium (4-6), and high (7-10) risk. Part of the analysis for this study involved comparing the predictive abilities of the solely static-based DCJS risk scores to the abilities of the dynamic risk/needs COMPAS risk scores.

Outcome Measures

For each individual who had been administered a COMPAS assessment, recidivism measures were derived from CCH data using a reference date of most recent release to parole supervision after randomization. One-year follow-up variables of interest included any re-arrest, re-arrest for violent crimes, and parole revocation for a technical violation. Re-arrest was chosen as the primary indicator of recidivism for several reasons. For this study specifically, a follow-up period of one-year was available and this time period does not generally allow enough time for the often lengthy process of a case's disposition that would result in a new conviction. Most importantly, the generally used cutting points for the composite risk scores were developed by

Northpointe using data about re-arrests within a two year follow-up period for the norm group (Northpointe, 2013). Additionally, much of the internal Northpointe and scholarly research testing the predictive validity of the COMPAS has also utilized re-arrest as the predominant indicator of recidivism. A parole revocation for a technical violation was chosen as the most suitable indicator of non-compliance since a technical violation results from non-compliance with an individual's parole conditions.

The first outcome of interest was any re-arrest following release, classified as a dichotomous, categorical variable (0 = no re-arrest, 1 = re-arrest). This outcome measure represents the presence or absence of any arrest occurring after the date of release to parole supervision following randomization. Days to re-arrest for survival analysis was also computed using the parole release date and the date of re-arrest. The COMPAS composite risk score will be examined for its validity in predicting this outcome measure.

The second outcome of interest was any re-arrest for violence following release to parole supervision. This outcome measure was also classified as a dichotomous, categorical variable (0=no re-arrest for violence, 1= re-arrest for violence) and represents the presence or absence of any arrest for a violent crime occurring after the date of release to parole supervision following randomization. The COMPAS composite risk for violence score will be examined for its validity in predicting this outcome measure.

Lastly, the third outcome measure of interest is a revocation of parole due to a parole violation (PV). Classified as a dichotomous, categorical variable (0=no revocation for a PV, 1= revocation for a PV), this outcome measure represents the presence or absence of any revocation for a parole violation occurring after the date of release to

parole supervision following randomization. The COMPAS sub-scale of history of noncompliance will be examined for its validity in predicting this outcome measure.

CHAPTER 7 - Results

Descriptive Statistics

Table 1 displays sample descriptives for the parolees in this sample. The parolees (n=202) in this sample were all male, and predominantly Black (64.9%) or Hispanic (33.7%). The majority of parolees were born in the United States (71.8%). At the time of assessment, most of the parolees were single (86.6%) and were an average age of 33.58 years old (sd = 10.84). About half of the parolees were being paroled following incarceration for a drug offense (50.5%), followed by violent offense (29.2%), weapons offense (13.4%), and other offense (17.3%). It was possible, in some cases, for two categories of offenses to be noted for the instant offense for the same parolee.

A review of criminal history information revealed that parolees in the sample had fairly extensive criminal histories. On average, parolees had 9.18 total prior arrests (sd=9.18), including an average of 4.84 felony arrests (sd = 5.32) and 4.34 misdemeanor arrests (sd = 6.72). Parolees also had 4.23 average convictions (sd = 7.54) in total with 1.24 felony convictions (sd = 1.34) and 3.00 misdemeanor convictions (sd = 6.91). The average number of prior arrests for violent offenses was 1.50 arrests (sd = 2.13) with 0.22 associated convictions (sd = 0.51). However, histories involving drug offenses were more lengthy with 4.57 arrests (sd = 6.94) and 2.30 convictions (sd = 4.35) on average.

Risk variables of interest included both DCJS risk data and COMPAS risk data. The average DCJS risk score for recidivism for this sample was 5.62 (moderate risk) (sd = 2.50). The highest proportion of parolees was classified as high risk (40.2%), followed by moderate risk (37.0%), and low risk (22.8%). The average DCJS risk score for violent recidivism was 5.10 (moderate risk) (sd = 2.73). Like overall recidivism risk, the majority

of parolees were classified as high risk (38.6%), with equal percentages being classified as moderate (30.7%) and low risk (30.7%). The average COMPAS recidivism score was 4.93 (low to moderate risk) ($sd = 2.86$), slightly lower, on average, than the DCJS risk score for overall recidivism. However, in direct contrast with the DCJS overall recidivism risk, the majority of parolees were classified by the COMPAS as low risk (49.5%), followed by moderate risk (25.7%) and high risk (24.8%). The average COMPAS risk for violent recidivism score was 4.51 (low to moderate risk) ($sd = 2.86$). Similar to overall recidivism risk, the majority of parolees were classified as low risk for violence (53.5%) followed by moderate risk (26.7%), and high risk (19.8%). Overall, the COMPAS classified the majority of the parolees in this sample as low risk, while the DCJS risk score classified the majority of parolees as high risk for both overall and violent recidivism.

When considering explanatory typology categories, parolees were most frequently assigned to Category 2 – low risk, “situational” offender (22.3%) and Category 7 – high risk, older, criminally versatile offender (19.8%) typologies. The next most frequent typology categories were Category 3 – low risk, older, chronic alcohol use offender (16.3%) and Category 8 – low risk, “situational” offenders with some “faking good” (9.9%). When re-classified based on the anti-social propensity, the majority of parolees were assigned a low anti-social propensity typology (61.4%) rather than a high anti-social propensity typology (38.6%).

The recidivism of this sample was assessed during the follow-up period of one year following release to parole supervision. Almost half of the sample (42.1%) was re-arrested within one year of release for any crime. Of those arrested, about two-thirds were

Table 1. Sample Descriptives (N=202)

Variable	Percent (n)	Mean (SD)	n
DEMOGRAPHICS			
Race/Ethnicity			
Black	64.9 (131)		202
Hispanic	33.7 (68)		
White/Other	1.5 (3)		
US-Born			
Yes	71.8 (145)		202
No	28.2 (57)		
Marital Status			
Single	86.6 (175)		202
Married	9.9 (20)		
Other (Significant Other, Separated, Unknown)	3.5 (7)		
Age at Assessment		33.58 (10.84)	202
Instant Offense ¹			
Drug	50.5 (102)		202
VFO	29.2 (59)		
Weapon	13.4 (27)		
Other	17.3 (35)		
CRIMINAL HISTORY			
Total Number of Prior Arrests		9.18 (10.71)	202
Prior Felony Arrests		4.84 (5.32)	
Prior Misdemeanor Arrests		4.34 (6.72)	
Total Number of Prior Convictions		4.23 (7.54)	
Prior Felony Convictions		1.24 (1.34)	
Prior Misdemeanor Convictions		3.00 (6.91)	
Total Number of Prior VFO Arrests		1.50 (2.13)	
Total Number of Prior VFO Convictions		0.22 (0.51)	
Total Number of Prior Drug Arrests		4.57 (6.94)	
Total Number of Prior Drug Convictions		2.30 (4.35)	
DCJS RISK SCORES			
DCJS Recidivism Risk		5.63 (2.50)	202
Low (1-3)	22.8 (46)		
Moderate (4-6)	37.1 (75)		
High (7-10)	40.1 (81)		
DCJS Violent Recidivism Risk		5.10 (2.73)	202
Low (1-3)	33.2 (67)		
Moderate (4-6)	29.7 (60)		
High (7-10)	37.1 (75)		
COMPAS COMPOSITE SCORES			
COMPAS Recidivism Risk		4.93 (2.86)	202
Low (1-4)	49.5 (100)		
Moderate (5-7)	25.7 (52)		
High (8-10)	24.8 (50)		
COMPAS Violent Recidivism Risk		4.51 (2.75)	202
Low (1-4)	53.5 (108)		
Moderate (5-7)	26.7 (54)		
High (8-10)	19.8 (40)		

Variable	Percent (n)	Mean (SD)	n
History of Noncompliance Subscale Score		3.60 (2.85)	
Low (1-4)	68.3 (138)		
Moderate (5-7)	17.3 (35)		
High (8-10)	14.4 (29)		
Typology Category			
Category 1	2.5 (5)		
Category 2	22.3 (45)		
Category 3	16.3 (33)		
Category 4	2.5 (5)		
Category 5	6.9 (14)		202
Category 6	6.9 (14)		
Category 7	19.8 (40)		
Category 8	9.9 (20)		
Border/Hybrid Unclassified	12.9 (26)		
COMPAS SUB-SCALE SCORES			
Criminal Involvement		3.13 (2.22)	
History of Violence		4.48 (2.76)	
Current Violence		4.08 (3.25)	
Criminal Associates/Peers		4.26 (2.93)	
Criminal Opportunity		5.51 (2.76)	
Leisure/Recreation		4.79 (3.07)	
Social Isolation		4.46 (2.84)	
Substance Abuse		4.58 (3.11)	
Criminal Personality		6.48 (2.81)	202
Criminal Thinking		5.78 (2.91)	
Cognitive Behavioral		4.65 (2.84)	
Family Criminality		3.00 (2.52)	
Socialization Failure		3.55 (2.94)	
Financial		4.51 (2.76)	
Vocational/Education		5.94 (2.80)	
Social Environment		6.08 (3.28)	
Residential Instability		2.10 (2.68)	
Social Adjustment		3.61 (2.56)	
RECIDIVISM			
Re-arrest for any crime			
Yes	42.1 (85)		202
No	57.9 (117)		
Type of Re-arrest			
Felony	32.9 (28)		85
Misdemeanor	67.1 (57)		
Number of days to re-arrest for any crime		156.87 (98.14)	85
Re-arrest for a violent crime			
Yes	5.9 (12)		202
No	94.1 (190)		
Number of days to re-arrest for a violent crime		230 (238.63)	
Revocation for technical violation (TV)			
Yes	22.8 (46)		202
No	77.2 (156)		
Number of days to revocation for TV		255.89 (102.02)	46

¹. Percentage will total above 100 due to some instant offenses being recorded as two types.

re-arrested for a misdemeanor (67.1%) while one-third was re-arrested for a felony (32.9%). Only a very small percentage of parolees were re-arrested within one year for a violent offense (5.9%). The average number of days to re-arrest following release to parole supervision was about 157 days. Almost one-quarter (22.8%) of parolees experienced a parole revocation as a result of a technical violation during the one year follow-up period. The average number of days to revocation for a technical violation following release to parole supervision in this sample was 256 days.

Research Question #1: Evaluating the Reliability of the COMPAS

This study sought to determine whether or not the COMPAS tool was a reliable recidivism prediction tool for use in a diverse sample of parolees in New York. The psychometric properties of the COMPAS were assessed through a reliability analysis designed to examine the quality of measurement of the instrument. The internal consistency of the COMPAS involved the ability of an instrument to reliably measure underlying constructs. While it is not an absolute requirement for a risk assessment tool to have sub-scales that are correlated, empirical research on recidivism has shown that predictors of recidivism are often inter-correlated (Butler, 2008; Serin, Mailloux, & Hucker, 2000).

COMPAS composite and sub-scale descriptives and inter-scale correlations are presented in Table 2. Inter-correlations between sub-scales ranged from $r=-0.24$ (weak negative) to $r=0.77$ (strong positive). In addition to current violence, four of the sub-scales, history of non-compliance, social isolation, financial problems, and residential instability were not significantly correlated with the composite risk score. All of the other

sub-scales were significantly positively correlated with the composite risk score, ranging from $r = 0.21$ (*weak*) to $r=0.60$ (*strong*).

Similar to previous reliability analyses conducted by Northpointe, the composite risk for recidivism score was not included in the internal consistency analysis due to the fact that the score is based on a linear equation. The overall internal consistency of the COMPAS tool was $\alpha = 0.86$. The internal consistency for the sub-scales of the COMPAS tool ranged from $\alpha = 0.84$ to $\alpha = 0.87$. The removal of only one sub-scale, current violence, would yield a very slight increase in the overall consistency of the COMPAS (to $\alpha = 0.87$). The removal of any other sub-scales would reduce the internal consistency of the tool albeit minimally. Overall, the COMPAS displayed good internal consistency and was very close to achieving the threshold for excellent reliability ($\alpha \geq 0.90$) with this sample.

Research Question #2: Evaluating the Validity of the COMPAS

The second research question in this study focused on an evaluation of the predictive validity of the COMPAS tool for a sample of parolees in New York. Predictive validity was assessed based on the extent to which the COMPAS predicted the outcomes of interest, re-arrest for any crime, re-arrest for a violent crime, and parole revocation for a technical violation, using both composite risk scores and a particular subscale score. Preliminary descriptive statistics documented the base rates for recidivism and time to failure for the sample of parolees. The base rates for each outcome of interest and time to failure in days were presented in Table 1. Based on 202 parolees, 42.1% were re-arrested for any crime within one year of release and 5.9% were re-arrested for a violent crime within one year of release. Slightly over one-fifth of the parolees (22.8%) experienced a

Table 2. Descriptive Statistics and Inter-Correlations for Sub-Scale and Composite COMPAS Scores (N=202)

<i>COMPAS Sub-Scale</i>	<i>A</i>	<i>B</i>	<i>C</i>	<i>D</i>	<i>E</i>	<i>F</i>	<i>G</i>	<i>H</i>	<i>I</i>	<i>J</i>	<i>K</i>	<i>L</i>	<i>M</i>	<i>N</i>	<i>O</i>	<i>P</i>	<i>Q</i>	<i>R</i>	<i>S</i>	<i>T</i>	<i>U</i>
A. Criminal Involvement	(0.86)																				
B. History of Non-Compliance	0.56	(0.86)																			
C. History of Violence	0.22	0.10	(0.86)																		
D. Current Violence	0.21	0.24	0.29	(0.87)																	
E. Criminal Associates/Peers	0.33	<i>0.15</i>	0.26	0.06	(0.85)																
F. Criminal Opportunity	0.09	-0.06	0.23	0.07	0.53	(0.85)															
G. Leisure/Recreation	0.22	0.07	0.07	-0.06	0.24	0.58	(0.85)														
H. Social Isolation	0.13	<i>0.15</i>	0.05	-0.14	<i>0.18</i>	0.33	0.40	(0.86)													
I. Substance Abuse	0.41	0.31	0.00	-0.22	0.32	0.24	0.23	0.26	(0.86)												
J. Criminal Personality	0.23	<i>0.16</i>	0.25	0.09	0.38	0.42	0.48	0.35	<i>0.17</i>	(0.85)											
K. Criminal Thinking	0.09	-0.02	<i>0.14</i>	0.03	0.23	0.29	0.26	0.25	0.07	0.50	(0.86)										
L. Cognitive Behavioral	0.24	0.12	0.38	0.09	0.72	0.77	0.46	0.31	0.32	0.56	0.54	(0.84)									
M. Family Criminality	0.03	0.06	0.22	0.04	0.33	0.38	<i>0.17</i>	0.19	0.11	0.20	0.09	0.42	(0.86)								
N. Socialization Failure	0.24	0.22	0.41	<i>0.15</i>	0.43	0.45	0.29	0.12	0.28	0.39	0.25	0.76	0.43	(0.85)							
O. Financial	0.19	0.23	0.08	-0.17	0.13	<i>0.16</i>	0.27	0.31	0.36	0.14	0.08	0.30	0.09	0.23	(0.86)						
P. Vocation/Education	-0.01	-0.02	0.32	0.06	0.26	0.66	0.30	0.19	0.12	0.35	0.30	0.61	0.23	0.45	0.20	(0.85)					
Q. Social Environment	<i>0.14</i>	0.06	0.12	0.10	0.39	0.47	0.23	0.04	0.21	0.25	0.12	0.43	0.24	0.31	0.06	<i>0.16</i>	(0.86)				
R. Residential Instability	0.12	0.09	0.04	-0.07	0.10	0.25	0.10	<i>0.18</i>	0.10	0.06	0.03	0.21	0.06	0.08	0.12	0.07	-0.02	(0.86)			
S. Social Adjustment	<i>0.16</i>	0.12	0.35	-0.01	0.34	0.53	0.33	0.26	0.27	0.34	0.23	0.72	0.24	0.53	0.48	0.61	0.19	0.33	(0.85)		
T. Composite Violence Risk	0.11	0.39	0.59	0.22	0.23	0.38	<i>0.15</i>	0.09	0.04	0.32	<i>0.17</i>	0.46	0.25	0.52	0.07	0.50	0.13	-0.01	0.37	(0.85)	
U. Composite FTA Risk	0.57	0.36	0.19	-0.09	0.30	0.27	<i>0.15</i>	0.23	0.26	0.21	0.09	0.34	0.14	0.23	0.20	0.07	0.10	0.73	0.36	<i>0.16</i>	(0.85)
Composite Risk Score	0.30	<i>0.18</i>	0.23	0.01	0.40	0.58	0.28	0.13	0.35	0.31	0.21	0.58	0.21	0.47	0.14	0.60	0.30	0.08	0.45	0.57	0.32
Mean	3.1	3.6	4.5	4.1	4.3	5.5	4.8	4.5	4.6	6.5	5.8	4.7	3.0	3.6	4.5	5.9	6.1	3.1	3.6	4.5	4.9
Standard Deviation	2.2	2.9	2.8	3.2	2.9	2.8	3.1	2.8	3.1	2.8	2.9	2.8	2.5	2.9	2.8	2.8	3.3	2.7	2.6	2.9	2.8

NOTE: Internal consistency estimates for attenuation (Chronbach alpha) are in parantheses. Significant correlations at the $p = 0.05$ level are *italicized*. Significant correlations at the $p = 0.01$ level are **bold**.

revocation of their parole due to a technical violation within one year of release. The mean number of days to re-arrest (for both any crime and violent crime) was about 157 days and the mean number of days to revocation for a technical violation was about 256 days.

Analyses were then conducted to test the predictive validity of the COMPAS on re-arrest for any crime, re-arrest for violent crime, and revocation for a technical violation. Logistic regression was used to analyze the relationship between each composite risk score and its related recidivism outcome. AUC analysis and RIOC analysis tested the hypotheses that each of the chosen risk measures predicted its related outcome greater than 50% of the time tested. Survival analyses were also conducted to explore the time to failure for re-arrest and revocation for the parolees in this sample.

Regression Analyses. Logistic regression was conducted to examine each risk measure on its related outcome measure and results are presented in Table 3. A logistic regression analysis was completed for each set of risk and outcome measures. The analysis for composite recidivism risk and re-arrest for any crime yielded statistically significant results ($\chi^2=15.24(1)$, $p<0.001$). Model summary results produced a -2 log likelihood of 259.70 and Nagelkerke R Square of 0.10. The COMPAS composite risk score had a positive and statistically significant impact on re-arrest for any crime [$b=0.20$, $Wald=14.27$, $Odds\ Ratio=1.22$, $p<0.001$]. As COMPAS composite recidivism scores increased, the assessment was more likely to predict re-arrest for any crime.

The logistic regression analysis of composite violent recidivism risk score for re-arrest for a violent crime produced results that were not significant ($\chi^2= 3.28(1)$, $p=0.08$). Model summary results produced a -2 log likelihood of 87.76 and a Nagelkerke R Square

of 0.04. The composite violent risk score did not have a statistically significant effect on re-arrest for a violent crime [$b=0.20$, $Wald=3.16$, $Odds\ Ratio=1.22$, $p=0.08$].

Table 3. Logistic Regression Analysis of COMPAS Risk Measures and Outcomes

	<i>logit (b)</i>	<i>s.e. of logit</i>	<i>Odds Ratio</i>	<i>Wald Statistic (df)</i>	<i>p-value</i>
Any Risk and Re-arrest	0.20	0.05	1.22	14.27 (1)	0.000
Violent Risk and Violent Re-arrest	0.20	0.11	1.22	3.16 (1)	0.08
History of Non-compliance and Revocation	0.15	0.06	1.17	7.44 (1)	0.000

The relationship between history of non-compliance score and revocation for a technical violation was statistically significant ($\chi^2=7.39(1)$, $p=0.007$). Model summary results produced a -2 log likelihood of 209.36 and a Nagelkerke R Square of 0.06. The history of non-compliance subscale score had a statistically significant, positive effect on revocation for a technical violation [$b=0.15$, $Wald=7.44$, $Odds\ Ratio=1.17$, $p<0.001$]. As the history of non-compliance score increased, the tool was more likely to predict revocation for a technical violation.

AUC and RIOC Analysis. AUC and RIOC analyses were conducted to evaluate the predictive power of the COMPAS assessment, or its ability to classify offenders correctly as recidivists. An AUC analysis measures prediction accuracy using a graph or receiver operating curve (ROC). The ROC maps the rate of true positives versus the rate of false positives, and the area under the curve measures the predictive power of the assessment. AUC analyses consist of diagonal lines representing random prediction (50%) and a curved line, the ROC curve. In this study, the area under the ROC curve represented the ability of the COMPAS risk measures to predict the outcomes of interest above chance. ROC curve coordinates measure the relative rates of benefits (valid

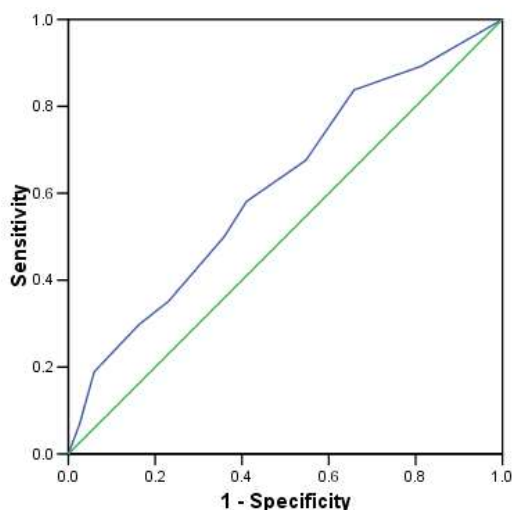
positives) vs. costs (false positives). AUC statistics are insensitive to the base rates of recidivism and can be used to measure prediction power differences between multiple instruments.

Relative Improvement Over Chance (RIOCI) analysis expands upon the AUC analysis and measures the predictive efficacy of the tool using the agreement between predicted and actual outcomes (Farrington & Loeber, 1989; Loeber & Dishion, 1983). This analysis classifies outcomes into four categories in a 2 X 2 table: valid positives, false positives, false negatives, and valid negatives and examines the proportion of predictions that were correct (valid). This study divided the distribution of each composite or subscale score for each risk measure into equal halves and established the cut-point for dividing predicted successes (no recidivism outcome, <6) and predicted failures (recidivism outcome, ≥ 6). It can be assumed that the results of this analysis are statistically significant when the results of the AUC/ROC analysis are found to be statistically significant.

Composite Risk Score and Prediction of Re-arrest. Figure 2 represents the AUC analysis for the COMPAS composite risk score and its prediction of re-arrest for any crime. The COMPAS composite risk score significantly predicted re-arrest for any crime 62% of the time ($CI = 0.53-0.70$), improving prediction over random chance by 12% ($p = 0.007$). Curve coordinates indicated there were substantial trade-offs between correct predictions of re-arrest and predictions of re-arrest that did not occur. Trade-offs were evident at the normalized cut-points for low risk and moderate risk. At the highest cut-point for low risk (4), 67.6% of parolees in the total sample that scored at or above 4 were correctly

identified as failures, while 54.7% of those at or above the cut-off who did not fail were incorrectly identified.

Figure 2. ROC Curve for COMPAS Composite Risk Score



RIOC analysis cut the composite recidivism risk scale into equal parts based on number of values, analyzing predicted failures (≥ 6) and predicted successes (< 6). Results suggested that the COMPAS composite recidivism risk score correctly predicted re-arrest for any crime in this sample 61% of the time.¹

Most of the observed errors (21%) were false positives or parolees that were predicted to recidivate, but ultimately, were not re-arrested within the first year. By random prediction alone, 55% of valid positives and valid negatives would be predicted, yielding an improvement over chance utilizing the COMPAS composite recidivism risk score of 6%. Observed and random correct predictions of re-arrests for any crime using the composite risk score are presented in Figures 3 and 4.

¹ Correct predictions are reflected as the total number of valid positives (parolees who the COMPAS predicted would recidivate and did) and valid negatives (parolees who the COMPAS predicted would not recidivate and did not).

Solving for the maximum number of correct, valid predictions, the composite risk score can never predict more than 97% of the correct outcomes. Using the RIOC formula of the improvement over chance (IOC) divided by the difference between the maximum correct percentage and the random correct percentage, the relative improvement over chance of the composite risk score is 14%.

Figure 3. Observed Correct Predictions of Re-arrest Using the Composite Risk Score

	<i>Re-arrest</i> (Valid Positive)	<i>No Re-arrest</i> (False Positive)	
Composite Risk ≥ 6	48 (24%)	42 (21%)	90 (45%)
	(False Negative)	(Valid Negative)	
Composite Risk < 6	37 (18%)	75 (37%)	112 (55%)
	85 (42%)	117 (58%)	202

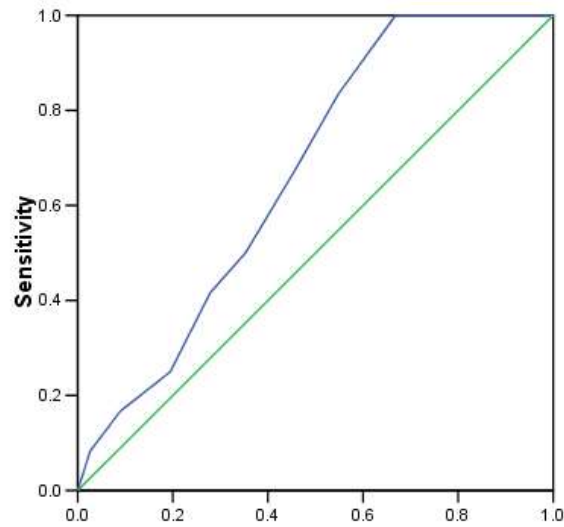
Figure 4. Random Correct Predictions of Re-arrest Using the Composite Risk Score

	<i>Re-arrest</i> (Valid Positive)		
Composite Risk ≥ 6	47 (23%)		102
		(Valid Negative)	
Composite Risk < 6		65 (32%)	100
	85	117	202

Composite Violence Risk Score and Re-arrest for Violent Crime. Figure 5 represents the AUC analysis for the COMPAS composite violent risk score and its prediction of re-arrest for a violent crime. This analysis produced results that were not statistically significant indicating the COMPAS composite violent risk score did not increase prediction above random chance ($AUC = 0.67$, $CI = 0.54-0.79$, $p = 0.07$).

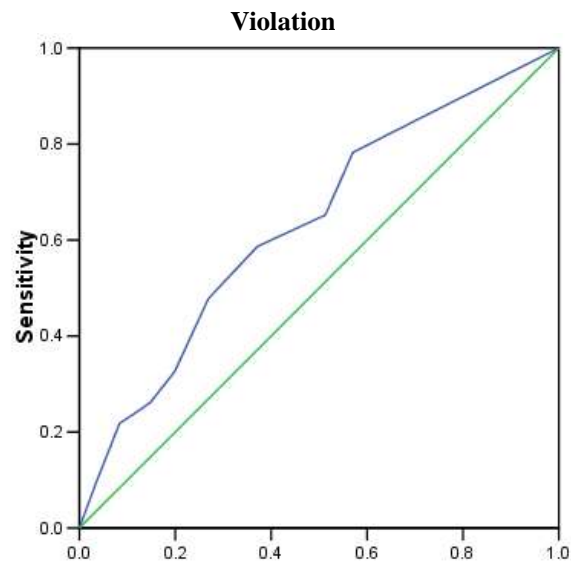
Due to the fact that the results of the AUC analysis were not significant, an RIOC analysis was not conducted for the violent recidivism risk score.

Figure 5. ROC Curve for COMPAS Composite Violent Risk Score



History of Non-Compliance Subscale and Revocation. Figure 6 represents the AUC analysis for the history of non-compliance subscale score and its prediction of revocation for a technical violation. The history of non-compliance score significantly predicted revocation 63% of the time ($CI = 0.54-0.73$), improving prediction over random chance by 13% ($p=0.006$).

Figure 6. ROC Curve for History of Non-Compliance Subscale and Revocation for Technical



Curve coordinates indicated there were substantial trade-offs between correct predictions of revocation and predictions of revocation that did not occur. Trade-offs were evident at the normalized cut-points for low risk and moderate risk. At the highest cut-point for low risk, only 58.7% of parolees in the total sample that scored at or above 4 would be correctly identified as failures, while 37.2% of those at or above the cut-off who were not failures would be incorrectly identified.

For history of noncompliance, analysis cut the parolees into predicted failures or those parolees who were revoked for a technical violation (≥ 6) and predicted successes or those parolees who were not revoked for a technical violation (< 6). The analysis showed that the history of noncompliance subscale score correctly predicted both valid positives and valid negatives about 70% of the time. An equal percentage of false responses (15%) were positive (predicted failure who were not revoked) and negative (predicted successes who were revoked).

By random prediction alone, 65% of valid positives and valid negatives were correctly predicted, so the improvement over chance (IOC) is 5%. The maximum number of correct responses that the history of noncompliance score can predict is actually 100%. Using the RIOCI formula, the relative improvement over chance of the history of noncompliance outcome in predicting valid positives and negatives is 14%.

Figure 7. Observed Correct Predictions of Revocation for TV Using History of Noncompliance Score

	<i>Revocation</i> (Valid Positive)	<i>No Revocation</i> (False Positive)	
History of Noncompliance ≥ 6	15 (8%)	31 (15%)	46 (23%)
	(False Negative)	(Valid Negative)	
History of Noncompliance < 6	31 (15%)	125 (62%)	156 (77%)
	46 (23%)	156 (77%)	202

Figure 8. Random Correct Predictions of Revocation for TV Using History of Noncompliance Score

	<i>Re-arrest</i> (Valid Positive)		
History of Noncompliance ≥ 6	11 (5%)		46
		(Valid Negative)	
History of Noncompliance < 6		121 (60%)	156
	46	156	202

Survival Analyses. Survival analyses, using both Kaplan-Meier product-limit analyses and Cox regression analysis, were conducted to determine time to recidivism outcome (re-arrest for any crime and revocation) and the relationship of each composite risk score on survival. Due to the low base rate of re-arrest for violent crime, this outcome of interest was excluded from the survival analysis. These analyses allow the measurement of how well the COMPAS is able to predict an outcome measure at a given point in time. Kaplan-Meier product-limit analysis estimates the time-to-event in the presence of censored cases (cases with no recidivism outcome recorded) and estimates the survival rate at each point in time. Cox regression also estimates the time-to-event in the presence of censored cases, but also allows the measurement of how predictor variables impact the outcome of interest.

The Kaplan-Meier analysis of re-arrest for any crime included 202 offenders, of which 117 (58%) were censored, and 85 events. Figure 9 depicts the survival curve for re-arrest for any crime, indicating a mean survival time of 278 days.

Figure 10 depicts the differences in survival between the risk groups. The low risk group included 100 parolees, of which 69 (69%) were censored, and 31 events. The mean survival time for low risk parolees was 301 days. The moderate risk group included 52 parolees, of which 29 (56%) were censored, and 23 events. The mean survival time for

Figure 9. Kaplan-Meier Survival Curve of Parolees (N=202) Re-arrested within One Year of Release

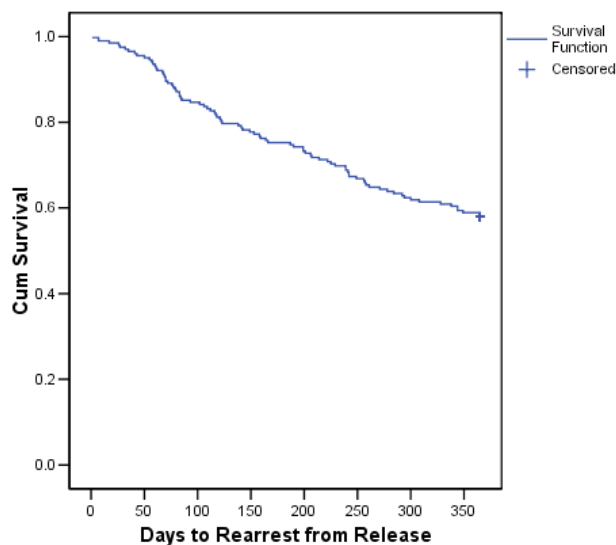
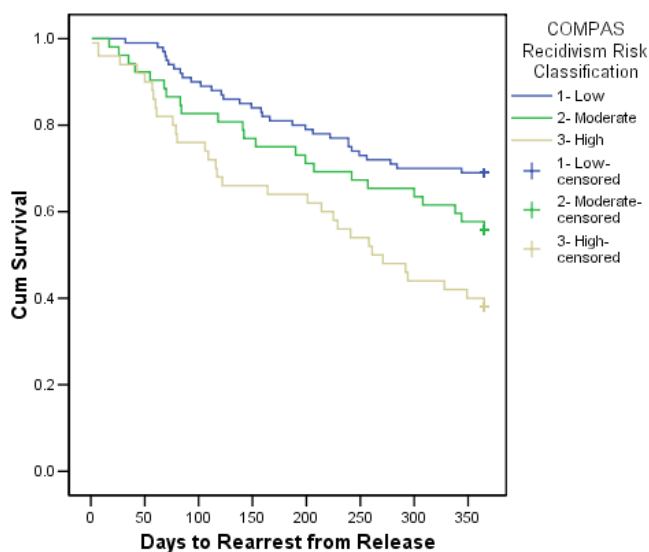


Figure 10. Kaplan-Meier Survival Curve of Parolees (N=202) Re-arrested within One Year of Release by COMPAS Risk Group

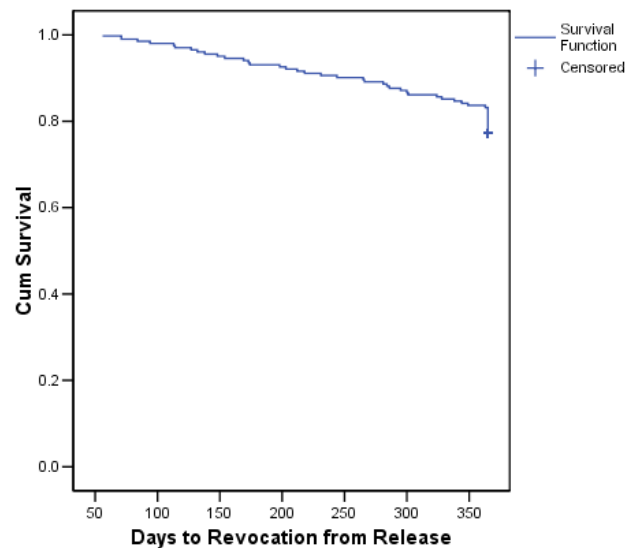


moderate risk parolees was 276 days. The high risk group included 50 parolees, of which 19 (38%) were censored, and 31 events. The mean survival time for the high risk group was 236 days. Low risk parolees survived the longest, while high risk parolees survived

the shortest period of time following release. A log-rank test of equality of the survivor functions indicated that there was a statistically significant difference in survival time between the risk groups [$\chi^2_p=14.19, p<0.001$].

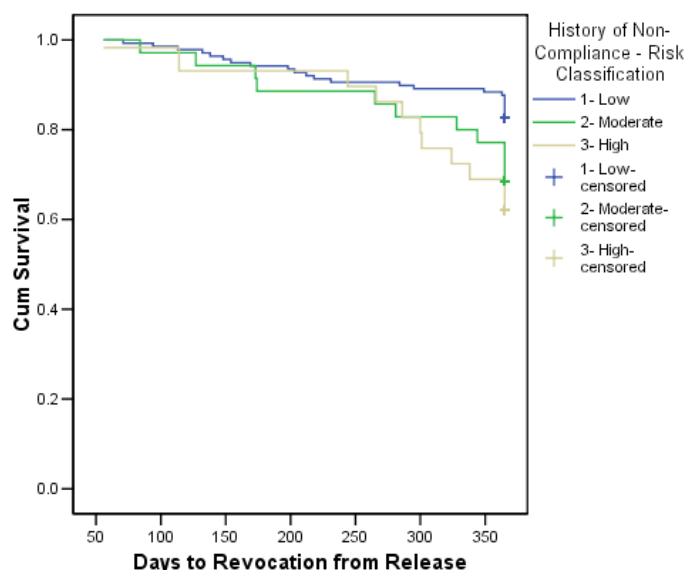
The Kaplan-Meier analysis of revocation for a technical violation, however, included 202 offenders, of which 156 cases (77%) were censored. Mean survival time for parole revocation was fairly long, 350 days, as depicted in Figure 11.

Figure 11. Kaplan-Meier Survival Curve of Parolees (N=202) Revoked within One Year of Release



Due to the high mean survival time for all parolees in this sample, the risk groups for history of noncompliance score appeared to show very minimal differences in survival time following release (depicted in Figure 12). However, a log-rank test for equality of the survivor functions revealed significant differences between the risk groups on time to revocation [$\chi^2_p=7.65, p=0.02$]. Low risk parolees survived 344 days before revocation, moderate risk parolees survived 332 days before revocation, and high risk parolees survived 329 days before revocation.

**Figure 12. Kaplan-Meier Survival Curve of Parolees (N=202) Revoked within One Year of Release
by COMPAS Risk Group**



Cox proportional-hazards regression analyses were also conducted. Results indicated that increases in composite risk score representing higher risk level were significantly associated with risk for re-arrest during the follow-up period ($p=0.000$). The estimated risk of re-arrest increases by 1.16 times for each additional point of composite recidivism risk. Similarly, increases in history of noncompliance subscale score were significantly associated with an increase in risk for revocation during the follow-up period ($p=0.012$). The estimated risk of revocation increases by 1.13 times for each additional point of history of noncompliance score. However, increases in the composite violence risk score did not significantly yield increases in risk for re-arrest for a violent crime in this sample. The results of the Cox proportional-hazards regression analyses are found in Table 4.

Table 4. Cox Regression Analysis of COMPAS Risk and Outcome Measures

	<i>Logit (b)</i>	<i>s.e. of logit</i>	<i>Odds Ratio</i>	<i>Wald Statistic (df)</i>	<i>p</i>
Composite Risk and Re-arrest	0.15	0.04	1.16	15.42	0.000
Composite Violent Risk and VFO Re-arrest	0.22	0.11	1.25	4.67	0.07
Noncompliance Score and Revocation	0.12	0.05	1.13	6.50	0.012

Cox proportional-hazards regression analysis were re-analyzed for composite risk score and re-arrest for any crime with additional covariates dependent on time that could influence risk for re-arrest, including total prior arrests, total prior convictions, and age at release. The results of this analysis are provided in Table 5. Even with the other covariates, increases in composite risk score were significantly associated with an increase in risk of re-arrest for any crime ($p=0.004$). A test for multi-collinearity revealed that none of the other variables were significantly correlated with the composite risk score and were also not significantly associated with risk in this sample. The estimated risk of re-arrest increases by 1.14 times for each additional composite risk point.

Table 5. Cox Regression Analysis of Composite Risk and Covariates on Re-arrest for Any Crime

	<i>Logit (b)</i>	<i>s.e. of logit</i>	<i>Odds Ratio</i>	<i>Wald Statistic (df)</i>	<i>p-value</i>
Composite Risk	0.13	0.04	1.14	8.40 (1)	0.004
Total Prior Arrests	0.02	0.03	1.02	0.22 (1)	0.75
Total Prior Convictions	0.02	0.04	1.03	0.37 (1)	0.45
Age at Release (years)	-0.02	0.01	0.99	1.40 (1)	0.99

Research Question #3: Subscale Predictors of Re-arrest for Any Crime

The third component of this study examined the subscales of the COMPAS tool that best predict recidivism in this diverse sample of parolees in New York City. Based on the results of prior research focused on risk factors that impact recidivism, it was hypothesized that the subscales of criminal associates, criminal involvement, criminal personality, criminal thinking, and vocation/education needs would best predict re-arrest for any crime for parolees within a year of release from incarceration. Point-biserial correlations between the 21 risk/needs subscales and re-arrest for any crime were generated and are displayed in Table 6.

Table 6. Correlation of COMPAS Subscales And Re-arrest for Any Crime (N=202)

COMPAS Subscale	r_{pb}	p
Criminal Involvement	0.13	0.07
History of Non-Compliance	0.20	0.005
History of Violence	0.04	0.55
Current Violence	-0.07	0.34
Criminal Associates/Peers	0.01	0.88
Criminal Opportunity	0.13	0.06
Leisure/Recreation	0.06	0.36
Social Isolation	0.03	0.70
Substance Abuse	0.05	0.51
Criminal Personality	0.01	0.87
Criminal Thinking	0.10	0.17
Cognitive Behavioral	0.16	0.02
Family Criminality	0.03	0.71
Socialization Failure	0.15	0.04
Financial	0.07	0.36
Vocation/Education	0.22	0.001
Social Environment	0.00	0.99
Residential Instability	0.14	0.06
Social Adjustment	0.16	0.02

Note: Bold rows are components with a significant correlation with re-arrest for any crime.

The following scores and sub-scale scores were significantly correlated with re-arrest: composite risk score ($r_{pb}=0.27, p<0.001$), history of noncompliance subscale ($r_{pb}=0.20, p = 0.005$), vocation/education subscale ($r_{pb}=0.22, p=0.001$), cognitive-behavioral subscale ($r_{pb}=0.16, p =0.02$), socialization failure subscale ($r_{pb}=0.15, p$

$=0.04$), and social adjustment subscale ($r_{pb}=0.16$, $p=0.02$). No other subscales were significantly correlated with re-arrest for any crime in this sample.

A Wilcoxon-Mann-Whitney rank-sum test was conducted to examine the differences between recidivists (those who were re-arrested for any crime within one year of release) and non-recidivists on the COMPAS composite risk and subscale scores. The results indicate that there are statistically significant differences between recidivists and non-recidivist on both composite risk scores, any risk [$z(200)=-3.796$, $p<0.001$] and violent risk [$z(200)=-3.246$, $p=0.001$], and the vocation/education subscale [$t(200)=-3.167$, $p=0.002$].

Though not included as subscales in this hypothesis, there were statistically significant differences between recidivists and non-recidivists on the composite failure to appear (FTA) score [$z(200)=-2.172$, $p=0.030$], history of noncompliance subscale [$z(200)=-2.781$, $p=0.005$], cognitive-behavioral subscale [$z(200)=-2.298$, $p=0.022$], socialization failure subscale [$z(200)=-2.107$, $p=0.035$], residential instability subscale [$z(200)=-1.908$, $p=0.046$], and social adjustment subscale [$z(200)=-2.303$, $p=0.021$]. Table 7 highlights additional results.

The results of a binary logistic regression of re-arrest for any crime on the COMPAS subscales are presented in Table 8. This model combined all of the risk/needs subscales as covariates to determine the significant predictors of re-arrest. The overall relationship between the sub-scales and re-arrest was statistically significant ($X^2=29.91$ (19), $p=0.05$). Model summary results produced a -2 log likelihood of 245.03 and a Nagelkerke R Square of 0.19.

Table 7. COMPAS Subscale and Composite Risk Scores by Recidivism Group (N=202)

COMPAS Component	Group Means (SD)		Test Statistic	
	Recidivists (N=85)	Non-Recidivists (N=117)	z (200)	p-value
Criminal Involvement	3.38 (2.1)	2.95 (2.3)	-1.819	0.069
History of Non-Compliance	4.13 (2.8)	3.22 (2.8)	-2.781	0.005
History of Violence	4.61 (2.7)	4.38 (2.8)	-0.604	0.546
Current Violence	3.82 (3.2)	4.30 (3.3)	0.956	0.339
Criminal Associates/Peers	4.34 (3.1)	4.20 (2.8)	-0.153	0.878
Criminal Opportunity	5.94 (2.7)	5.20 (2.8)	-1.874	0.061
Leisure/Recreation	5.04 (3.3)	4.61 (2.9)	-0.914	0.361
Social Isolation	4.53 (2.8)	4.41 (2.9)	-0.389	0.697
Substance Abuse	4.73 (3.1)	4.48 (3.1)	-0.656	0.512
Criminal Personality	6.47 (3.0)	6.48 (2.7)	-0.170	0.865
Criminal Thinking	6.13 (2.8)	5.52 (3.0)	-1.391	0.164
Cognitive Behavioral	5.18 (2.8)	4.27 (2.8)	-2.298	0.022
Family Criminality	3.04 (2.4)	2.97 (2.6)	-0.370	0.711
Socialization Failure	4.06 (3.1)	3.19 (2.8)	-2.107	0.035
Financial	4.74 (2.9)	4.35 (2.7)	-0.920	0.358
Vocation/Education	6.71 (2.5)	5.38 (2.9)	-3.167	0.002
Social Environment	6.04 (3.4)	6.11 (3.2)	0.014	0.989
Residential Instability	3.55 (2.9)	2.78 (2.4)	-1.908	0.046
Social Adjustment	4.06 (2.6)	3.29 (2.5)	-2.303	0.021
Composite Risk	5.84 (2.6)	4.26 (2.9)	-3.796	0.000
Composite Violent Risk	5.28 (2.9)	3.95 (2.5)	-3.246	0.001
Composite FTA Risk	3.36 (2.8)	2.34 (1.9)	-2.172	0.030

Note: Standard deviations are presented in parantheses. Bold rows are components with a significant difference between the groups.

Table 8. Regression Analysis of COMPAS Subscales on Re-arrest for Any Crime

COMPAS Subscale	<i>b</i>	<i>s.e. of b</i>	<i>Exp(B)</i>	<i>Wald Statistic (df)</i>	<i>p-value</i>
Criminal Involvement	0.05	0.10	1.05	0.29	0.59
History of Non-Compliance	0.14	0.07	1.15	3.92	0.05
History of Violence	-0.03	0.07	0.97	0.22	0.64
Current Violence	-0.02	0.06	0.98	0.11	0.75
Criminal Associates/Peers	-0.13	0.13	0.88	0.90	0.34
Criminal Opportunity	-0.07	0.17	0.93	0.20	0.65
Leisure/Recreation	0.03	0.07	1.03	0.15	0.70
Social Isolation	-0.03	0.07	0.97	0.21	0.65
Substance Abuse	-0.04	0.06	0.97	0.32	0.57
Criminal Personality	-0.15	0.08	0.86	3.69	0.06
Criminal Thinking	0.00	0.12	1.00	0.00	0.99
Cognitive Behavioral	0.34	0.39	1.40	0.77	0.38
Family Criminality	-0.04	0.07	0.96	0.29	0.59
Socialization Failure	-0.03	0.14	0.97	0.03	0.86
Financial	0.00	0.07	1.00	0.00	0.99
Vocation/Education	0.25	0.10	1.29	6.76	0.01
Social Environment	-0.03	0.06	0.97	0.20	0.65
Residential Instability	0.12	0.07	1.13	3.15	0.05
Social Adjustment	-0.17	0.15	0.84	1.32	0.25

Note: Bold rows indicate variables in the regression analysis that are significant.

In this sample, the only significant sub-scale predictors of re-arrest are the history of noncompliance, vocation/education, and residential instability sub-scales. Each point increase in the history of non-compliance subscale score increases the odds of re-arrest by a factor of 1.05 times. Each point increase in the vocation/education subscale, indicating a higher probability of need in this area, increases the odds of re-arrest by a factor of 1.29 times. Lastly, each point increase in the residential instability subscale increases the odds of re-arrest by a factor of 1.13 times.

Research Question #4: Predictive Validity of the COMPAS compared to DCJS Risk

The last component of this study was to determine whether the predictive validity of the COMPAS composite risk scores for any re-arrest and re-arrest for a violent crime could be challenged by a risk score developed using static factors from an individual parolee's computerized case history (CCH). Though COMPAS composite risk scores have achieved moderate predictive validity in studies of parolees, including the present study, it has also been shown that static factors taken from an individual's CCH can perform just as well as the COMPAS (Zhang, et al., 2011) in predicting re-arrest. The DCJS risk scores for recidivism and violent recidivism were available for this sample of parolees and provided a suitable replacement as a cost-efficient, static risk assessment for comparison with the COMPAS. Analyses conducted for the validation of the COMPAS assessment were repeated for the DCJS risk score and compared to the COMPAS results.

Regression Analyses. Logistic regression analysis was repeated for the DCJS composite risk scores to determine the degree of impact of each risk measure on its related outcome measure. A logistic regression was completed for the DCJS any risk score and re-arrest for any crime, and the DCJS violent risk score and re-arrest for a

violent crime and the results are presented in Table 9. The analysis of DJCS any risk score and re-arrest for any crime yielded statistically significant results ($X^2=21.08(1)$, $p<0.001$). Model summary results produced a -2 log likelihood of 253.86 and Nagelkerke R Square of 0.13. The DCJS any risk score had a positive and statistically significant impact on re-arrest for any crime [$b=0.28$, $Wald=18.82$, $Odds\ Ratio=1.32$, $p<0.001$]. As the DCJS any risk score increased, the score was more likely to predict re-arrest for any crime.

The logistic regression analysis for DCJS violent risk score and re-arrest for a violent crime produced results that were not statistically significant ($X^2=3.05(1)$, $p=0.08$). The model summary produced a -2 log likelihood of 87.99 and a Nagelkerke R square of 0.04. The DCJS violent risk score did not have a statistically significant effect on re-arrest for a violent crime [$b=0.19$, $Wald=2.88$, $Odds\ Ratio=1.21$, $p=0.09$].

Table 9. Logistic Regression Analysis of DCJS Risk Measures and Outcomes

	<i>Logit (b)</i>	<i>s.e. of logit</i>	<i>Odds Ratio</i>	<i>Wald Statistic (df)</i>	<i>p-value</i>
DCJS Any Risk and Re-arrest	0.28	0.06	1.32	18.82 (1)	0.000
DCJS Violent Risk and Violent Re-arrest	0.19	0.12	1.21	2.88 (1)	0.09

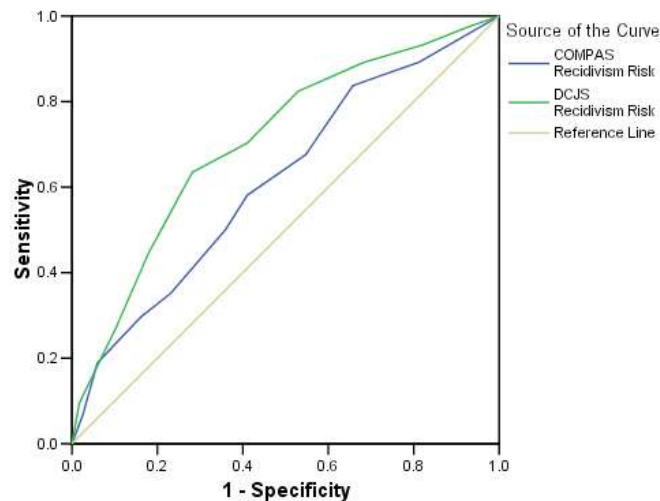
AUC and RIOC Analyses. AUC and RIOC analyses were repeated to compare the predictive validity of the DCJS risk scores with the predictive validity of the COMPAS risk scores.

Any Risk Score and Prediction of Re-arrest. Figure 13 represents the AUC analysis for the DCJS any risk score and its prediction of re-arrest. For comparative purposes, the ROC curve for the COMPAS composite risk score is also provided. The

DCJS any risk score significantly predicted re-arrest for any crime 71% of the time ($CI=0.64-0.79$), improving prediction over random chance by 21% ($p<0.001$).

Curve coordinates for the DCJS any risk score indicated that like the COMPAS composite risk score, there were substantial trade-offs for the normalized cut-points of low risk (3). At the highest cut-point for low risk, 89.2% of parolees in the sample that scored at or above a 3 would be correctly identified as failures, but 68.4% of those at or above the cut-off who were not failures would be incorrectly identified.

Figure 13. ROC Curve for DCJS Any Risk Score Compared to COMPAS Composite Risk Score



RIOC analysis cut the DCJS any risk scale into equal parts based on the number of values, analyzing predicted failures (≥ 6) and predicted successes (< 6). Results from the RIOC analysis suggested that the DCJS any risk score correctly predicted re-arrest for any crime in this sample 61% of the time. Most of the observed errors (24%) were false positives or parolees that were predicted to recidivate, but ultimately, were not re-arrested within the year follow-up period. By chance alone, 49% of valid positives and valid negatives would be predicted, yielding an improvement over chance of 12%. Observed

and random correct predictions of re-arrests for any crime using the DCJS any risk score are presented in Figures 14 and 15.

Figure 14. Observed Correct Predictions of Re-arrest Using the DCJS Any Risk Score

	<i>Re-arrest</i> (Valid Positive)	<i>No Re-arrest</i> (False Positive)	
Any Risk ≥ 6	55 (27%)	48 (24%)	103 (51%)
	(False Negative)	(Valid Negative)	
Any Risk < 6	30 (15%)	69 (34%)	99 (49%)
	85 (42%)	117 (58%)	202

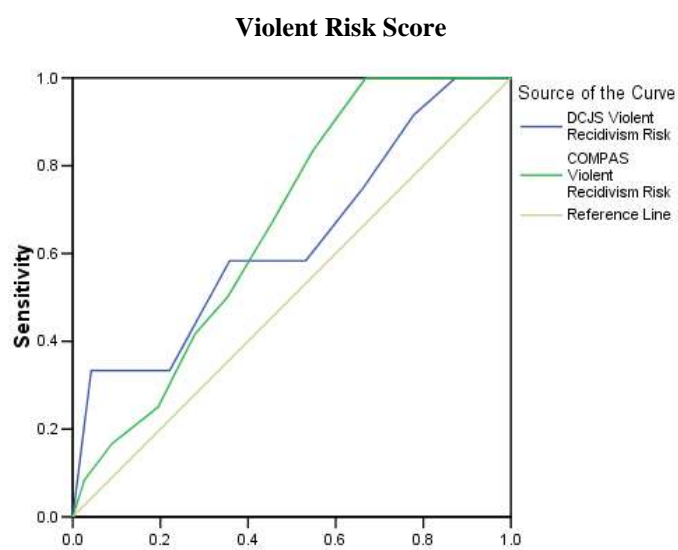
Figure 15. Random Correct Predictions of Re-arrest Using the DCJS Any Risk Score

	<i>Re-arrest</i> (Valid Positive)		
Any Risk ≥ 6	43 (21%)		103
		(Valid Negative)	
Any Risk < 6		57 (28%)	99
	85	117	202

Solving for the maximum number of correct valid predictions (both positive and negative), the DCJS any risk score can never predict more than 91% of correct outcomes. Using the RIOCI formula, the relative improvement over chance of the DCJS any risk score is 29%, higher than the RIOCI value for the COMPAS composite recidivism risk score (14%).

Violent Risk Score and Prediction of Re-arrest for Violent Crime. Figure 16 represents the AUC analysis for the DCJS violent risk score and its prediction of re-arrest for a violent crime. This analysis produced results that were not statistically significant ($AUC = 0.63$, $CI = 0.46 - 0.81$, $p=0.125$) indicating the DCJS violent risk score did not increase prediction above random chance.

Figure 16. ROC Curve for DCJS Violent Risk Score Compared to COMPAS Composite



Due to the fact that the AUC analysis was not significant, an RIOC analysis was not conducted for the violent recidivism risk score. Based on the results of the AUC analyses, neither the DCJS or the COMPAS violent risk scores produced statistically significant ROC curves when measuring predictive validity on re-arrest for a violent crime.

CHAPTER 8 - Discussion

Research Question #1: *Is the COMPAS tool a reliable recidivism prediction instrument for a diverse parolee sample in New York?*

Though some researchers argue that internal consistency reliability is not essential for risk assessment tools that predict a measurable outcome (Baird, 2009; Courtney & Howard, 2011), the reliability analysis in this study was designed purely to test whether or not the strong internal consistency reliability estimates obtained by Northpointe studies would hold up in a sample of minority parolees returning to a very risky area in Harlem, a much different sample than some of the reference groups.

In this study, the overall internal consistency estimate for the COMPAS tool in this sample was $r=0.86$, while sub-scale consistency estimates ranged from $r=0.84$ to $r=0.87$, indicating statistically significant internal reliability for the tool as a whole as well as for its subscales. When compared to normative reliability data, the internal consistency and reliability findings of the COMPAS with this sample are more consistent than the previous studies. The results from this analysis, therefore, support the hypothesis that the COMPAS is a reliable recidivism prediction assessment for use in a diverse parolee population in New York.

Prior studies of the reliability of the COMPAS have been conducted with parole populations in Michigan, California, and Georgia (Brennan, Dieterich, & Ehret, 2007). Inter-correlations between sub-scales for these studies were not provided and therefore, could not be compared. However, these studies did produce subscale internal consistency estimates, ranging from $r=0.52$ to $r=0.90$. The majority of subscales in the samples, however, show alpha coefficients of 0.70 or higher, indicating acceptable reliability. The

remaining subscales in those samples without good reliability also show satisfactory internal consistency based on the current standards. These reliability findings are also maintained across sites with different populations of offenders, including probationers. The results of this particular study with this sample are comparable to the findings of the other large-scale studies.

Research Question #2: *Is the COMPAS tool a valid recidivism prediction instrument for a diverse parolee sample in New York?*

The results from the analyses of the predictive validity of the COMPAS supported the study hypotheses to a degree. Analyses revealed that the composite recidivism risk score does predict re-arrest for any crime greater than 50% of the time (chance alone). The predictive validity of the composite recidivism risk score (0.62), however, falls short of the standard of strong association of 0.70, but comes within the reasonable range of moderate association and predictive value. Though ROC curve coordinates showed substantial trade-offs between valid positives and false positives, the relative improvement over chance of the composite risk score was 14%.

Analyses of the history of noncompliance subscale score also supported the hypothesis that this score does predict revocation for a technical violation greater than 50% of the time. The area under the curve for history of noncompliance score does not meet the threshold for strong predictive validity at 0.63, but does meet the requirements for moderate predictive validity. ROC curve coordinates showed that the history of noncompliance score was much better at reducing the identification of individuals who were not revoked as perceived failures (false positives) than it was at correctly identifying individuals who were revoked as perceived failures (valid positives). Like the

composite risk score, the relative improvement over chance of the history of noncompliance score was 14%.

However, the hypothesis that the composite violent recidivism risk score predicted re-arrest for a violent crime greater than 50% of the time yielded results that were not statistically significant. Violent offenders do not always resort only to violent crime – violence can be used as a method of committing a crime, as in a robbery, or as the crime itself, as in aggravated assault or homicide. Therefore, it can be assumed that violent people will continue to be violent, but the motivation for the violence is important in understanding their risk. It is also possible that offenders who have committed violent crimes in the past may commit another crime upon release that prevents them from committing another violent offense. Not surprisingly, most risk assessments have significantly greater difficulty in predicting violent behavior when compared to other outcomes and generally only achieve moderate predictive accuracy (Min, Wong, & Coid, 2010).

In comparing the results of this analysis to validation samples of aggregated validity analyses of the COMPAS, this study was unable to produce similarly strong predictive validity of the composite recidivism risk and violent recidivism risk scores which have surpassed an area under the curve of 0.70 and 0.80, in some cases (Brennan, Dieterich, & Ehret, 2009). This study did produce similar effects for composite recidivism and violent recidivism risk scores when compared to a large-scale validation of the COMPAS with California parolees (Zhang, et al., 2011). Thus far, no other validation study of the COMPAS has focused on the history of noncompliance subscale and its ability to predict revocation, and therefore, the results of this study are the first.

Research Question #3: *What sub-scales of the COMPAS tool will best predict recidivism for a diverse parolee sample in New York?*

An analysis of the individual subscales was conducted to determine which were best at predicting recidivism. It was hypothesized, based on empirical research identifying the “big five” risk factors for recidivism, that the criminal associates, criminal involvement, criminal personality, criminal thinking, and vocation/education needs subscales would be the best predictors of risk for recidivism. The results of this analysis partially support this hypothesis.

Inter-correlations yielded some statistically significant, but modest results between the history of non-compliance subscale, socialization failure subscale, vocation/education subscale, cognitive-behavioral subscale, and social adjustment subscales with re-arrest. Only the vocation/education subscale was part of the original hypothesis for this research question in this sample. No other subscales were significantly correlated with re-arrest for any crime in this sample.

Additional analysis tested the differences between recidivists (those re-arrested for any crime within one year of release) and non-recidivists. Recidivists, as expected, had higher mean COMPAS composite risk score and composite violent risk scores than non-recidivists in this sample. However, only one of the predicted subscales, vocation/education showed a statistically significant difference between the two groups. Differences in criminal associates, criminal involvement, criminal personality, and criminal thinking were all expected, but were not found. But significant differences between other subscales, not supported by the meta-analysis of Gendreau (1996) and

others, were found between the groups, including history of noncompliance, cognitive-behavioral needs, socialization failure, residential instability, and social adjustment.

Using binary logistic regression analysis of the COMPAS subscales on re-arrest for any crime, the most significant predictor of recidivism in this sample was the vocation/education subscale. Only two other subscales, not included in this hypothesis, were also statistically significant predictors of re-arrest - history of noncompliance and residential instability.

The finding that the vocation/education subscale was the most significant predictor of re-arrest for any crime in this sample supports the mounting focus on targeting employment and education risk factors as integral to reduction in recidivism. Empirical research studying the effects of employment and educational attainment on recidivism is still limited, but early research and meta-analyses have indicated that education, job training and placement programs, and employment yield significant reductions in recidivism (Davis, et al., 2013; Solomon, et al., 2004).

The subscales not included in this hypothesis, specifically history of noncompliance and residential instability, which showed significant differences between recidivism groups and were statistically significant predictors of recidivism, are not represented by the “big five” major risk factors for recidivism in the Gendreau, et al. (1996) analysis. However, that is not to suggest that the risk/needs that these subscales measure are also not important contributors to recidivism. Inter-correlations in this study show that history of noncompliance is significantly correlated with criminal personality ($r=0.16, p=0.05$). Criminal personality, or anti-social personality pattern, is marked by a number of characteristics, including low self-control (Andrews, Bonta, & Wormith,

2006). Research has indicated that low self-control, present in those with an anti-social personality pattern, is linked to an increase in offender non-compliance (DeLisi, et al., 2008). The relationship between the history of noncompliance and criminal personality subscale, in this study, is not surprising. The history of noncompliance subscale may be measuring a construct similar to criminal personality, making it an indirect member of the “big five” risk factors and supporting its significant relationship in predicting risk to re-arrest in this study.

Additionally, there has been an increased focus on targeting residential instability with programs providing stable housing as an important target for recidivism reduction. Though parole authorities are responsible for verifying a residence prior to release, only a small percentage of returning offenders return to the home they lived in prior to incarceration (Visser & Courteney, 2007). A large number of parolees are released to shelters or temporary housing programs that do not provide a stable place to live. Even those with a verified residence are not guaranteed to return to a stable home. They may be returning to homes where family turmoil or location of the home can cause instability. Recent research has suggested that there is a strong relationship between residential instability, marked by homelessness or unstable housing, and recidivism, and programs that address residential instability have shown successful outcomes in reducing recidivism among those released from prison (Fontaine, 2013; Metraux & Culhane, 2004). This analysis provides support to an increased focus on programs that provide stable housing to reduce residential instability for parolees returning from prison.

Research Question #4: *Is the COMPAS tool a better predictor of recidivism than a DCJS risk score developed solely based on static factors from an offender's computerized case history (CCH)?*

This component of the study sought to compare the predictive validity of the COMPAS composite risk scores, a dynamic risk tool, to the predictive validity of the DCJS composite risk scores, a static risk tool. Hypotheses focused on the ability of the COMPAS composite risk scores, to predict recidivism more accurately than the DCJS composite risk scores. Analyses conducted for the COMPAS composite risk score were repeated for the DCJS any risk score and re-arrest for any crime in the follow-up period. Analyses conducted for the COMPAS composite violent risk score were also repeated for the DCJS violent risk score and re-arrest for a violent crime during the follow-up period.

Both the COMPAS composite risk score and DCJS any risk score were significantly correlated with a re-arrest for any crime during the year follow-up period. However, the DCJS any risk score ($r=0.32$, $p=0.01$) had a higher correlation than the COMPAS composite risk score ($r=0.27$, $p=0.05$). Results of the logistic regression analyses indicate that increases in DCJS any risk score are responsible for higher odds of re-arrest for any crime when compared to increases in the COMPAS composite risk score.

In an AUC/RIOC comparison, the hypothesis that the COMPAS composite risk score would more accurately predict re-arrest for any crime was not supported. The DCJS any risk score (0.71) meets the threshold for strong association and has higher predictive validity than the COMPAS composite risk score (0.62). A significance test for equality between two or more ROC curves using the same sample revealed a probability of 0.046,

indicating that the DCJS any risk score provided improved predictive performance compared to the COMPAS composite risk score. When comparing the results of the RIOC analyses, the DCJS any risk score also demonstrated a much higher relative improvement over chance (29%) than the COMPAS composite risk score (14%). Based on these analyses, the dynamic-based COMPAS composite risk score is not a more accurate predictor of re-arrest for any crime than the static-based DCJS any risk score in this sample.

Both the COMPAS composite violent risk score and the DCJS violent risk score were not significantly correlated with re-arrest for a violent crime. ROC analysis of the DCJs violent risk score revealed that similar to the COMPAS violent risk score, the increase above chance in predictive utility of 13% was not significant at any acceptable alpha level. The COMPAS violent risk score represented a 17% increase above chance in predictive utility, but the results of that analysis were also not significant. Therefore, neither the COMPAS nor the DCJS violent risk scores are accurate predictors of re-arrest for violent crimes in this sample.

Summary. In comparison with findings of previous validations of the tool, this study indicated that the COMPAS recidivism risk score has more moderate predictive validity related to re-arrest for any crime. Analyses of the COMPAS violent recidivism risk score was unable to reproduce statistically significant predictive accuracy of the score on re-arrest for a violent crime. Though there is a lack of comparative data from previous validation studies, the history of noncompliance subscale score demonstrated high predictive efficacy and validity on its associated outcome, parole revocation for a technical violation, in this study.

CHAPTER 9 - Limitations and Suggestions for Future Research

Discussed in this chapter are several known limitations of this study that may affect the results found throughout this study. Suggestions for future research that would help in addressing these limitations and a discussion of the generalizability of the results of this analysis are also presented.

Limitations

Sample Size and Composition. One limitation in the evaluation of the predictive validity of the COMPAS tool is the issue of sample size. The sample in this study was relatively small compared to some of the other independent validation studies, but was only slightly smaller in size when compared to some of the validation studies conducted by Northpointe that produced higher predictive validity results (Brennan, Dieterich, & Ehret, 2007).

An important contention in risk assessment scholarship is that prediction of risk should be accurate regardless of the person or the place, and tools should predict risk with similar accuracy regardless of demographic characteristics. Studies have suggested that risk assessment tools over-classify both minority offenders, particularly African-Americans, as higher risk with increased rates of false positives (Fass, Heilbrun, DeMatteo, & Fretz, 2008; Fowler, 1993). This sample was comprised almost exclusively of African-American and Hispanic parolees (98.5%). If the COMPAS is susceptible to errors in minority over-classification, then the results of this study would be affected, producing lower AUC results than previously obtained with more racially heterogeneous samples. An important direction for future research would be to duplicate this study with

a larger sample including both Caucasian and minority parolees to test for differences in classification using the COMPAS risk score.

The homogeneity of this sample, however, may actually contribute some benefit to this study. Some research has shown that offenders who return to disadvantaged neighborhoods recidivate at a greater rate than those returning to more affluent communities when controlling for individual-level factors (Kubrin & Stewart, 2006; Morenoff & Harding, 2011). Neighborhood-level factors, including measures of social disadvantage like poverty and unemployment rates, create distinct disadvantages to offenders leaving prison who return to these neighborhoods. Additionally, neighborhood disadvantage often creates differences in policing practice where officers might be more vigilant in higher crime areas or more likely to arrest individuals for more minor crimes. This study, using only offenders returning to a very specific area in East and Central Harlem in New York City, produces results that control for the neighborhood-level factors, including poverty and police practices, that can contribute to recidivism rates and in turn, allow for the focus on individual-level factors, like the COMPAS and DCJS risk measures, in the analyses.

Sampling Method. Another limitation of this study and possible explanation for lower AUC results was the sampling method. By chance rather than design, this sample contained both parolees who were released to traditional supervision and parolees released to the Reentry Court. Parolees who were randomized to report to the Reentry Court did not always end up in the program upon release from incarceration for several reasons. These individuals were still administered a COMPAS and included in this sample. It is a reasonable concern, then, that participation in the Reentry Court might

contribute to the base rates of recidivism in this study due to the treatment effect. The goal of the program is to reduce recidivism through more intensive programming which would affect the base rates of recidivism for Reentry Court participants and not traditional parolees. Analyses were conducted to examine for differences between these two groups in the current study. Tables 10 and 11 depict the results of tests for differences between the traditional parole and Reentry Court parolees on recidivism outcomes.

Table 10. Chi-Square Results for Differences in Recidivism for Traditional Parole (N=107) and Reentry Court Parolees (N=95)

	<i>Test Statistic X^2 (df)</i>	<i>p-value</i>
Re-arrest for Any Crime	0.09 (1)	0.77
Re-arrest for a Violent Crime	0.96 (1)	0.33
Revocation for a Technical Violation	0.30 (1)	0.58

Table 11. t-test for Differences between Mean Risk Measures and Survival Time for Traditional Parole (N=107) and Reentry Court Parolees (N=95)

	<i>Test Statistic t (df)</i>	<i>p-value</i>
COMPAS Composite Risk Score	-0.97 (200)	0.33
COMPAS Composite Violent Risk Score	0.024 (200)	0.81
COMPAS History of Noncompliance Subscale Score	-1.10 (200)	0.27
Number of Days to Re-arrest	-1.28 (82)	0.20
Number of Days to Revocation	-1.13 (44)	0.27

A chi-square analysis for the dichotomous outcome variable indicated no significant differences between traditional parolees and Reentry Court parolees on any of the recidivism outcomes. A t-test for differences between means of risk measures and survival time also indicated that there were no significant differences in any of the risk measures or in the average number of days to re-arrest and revocation between traditional parolees and Reentry Court parolees. There are no significant differences between the

two groups on recidivism outcomes and therefore, Reentry Court participation does not appear to present a substantial limitation to the results of the validation study of the COMPAS in relation to recidivism.

Secondary Data Analysis. Secondary data analysis has many advantages, but those advantages are also balanced by disadvantages and limitations to its use. The dataset used in the present study was collected by a state agency with a vested interest in high quality data and accurate computerized criminal histories that are used by criminal justice agencies in New York. However, as result of this broad utilization, the dataset was also very large and contained a large number of variables and had to be significantly reduced into a manageable set of variables for this analysis. Improving the manageability of the dataset was a difficult task. Most recidivism data was transformed into dichotomous variables, potentially losing some of the initial value of the measure. Secondary data analysis, no matter how high quality the data, are subject to human errors in data collection and data entry at various steps in the criminal justice process.

Official Arrest Records and Outcome Measures. Other obvious limitations of this study that may have affected the study's findings are the choice of re-arrest and reconviction as the primary recidivism indicators, the use of official records to determine re-arrest and revocation, and the length of the follow-up period. Cohort studies of recidivism have indicated that re-arrest rates are highly variable over time (Langan & Levin, 2002). Variability in arrest rates is most likely produced by differences in police use of discretion in making an arrest. However, reconviction rates remain relatively stable over those same periods of time, indicating little to no change in court processing and conviction probabilities. As a result of temporal stability, reconviction rates are

considered, by some, to be a more reliable measure of recidivism in these kinds of studies (Florida Department of Corrections, 2003).

Official arrest records, used in the secondary data analysis, only serve as a proxy for real involvement in criminal behavior. Risk assessment tools, like the COMPAS, were designed and developed to predict actual criminal behavior, rather than just criminal involvement captured by the justice system. An official arrest for a crime is dependent on the detection of the actual criminal activities. However, a large percentage of criminal behavior is never detected by authorities and therefore, arrest statistics are not a reliable measure of actual crimes committed when compared to self-reported data on criminal activity (Elliot, 1995).

On the other hand, an arrest is also not necessarily a reliable indicator of actual wrongdoing on behalf of that individual, and only about half of all arrests result in a conviction. As one example of this issue relevant to the sample in this study, stop-and-frisk policies in New York City resulted in 150,000 arrests between 2009 and 2012, but only 50% of those arrests actually resulted in a conviction (Office of the Attorney General, 2013). The policy has been widely criticized as a form of racial profiling, leading to increases in arrests of minorities in New York City during its tenure. Parolees in this sample were predominantly minority and out on parole during the height of this initiative. Therefore, it is a possibility that the stop-and-frisk initiative may have affected re-arrest rates and produced more moderate predictive validity as a result of higher rates of false positives for the COMPAS tool. This hypothesis, though, is purely speculative, but is a useful example in demonstrating this particular limitation of choosing re-arrest as the primary indicator of recidivism in this study.

Reconviction data from official criminal history records was available for this study, but was not considered a reliable indicator of recidivism due to the limitations of the one year follow-up period. In 2011, in New York City, it took an average of 400 days to bring a case to a jury trial and result in a verdict (Lindsay & Barry, 2012). Due to this considerable lag in time from arrest to case disposition in the city, one year was not considered an ample follow-up period for this study. Parolees who were re-arrested in this sample may not have received a potential new conviction within a year of release that could be used to measure the predictive validity of the COMPAS composite risk and violent risk scores with reconviction for a new crime. Future research should focus on including reconvictions as an additional measure of recidivism to further validate the ability of the COMPAS tool to predict recidivism. This could be achieved by collecting data using lengthier follow-up periods in order to account for case processing times that affect the recording of reconvictions for new crimes.

In this study, the utilization of a revocation for a technical violation as a measure of recidivism predicted by the history of non-compliance score suffers from similar limitations to re-arrest. The rates of revocation for a technical violation in New York are highly variable and have been steadily increasing since 2004. This variability is produced by a variety of factors, including better supervision practices that enhance the ability to detect technical violations and differences in parole practice and revocation policies for technical violations at both the state and local levels.

Like re-arrest for a new crime, a revocation for a technical violation is not necessarily a reliable indicator of the actual levels of noncompliance in a sample of parolees. Revocation decisions for technical violations vary widely by parole officer,

with many legal and extralegal factors influencing a parole officer's response to a technical violation (Kerbs, Jones, & Jolley, 2009). However, some level of discretion is deemed necessary in order to make parole more responsive to parolee's challenges and needs following release from incarceration and reduce over-crowding issues that have resulted from the revolving door of prisons and parole (Rowland, 2013).

There are certain cases in which a parole officer's discretion in revoking a parolee for a technical violation is removed, but in most cases, the parole officer has discretion in recommending revocation for a violation of parole conditions. Therefore, one parolee could be revoked for a technical violation while another parolee with a different parole officer will not be recommended for revocation for the same violation. In the context of this study, higher rates of false positives and false negatives may have resulted due to this necessary lack of standardization in responses to technical violations.

On the other hand, there are also many instances of noncompliance that are not able to be detected by parole officers regardless of supervision intensity. Rates of actual noncompliance might be much higher than detected rates of noncompliance among parolees. Without the initial detection of a technical violation, there can be no recommendation for revocation for noncompliance with parole conditions. More specific data on technical violations was not available for this study, and though it presents a limitation, a revocation for a technical violation was chosen as a suitable proxy for noncompliance for this parolee sample. Future research might include more robust parole relevant data, including a record of all technical violations, rather than just a revocation for a technical violation, in order to more fully explore the history of noncompliance score and its predictive validity.

Generalizability and Suggestions for Future Research

Due to these limitations, any generalizations of the results of this study should be made carefully. More empirically rigorous studies of the predictive validity of the COMPAS tool are important to fully understand the utility of this risk assessment in the supervision and treatment of community corrections populations. Many of the other widely used and established risk assessment tools, like the LSI-R, have a plethora of validation evidence that demonstrates its predictive validity in community corrections populations, including parolees.

Currently, there are a limited number of validation studies of the COMPAS tool, and an even more limited body of independent studies of the validity of the tool with community corrections samples, specifically parolees. This study not only demonstrates the need for more independent empirical research that focuses on parolees but also more independent research that focuses on different sub-sets of parolees like minorities and women to establish predictive validity of the tool invariable to person or place. With large number of offenders exiting prison facilities each year, the ability to accurately predict risk and target specific needs to reduce that risk under parole supervision remains an important strategic endeavor.

Extensive research on other tools has focused on not only the ability of the overall score to predict recidivism, but also the ability of certain subsets or subscales that are better at predicting risk than others. Future independent research of the COMPAS should also include the validity of the subscales since no other independent research to date, aside from this study, has examined these issues with the parolee population. Understanding if there are certain subscales that are better predictors of recidivism might

contribute to both tool refinement and the provision of necessary evidence to inform parole practice on appropriate supervision and treatment-related decisions to reduce recidivism risk among parolees.

CHAPTER 10 - Implications for Community Corrections Policy and Practice

Despite the limitations of this study that have been addressed, this research makes significant contributions to scholarship, practice, and policy focused on risk assessment in community corrections. This research contributes to the body of scholarship on risk assessment in general, as well as the COMPAS tool specifically. In addition, this research has important implications for community corrections practice and policy. This study connects the body of scholarship around valid risk assessment tools and risk-needs theory with the real world application of policies and practices for addressing offender needs to manage and reduce recidivism risk in community corrections. In an age of evidence-based practice and fiscal responsibility, it is important for policy and practice in community corrections to align with empirical evidence that identifies the most efficient and cost-effective assessment tools for accurately identifying risk level, targeting services and supervision to offender needs, and reducing recidivism risk.

Implications for Scholarship

Though there has been significant scholarship on risk assessment in community corrections, there is a lack of current scholarship on the utility of the COMPAS tool specifically, due to its relatively new arrival to the risk assessment scene. This study contributes to the void in empirical scholarship on the COMPAS tool as a risk assessment in several meaningful ways.

Though there have been several studies focused on the predictive validity of the COMPAS, most of these studies have been conducted by the internal developing agency, Northpointe. Studies conducted by internal developing agencies are potentially subject to a phenomenon known as the allegiance effect, or the fact that developing agencies often

find greater effect sizes when validating their own instruments compared to the effect sizes found by independent researchers. In a meta-analysis of three other widely used risk assessments, it was found that authors of the tools found greater effect sizes than independent research studies, even when controlling for other alternative explanations for the difference (Blair, Marcus, & Boccaccini, 2008). Independent research on the validity of the COMPAS tool is currently very scarce, and this research represents one of the few studies that have assessed the predictive validity of the tool independently of the developing agency. Additionally, this research study is one of the few that has focused not only on the predictive validity of the COMPAS composite risk scores, but also the validity of the various sub-scales in the prediction of recidivism.

Of the existing research conducted independently on the predictive validity of the COMPAS, this study also contributes to the few that are both empirically rigorous and focus on its utility with the parole population. Some independent studies have focused on the utility of the COMPAS tool exclusively with probationers (Lansing, 2012), while other studies have focused on a mix of populations including jail releases, but without the rigorous statistical analyses employed in this study (Blomberg, et al., 2010).

Understanding the predictive accuracy of the COMPAS with this particular sub-set of offenders is important in the implementation of the instrument by parole agencies.

Implications for Community Corrections Practice and Policy.

With the statewide implementation of the COMPAS assessment in New York State in 2013, there are several implications for this research in community corrections practice locally, and more broadly.

Local-Level Implications for Parole. Based on testimony given to the New York State Standing Committee on Corrections, the Department of Corrections and Community Supervision (DOCCS) is utilizing the COMPAS tool solely for the purpose of assigning offenders to tiered case levels (NYS Assembly, 2011). Parolees are assigned to one of four risk levels based on their composite recidivism risk score and those risk levels determine the number of parolees on a parole officer's caseload. Using the COMPAS solely as a risk prediction instrument with lower predictive accuracy than the previously used DCJS risk score represents a significant issue to implementation fidelity and resource utilization. The COMPAS was designed to be used not only to provide guidance in the placement of offenders by risk level, but also to inform the supervision and case management decisions integral in managing and reducing offender risk (Northeastpointe, 2013).

Implementation fidelity and issues with predictive accuracy present interesting implications regarding resource utilization. The COMPAS instrument represents a much greater cost to DOCCS, both in monetary and staff resources, to maintain and administer annually. To purchase and maintain the COMPAS tool, an agency must pay for licenses to access the tool, pay for agency-wide training for all users, and pay for an annual maintenance fee for the web-based data system. The COMPAS tool is lengthy, containing a large number of questions, and requires a significant additional resource, staff time, to implement and administer. However, the DCJS risk score, used previously to classify offenders into risk level, did not require a significant amount of monetary or staff resources to maintain, as the data was already being collected and aggregated by staff for other purposes. If the COMPAS instrument does not improve on the predictive accuracy

of the DCJS risk score in the practice of risk prediction, then the relative cost of the instrument may not be worthwhile in the long-term as long as the tool is not used for its other intended purposes, including case management and risk reduction.

Broader Implications for Parole and Risk Assessment. This research also holds implications for both the utility of risk assessment tools, including the COMPAS instrument, and community corrections practice on a larger scale.

It is suggested that the composite risk scores, risk/needs profile (subscales), and explanatory typology of the COMPAS be used collectively to develop a complex understanding of an individual and select appropriate supervision levels and treatment interventions (Northpointe, 2009). However, there is very little research and information about the use of the risk/needs profile and explanatory typology in discretionary release decisions or by community corrections agencies utilizing the COMPAS instrument. The results of this study, though limited by several shortcomings, show that the composite recidivism risk score does not meet the threshold for strong predictive validity and should not be used as the sole indicator of an individual's potential success in the community.

In this respect, there are also implications for the related community corrections practice of measuring performance and success based solely on recidivism rates. At present, most recidivism data is reported at an aggregated level, producing an imprecise and inaccurate measure of success at a more local level (King & Elderbroom, 2014). Most recidivism measures also ignore the context of recidivism rates when criminal justice populations change on a yearly basis. Changes in the population, fueled by changes in individual offender characteristics, may have significant effects on this measure designed to assess agency and intervention performance and success. In this

context, a previously successful agency may have remained unchanged, but changes in the individuals they serve may cause drops in the success of the program.

While recidivism is an important component of measuring success once an offender is released from prison, there are also many other measures and outcomes that determine the success of a community corrections agency or program. Using measures of program success indicative of other positive outcomes, like employment and education, not only assesses whether a program has prevented future criminal behavior, but also assesses whether an offender is transitioning to a productive life following release (National Reentry Resource Center, 2014; Visser & Travis, 2003). Focusing on other outcomes aside from recidivism aligns community corrections practice further with strengths-based approaches to offender rehabilitation and obtain reductions in risk that achieve the main goals of community corrections (Ward & Fortune, 2013; Willis, Prescott, & Yates, 2013).

However, the most broad implications of this research involve the debate between the accuracy of actuarial, static risk prediction tools to third- and fourth-generation tools, like the LSI-R and COMPAS (Andrews, Bonta, & Wormith, 2006; Barnoski & Drake, 2007; Hemphill & Hare, 2004). Studies have shown that the best predictors of recidivism are generally static variables, including criminal history and demographic variables (Barnoski, 2006; Philipse, Koeter, van der Staak, & van den Brink, 2006). Variables based on offender need may weaken the ability of a risk prediction tool to accurately predict risk (Austin, et al., 2003). Both this study and Zhang and colleagues (2004) demonstrated that the fourth-generation COMPAS prediction of risk was not on par with risk prediction using static variables in parolee populations, demonstrating that certain

needs measures incorporated into newer assessment tools may decrease the accuracy of the risk prediction component of the tool.

Based on the importance of risk reduction and risk management in offender reentry, the value of understanding and utilizing criminogenic risk and needs remains an absolutely integral piece of the community corrections process. The assessment of risk and the targeting of interventions based on risk and needs remain essential principles in achieving successful outcomes with offenders on parole. However, these two principles, though related, have two separate goals. The assessment of risk is involved in the business of risk prediction, focused on predicting recidivism in offenders to make release and supervision-related decisions based on risk level for public safety purposes. The targeting of criminogenic needs is focused on risk reduction and management, or the ways to reduce an offender's risk and as a result, reduce an offender's future criminal behavior. Somewhere along the evolutionary path of risk assessment instruments, these two principles became inextricably connected in one assessment process.

It is also worth noting that when using one assessment tool or strategy to both predict and manage/reduce risk, the two processes and goals become conflicted with one another. Risk management and risk reduction strategies are designed to reduce the risk of or prevent the negative outcome from occurring. The goal of agencies using the COMPAS is to use the tool to make targeted case management and supervision decisions that would prevent recidivism from occurring and improve outcomes for parolees. Offenders predicted to be high risk would be provided risk-appropriate services using the COMPAS profile. If this proves to be an effective strategy, then recidivism behavior is reduced or eliminated and those who are predicted to be high risk using the COMPAS

tool will become false positives. The prevention of the outcome through effective parole practices will in turn, reduce the predictive validity of the assessment tool itself. The presence of successful and effective risk management and reduction strategies with parolees and other community corrections populations could render risk prediction instruments inaccurate and ineffective.

Based on the important fundamental differences in risk prediction and risk reduction, the results of this study and others suggest that it may be necessary for community corrections agencies, and the field at large, to consider a way to separate the practice of risk prediction from risk management and reduction. Risk prediction errors represent a significant concern both to individual offenders, criminal justice agencies, and the community. A two-prong approach would enable agencies to obtain more accurate assessments of an offender's risk for recidivism on which to base a variety of risk-related determinations, including discretionary release decisions and supervision intensity.

An actuarial-based tool with strong predictive validity for predicting risk could be used where risk prediction is warranted. These tools could be evaluated using prison "max-outs" to establish an accurate estimate of their ability to predict risk in populations of individuals released from prison. Subsequently, risk prediction tools could then be utilized with parole populations to determine the risk for that offender if no supervision or intervention was administered. A more dynamic, comprehensive risk/needs assessment, like the COMPAS, would then produce a more complete, descriptive profile of an offender. That profile would then enable criminal justice professionals, including parole officers, to target an offender's specific criminogenic risks and needs with treatment and interventions that effectively manage and reduce offender risk and prevent

future criminal behavior. Effective interventions could then be measured, not by their ability to eliminate recidivism which is an impossible task, but rather, on their ability to reduce an offender's risk over time through management strategies.

Improving the practice of risk prediction and preserving the assessment of offender needs for case management, treatment decisions, and risk reduction is important to support the goals of evidence-based practice in community corrections. It is integral, then, that any exercise in risk assessment have fidelity in implementation of the tool and in using the results of the tool for their intended purpose. Risk prediction using more static-based assessment tools to measure risk upon release, and risk management using more dynamic tools, like the COMPAS, to reduce risk through targeted supervision and intervention might be a step in the right direction.

APPENDIX A – Sample COMPAS Assessment

COMPAS Core ASSESSMENT - OFFICIAL RECORDS

Name: _____ **Screening Date:** _____
NYSID Number: _____ **DOB:** _____
Gender: _____ **Ethnicity:** _____
Scale Set: All CORE COMPAS Scales
Screener Name: _____
Agency: _____

Current Charges

Note to Screener: Throughout the assessment, scroll over questions to reveal help hyperlinks. Click on the hyperlinks for clarification of question and answer options.

- | | | | |
|---|--|---|--------------------------------|
| <input type="checkbox"/> Homicide | <input type="checkbox"/> Weapons | <input type="checkbox"/> Assault | <input type="checkbox"/> Arson |
| <input type="checkbox"/> Robbery | <input type="checkbox"/> Burglary | <input type="checkbox"/> Property/Larceny | <input type="checkbox"/> Fraud |
| <input type="checkbox"/> Drug Trafficking/Sales | <input type="checkbox"/> Drug Possession/Use | <input type="checkbox"/> DUI/OUIL | <input type="checkbox"/> Other |
| <input type="checkbox"/> Sex Offense with Force | <input type="checkbox"/> Sex Offense w/o Force | | |

- Do any current offenses involve family violence?
☐ No ☐ Yes
- Which offense category represents the most serious current offense?
☐ Misdemeanor ☐ Non-violent Felony ☐ Violent Felony
- Was this person on probation or parole at the time of the current offense?
☐ Probation ☐ Parole ☐ Both ☐ Neither
- Based on the screener's observations, is this person a suspected or admitted gang member?
☐ No ☐ Yes

Criminal History

Exclude the current case for these questions.

5. How many times has this person been arrested before as an adult or juvenile (criminal arrests only)?

6. What was the age of this person when he or she was first arrested as an adult or juvenile (criminal arrests only)?

7. How many prior juvenile felony offense arrests?
☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5+
8. How many prior juvenile violent felony offense arrests?
☐ 0 ☐ 1 ☐ 2+
9. How many prior commitments to a juvenile institution?
☐ 0 ☐ 1 ☐ 2+
10. How many times has this person been arrested for a felony property offense that included an element of violence?
☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5+

Note to Screener: The following Criminal History Summary questions require you to add up the total number of specific kinds of offenses in the person's criminal history.

For each of the questions below, record the number of arrests or convictions (felony or misdemeanors). Record whichever is higher, the number of arrests or convictions.

Do not include the current case.

11. How many prior murder/voluntary manslaughter offense arrests as an adult?
☐ 0 ☐ 1 ☐ 2 ☐ 3+
12. How many prior felony assault offense arrests (not murder, sex, or domestic violence) as an adult?
☐ 0 ☐ 1 ☐ 2 ☐ 3+

13. How many prior misdemeanor assault offense arrests (not sex or domestic violence) as an adult?
☐ 0 ☐ 1 ☐ 2 ☐ 3+
14. How many prior family violence offense arrests as an adult?
☐ 0 ☐ 1 ☐ 2 ☐ 3+
15. How many prior sex offense arrests (with force) as an adult?
☐ 0 ☐ 1 ☐ 2 ☐ 3+
16. How many prior weapons offense arrests as an adult?
☐ 0 ☐ 1 ☐ 2 ☐ 3+
17. How many prior drug trafficking/sales offense arrests?
☐ 0 ☐ 1 ☐ 2 ☐ 3+
18. How many prior drug possession/use offense arrests?
☐ 0 ☐ 1 ☐ 2 ☐ 3+
19. How many times has this person been sentenced to jail for 30 days or more?
☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5+
20. How many times has this person been sentenced (new commitment) to state or federal prison (include current)?
☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5+

Include the current case for the following question(s).

21. Has this person, while incarcerated in jail or prison, ever received serious or administrative disciplinary infractions for fighting/threatening other inmates or staff?
☐ No ☐ Yes
22. How many times has this person been sentenced to probation as an adult?
☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5+

Non-Compliance

Include the current case for these questions.

23. How many times has this person violated his or her parole?
☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5+
24. How many times has this person been returned to prison while on parole?
☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5+
25. How many times has this person had a new charge/arrest while on probation?
☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5+
26. How many times has this person's probation been violated or revoked?
☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5+
27. How many times has this person failed to appear for a court appearance?
☐ 0 ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5+
28. How many times has the person been arrested/charged w/new crime while on pretrial release (includes current)?
☐ 0 ☐ 1 ☐ 2 ☐ 3+

INTERVIEW & SELF REPORT

Residence/Stability

29. In the 12 months before this incarceration, how often did you have contact with your family?
☐ No family ☐ Never ☐ Less than once/month ☐ Once per week ☐ Daily
30. In the last 12 months before this incarceration, how often did you move?
☐ Never ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5+
31. Did you have a regular living situation prior to your current incarceration (an address where you usually stayed and could be reached)?
☐ No ☐ Yes
32. How long had you been living at your last address prior to this incarceration?
☐ 0-5 mo. ☐ 6-11 mo. ☐ 1-3 yrs. ☐ 4-5 yrs. ☐ 6+ yrs.
33. Was there a telephone at this residence (a cell phone is an appropriate alternative)?
☐ No ☐ Yes
34. Could you provide a verifiable residential address?
☐ No ☐ Yes
35. How long had you been living in that community or neighborhood (before this current incarceration)?
☐ 0-2 mo. ☐ 3-5 mo. ☐ 6-11 mo. ☐ 1+ yrs.
36. In the 12 months before this incarceration, did you live with family—natural parents, primary person who raised you, blood relative, spouse, children or boy/girl friend if living together for more than 1 year?
☐ No ☐ Yes
37. Did you live with friends (prior to this incarceration)?
☐ No ☐ Yes
38. Were you living alone (prior to this incarceration)?
☐ No ☐ Yes
39. In the last 12 months before this incarceration, did you have an alias (do you sometimes call yourself by another name)?
☐ No ☐ Yes

Family Criminality

The next few questions are about the family or caretakers that mainly raised you when growing up.

40. Which of the following best describes who principally raised you?
 - ☐ Both Natural Parents
 - ☐ Natural Mother Only
 - ☐ Natural Father Only
 - ☐ Relative(s)
 - ☐ Adoptive Parent(s)
 - ☐ Foster Parent(s)
 - ☐ Other arrangement
41. If you lived with both parents and they later separated, how old were you at the time?
 - ☐ Less than 5
 - ☐ 5 to 10
 - ☐ 11 to 14
 - ☐ 15 or older
 - ☐ Does Not Apply
42. Was your father (or father figure who principally raised you) ever arrested, that you know of?
 - ☐ No
 - ☐ Yes
43. Was your mother (or mother figure who principally raised you) ever arrested, that you know of?
 - ☐ No
 - ☐ Yes
44. Were your brothers or sisters ever arrested, that you know of?
 - ☐ No
 - ☐ Yes
45. Was your wife/husband/partner ever arrested, that you know of?
 - ☐ No
 - ☐ Yes
46. Did a parent or parent figure who raised you ever have a drug or alcohol problem?
 - ☐ No
 - ☐ Yes
47. Was one of your parents (or parent figure who raised you) ever sent to jail or prison?
 - ☐ No
 - ☐ Yes

Peers

Please think of your friends and the people you hung out with before your most recent arrest/incarceration.

48. In the last couple of years before this incarceration, how many of your friends/acquaintances had ever been arrested?
 - ☐ None
 - ☐ Few
 - ☐ Half
 - ☐ Most
49. In the last couple of years before this incarceration, how many of your friends/acquaintances served time in jail or prison?
 - ☐ None
 - ☐ Few
 - ☐ Half
 - ☐ Most

50. In the last couple of years before this incarceration, how many of your friends/acquaintances were gang members?
☐ None ☐ Few ☐ Half ☐ Most
51. In the last couple of years before this incarceration, how many of your friends/acquaintances were taking illegal drugs regularly (more than a couple times a month)?
☐ None ☐ Few ☐ Half ☐ Most
52. Have you ever been a gang member?
☐ No ☐ Yes
53. In the last couple of years before this incarceration, were you a gang member?
☐ No ☐ Yes

Substance Abuse

What were your usual habits in using alcohol and drugs in the period before this recent arrest/incarceration?

54. Do you think your current/past legal problems are partly because of alcohol or drugs?
☐ No ☐ Yes
55. Were you using alcohol or under the influence when arrested for your current offense?
☐ No ☐ Yes
56. Were you using drugs or under the influence when arrested for your current offense?
☐ No ☐ Yes
57. Are you currently in formal treatment for alcohol or drugs such as counseling, outpatient, inpatient, residential?
☐ No ☐ Yes
58. Have you ever been in formal treatment for alcohol such as counseling, outpatient, inpatient, residential?
☐ No ☐ Yes
59. Have you ever been in formal treatment for drugs such as counseling, outpatient, inpatient, residential?
☐ No ☐ Yes
60. Do you think you would benefit from getting treatment for alcohol?
☐ No ☐ Yes
61. Do you think you would benefit from getting treatment for drugs?
☐ No ☐ Yes

62. Did you use heroin, cocaine, crack or methamphetamines as a juvenile?

☐ No ☐ Yes

Social Environment

Think of the neighborhood where you lived during the time before your current offense.

63. In the neighborhood you lived in before this incarceration, was there much crime?

☐ No ☐ Yes

64. In the neighborhood you lived in before this incarceration, did some of your friends or family feel they needed to carry a weapon to protect themselves?

☐ No ☐ Yes

65. In the neighborhood you lived in before this incarceration, had some of your friends or family been crime victims?

☐ No ☐ Yes

66. In the neighborhood you lived in before this incarceration, did some of the people feel they needed to carry a weapon for protection?

☐ No ☐ Yes

67. In the neighborhood you lived in before this incarceration, was it easy to get drugs?

☐ No ☐ Yes

68. In the neighborhood you lived in before this incarceration, were there gangs?

☐ No ☐ Yes

Education

Think of your school experiences when you were growing up.

69. Did you complete your high school diploma or GED?

☐ No ☐ Yes

70. What was your final grade completed in school?

71. What were your usual grades in high school?

☐ A ☐ B ☐ C ☐ D ☐ E/F ☐ Did Not Attend

72. Were you ever suspended or expelled from school?

☐ No ☐ Yes

73. Did you fail or repeat a grade level?

☐ No ☐ Yes

74. How often did you have conflicts with teachers at school?
☐ Never ☐ Sometimes ☐ Often
75. How many times did you skip classes while in school?
☐ Never ☐ Sometimes ☐ Often
76. How strongly do you agree or disagree with the following: I always behaved myself in school?
☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree
77. How often did you get in fights while at school?
☐ Never ☐ Sometimes ☐ Often

Vocation (Work)

Please think of your past work experiences, job experiences, and financial situation in the period of time before your current incarceration.

78. Did you have a job prior to this incarceration?
☐ No ☐ Yes
79. Do you currently have a skill, trade or profession at which you usually find work?
☐ No ☐ Yes
80. Could you verify your employer or school (if attending) prior to this incarceration?
☐ No ☐ Yes
81. In the 12 months before this incarceration, how much time did you work or attend school?
☐ 12 Months Full-time ☐ 12 Months Part-time ☐ 6+ Months Full-time ☐ 0 to 6 Months PT/FT
82. Have you ever been fired from a job?
☐ No ☐ Yes
83. About how many times have you been fired from a job?

84. Right now, do you feel you need more training in a new job or career skill?
☐ No ☐ Yes
85. Right now, if you were to get (or have) a good job how would you rate your chance of being successful?
☐ Good ☐ Fair ☐ Poor
86. Thinking of your financial situation prior to this incarceration, how often did you have conflicts with friends/family over money?
☐ Often ☐ Sometimes ☐ Never

87. Thinking of your financial situation prior to this incarceration, how hard was it for you to find a job ABOVE minimum wage compared to others?
☐ Easier ☐ Same ☐ Harder ☐ Much Harder
88. Thinking of your financial situation prior to this incarceration, how often did you have barely enough money to get by?
☐ Often ☐ Sometimes ☐ Never
89. Thinking of your financial situation prior to this incarceration, did anyone accuse you of not paying child support?
☐ No ☐ Yes
90. Thinking of your financial situation prior to this incarceration, how often did you have trouble paying bills?
☐ Often ☐ Sometimes ☐ Never
91. Thinking of your financial situation prior to this incarceration, did you frequently get jobs that did not pay more than minimum wage?
☐ Often ☐ Sometimes ☐ Never
92. Thinking of your financial situation prior to this incarceration, how often did you worry about financial survival?
☐ Often ☐ Sometimes ☐ Never

Leisure/Recreation

Thinking of your leisure time in the past few (3-6) months before this incarceration, how often did you have the following feelings?

93. In your leisure time prior to this incarceration, how often did you feel bored?
☐ Never ☐ Several times/mo ☐ Several times/wk ☐ Daily
94. In your leisure time prior to this incarceration, how often did you feel you had nothing to do in your spare time?
☐ Never ☐ Several times/mo ☐ Several times/wk ☐ Daily
95. In your leisure time prior to this incarceration how much would you agree or disagree with the following - You felt unhappy at times?
☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree
96. In your leisure time prior to this incarceration, did you feel discouraged at times?
☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree
97. In your leisure time prior to this incarceration how much would you agree or disagree with the following - You were often restless and bored?
☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree

98. In your leisure time prior to this incarceration, did you often become bored with your usual activities?
☐ No ☐ Yes ☐ Unsure
99. In your leisure time prior to this incarceration, did you feel that the things you did were boring or dull?
☐ No ☐ Yes ☐ Unsure
100. In your leisure time prior to this incarceration, was it difficult for you to keep your mind on one thing for a long time?
☐ No ☐ Yes ☐ Unsure

Social Isolation

Think of your social situation with friends, family, and other people in the past few (3-6) months. Did you have many friends or were you more of a loner? How much do you agree or disagree with these questions?

101. "I had friends who helped me when I had troubles."
☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree
102. "I felt lonely."
☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree
103. "I had friends who enjoyed doing things with me."
☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree
104. "No one really knew me very well."
☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree
105. "I felt very close to some of my friends."
☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree
106. "I have often felt left out of things."
☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree
107. "I could find companionship when I wanted."
☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree
108. "I had a best friend I could talk with about everything."
☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree
109. "I have never felt sad about things in my life."
☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree

Criminal Personality

The next few questions are about what you are like as a person, what your thoughts are, and how other people see you. There are no 'right or wrong' answers. Just indicate how much you agree or disagree with each statement.

110. "I am seen by others as cold and unfeeling."
☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree
111. "I always practice what I preach."
☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree
112. "The trouble with getting close to people is that they start making demands on you."
☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree
113. "I have the ability to "sweet talk" people to get what I want."
☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree
114. "I have played sick to get out of something."
☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree
115. "I'm really good at talking my way out of problems."
☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree
116. "I have gotten involved in things I later wished I could have gotten out of."
☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree
117. "I feel bad if I break a promise I have made to someone."
☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree
118. "To get ahead in life you must always put yourself first."
☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree

Anger

119. "Some people see me as a violent person."
☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree
120. "I get into trouble because I do things without thinking."
☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree
121. "I almost never lose my temper."
☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree
122. "If people make me angry or lose my temper, I can be dangerous."
☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree
123. "I have never intensely disliked anyone."
☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree

124. "I have a short temper and can get angry quickly."

☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree

Criminal Attitudes

The next statements are about your feelings and beliefs about various things. Again, there are no 'right or wrong' answers. Just indicate how much you agree or disagree with each statement.

125. "A hungry person has a right to steal."

☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree

126. "When people get into trouble with the law it's because they have no chance to get a decent job."

☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree

127. "When people do minor offenses or use drugs they don't hurt anyone except themselves."

☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree

128. "If someone insults my friends, family or group they are asking for trouble."

☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree

129. "When things are stolen from rich people they won't miss the stuff because insurance will cover the loss."

☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree

130. "I have felt very angry at someone or at something."

☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree

131. "Some people must be treated roughly or beaten up just to send them a clear message."

☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree

132. "I won't hesitate to hit or threaten people if they have done something to hurt my friends or family"

☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree

133. "The law doesn't help average people."

☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree

134. "Many people get into trouble or use drugs because society has given them no education, jobs or future."

☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree

135. "Some people just don't deserve any respect and should be treated like animals."

☐ Strongly Disagree ☐ Disagree ☐ Not Sure ☐ Agree ☐ Strongly Agree

APPENDIX B – IRB Approval Letter

RUTGERS UNIVERSITY
Office of Research and Sponsored Programs
ASB III, 3 Rutgers Plaza, Cook Campus
New Brunswick, NJ 08901

September 27, 2012

P.I. Name: Herrschaft
Protocol #: E13-182

Bryn Herrschaft
712 Deane Street
Ridley Park PA 19078

Dear Bryn Herrschaft:

Re-Issued - Notice of Exemption from IRB Review

Protocol Title: "Evaluating the Reliability and Predictive Validity of the COMPAS Tool: Implications for Community Corrections Policy"

The project identified above has been approved for exemption under one of the six categories noted in 45 CFR 46, and as noted below:

Exemption Date: 9/24/2012 **Exempt Category:** 4

This exemption is based on the following assumptions:

- **This Approval** - The research will be conducted according to the most recent version of the protocol that was submitted.
- **Reporting** – ORSP must be immediately informed of any injuries to subjects that occur and/or problems that arise, in the course of your research;
- **Modifications** – Any proposed changes MUST be submitted to the IRB as an amendment for review and approval prior to implementation;
- **Consent Form (s)** – Each person who signs a consent document will be given a copy of that document, if you are using such documents in your research. The Principal Investigator must retain all signed documents for at least three years after the conclusion of the research;

Additional Notes: None

Failure to comply with these conditions will result in withdrawal of this approval.

The Federalwide Assurance (FWA) number for Rutgers University IRB is FWA00003913; this number may be requested on funding applications or by collaborators.

Sincerely yours,

Sheryl Goldberg
acting for

Sheryl Goldberg
Director of Office of Research and Sponsored Programs
gibel@grants.rutgers.edu

cc: Bonita Veysey

WORKS CITED

- Agostinelli, G., Brown, J.M., & Miller, W.R. (1995). Effects of normative feedback on consumption among heavy drinking college students. *Journal of Drug Education*, 25, 31-40.
- Alvero, A.M., Bucklin, B.R., & Austin, J. (2001). A objective review of the effectiveness and essential characteristics of performance feedback in organizational settings. *Journal of Organizational Behavior Management*, 21(1), 3-29.
- Andrews, D.A., & Bonta, J. (1995). *The Level of Service Inventory – Revised*. Toronto: Multi-Health Systems.
- Andrews, D.A., & Bonta, J. (1998). *The Psychology of Criminal Conduct*. Cincinnati: Anderson Publishing.
- Andrews, D.A., & Bonta, J. (2006). *The Psychology of Criminal Conduct* (4th ed.). Albany, NY: Anderson Publishing.
- Andrews, D.A., & Bonta, J. (2003). *Level of Service Inventory-Revised US Norms Manual Supplement*. Tonawanda, NY: Multi-Health Systems.
- Andrews, D.A., Bonta, J., & Hoge, R.D. (1990). Classification for effective rehabilitation: Rediscovering psychology. *Criminal Justice and Behavior*, 17, 19-52.
- Andrews, D.A., Bonta, J., & Wormith, S. (2004). *The Level of Service/Case Management Inventory*. Toronto: Multi-Health Systems.
- Andrews, D.A., Bonta, J., & Wormith, S. (2006). The Recent past and near future of risk and/or need assessment. *Crime & Delinquency*, 52(1), 7-27.
- Andrews, D.A., Bonta, J., & Wormith, S. (2008). *Level of Service/Case Management Inventory (LS/CMI): A Gender-Informed Risk/Need/Responsivity Assessment*. Toronto: Multi-Health Systems.
- Andrews, D.A., Bonta, J., & Wormith, S. (2011). The Risk-Need-Responsivity (RNR) Model: Does adding the Good Lives Model contribute to effective crime prevention?, *Criminal Justice and Behavior*, 38(7), 735-755.
- Andrews, D.A., Bonta, J., Wormith, J.S., Guzzo, L., Brews, A., Rettinger, J., & Rowe, R. (2011). Sources of variability in estimates of predictive validity: A Specification with Level of Service general risk and need. *Criminal Justice and Behavior*, 38(5), 413-432.
- Andrews, D.A., Dowden, C., & Rettinger, J.L. (2001). Special populations within

- corrections. In J.A. Winterdyk (Ed.), *Corrections in Canada: Social Reactions to Crime* (pp.170-212). Toronto: Prentice Hall.
- Andrews, D.A., Guzzo, L., Raynor, P., Rowe, R.C., Rettinger, L.J., Brews, A., & Wormith, J.S. (2012). Are the major risk/need factors predictive of both female and male reoffending?: A test with the eight domains of the Level of Service/Case Management Inventory. *International Journal of Offender Therapy and Comparative Criminology*, 56(1), 113-133.
- Andrews, D.A., & Kiessling, J.J. (1980). Program structure and effective correctional practices: A Summary of the CaVIC Research. In R.R. Ross & P. Gendreau (Eds.), *Effective Correctional Treatment* (Vol 1, pp. 439-463). Toronto: Butterworth.
- Andrews, D.A., & Robinson, D. (1984). *The Level of Supervision Inventory: Second Report*. Toronto: Ontario Ministry of Correctional Services.
- Auerhahn, K. (2006). Conceptual & methodological issues in the prediction of dangerous behavior. *Criminology*, 5(4), 771-778.
- Austin, J., Coleman, D., Peyton, J., & Johnson, K.D. (2003). *Reliability and Validity Study of the LSI-R Risk Assessment Instrument*. Washington, DC: Institute on Crime, Justice, & Corrections at The George Washington University.
- Baillargeon, J., Penn, J.V., Knight, K., Baillargeon, G., & Becker, E.A. (2010). Risk of reincarceration among prisoners with co-occurring severe mental illness and substance abuse disorders. *Administration and Policy in Mental Health and Mental Health Services Research*, 37(4), 367-374.
- Baird, C. (1981). Probation and parole classification – The Wisconsin Model. *Corrections Today*, 43(3), 36-41.
- Baird, C. (1991). *Validating Risk Assessment Instruments Used in Community Corrections*. Madison, WI: National Council on Crime & Delinquency.
- Baird, C. (2009). *A Question of Evidence: A Critique of Risk Assessment Models Used in the Justice System*. Washington, DC: National Council on Crime & Delinquency.
- Baird, C., & Neuenfeldt, D. (1990, August). The Client Management Classification System.
- Bandura, A., Barbaranelli, C., Caprara, G.V., & Pastorelli, C. (1996). Mechanisms of moral disengagement in the exercise of moral agency. *Journal of Personality and Social Psychology*, 71(2), 364-374.
- Barnoski, R. (2006). *Sex Offender Sentencing in Washington State: Predicting*

Recidivism Based on Demographics and Criminal History. Olympia, WA: Washington State Institute for Public Policy.

Barnoski, R., & Aos, S. (2003). *Washington Offender Accountability Act: An Analysis of the Department of Corrections Risk Assessment*. Olympia, WA: Washington State Institute for Public Policy.

Barnoski, R., & Drake, E. (2007). *Washington's Offender Accountability Act: Department of Corrections' Static Risk Assessment*. Olympia, WA: Washington State Institute for Public Policy.

Barnum, G., & Gobeil, R. (2012). *Prediction of Re-Offence Using the SIR-R1 and a Proxy*. Ottawa, ON: Correctional Service of Canada.

Beck, A.J., & Maruschak, L.M. (2004). *Hepatitis Testing and Treatment in State Prisons*. Washington, DC: Bureau of Justice Statistics.

Beck, A.J., & Mumola, C.J. (1999). *Prisoners in 1998*. Washington, DC: Bureau of Justice Statistics.

Blair, P.R., Marcus, D.K., & Boccaccini, M.T. (2008). Is there an allegiance effect for assessment instruments? Actuarial risk assessment as an exemplar. *Clinical Psychology: Science and Practice*, 15, 346-360.

Blumstein, A., & Beck, A.J. (1999). Population growth in U.S. prisons, 1980-1996. In M. Tonry & J. Petersilia (Eds.), *Prisons*. Chicago: University of Chicago Press.

Boles, S.M., Joshi, V., Grella, C., & Wellisch, J. (2005). Childhood sexual abuse patterns, psychosocial correlates, and treatment outcomes among adults in drug abuse treatment. *Journal of Child Sexual Abuse*, 14(1), 39-55.

Bonta, J. (1996). Risk-needs assessment & treatment. In A.T. Harland (Ed.), *Choosing Correctional Options That Work: Defining the Demand & Evaluating the Supply* (pp. 18-32). Thousand Oaks, CA: Sage.

Bonta, J. (2002). Offender risk assessment: Guidelines for selection and use. *Criminal Justice & Behavior*, 29, 355-379.

Bonta, J., & Andrews, D.A. (2007). *Risk-Need-Responsivity Model for Offender Assessment & Rehabilitation*. Ottawa, Ontario, Canada: Public Safety Canada.

Bonta, J., Law, M., & Hanson, R.K. (1998). The Prediction of criminal and violent recidivism among mentally disordered offenders: A Meta-analysis. *Psychological Bulletin*, 123(2), 123-142.

Bonta, J., Parkinson, R., Pang, B., Barkwell, L., & Wallace-Capretta, S. (1994). *The*

Revised Manitoba Classification System for Probationers. Ottawa: Solicitor General Canada.

- Bonta, J., Rugge, T., Scott, T.L., Bourgon, G., & Yessine, A.K. (2008). Exploring the black box of community supervision. *Journal of Offender Rehabilitation*, 47, 248-270.
- Bonta, J., Wallace-Capretta, S., & Rooney, J. (2000). A Quasi-experimental evaluation of an intensive rehabilitation supervision program. *Criminal Justice and Behavior*, 27, 312-329.
- Bourgon, G. & Armstrong, B. (2005). Transferring the principles of effective treatment into a “real world” prison setting. *Criminal Justice and Behavior*, 32(1), 3-25.
- Bourgon, G., & Guitierrez, L. (2012). The General responsivity principle in community supervision: The importance of probation officers using cognitive intervention techniques and its influence on recidivism. *Journal of Crime and Justice*, 35(2), 149-156.
- Brennan, T., & Breitenbach, M. (2009). The Taxonomic challenge to general theories of delinquency: Linking taxonomy development to delinquency theory. In O. Sahin & J. Maier (Eds.), *Delinquency: Causes, Reduction, & Prevention*. Hauppauge, NY: Nova Science Publishers.
- Brennan, T., & Dieterich, W. (2008). *Michigan Department of Corrections Core COMPAS Pilot Study: One-Year Follow-up*. Traverse City, MI: Northpointe Institute for Public Management.
- Brennan, T., Dieterich, W., & Breitenbach, M. (2008). *New York State Division of Parole COMPAS Reentry Pilot Study: Two-Year Follow-up*. Traverse City, MI: Northpointe Institute for Public Management.
- Brennan, T., Dieterich, B., & Ehret, B. (2007). *Research Synthesis: The Reliability and Validity of COMPAS*. Traverse City, MI: Northpointe.
- Brennan, T., Dieterich, B., & Ehret, B. (2009). Evaluating the predictive validity of the COMPAS risk & needs assessment system. *Criminal Justice and Behavior*, 36(1), 21-40.
- Brennan, T., Dieterich, B., & Oliver, W. (2005). *The COMPAS Scales: Normative Data for Males and Females in Community and Incarcerated Samples*. Traverse City, MI: Northpointe Institute for Public Management.
- Brennan, T., Dieterich, B., & Oliver, W. (2006). *San Bernardino County Probation Department COMPAS Psychometric Reports*. Traverse City, MI: Northpointe Institute for Public Management.

- Brennan, T., & Oliver, W.L. (2000). *Evaluation of Reliability and Validity of COMPAS Scales: National Aggregate Sample*. Traverse City, MI: Northpointe Institute for Public Management.
- Bureau of Justice Statistics (1999). *Correctional Populations in the United States, 1996*. Washington, DC: US Department of Justice.
- Bushway, S., & Reuter, P. (1997). Labor markets and crime risk factors. In *Preventing Crime: What Works, What Doesn't, What's Promising: A Report to the United States Congress*. Washington, DC: National Institute of Justice.
- Bushway, S., & Reuter, P. (2002). Labor markets and crime. In J.Q. Wilson & J. Petersilia (Eds.), *Crime: Public Policies for Crime Control* (Vol. 1, pp. 191-224). San Francisco: ICS Press.
- Busy, J., Glick, B., & Taymans, J. (2011). *Thinking for a Change: Integrated Cognitive Behavior Change Program*. Washington, DC: National Institute of Corrections.
- Butler, M.A. (2008). *Actuarial Prediction of Institutional Maladjustment and Recidivism in Severe Male Juvenile Offenders*. (Doctoral Dissertation). Florida State University: Tallahassee, FL.
- Caher, J. (2007). Effect of risk assessment rule on parole decisions is unclear. *New York Law Journal*, 247(82), 1.
- Campbell, M.A., French, S., & Gendreau, P. (2009). The Prediction of violent in adult offenders: A Meta-analytic comparison of instruments and methods of assessment. *Criminal Justice and Behavior*, 36, 567-590.
- Carey, M. (2010). *Shaping Offender Behavior*. Silver Spring, MD: Center for Effective Public Policy.
- Clark, P.M. (2011). Cognitive-behavioral therapy: An Evidence-based intervention for offenders. *Corrections Today*, 73(1), 62-64.
- Cohen, L.E., & Felson, M. (1979) Social change and crime rate trends: A Routine Activity approach. *American Sociological Review*, 44(4), 588-608.
- Connelly, M. (2003). Critical examination of actuarial offender-based prediction assessments: Guidance for the next generation of assessments. *Dissertation Abstracts International*, 64(12), 4635.
- Cook, S.L., Smith, S.G., Tusher, C.P., & Raiford, J. (2005). Self-reports of traumatic events in a random sample of incarcerated women. *Women and Criminal Justice*, 16(1), 107-126.

- Courtney, K.O., & Howard, J. (2011). Assessing and improving the reliability of risk instruments: The New Mexico Juvenile Justice Reliability model. *Journal of Juvenile Justice*, 1(1).
- Craig, L., Browne, K., Stringer, I., & Beech, A. (2004). Limitations in actuarial risk assessment of sexual offenders: A Methodological note. *The British Journal of Forensic Practice*, 6(1), 16-32.
- Crime and Justice Institute (2004). *Implementing Evidence-Based Practice in Community Corrections: The Principles of Effective Intervention*. Washington, DC: National Institute of Corrections.
- Cronin, J. (2001, September). *The Path to Successful Reentry: The Relationship Between Correctional Education, Employment, and Recidivism*. Columbia, MO: Institute of Public Policy at the University of Missouri.
- Cullen, F.T. (2002). Rehabilitation and treatment programs. In J.Q. Wilson & J. Petersilia (eds.), *Crime: Public Policies for Crime Control* (2nd edition). San Francisco: ICS Press.
- Dahle, K.P. (2006). Strengths and limitations of actuarial prediction of criminal re-offence in a German prison sample: A Comparative study of LSI-R, HCR-20, and PCL-R. *International Journal of Law and Psychiatry*, 29(5), 431-442.
- Davis, L.M., Bozick, R., Steele, J.L., Saunders, J., & Miles, J.N.V. (2013). *Evaluating the Effectiveness of Correctional Education: A Meta-Analysis of Programs that Provide Education to Incarcerated Adults*. Washington, DC: RAND Corporation.
- Day, S. (2005). Mothers in prison: How the Adoption and Safe Families Act of 1997 threatens parental rights. *Wisconsin Women's Law Journal*, 20, 217.
- DeLisi, M., Hochstetler, A., Higgins, G.E., Beaver, K.M., & Graeve, C.M. (2008). Toward a general theory of criminal justice: Low self-control & offender noncompliance. *Criminal Justice Review*, 33(2), 141-158.
- Department of Corrections and Community Supervision (2012). *Community Supervision Legislative Report*. Albany, NY: State of New York.
- Department of Corrections and Community Supervision (2013). *Community Supervision Legislative Report*. Albany, NY: State of New York.
- Department of Corrections and Community Supervision (2014). *Community Supervision Legislative Report*. Albany, NY: State of New York.
- Dieterich, W., Brennan, T., & Oliver, W. (2011). *Predictive Validity of the COMPAS*

Core Risk Scales: A Probation Outcomes Study Conducted for the Michigan Department of Corrections. Traverse City, MI: Northpointe Institute for Public Management.

Dieterich, W. Oliver, W., & Brennan, T. (2011). *Predictive Validity of the Reentry COMPAS Risk Scales: An Outcomes Study with Extended Follow-up Conducted for the Michigan Department of Corrections.* Traverse City, MI: Northpointe Institute for Public Management.

Ditton, P.M. (1999). *Mental Health and Treatment of Inmates and Probationers.* Washington, DC: Bureau of Justice Statistics.

Ditton, P.M., & Wilson, D.J. (1999). *Truth in Sentencing in State Prisons.* Washington, DC: Bureau of Justice Statistics.

Division of Criminal Justice Services (2011). *2009 Profile: County Reentry Task Force Participants.* Albany, NY: State of New York.

Dowdy, E.R., Lacy, M., & Unnithan, P. (2002). Correctional prediction and the Level of Supervision Inventory. *Journal of Criminal Justice*, 30, 29-39.

Durlak, J.A. (1998). Why program implementation is important. *Journal of Prevention and Intervention in the Community*, 17, 5-18.

The Editorial Board (2014, February 16). New York's Broken Parole System. *The New York Times*, Retrieved from http://www.nytimes.com/2014/02/17/opinion/new-yorks-broken-parole-system.html?_r=0.

Eisenberg, M., Bryl, J., & Fabelo, T. (2009). *Validation of the Wisconsin Department of Corrections Risk Assessment Instrument.* Lexington, KY: Council of State Governments Justice Center.

Elliott, D.S. (1995). *Lies, Damn Lies, & Arrest Statistics.* Sutherland Award Presentation, American Society of Criminology Meeting, Boston, MA.

Enos, S. (1998). Managing motherhood in prison: The Impact of race and ethnicity on child placements. *Women in Therapy*, 20(4), 57-73.

Enos, S. (2001). *Mothering From the Inside: Parenting in a Women's Prison.* Albany, NY: SUNY.

Estroff, S.E., & Zimmer, C. (1994). Social networks, social support, and violence among persons with severe, persistent mental illness. In J. Monahan & H.J. Steadman (Eds.), *Violence and Mental Disorder: Developments in Risk Assessment* (pp. 259-295). Chicago: University of Chicago Press.

- Farabee, D., Zhang, S., Roberts, R.E., & Yang, J. (2010). *COMPAS Validation Study: Final Report*. Los Angeles: Semel Institute of Neuroscience and Human Behavior, UCLA.
- Farole, D.J. (2003). *The Harlem Parole Reentry Court Evaluation: Implementation & Preliminary Impacts*. New York, NY: Center for Court Innovation.
- Farrington, D.P. (1991). Childhood aggression and adult violence: Early precursors and later life outcomes. In D.J. Pepler & K.H. Rubin (Eds.), *The Development and Treatment of Childhood Aggression* (pp. 5-29). Hillsdale, NJ: Lawrence Erlbaum.
- Farrington, D.P., & Loeber, R. (1989). Relative improvement over chance (RIOC) & phi as measures of predictive efficacy and strength of association in 2 X 2 tables. *Journal of Quantitative Criminology*, 5(3), 201-213.
- Farrington, D.P., & Tarling, R. (Eds.) (1985). *Prediction in Criminology*. Albany: State University of New York Press.
- Fass, T.L., Heilbrun, K., Dematteo, D. & Fretz, R. (2008). The LSI-R & the COMPAS: Validation data on two risk-needs tools. *Criminal Justice and Behavior*, 35(9), 1095-1108.
- Felitti, V.J. (2004). *The Origins of Addiction: Evidence from the Adverse Childhood Experiences Study*. San Diego, CA: Kaiser Permanente.
- Ferguson, A.M., James, R.P., & Ogloff, L.T. (2009). Predicting recidivism by mentally disordered offenders using the LSI-R: SV. *Criminal Justice and Behavior*, 36(1), 5-20.
- Flores, A.W., Lowenkamp, C.T., Holsinger, A.M., & Latessa, E.J. (2006). Predicting outcome with the Level of Service Inventory-Revised: The Importance of implementation integrity. *Journal of Criminal Justice*, 34, 523-529.
- Flores, A.W., Lowenkamp, C.T., Smith, P. & Latessa, E.J. (2006). Validating the Level of Service Inventory-Revised on a Sample of Federal Probationers. *Federal Probation*, 70(2), 44-48.
- Flores, A.W., Travis, L.F., & Latessa, E.J. (2004). *Case Classification for Juvenile Corrections: An Assessment of the Youth Level of Service/Case Management Inventory (YLS/CMI) - Executive Summary*. Washington, DC: U.S. Department of Justice.
- Florida Department of Corrections (2003). *Florida Department of Corrections Recidivism Report: Inmates Released from Florida Prisons, June 1995 to July 2001*. Tallahassee, FL: Florida Department of Corrections.

- Fontaine, J. (2013). The Role of supportive housing in successful reentry outcomes for disabled prisoners. *Cityscape: A Journal of Policy Development and Research*, 15(3), 53-75.
- Fortune, C.A., & Ward, T. (2013). The Rehabilitation of offenders: Striving for good lives, desistance, and risk reduction. In J. Helfgott (Ed.), *Criminal Psychology*. New York: Praeger Publishers.
- Fortune, C.A., Ward, T., & Willis, G.M. (2012). The Rehabilitation of offenders: Reducing risk and promoting better lives. *Psychiatry, Psychology, and Law*, 19, 646.
- Fowler, L.T. (1993). What classification for women? In *Classification: A Tool for Managing Today's Offenders* (pp. 37-45). Arlington, VA: American Correctional Association.
- Gaes, G.G., Flanagan, T.J., Motiuk, L.L., & Stewart, L. (1999). Adult correctional treatment. In M. Tonry & J. Petersilia (Eds.), *Prisons*. Chicago: University of Chicago Press.
- Gendreau, P., Little, T., & Goggin, C. (1996). A Meta-analysis of the predictors of adult offender recidivism: What works! *Criminology*, 34, 575-607.
- Girard, L., & Wormith, J. (2004). The Predictive validity of the Level of Service Inventory-Ontario Revision on general and violent recidivism among various offender groups. *Criminal Justice and Behavior*, 31, 150-181.
- Glaze, L.E., & Bonczar, T.P. (2006). *Probation and Parole in the United States, 2005*. Washington, DC: Bureau of Justice Statistics.
- Glaze, L.E., & Bonczar, T.P. (2010). *Probation and Parole in the United States, 2009*. Washington, DC: Bureau of Justice Statistics.
- Glaze, L.E., & Maruschak, L.M. (2008). *Parents in Prison and Their Minor Children*. Washington, DC: Bureau of Justice Statistics.
- Gottfredson, D.M. (1978). *Guidelines for Parole and Sentencing: A Policy Control Method*. Washington, DC: Lexington.
- Gottfredson, M.R., & Hirschi, T. (1990). *A General Theory of Crime*. Stanford, CA: Stanford University Press.
- Gottfredson, S.D., & Moriarty, L.J. (2006). Statistical risk assessment: Old problems and new applications. *Crime and Delinquency*, 52(1), 178-200.
- Government Accounting Office (2000). *State and Federal Prisoners: Profile of Inmate*

Characteristics. Washington, DC: Government Accounting Office.

- Grove, W.M., & Meehl, P.E. (1996). Comparative efficiency of informal (subjective impressionistic) & formal (mechanical, algorithmic) prediction procedures: The Clinical-statistical controversy. *Psychology, Public Policy, and Law*, 2(2), 293-323.
- Grove, W.M., Zald, D.H., Lebow, B.S., Smitz, B.E., & Nelson, C. (2000). Clinical versus mechanical prediction: A Meta-analysis. *Psychological Assessment*, 12(1), 19-30.
- Guevara, M., & Solomon, E. (2009). *Implementing Evidence-Based Policy and Practice in Community Corrections* (2nd ed.). Washington, D.C.: National Institute of Corrections.
- Hairston, C.F. (1988). Family ties during imprisonment: Do they influence future criminal activity? *Federal Probation*, 51(1), 48-52.
- Hairston, C.F. (2002). *Prisoners and Families: Parenting Issues During Incarceration*. Washington, DC: Urban Institute.
- Hamilton, Z. (2010). *Do Reentry Courts Reduce Recidivism?: Results from the Harlem Parole Reentry Court*. New York, NY: Center for Court Innovation.
- Hammett, T.M., Roberts, C., & Kennedy, S. (2000). Health-related issues in prisoner reentry. *Crime and Delinquency*, 47(3), 390-409.
- Hanson, R.K., & Wallace-Capretta, S. (2000a). *Predicting Recidivism Among Male Batterers*. Ottawa: Solicitor General of Canada.
- Hanson, R.K., & Wallace-Capretta, S. (2000b). *A Multi-Site Study of Treatment for Abusive Men*. Ottawa: Solicitor General of Canada.
- Hare, R.D. (1991) *Manual for the Hare Psychopathy Checklist-Revised*. Toronto: Multi-Health Systems.
- Harlow, C.W. (2003). *Education and Correctional Populations*. Washington, DC: Bureau of Justice Statistics.
- Harper, R., & Hardy, S. (2000). An evaluation of motivational interviewing as a method of intervention with clients in a probation setting. *British Journal of Social Work*, 30, 393-400.
- Harris, P.M. (1994). Client management classification and prediction of probation outcomes. *Crime & Delinquency*, 40(2), 154-174.
- Harrison, P.M., & Beck, A.J. (2006). *Prison and Jail Inmates at Midyear 2005*.

Washington, DC: Bureau of Justice Statistics.

- Healey, K.M. (1999). *Case Management in the Criminal Justice System: Research in Action*. Washington, DC: National Institute of Justice.
- Hemphill, J., & Hare, R.D. (2004). Some misconceptions about the Hare PCL-R and risk assessment: A Reply to Gendreau, Goggin, and Smith. *Criminal Justice and Behavior*, 31(2), 203-243.
- Henderson, H., & Miller, H.A. (2011). The (Twice) failure of the Wisconsin Risk Need Assessment in a sample of probationers. *Criminal Justice Policy Review*, 24(2), 199-221.
- Henggeler, S.W., Melton, G.B., Brondino, M.J., Scherer, D.G., & Hanley, J.H. (1997). Multisystemic therapy with violent and chronic juvenile offenders and their families: The Role of treatment fidelity in successful dissemination. *Journal of Consulting and Clinical Psychology*, 65, 0-13.
- Herrschaft, B.A., & Hamilton, Z. (2011). *Recidivism Among Parolees in New York City, 2001-2008*. New York, NY: Center for Court Innovation.
- Higgins, S.T., Heil, S.H., & Lussier, J.P. (2004). Clinical implications of reinforcement as a determinant of substance use disorders. *Annual Review of Psychology*, 55, 431-461.
- Hirschi, T. (1969). *Causes of Delinquency*. Berkeley, CA: University of California Press.
- Ho, A. (2013). *The Impact of Error on Offender Risk Assessment* (Unpublished dissertation) Rutgers University, Newark, NJ.
- Hochstetler, A., DeLisi, M., & Pratt, T.C. (2010). Social support and feelings of hostility among released inmates. *Crime and Delinquency*, 56(4), 588-607
- Hoffman, P.B. (1994). Twenty years of operational use of a risk prediction instrument: The United States Parole Commission's Salient Factor Score. *Journal of Criminal Justice*, 22(6), 477-494.
- Hoffman, P.B., & Beck., J.L. (1974). Parole decision-making: A Salient Factor Score. *Journal of Criminal Justice*, 2, 195-206.
- Holsinger, A.M., Lowenkamp, C.T., & Latessa, E.J. (2003). Ethnicity, gender, and the Level of Service Inventory-Revised. *Journal of Criminal Justice*, 31, 309-320.
- Holsinger, A.M., Lowenkamp, C.T., & Latessa, E.J. (2006). Exploring the validity of the Level of Service Inventory-Revised with Native American Offenders. *Journal of Criminal Justice*, 34, 331-337.

- Holzer, H., Raphael, S., & Stoll, M. (2003). *Employment Barriers Facing Ex-Offenders*. Paper presented at the Urban Institute Reentry Roundtable, New York University Law School.
- James, D.J., & Glaze, L.E. (2006). *Mental Health Problems of Prison and Jail Inmates*. Washington, DC: Bureau of Justice Statistics.
- Justice Policy Center (2006). *Understanding the Challenges of Prisoner Reentry: Research Findings from the Urban Institute's Prisoner Reentry Portfolio*. Washington, DC: Urban Institute.
- Justice System Assessment & Training (2010). *Wisconsin Risk & Needs Tool (WRN)*. Retrieved from <http://www.j-satresources.com/Toolkit/Adult/adf6e846-f4dc-4b1e-b7b1-2ff28551ce85>.
- Kane, M., Bechtel, K., Revicki, J., McLaughlin, E., & McCall, J. (2011). *Exploring the Role of Responsivity and Assessment with Hispanic and American Indian Offenders*. Boston, MA: Crime and Justice Institute at Community Resources for Justice.
- Kates, E., Ransford, P., & Cardozo, C. (2005). *Women in Prison in Massachusetts: Maintaining Family Connections*. Boston: Center for Women in Politics and Public Policy at the University of Massachusetts.
- Kerbs, J.J., Jones, M., & Jolley, J.M. (2009). Discretionary decision-making by probation and parole officers: The Role of extralegal variables as predictors of responses to technical violations. *Journal of Contemporary Criminal Justice*, 25(4), 424-441.
- Kelly, C.E., & Walsh, W.N. (2008). The Predictive validity of the Level of Service Inventory-Revised with drug-involved offenders. *Criminal Justice and Behavior*, 35, 819-831.
- Kennedy, S.M. (2000). *Treatment Responsivity: Reducing Recidivism by Enhancing Treatment Effectiveness*. Ottawa: Correctional Service Canada.
- King, R., & Elderboom, B. (2014). *Improving Recidivism as a Performance Measure*. Washington, DC: Urban Institute.
- Kirby, K.C., Marlowe, D.B., Festinger, D.S., Garvey, K.A., & La Monaca, V. (1999). Community reinforcement training for family and significant others of drug abusers: A Unilateral intervention to increase treatment entry for drug users. *Drug and Alcohol Dependence*, 56(1), 85-96.
- Kubrin, C.E., & Stewart, E.A. Predicting who re-offends: The Neglected role of

- neighborhood context in recidivism studies. *Criminology*, 44(1), 165-197.
- La Vigne, N., Davies, E., Palmer, T., & Halberstadt, R. (2008). *Release Planning for Successful Reentry: A Guide for Corrections, Service Providers, and Community Groups*. Washington, DC: Urban Institute.
- La Vigne, N.G., Visser, C., & Castro, J. (2004). *Chicago Prisoners' Experiences Turning Home*. Washington, DC: Urban Institute.
- Landenberger, N.A., & Lipsey, M. (2005). The Positive effects of cognitive-behavioral programs for offenders: A Meta-analysis of factors associated with effective treatment. *Journal of Experimental Criminology*, 1, 451-476.
- Langan, P.A., & Levin, D.J. (2002). *Recidivism of Prisoners Released in 1994*. Washington, DC: Bureau of Justice Statistics.
- Latessa, E.J., Cullen, F., & Gendreau, P. (2002). Beyond correctional quackery: Professionalism and the possibility of professional treatment. *Federal Probation*, 66(2), 43-49.
- Latessa, E.J., Lemke, R., Makarios, M., Smith, P., & Lowenkamp, C.T. (2009). *Creation and Validation of the Ohio Risk Assessment System: Final Report*. Cincinnati, OH: University of Cincinnati. Retrieved from http://www.ocjs.ohio.gov/ORAS_FinalReport.pdf.
- Latessa, E.J., Lemke, R., Makarios, M., Smith, P., & Lowenkamp, C.T. (2010). The Creation and validation of the Ohio Risk Assessment System (ORAS). *Federal Probation*, 74(1), 16-22.
- Latessa, E.J., & Lowenkamp, C. (2005). *What are Criminogenic Needs and Why Are They Important?* Ohio Judicial Conference.
- Latimer, J., Dowden, C., Morton-Bourgon, K.E., Edgar, J., & Bania, M. (2003). Treating youth in conflict with the law: A New meta-analysis. *Youth Justice Research Series*. Ottawa: Department of Justice Canada.
- Lindsay, L., & Barry, J. (2012). *Criminal Court of the City of New York: Annual Report 2011*. New York City: Office of the Chief Clerk of New York City Criminal Court.
- Lipsey, M. (1995). What do we learn from 400 research studies on the effectiveness of treatment with juvenile delinquents? In J. McGuire (Ed.), *What Works: Reducing Reoffending – Guidelines from Research and Practice* (pp. 63-78). Chichester, UK: Wiley.
- Lipsey, M.W., Chapman, G.L., & Landenberger, N.A. (2001). Cognitive behavioral

- programs for offenders. *The Annals of the American Academy of Political and Social Sciences*, 578, 144-157.
- Lipton, D.S., Martinson, R., & Wilks, J. (1975). *The Effectiveness of Correctional Treatment: A Survey of Treatment Evaluation Studies* (Vol. 1). New York: Praeger.
- Loeber, R., & Dishion, T. (1983). Early predictors of male delinquency: A Review. *Psychological Bulletin*, 94(1), 68-99.
- Lowenkamp, C.T., & Bechtel, K. (2007). The Predictive validity of the LSI-R on a sample of offenders drawn from the records of the Iowa Department of Corrections Management System. *Federal Probation*, 71(3), 25-29.
- Lowenkamp, C.T., Hubbard, D., Makarios, M.D., & Latessa, E.J. (2009). A Quasi-experimental evaluation of Thinking for a Change: A 'real-world' application. *Criminal Justice and Behavior*, 36(2), 137-146.
- Lowenkamp, C.T., & Latessa, E.J. (2000). *Validating the Level of Service Inventory-Revised in Ohio's Community-Based Correctional Facilities*. Cincinnati, OH: University of Cincinnati.
- Lowenkamp, C.T., & Latessa, E.J. (2004). Increasing the effectiveness of correctional programming through the risk principle: Identifying offenders for residential placement. *Criminology and Public Policy*, 4(2), 263-290.
- Lowenkamp, C.T., Latessa, E.J., & Holsinger, A.M. (2004). Empirical evidence on the importance of training and experience in using the Level of Service Inventory-Revised. *Topics in Community Corrections*, 49-53. Retrieved from http://www.cj-resources.com/CJ_Corrections_pdfs/Empirical%20Evidence%20on%20the%20Importance%20of%20training%20and%20the%20experience%20in%20using%20the%20LSI%20-%20Lowenkamp%20et%20al%202004.pdf.
- Lowenkamp, C.T., Latessa, E.J., & Holsinger, A.M. (2006). The risk principle in action: What have we learned from 13,676 offenders and 97 correctional programs. *Crime & Delinquency*, 51(1), 1-17.
- Lowenkamp, C.T., Lovins, B., & Latessa, E.J. (2009). Validating the Level of Service Inventory-Revised and the Level of Service Inventory: Screening Version with a sample of probationers. *The Prison Journal*, 89(2), 192-204.
- Luborsky, L., Diguer, L., Seligman, D.A., Rosenthal, R., Krause, E.D., Johnson, S., et al. (1999). The Researcher's own therapy allegiances: A "Wild card" in comparisons of treatment efficacy. *Clinical Psychology: Science and Practice*, 6, 95-106.
- Lurigio, A.J. (2001). Effective services for parolees with mental illnesses. *Crime and*

Delinquency, 47(3), 446-461.

Lynch, J.P., & Sabol, W.J. (2001). *Prisoner Reentry in Perspective*. Washington, DC: Urban Institute.

Mackenzie, D.L. (2001). *Sentencing and Corrections in the 21st Century: Setting the Stage for the Future*. College Park, MD: University of Maryland.

Martinson, R. (1974). What Works? Questions and answers about prison reform. *The Public Interest*, 35, 22-54.

Martinson, R. (1979). New findings, new views: A Note of caution regarding prison reform. *Hofstra Law Review*, 7, 243-258.

Maruschak, L.M. (2006). *Medical Problems of Jail Inmates*. Washington, DC: Bureau of Justice Statistics.

Maruschak, L.M. (2009). *HIV in Prisons, 2007-2008*. Washington, DC: Bureau of Justice Statistics.

Maruschak, L.M., & Bonczar, T.P. (2013). *Probation and Parole in the United States, 2012*. Washington, DC: Bureau of Justice Statistics, US Department of Justice.

Mears, D.P., Winterfield, L., Hunsaker, J., Moore, G.E., & White, R. (2003). *Drug Treatment in the Criminal Justice System: The Current State of Knowledge*. Washington, DC: Urban Institute.

Messina, N., & Grella, C. (2006). Childhood trauma and women's health outcomes in a California prison population. *American Journal of Public Health*, 96(10), 1842-1848.

Metraux, S., & Culhane, D.P. (2004). Homeless shelter use & reincarceration following prison release. *Criminology and Public Policy*, 3(2), 139-160.

Meyers, R.J., Miller, W.R., Smith, J.E., & Tonnigan, S. (2002). A Randomized trial of two methods for engaging treatment-refusing drug users through concerned significant others. *Journal of Consulting and Clinical Psychology*, 70 (5), 1182-1185.

Mihalic, S. (2004). The Importance of implementation fidelity. *Emotional & Behavioral Disorders in Youth*, 4(4), 83-86, 99-105.

Mihalic, S., & Irwin, K. (2003). Blueprints for violence prevention: From research to real world settings – factors influencing the successful replication of model programs. Boulder, CO: Center for the Study and Prevention of Violence.

- Milkman, H., & Wanberg, K. (2007). *Cognitive-Behavioral Treatment: A Review and Discussion for Correction Professionals*. Washington, DC: National Institute of Corrections.
- Miller, N.A., & Najavits, L.M. (2012). Creating trauma-informed correctional care: A Balance of goals and environment. *European Journal of Psychotraumatology*, 3, 1-8.
- Miller, W., & Rollnick, S. (2002). *Motivational Interviewing: Preparing People for Change*. New York: Guilford Press.
- Mitchell, O., Wilson, D.B., & Mackenzie, D.L. (2006). *The Effectiveness of Incarceration-Based Drug Treatment on Criminal Behavior*. Oslo, Norway: Campbell Collaboration.
- Monahan, J. (1996). *Mental Illness and Violent Crime*. Washington, DC: National Institute of Justice.
- Moore, G.E., & Mears, D.P. (2003). *Voices from the Field: Practitioners Identify Key Issues in Corrections-Based Drug Treatment*. Washington, DC: Urban Institute.
- Morenoff, J.D., & Harding, D.J. (2011). *Final Technical Report: Neighborhoods, Recidivism, and Employment Among Returning Prisoners*. Ann Arbor, MI: Institute for Social Research, University of Michigan.
- Motiuk, L.L. (1993). Where are we in our ability to assess risk? *Forum on Corrections Research*, 5, 14-18.
- Motiuk, L.L., Bonta, J., & Andrews, D.A. (1990). *Dynamic Predictive Criterion Validity in Offender Assessment*. Paper presented at the Canadian Psychological Association Annual Convention, Ottawa.
- Motiuk, L.L., & Porporino, F. (1989). *Offender Risk/Needs Assessment: A Study of Conditional Releases*. Ottawa: Information Canada.
- Moore, R.F. (2007, March 18). Convict alley in the Harlem nabe. *New York Daily News*, Retrieved from: <http://www.nydailynews.com/news/convict-alley-harlem-nabe-article-1.216837>.
- Mumola, C.J. (1999). *Drug Use and Dependence, State and Federal Prisoners, 1997*. Washington, DC: Bureau of Justice Statistics.
- Mumola, C.J. (2000). *Incarcerated Parents and Their Children*. Washington, DC: Bureau of Justice Statistics.
- Mumola, C.J., & Karberg, J.C. (2006). *Drug Use and Dependence, State and Federal*

- Prisoners, 2004*. Washington, DC: Bureau of Justice Statistics.
- Myers, R., Villanueva, M., & Smith, J.E. (2005). The Community Reinforcement Approach: History and new direction. *Journal of Cognitive Therapy*, 19(3), 247-260.
- Nally, J.M., Lockwood, S., Ho, T., & Knutson, K. (2012). The Post-release employment and recidivism among different types of offenders with a different level of education: A 5 year follow-up study in Indiana. *Justice Policy Journal*, 9(1).
- National Center on Addiction and Substance Abuse (CASA) at Columbia University (1998). *Behind Bars: Substance Abuse and America's Prison Population*. New York: CASA.
- National Commission on Correctional Health Care (NCCHC) (2002). *The Health Status of Soon-to-Be-Released Inmates: A Report to Congress, Volume 1*. Washington, DC: National Institute of Justice.
- National Reentry Resource Center (2014). *Measuring and Using Juvenile Recidivism Data to Inform Policy, Practice, and Resource Allocation*. Retrieved from <http://csgjusticecenter.org/wp-content/uploads/2014/07/Measuring-and-Using-Juvenile-Recidivism-Data-to-Inform-Policy-Practice-and-Resource-Allocation.pdf>.
- Northpointe Institute for Public Management (2009). *Treatment relevant typologies in COMPAS Reentry*. Traverse City, MI: Northpointe.
- Northpointe Institute for Public Management (2012). *COMPAS Risk & Need Assessment System: Selected Questions Posed by Inquiring Agencies*. Traverse City, MI: Northpointe.
- Northpointe Institute for Public Management (2013). *Practitioner's guide to COMPAS*. Traverse City, MI: Northpointe.
- Nuffield, J. (1982). *Parole Decision-making in Canada*. Ottawa: Solicitor General of Canada.
- O'Brien, P. (2002). *Reducing Barriers to Employment for Women Ex-Offenders: Mapping the Road to Reintegration*. Chicago, IL: University of Illinois at Chicago, Jane Addams College of Social Work.
- Office of the Attorney General (2013). *A Report on Arrests Arising from the New York City Police Department's Stop-and-Frisk Practices*. Albany, NY: New York State Office of the Attorney General.

- Onifade, E., Davidson, W., Campbell, C., Turke, G., Malinowski, J., & Turner, K. (2008). Predicting recidivism in probationers with the Youth Level of Service/Case Management Inventory (LS/CMI). *Criminal Justice and Behavior*, 35(4), 474-483.
- Ore, W., & Baird, C. (2014). *Beyond Risk and Needs Assessments*. Washington, DC: National Council on Crime & Delinquency.
- Ostermann, M., & Herrschaft, B.A. (2013). Validating the Level of Service Inventory-Revised: A Gendered Perspective. *The Prison Journal*, 93(3), 291-312.
- Palmer, T. (1975). Martinson revisited. *Journal of Research in Crime and Delinquency*, 12, 133-152.
- Palmer, T. (1995). Programmatic and non-programmatic aspects of successful intervention: New directions for research. *Crime and Delinquency*, 41(1), 100-131.
- Petersilia, J. (1999). Parole and prisoner reentry in the United States. *Crime and Justice*, 26(Prisons), 479-529.
- Petersilia, J. (2000). *When Prisoners Return to the Community: Political, Economic, and Social Consequences*. Washington, DC: National Institute of Justice.
- Petersilia, J. (2003). *When Prisoners Come Home: Parole and Prisoner Reentry*. New York: Oxford University Press.
- Petry, N., & Bohn, M.J. (2003). Fishbowls and candy bars: Using low-cost inventives to increase treatment retention. *Science and Practice Perspectives*, 2, 55-61.
- Petry, N., & Simcic, F. Jr. (2002). Recent advances in the dissemination of contingency management techniques: Clinical and research perspectives. *Journal of Substance Abuse Treatment*, 23, 81-86.
- Pew Center on the States (2008). *One in 100: Behind Bars in America*. Washington DC: The Pew Charitable Trusts.
- Pew Center on the States (2009). *One in 31: The Long Reach of American Corrections*. Washington DC: The Pew Charitable Trusts.
- Philipse, M.W., Koeter, M.W., van der Staak, C.P., & van den Brink, W. (2006). Static and dynamic patient characteristics as predictors of criminal recidivism: A Prospective study in a Dutch forensic psychiatric sample. *Law and Human Behavior*, 30(3), 309-327.
- Prashaw, R. (2001). *Restorative justice: Lessons in empathy and connecting people*.

Canadian Journal of Community Mental Health, 20(2), 23-27.

Prendergast, M.L., Podus, D., Chang, E., & Urada, D. (2002). The Effectiveness of drug abuse treatment: A Meta-Analysis of comparison group studies. *Drug and Alcohol Dependence*, 67, 53-72.

Quinsey, V. L., Harris, G.T., Rice, M.E., & Cormier, C.A. (1998). *Violent Offenders: Appraising and Managing Risk*. Washington, DC: American Psychological Association.

Ragusa-Salerno, L.M., Ostermann, M., & Thomas, S.S. (2013). Does the LSI-R have utility for sex offenders?. *Criminal Justice and Behavior*, 40(9), 952-969.

Raynor, P. (2007). Risk and need assessment in British probation: The Contribution of the LSI-R. *Psychology, Crime, and Law*, 13, 125-138.

Raynor, P., Kynch, J., Roberts, C., & Merrington, S. (2000). *Risk & Need Assessment in Probation Services: An Evaluation*. London: Home Office.

Rettinger, L.J. (1998). *A Recidivism Follow-up Study Investigating Risk and Need Within A Sample of Provincially Sentenced Women* (Unpublished dissertation). Retrieved from <https://curve.carleton.ca/theses/25234>.

Rettinger, L.J., & Andrews, D.A. (2010). General risk and need, gender, specificity, and the recidivism of female offenders. *Criminal Justice and Behavior*, 37, 29-46.

Roozen, H.G., Boulogne, J.J., van Tulder, M.W., van den Brink, W., De Jong, C.A., & Kerkhof, A. (2004). A Systematic review of the effectiveness of the Community Reinforcement Approach in alcohol, cocaine, and opioid addiction. *Drug & Alcohol Dependence*, 74(1), 1-13.

Rosenfeld, R., Wallman, J., & Fornango, R.J. (2005). The Contribution of ex-prisoners to crime rates. In J. Travis & C. Visher (Eds.), *Prisoner Reentry and Public Safety in America*. New York: Cambridge University Press.

Rothfeld, M. (2009, October 17). As rehab programs are cut, prisons do less to keep inmates from returning. *LA Times*. Retrieved from: <http://articles.latimes.com/2009/oct/17/local/me-rehab17>.

Rowland, M.G. (2013). Too many going back, not enough getting out? Supervision violators, probation supervision, and overcrowding in the Federal Bureau of Prisons. *Federal Probation*, 77 (2), 12-27.

Rubinstein, G. (2001). *Getting to Work: How TANF Can Support Ex-Offender Parents in the Transition to Self Sufficiency*. Washington, DC: Legal Action Center

- Rudes, D.S., Taxman, F.S., Portillo, S., Murphy, A., Rhodes, A., Stitzer, M., Luongo, P.F., & Friedmann, P.D. (2012). Adding positive reinforcement in justice settings: Acceptability and feasibility. *Journal of Substance Abuse Treatment*, 42(3), 260-270.
- Ryan, R.M., & Deci, E.L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist*, 55 66-78.
- Sampson, R.J., & Laub, J.H. (1993). *Crime in the Making: Pathways and Turning Points Through Life*. Cambridge, MA: Harvard University Press.
- Schlager, M. (2005). *Assessing the Reliability and Validity of the Level of Service Inventory-Revised (LSI-R) on a Community Corrections Sample: Implications for Corrections and Parole Policy*. (Unpublished dissertation) Rutgers University, Newark, NJ.
- Schlager, M.D., & Pacheco, D. (2011). An Examination of changes in LSI-R scores over time: Making the case for needs-based case management. *Criminal Justice and Behavior*, 38(6), 541-553.
- Schlager, M., & Simourd, D.J. (2007). Validity of the Level of Service Inventory-Revised (LSI-R) Among African American and Hispanic Male Offenders. *Criminal Justice and Behavior*, 34, 545-554.
- The Sentencing Project (2012). *Trends in U.S. Corrections*. Washington, DC: The Sentencing Project.
- Serill, M.S. (1977). Determinate sentencing: The History, the theory, the debate. *Corrections Magazine*, 3(3), 3-13.
- Serin, R.C., Mailloux, D.L., & Hucker, S. (2000). *The Utility of Clinical and Actuarial Risk Assessments for Offenders in Pre-Release Psychiatric Decision-Making*. Ottawa, ON: Correctional Service of Canada.
- Silver, E., & Miller, L.L. (2002). A Cautionary note on the use of actuarial risk assessment tools for social control. *Crime & Delinquency*, 48, 138-161.
- Simourd, D.J. (2004). Use of dynamic risk/need assessment instruments among long-term incarcerated offenders. *Criminal Justice and Behavior*, 31, 306-323.
- Simourd, D.J. (2006). *Validation of Risk/Needs Assessments in the Pennsylvania Department of Corrections: Final Report*. Collingswood, NJ: Volunteers of America-Delaware Valley.
- Sobol, W.J., Minton, T.D., & Harrison, P.M. (2007). Prison and jail inmates at midyear

2006. *Bureau of Justice Statistics Bulletin*, Washington, DC: Department of Justice.
- Solomon, A.L., Waul, M., Van Ness, A., & Travis, J. (2004). *Outside the Walls: A National Snapshot of Community-based Prisoner Reentry Programs*. Reentry National Media Outreach Campaign. Retrieved from: http://www.urban.org/UploadedPDF/410911_OTWResourceGuide.pdf.
- Sreenivasan, S., Weinberger, L.E., Frances, A., & Cusworth-Walker, S. (2010). Alice in actuarial-land: Through the looking glass of changing Static-99 norms. *Journal of the American Academy of Psychiatry and Law*, 38, 400-406.
- Stitzer, M.L., Petry, N.M., & Peirce, J. (2010). Motivational incentives research in the National Drug Abuse Treatment Clinical Trials Network. *Journal of Substance Abuse Treatment*, 38(Supp 1), S61-S69.
- Sullivan, E., Mino, M., Nelson, K., & Pope, J. (2002). *Families as a Resource in Recovery from Drug Abuse: An Evaluation of La Bodega de la Familia*. New York: Vera Institute of Justice.
- Tabachnick, B.G., & Fidell, L.S. (2012). *Using Multivariate Statistics* (6th ed.). Boston, MA: Pearson.
- Travis, J. (2000). *But They All Come Back: Rethinking Prisoner Reentry*. Washington, DC: National Institute of Justice.
- Travis, J. (2005). *But They All Come Back: Facing the Challenges of Prisoner Reentry*. Washington, DC: Urban Institute.
- Travis, J., Keegan, S., & Cadora, E. (2003). *A Portrait of Prisoner Reentry in New Jersey*. Washington, DC: Urban Institute.
- Travis, J., Solomon, A.L., & Waul, M. (2001). *From Prison to Home: The Dimensions and Consequences of Prisoner Reentry*. Washington, DC: Urban Institute.
- Van Voorhis, P., & Brown, K. (1996). *Risk Classification in the 1990's*. Unpublished Manuscript. Retrieved from: <http://static.nicic.gov/Library/013243.pdf>.
- Van Voorhis, P., Wright, E., Salisbury, E., & Bauman, A. (2010). Women's risk factors and their contributions to existing risk/needs assessment: The Current status of gender responsive assessment. *Criminal Justice and Behavior*, 37, 261-288.
- Visher, C., Debus, S., & Yahner, J. (2008). *Employment After Prison: A Longitudinal Study of Releasees in Three States*. Washington, DC: Urban Institute.
- Visher, C.A., & Courtney, S.M.E. (2007). *One Year Out: Experiences of Prisoners*

- Returning to Cleveland*. Washington, DC: Urban Institute – Justice Policy Center.
- Visher, C.A., & Travis, J., (2003). Transitions from prison to community: Understanding individual pathways. *Annual Review of Sociology*, 29, 89-113.
- Visher, C.A., Winterfield, L., & Coggeshall, M.B. (2005). Ex-offender employment programs and recidivism: A Meta-analysis. *Journal of Experimental Criminology*, 1(3), 295-315.
- Vose, B. (2008). *Assessing the Predictive Validity of the Level of Service Inventory-Revised: Recidivism Among Iowa Parolees and Probationers*. (Doctoral dissertation). University of Cincinnati, Cincinnati, OH.
- Vose, B., Cullen, F.T., & Smith, P. (2008). The Empirical status of the Level of Service Inventory. *Federal Probation*, 72(3), 22-29.
- Wagner, D. (2008). *Review of Alternatives to the Juvenile Assessment Generic (JAG)*. Madison, WI: National Council on Crime and Delinquency.
- Ward, T., & Fortune, C. (2013). The Good Lives Model: Aligning risk reduction with promoting offenders' personal goals. *European Journal of Probation*, 5(2), 29-46.
- Ward, T., & Maruna, S. (2007). *Rehabilitation: Beyond the Risk Paradigm*. New York: Routledge.
- Ward, T., Yates, P.M., & Willis, G.M. (2012). The Good Lives Model and the Risk Need Responsivity Model: A Critical response to Andrews, Bonta, and Wormith (2011). *Criminal Justice and Behavior*, 39(1), 94-110.
- West, H.C. (2010). *Prison Inmates at Midyear 2009*. Washington DC: Bureau of Justice Statistics, US Department of Justice.
- West, H.C., and Sabol, W.J. (2011). *Prisoners in 2009*. Washington DC: Bureau of Justice Statistics, US Department of Justice.
- Western, B., Kling, J., & Weiman, D. (2001). The Labor market consequences of incarceration. *Crime and Delinquency*, 47, 410-427.
- Western, B., & Pettit, R. (2000). Incarceration and racial inequality in men's employment. *Industrial and Labor Relations Review*, 54, 3-16.
- Wexler, H.K., Lipton, D.S., & Johnson, B.D. (1998). *A Criminal Justice System Strategy for Treating Cocaine-Heroin Abusing Offenders in Custody*. Washington, DC: National Institute of Justice.
- Whiteacre, K.W. (2006). Testing the Level of Service Inventory-Revised (LSI-R) for

- racial/ethnic bias. *Criminal Justice Policy Review*, 17(3), 330-342.
- Willis, G.M., Prescott, D.S., & Yates, P.M. (2013). The Good Lives Model (GLM) in theory and practice. *Sexual Abuse in Australia and New Zealand*, 5(1), 3-9.
- Wilper, A.P., Woolhandler, S., Boyd, J.W., Lasser, K.E., McCormick, D., Bor, D.H., & Himmelstein, D.U. (2009). The Health and health care of US prisoners: Results of a nationwide survey. *American Journal of Public Health*, 99(4), 666-672.
- Wilson, D.B., Bouffard, L.A., Mackenzie, D.L. (2005). A Quantitative review of structured, group-oriented, cognitive-behavioral programs for offenders. *Criminal Justice and Behavior*, 32(2), 172-204.
- Wolff, N., Huening, J., Shi, J., & Frueh, B.C. (2013). *Screening for and Treating PTSD and Substance Use Disorders Among Incarcerated Men*. New Brunswick, NJ: Center for Behavioral Health Services and Criminal Justice Research.
- Wormith, J.S., Hogg, S., & Guzzo, L. (2012). The Predictive validity of a general risk/needs assessment inventory on sexual offender recidivism and an exploration of the professional override. *Criminal Justice and Behavior*, 39(12), 1511-1538.
- Wright, K., Clear, T., & Dickson, P. (1984). Universal applicability of probation risk-assessment instruments: A Critique. *Criminology*, 22, 113-134.
- Yacus, G. (1998). Validation of the risk & needs assessment used in the classification for parole and probation of Virginia's adult criminal offenders. *Dissertation Abstracts International*, 60, 885.
- Zhang, S.X., Roberts, R.E.L., & Farabee, D. (2011). An Analysis of prisoner reentry & parole risk using COMPAS & traditional criminal history measures. *Crime & Delinquency*, 60(2), 167-192.

CURRICULUM VITAE

I. Date of Birth

April 5, 1985

II. Education

Rutgers, the State University of New Jersey, School of Criminal Justice
Ph.D. in Criminal Justice, January 2015

Rutgers, the State University of New Jersey, School of Criminal Justice
M.A. in Criminal Justice, May 2009

New York University, College of Arts and Sciences
B.A. in Psychology, Sociology, May 2007

Wayne Hills High School
High School Diploma, June 2003

III. Employment

American Board of Internal Medicine
Philadelphia, Pennsylvania
Research Innovations Specialist, October 2013 – present

Temple University, Department of Criminal Justice
Philadelphia, Pennsylvania
Adjunct Instructor, September 2011 – present

Camden Coalition of Healthcare Providers
Camden, New Jersey
Evaluation Manager, September 2012 – July 2013

Rutgers, the State University of New Jersey, Department of Sociology,
Anthropology, and Criminal Justice
Camden, New Jersey
Adjunct Instructor, September 2011 – September 2012

Center for Court Innovation
New York, New York
Senior Research Associate, July 2010 – September 2012

Corrections & Reentry Policy Research Center, Rutgers University
Newark, New Jersey
Project Director, December 2009 – July 2010

Economic Development Research Group, Rutgers University
New Brunswick, New Jersey

Research Associate, September 2008 – December 2009

Rutgers, the State University of New Jersey, School of Criminal Justice
Newark, New Jersey

Part-time Lecturer, September 2009 – September 2011

IV. Publications

1. Lindquist, C.H., **Herrschaft, B.A.**, & Lattimore, P.K. (2014). Reentry courts. In *Encyclopedia of Criminology & Criminal Justice* (pp. 4351-4360). New York, NY: Springer.
2. Ostermann, M., & **Herrschaft, B.A.** (2013). Validating the Level of Service Inventory-Revised: A Gendered perspective. *The Prison Journal*, 93(3), 291-312.
3. **Herrschaft, B.A.**, & Dolan, S. (2013). *Responses to Domestic Violence in Tribal Communities: A Regional Survey of Northern California*. New York, NY: Center for Court Innovation.
4. **Herrschaft, B.A.** (2012). *New York City Community Cleanup: The Impact of a Program for Low-Level Offenders*. New York, NY: Center for Court Innovation.
5. Barbieri, R., Watler, C., Megaw, J., Osorno-Crandall, S., & **Herrschaft, B.** (2011). *East Harlem Juvenile Gang Task Force: 2011 Needs Assessment and Strategic Plan*. New York, NY: Center for Court Innovation.
5. **Herrschaft, B.A.** (with Hamilton, Z.) (2011). *Recidivism Among Parolees in New York City (2001– 2008)*. New York, NY: Center for Court Innovation.
6. **Herrschaft, B.A.**, Veysey, B.V., Tubman-Carbone, H., & Christian, J. (2009). Gender Differences in the Transformation Narrative: Implications for Revised Reentry Strategies for Female Offenders. *Journal of Offender Rehabilitation*, 48(6), 463-482.
7. Christian, J., Veysey, B.V., **Herrschaft, B.A.**, and Tubman-Carbone, H. (2009). Moments of Transformation: Formerly Incarcerated Individuals' Narratives of Change. In B. Veysey, J. Christian, and D.J. Martinez (Eds.). *How Offenders Transform Their Lives*. Devon, UK: Willan Publishing.
8. McKay, H., Murphree, M., **Herrschaft, B.**, and Morris, P. (2008). *Raising the Bars: Early Findings from the Prison to Community Project*. New Brunswick, NJ: Rutgers University Center for Women and Work and the Sloan Center for Innovative Training and Workforce Development.
9. Ward, D.E., Tubman-Carbone, H., **Herrschaft, B.**, Petrossian, G., and Block, S. (2009). *How Does Prison to Community (P2C) Affect Recidivism: A Summary of Quantitative Findings*. Economic Development Research Group - Rutgers University: School of Management and Labor Relations.