MINIMUM SUPERVISION: WHO PERFORMS BETTER?

by

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A Thesis
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of
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DEDICATION

First and foremost, this thesis project is dedicated to my husband. He has been (and continues to be) my rock, my constant supporter, and my biggest cheerleader. Second, I dedicate this to my children as evidence that there is nothing stopping us from achieving our greatest goals.

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LIST OF ABBREVIATIONS

Cognitive-Behavioral Therapy	CBT
Community Supervision Officer	CSO
Community Supervision Services	CSS
Court Services and Offender Supervision Agency	CSOSA
District of Columbia Superior Court	DCSC
Evidence-Based Practices	EBP
General Equivalency Diploma	GED
New Parole Model	NPM
Probation Officer	PO
Risk-Needs-Responsivity	RNR
Sending State Court	SSC
United States	U.S.
United States Parole Commission	USPC
Vocational Opportunities, Training, Education, and Employment	VOTEE

ABSTRACT

MINIMUM SUPERVISION: WHO PERFORMS BETTER?

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Interventions that are better suited for high-risk offenders do damage to the low-risk population, leading to an increase in recidivism (Lowenkamp et al., 2006). This argument is made based on limited evidence that all low-risk offenders are better suited for administrative handling than higher risk offenders. Randomized controlled trials conducted by Barnes et al. (2010, 2012) found that administrative caseloads of 400+ low-risk offenders had no significant impact on the rate of recidivism for this population. This suggests that the low-risk population can largely be left alone, an assumption agencies have embraced to reduce workload. However, the question remains: does this make sense? Can an agency responsible for supervising justice involved people in the community simply leave low-risk offenders alone? This thesis project attempts to answer this question by exploring the factors that influence supervision outcomes for the low-risk population supervised by the Court Services and Offender Supervision Agency in Washington, D.C. Case and offender-level characteristics were analyzed to examine the supervision outcomes of this population. Logistic regression results found that low-risk

offenders on parole or supervised release were over 11 times more likely to end supervision unsuccessfully than low-risk probationers. Results also show that low-risk offenders who incurred a rearrest during their supervision term were over 43 times more likely to be removed from low-risk supervision altogether, regardless of case type. Findings indicate that differences between low-risk offenders do exist and influence supervision outcomes. This encourages discussion as to whether or not administrative management of this population should be reconsidered.

CHAPTER ONE: INTRODUCTION

The field of community corrections has benefited greatly from the implementation of evidence-based practices across several decades. Discussions about what works guide jurisdictions responsible for the supervision of offenders, currently comprised of one in every 37 adults in the nation (Kaeble & Glaze, 2016; Barnes, Hyatt, Ahlman, & Kent, 2012). This, however, does not mean that appropriate implementation of evidence-based practices is occurring in these jurisdictions. Agencies continue to struggle with how to effectively embrace what works, which impacts policy development, resource allocation, and, most importantly, the offenders themselves.

This thesis discusses the dilemma with low-risk offenders by first reviewing the basic tenets of the risk-need-responsivity model and how they relate to those who pose the lowest risk to reoffend. A discussion of the literature ensues, followed by an examination of supervision practices at the Court Services and Offender Supervision Agency (CSOSA) in the District of Columbia, where a gradual shift in strategy has affected its low-risk offender population in recent years. The study then explores the characteristics of the low-risk offender that most impact supervision outcomes and attempts to answer whether or not administrative management of this population is appropriate. And, it concludes with recommendations on future strategy enhancements that may benefit the low-risk offender population.

CHAPTER TWO: REVIEW OF LITERATURE

A Review of RNR

The risk-need-responsivity model (RNR) was officially first introduced in 1990 as having the most effective outcomes in offender rehabilitation and treatment (Andrews, Bonta, & Hoge, 1990). The model was developed based on research that began twenty years earlier in growing support of actuarial risk in lieu of professional judgement in the assessment of offender propensity to recidivate (Bonta & Andrews, 2007). Overwhelmingly, science-based risk assessments focusing on static factors (e.g., age at first arrest, offense history, past substance abuse, etc.) were found to better predict criminal behavior than traditional subjective assessments made by practitioners in corrections, the latter of which were largely based on experience, training, and gut feeling (Bonta & Andrews, 2007; Taxman, Shepardson, & Byrne, 2004; Taxman, 2006). Moving from judgements (i.e., first generation assessment) to actuarial tools (i.e., second generation assessment) marked a shift in risk classification in the field of corrections, to include community supervision. This shift led to the third generation assessment when continued research encouraged the inclusion of dynamic factors in risk prediction, such as familial relationships and employment status, instead of a strict focus on unchanging static elements (Bonta & Andrews, 2007).

Effective risk assessment has grown to depend on a combination of both static and dynamic elements. Because of the importance of risk assessment in predicting reoffending, it is the first and foundational element of the risk-need-responsivity model. In the model, the risk principle requires that interventions match offender risk to reoffend. In order for this principle to be honored, a validated risk assessment must be used and appropriate services matched to said risk (Bonta & Andrews, 2007). It is important to note that Andrews et al. (1990) describe this principle by drawing a clear distinction between high and low-risk offenders (Lowenkamp & Latessa, 2004). Specifically, the authors emphasize that intensive services should be offered to offenders identified as higher risk because they respond better to such interventions than those geared toward the lower risk offender population (Lowenkamp & Latessa, 2004). Conversely, offenders who pose a lower risk to reoffend do just as well or even better to minimal intervention as opposed to more intensive treatments (Lowenkamp & Latessa, 2004). We will return to this distinction in later discussion.

The second element of RNR is the need principle, which requires that treatment in corrections be focused on criminogenic needs in order to be effective (Andrews & Bonta, 2010). Criminogenic needs are comprised of eight factors (i.e., the Central Eight) found to be directly linked to criminal behavior (Andrews & Bonta, 2010). These are: history of antisocial behavior, antisocial personality pattern, antisocial attitudes/thinking, antisocial associates, family/marital problems, low education/employment, lack of prosocial recreational activities, and substance abuse (Andrews & Bonta, 2010; Taxman, 2014). Of these criminogenic needs, the first half is the most predictive of criminal behavior and, hence, deemed The Big Four (Andrews & Bonta, 2010). It is well supported by research that correctional treatments targeting criminogenic needs result in a larger impact on recidivism reduction (Taxman, 2014). This also means that undesirable outcomes result when interventions are misaligned.

The third and final principle of RNR is responsivity, which is traditionally two-fold. General responsivity calls for the use of cognitive behavioral treatment as the primary and most effective method to impact offender behavior (Bonta & Andrews, 2007). Specific responsivity requires that such treatments be tailored to the "risk, needs, psychosocial functioning, and strengths" of the individual (Taxman, 2014, p. 32). A third concept, systemic responsivity, has been introduced in recent literature, which requires more from corrections agencies for maximum reduction in recidivism (Taxman, 2014). Systemic responsivity calls for agencies to have a diverse set of appropriate treatment programs available, a sufficient percentage of participants in such programming, a sufficient percentage of offenders who can access such programming, and programming that is in line with the offender's risk, needs and specific responsivity (Taxman, 2014). This is an emerging discussion within RNR that is important to offender success.

RNR provides a best practices standard for corrections agencies responsible for balancing public safety against offender rehabilitation. However, some agencies may not effectively adhere to RNR principles, hence causing more harm to offenders than good. Although it is troubling to think that inappropriate interventions can cause unfavorable outcomes for high-risk offenders, one could argue that even more disconcerting is the possibility that a practice could *worsen* outcomes for those who pose the lowest risk.

The Response to Low-Risk v. High-Risk

The risk principle calls for appropriate assessment and matching of services to offender risk (Bonta & Andrews, 2007). Bonta and Andrews (2007) make a specific distinction between high and low-risk offenders, namely, that the most intensive services should be targeted for the higher risk offenders and minimal services offered to those who pose the lowest risk. Supervision and interventions that focus on high-risk offenders will lower recidivism rates as well as victimization (Byrne, 2009). In a study of an intensive rehabilitation supervision program (i.e., the Learning Resources Program), Bonta, Wallace-Capretta, and Rooney (2000) found that high-risk offenders in the treatment group had lower recidivism rates than untreated high-risk offenders. The study also found that low-risk offenders who received the same intensive intervention had higher rates of recidivism than low-risk offenders who went untreated (Bonta et al., 2000). In a four-site blocked randomized trial of substance abusing probationers classified by risk level, Thanner and Taxman (2003) concluded that the benefits of intensive and targeted treatment for high risk offenders outweighed what was gained by the moderate risk offenders, with the former responding most to a seamless system rather than traditional supervision services. Improvements in outcomes resulted for the high-risk/drug abusing cohort in the form of reductions in crime and substance abuse, as well as an increase in employment (Thanner & Taxman, 2003).

Research has established that imposing intensive treatments on a low-risk population has the potential to cause more harm than if they are left untreated. Lowenkamp and Latessa (2004) detail this harm in a three-part explanation. First, the placement of low-risk offenders in settings that expose them to those at higher risk to reoffend directly contributes to an increase in antisocial associates, a Big Four criminogenic need; second, imposing an intervention better suited for a high-risk offender on one who poses low-risk has the potential to disrupt the latter's favorable pro-social supports, such as employment and family relationships; lastly, individual level characteristics of the low-risk offender, such as intellectual functioning and maturity, may be manipulated by more sophisticated and potentially predatory high-risk offenders when mixed-risk classifications are placed in intensive service settings (Lowenkamp & Latessa, 2004). Lowenkamp, Latessa, and Holsinger (2006) added that low-risk offenders who are subjected to increased supervision and/or more intensive conditions are also more likely to violate supervision than others.

Despite the research against it, the temptation for agencies to focus treatments incorrectly can permeate through all levels of correctional practices, causing particular harm to low-risk offenders. As a possible reason, Bonta and Andrews (2007) cite the pressure some agencies face to remain focused on lower risk offenders to maximize on this population's propensity toward compliance, which, for example, can superficially satisfy program participation and attendance rates. Another reason may be the result of errors in risk assessment leading to the over-classification (and over-treatment) of offenders, in particular those least likely to reoffend (Taxman, 2006). Such misdirected focus can force the low-risk population to be "punished and even treated beyond their threat to public safety" (Austin, 2006, p.63).

Dosage and Risk

As has been detailed above, correctional agencies must use care to ensure that distinctions are made between risk levels. However, identifying the *amount* of intervention or treatment that corresponds to each risk level has sparked significant discussion in the field. RNR confirms what a logical person may already suspect: someone with more criminogenic needs is at a higher risk to reoffend and, therefore, in need of higher level intervention (Bonta & Andrews, 2007). What is still unclear is what exactly constitutes a higher level of intervention. Sperber, Latessa, and Makarios (2013a) contributed to the dosage discussion with a study of 689 adult male probationers classified by risk level. Participants in the study were provided varying hours of cognitive behavioral intervention within a correctional treatment setting based on risk (Sperber et al., 2013a). Treatment dosage was imposed as follows: 0-99 hours for low-risk offenders, 100-199 hours for moderate-risk offenders, and 200 hours or more for the highest risk offenders (Sperber et al., 2013a). Findings revealed that the largest reduction in recidivism occurred for those at the highest risk of reoffending who were provided the most treatment hours (Sperber et al., 2013a). Although this study also yielded a nominal reduction in recidivism for low-risk cases when exposed to moderate level treatment, the authors advise that this may have been due to the low-risk offenders actually being misclassified, when they were more reflective of a moderate-risk population (Sperber et al., 2013a).

In a complimentary writing, Sperber, Latessa, and Makarios (2013b) outlined the parameters that correctional agencies should employ for successful implementation of risk-based treatment dosage. First, agencies must commit to the use of a risk assessment to appropriately determine offender risk and need; second, policies and practices should be modified to allow for dosage by risk; and, third, a mechanism must be in place that monitors offenders receiving treatment dosages based on criminogenic risk and need so that continuous adjustments can be made (Sperber et al., 2013b). Without these elements, the likelihood of harm being done, especially to the low-risk population, remains formidable. Unfortunately, there are challenges to such a specific shift in service provision, one of which may be the service providers themselves.

Barriers to Low-Risk Strategy

If the harm inherent in exposing low-risk offenders to more intensive interventions is known, why is the appropriate management of the low-risk population still a commonplace issue in community supervision (Taxman, 2012)? The answer to this question is likely embedded in the larger difficulty of effectively adhering to evidence-based practices in the field overall. In a study of probation officers and service delivery of evidence-based practices, Bonta, Rugge, Scott, Bourgon, and Yessine (2008) found low adherence to RNR principles. Specifically, the reporting frequency for high-risk offenders was, on average, not commensurate with their risk level; criminogenic needs were not well addressed in either an Intervention Plan or in face-to-face supervision sessions; and opportunities to reinforce desired behaviors in such sessions were not maximized (Bonta et al., 2008).

Rudes (2012) found similar difficulties in the State of California following the release of parole reform expectations known as the “New Parole Model” (NPM) (p. 252). Results from the 3-year ethnographic study showed overwhelming use of both resistance and non-resistance actions by parole officers to circumvent the alternatives to incarceration outlined by the NPM (Rudes, 2012). Resistance actions included partnering with law enforcement to increase both information sharing and opportunities to arrest suspected violators; piling charges on offenders to enhance technical violations; and paperwork enhancement, which included the use of templates as well as seeking assistance in completing reports from colleagues considered experts in ensuring revocations (Rudes, 2012). The study also revealed that officers engaged in non-resistance actions whenever they failed to effectively respond to violations in accordance with the NPM (Rudes, 2012). The resistance from officers contradicted the intent of the NPM and served as a challenge to organizational change for the state (Rudes, 2012). These studies show that, along with the higher level challenges that a correctional organization faces when implementing best practices, there also exists a front line barrier to the principles of RNR, in which the low-risk offender could be a direct and more immediate casualty.

Another challenge to the effective implementation of a low-risk supervision strategy is the fact that the literature needed to guide such a shift is scant. Although studies have informed that low-risk offenders have worse outcomes if subjected to higher-intensity supervision, there exists little research on how *decreased* supervision impacts offender outcomes (Barnes, Ahlman, Gill, Sherman, Kurtz, & Malvestuto, 2010). As indicated by Barnes et al. (2010), "[m]uch less is known about the effects of *reduction* of the intensity of supervision of clients, regardless of their risk of any new crimes or very serious crimes" (p. 166). Even less is known about *the type* of low-risk offender who may benefit most from such a reduction.

Decreased Supervision and Caseload Realignment

Taxman (2002) defines supervision contacts as the framework upon which offender supervision has been built. Understandably, when one thinks of probation or parole, an image of an officer engaging an offender in face-to-face sessions generally comes to mind. However, if not aligned to risk, supervision contacts can adversely impact supervision success. Byrne (2009) found that closer supervision of probationers and parolees serves to increase revocation and re-incarceration rates. To prevent this, some jurisdictions have revamped contact standards and/or realigned caseloads based on risk, focusing on reducing supervision of low-risk offenders to make better use of resources (Barnes et al., 2010).

Cohen, Cooke, and Lowenkamp (2016) examined the low-risk contact policy implemented by the federal probation system beginning in 2012 to determine what, if any, impact it had on low-risk offenders. The policy mandated that federal probationers who screened at low-risk be seen by officers only to monitor supervision conditions and to address any changes in circumstance (Cohen et al., 2016). The study showed that the change in policy lowered supervision contacts for this population without impacting recidivism rates, which remained steady (Cohen et al., 2016). The authors concluded that there was evidence to support supervision reduction for low-risk offenders, but encouraged more rigorous study to determine effect (Cohen et al., 2016).

In 1997, the Multnomah County Department of Community Justice in Oregon made significant strides in the realignment of caseloads to reflect risk-based supervision, also resulting in little threat to community safety (Johnson, Austin, & Davies, 2002). The

State of New York and, to a lesser degree, the State of Maryland followed suit with risk-based supervision realignments, inclusive of automated reporting via Kiosk, with similar results (Barnes et al., 2012; Wilson, Naro, & Austin, 2007). Barnes et al. (2012) points out, however, that the afore-mentioned jurisdictions either had no comparison group (i.e., Oregon and New York) or the comparison group may have been different from the experimental group (i.e., Maryland), which resulted in interpretation issues. To address this, Barnes et al. (2012) recommended a randomized controlled trial as a more useful approach to assess the impact of decreased supervision for low-risk offenders. Such was successfully implemented in a study of the Adult Probation and Parole Department of the First District of Pennsylvania, yielding findings that are important to this thesis (Ahlman & Kurtz, 2008).

In this study of low-risk supervision protocols and their impact on rearrest, Ahlman and Kurtz (2008) used random assignment in their analysis of low-risk offender rearrest rates. Based in part on the New York risk-based supervision model introduced by Jacobson (2005), the authors set out to determine if large, low-risk caseloads increased public safety concerns or if rearrest rates remained comparable to those incurred on traditional supervision caseloads (Ahlman & Kurtz, 2008). To accomplish this, two officers on opposite ends of a supervision region were selected to manage a caseload of, approximately, 400 low-risk offenders each, while a control group of low-risk offenders totaling 758 remained on traditional supervision caseloads throughout both regions (Ahlman & Kurtz, 2008). Risk was determined by a validated risk tool used by the jurisdiction and cases lost in either the control or experimental group by attrition or arrest were replaced (Ahlman & Kurtz, 2008). The authors found considerable differences between the control and experimental groups, with the latter yielding a reduction in office contacts, drug testing referrals, and abscondence rates (Ahlman & Kurtz, 2008). With respect to rearrest, there was no statistically significant difference found between the control and experimental groups in either the time leading up to arrest or new offense type (Ahlman & Kurtz, 2008). Further, the overall failure rate in the study (i.e., cases in which a rearrest occurred and/or a warrant card was issued) yielded no statistically significant difference between the groups (Ahlman & Kurtz, 2008). Given these results, the authors concluded that the risk of rearrest for low-risk offenders is not increased by large caseloads (Ahlman & Kurtz, 2008).

In updated results of the study, Barnes et al. (2012) described how the findings in Ahlman and Kurtz (2008) led to a reorganization of supervision strategy for the Adult Probation and Parole Department in Philadelphia. Using a revised random forest forecasting model, offenders were subsequently placed on caseloads based on risk of rearrest projected over two years, with low-risk offenders placed on Administrative Supervision Units (Barnes et al., 2012). Results from this shift in practice were similar to those of the original study, with the Administrative Supervision Units handling 2.2 times more offenders, issuing 72% less drug tests, conducting 34% fewer office contacts, and consuming an estimated 32% less in court time for violation hearings than their higher risk counterparts (Barnes et al., 2012). Barnes et al. (2012) concluded that, "[w]hen paired with an appropriate means of risk forecasting, low-intensity supervision presents a potential way for agencies to reduce the total costs of managing lower-risk offenders, with no apparent detrimental effects on public safety" (p. 217).

Barnes et al. (2010) considers the Philadelphia Low-Intensity Community Supervision Experiment a strong test of policy versus theory, finding no evidence that reduction in supervision contacts for low-risk offenders is unsafe. Taxman (2012) echoes this finding, clarifying that "[a]dministrative or 'stacked' caseloads (where officers have 400+ offenders to supervise) *have no impact on recidivism rates for low-risk offenders*; although the results are not statistically significant the null results suggest that either method generates similar findings" (p. 140). This supports the realignment of resources, given that large, low-risk caseloads can have less supervision contact and less drug testing submissions without impacting rearrest or abscondence rates (Ahlman & Kurtz, 2008). Further, such resource reallocation could result in a decreased fiscal impact and subsequent increase in direct services toward higher risk offenders, allowing for the management of lower risk offenders in the community at lower cost and with better outcomes (Ahlman & Kurtz, 2008; Pew Center on the States, 2009).

A Review of Offender Characteristics

The literature review thus far has established that RNR principles should support community supervision practices, beginning with the identification of who is at risk to reoffend. The low-risk offender should be part of a larger supervision strategy that maximizes on resources and targets the high risk population first and foremost. This means that those at lowest risk to reoffend should not receive much attention and that treatment dosage should be low, if at all, for this population. Care should be taken to ensure that officers are adhering to these tenets and that they impose less supervision on those at the lowest risk. This allows for more administrative case management, a strategy that has been adopted by many local and federal jurisdictions in recent years.

The discussion about low-risk offenders has, however, been largely limited to risk level. Beyond the determination of being less likely to reoffend and better managed administratively without much intervention, the low-risk offender has not garnered as much interest as their high-risk counterparts. In other words, details about the low-risk offender—who they are, what type of supervision they are completing, what challenges they may face, etc.—are of little import once their risk level is identified. Even less is known about the low-risk offender who benefits *most* from what the research has recommended to date. For instance, it is not known if there is a common profile or set of factors that make one low-risk offender more successful than another when supervision is handled administratively. Differences in supervision outcomes between low-risk offenders based on these or other characteristics has been overshadowed in the literature by its focus on higher risk.

A review of the literature regarding different offender characteristics or case factors that may impact recidivism is offered next, with emphasis on the low-risk offender where possible. Using the Congressional Research Service Report, Offender Reentry: Correctional Statistics, Reintegration into the Community and Recidivism (James, 2015) as a guide, the review will focus on the following: mental health, domestic violence, substance use, education, housing, and employment.

Mental illness among the offender population has received significant attention particularly because of its assumed impact on crime by an often media-charged public. The high prevalence of mental disorders among offenders does not help to assuage the belief that mental illness is somehow connected to crime, resulting in the criminal justice system "becoming part of the de facto mental health care system" (Skeem, Emke-Francis, & Louden, 2006, p. 160). Although not directly related to recidivism, mental illness (like housing stability) is considered a non-criminogenic need that "reflect[s] lifestyle destabilization" (Taxman & Caudy, 2015). Ignoring mental illness will make it more difficult to address criminogenic needs, hence, offering services to help stabilize an offender becomes important.

To address mental illness among the supervised population, the last twenty years has yielded the development of specialized approaches in community supervision that have included mental health courts and specialty units catering to offenders with behavioral health diagnoses. Mental health courts in particular have been patterned after drug courts in offering a continuum of services for mentally ill offenders, to include a dedicated judge, prosecutor, and community-based agencies that encourage alternatives to incarceration. Studies on this initiative have been favorable, particularly as it relates to the wrap-around servicing of mentally ill offenders. For example, in a study of the Clark County Mental Health Court, Herinckx, Swart, Ama, Dolezal, and King (2005) found a four-fold reduction in the overall crime rate for participants at one year post-enrollment compared with one year pre-enrollment, with 54% of participants incurring no arrests and a reduction in probation violations by 62%. In another longitudinal study of 447 mental health court participants and 600 treatment-as-usual controls, Steadman, Redlich, Callahan, Robbins, and Vesselinov (2011) found the mental health court cohort had significantly better outcomes than the treatment-as-usual cohort. These studies support the philosophy that mentally ill offenders benefit from special intervention. Another example of this is specialty supervision.

Like mental health court, specialty supervision has grown in popularity with over 100 jurisdictions adopting such strategies to address the mental health needs of offenders (Manchak, Kennedy, Skeem, & Louden, 2014). These agencies generally hire officers who have specialized experience and background in mental health and assign each a smaller caseload of supervisees with serious mental illness (Skeem, Encandela, & Louden, 2003). This is done in an effort to improve the success rates of this population as it relates to treatment compliance, overall functioning, and recidivism reduction (Skeem et al., 2003). This was evidenced in a quasi-experimental study conducted by Manchak et al. (2014) that compared 176 probationers on traditional supervision against 183 probationers assigned to such specialty supervision. Along with greater boundary spanning, positive compliance strategies, higher quality of dual-role relationships, and better access to psychiatric and dual-diagnosis services, the results of the study also found a reduction of formal violation reports filed against mentally ill offenders in specialty units at a rate of two times less than those on traditional probation (Manchak et al., 2014). Research also suggests that specialty initiatives allow for better responses to criminogenic risk factors, which (unlike mental illness) are directly related to recidivism (Skeem, Kennealy, Winter, Louden, & Tatar, 2014).

Without improved or specialized strategies, supervision results can be especially detrimental to the mentally ill offender because correctional consequences are traditionally heavier-handed for this population. For example, Skeem et al. (2014) found no significant differences in the likelihood of arrest in a prospective longitudinal study of

221 parolees, 112 of which were diagnosed with serious mental illness. There was, however, a trend toward mentally ill parolees being more likely than those without mental illness to be returned to custody for technical violations (Skeem et al., 2014). The specialty agency that attempts to address this disparity by emphasizing care and rehabilitation instead of control and community safety produces better outcomes (Skeem et al., 2003). However, it is the latter combination that tends be the more traditional agency approach and remains a challenge (Skeem et al., 2003).

As has been the case with mental illness, the supervision response to domestic violence offenders has also involved specialty approaches. Olsen and Stalans (2001) define domestic violence as the "physical, emotional, and/or sexual violence against intimate partners" (p. 1164). According to the authors, probation supervision is the most common sentence imposed on domestic violence offenders in several jurisdictions and, like mental illness, assumed to be connected with repeat offending (Olsen & Stalans, 2001). However, in a study inclusive of 124 domestic violence probationers sentenced in Illinois, Olson and Stalans (2001) found no statistical differences in the prevalence of probation revocations, technical violations, or new arrests between domestic violence offenders and those on probation for other violent offenses. As noted by the study, "this affirms research by others (Ford & Regolia,1992; Hirschel & Hutchinson, 1991; Saunders, 1993) that domestic violence offenders are just as likely as other offenders to reoffend, even while they are being supervised on probation" (Olsen & Stalans, 2001, p. 1176). This finding was underscored by a 9-year longitudinal study conducted by Wilson and Klein (2006) that found domestic violence offenders who had incurred even a few offenses were not otherwise involved in the criminal justice system. Research also shows better outcomes for this population when specialized supervision is imposed.

In a year-long assessment of the Rhode Island specialized domestic violence probation unit beginning in January 2003, 370 domestic violence male misdemeanor probationers were compared to 182 on traditional supervision, with recidivism measured by new arrest, victim report, or police report (Klein, Wilson, Crowe, & DeMechile, 2008). The study showed that, when compared to the traditional probationer cohort, offenders in the domestic violence specialty unit had lower rearrest rates as well as longer periods arrest-free (Klein et al., 2008). The study also found that the lowest risk probationers under domestic violence specialty supervision had the highest reduction in recidivism at nearly 40% compared to their low-risk counterparts receiving traditional probation and waited twice as long to reoffend (Klein et al., 2008). Based on these findings, the authors concluded that specialty supervision of low-risk domestic violence probationers made a difference (Klein et al., 2008).

Specialty supervision has also been developed for substance abusing offenders based on the premise that the relationship between substance abuse and recidivism is direct. Gray, Fields, and Maxwell (2001) conducted a statewide study of recidivism among probationers in Michigan and found that prior drug use was one of the main predictors of probation failure, with drug users being violated on technical grounds sooner than non-drug users. Similarly, Dowden and Brown (2002) determined through a quantitative meta-analysis review of 45 studies that substance abuse was a statistically significant predictor of recidivism. To address substance abuse specifically, drug courts were established as a special intervention that has since been supported by research.

Wilson, Mitchell, and Mackenzie (2006) conducted a systematic review of drug court effectiveness studies and found that there is evidence to suggest this intervention yields less recidivism from participants than traditional approaches. Similar results were found in a matched cohort study conducted by Brown (2011) of the Wisconsin Circuit Court's Drug Court. Specifically, the 137 drug court participants recidivated less over a longer period of time than their matched traditional-court participants (Brown, 2011). Hence, drug courts have been viewed as favorable given that offenders receiving this specialty intervention tend to recidivate less when compared to untreated substance-using offenders.

Despite findings such as these, it is important to highlight the larger discussion being had about the relationship between crime and drug addiction. According to Tonry (2016), the laws that govern the American justice system, and particularly those for drug and violent offenses, are "unprecedented" in severity, breadth, and proportionality. This unprecedented response to substance use disproportionally impacts the drug dependent offender, who will likely incur more technical violations that are met with more severe responses by virtue of his or her addiction. Severity of supervision response may worsen when other factors are included. Gray et al. (2001) found that drug using probationers with less education, for example, were at higher risk of incurring technical violations sooner than their more educated cohorts. This particular population was subjected to an increase in imposed interventions, which provided more opportunities to fail and greater probability of technical violations (Gray et al., 2001).

With respect to the impact of education alone on recidivism, opposing views exist. Olson and Lurigio (2000) concluded that, although education was predictive of probation revocations as well as new arrests, it had little impact on technical violations on its own. Conversely, Gray et al. (2001) concluded that probationers with less education were at risk of incurring technical violations sooner than their higher educated cohorts, with the risk increasing when coupled with substance abuse. Another combination of factors was offered in a five-year study of over 6,500 offenders by Lockwood, Nally, Taiping, and Knutson (2012), which concluded that the more education an offender had, the less they recidivated. This study also showed that recidivism increased to 55.9% among those with education below high school and that education combined with employment (and not substance abuse) were the most predictive of reoffending (Lockwood et al., 2012). Education and confinement were also shown to have a significant relationship by Harlow (2003), who concluded that, once incarcerated, inmates with low education were more likely to recidivate than their more educated counterparts.

An additional factor that may impact recidivism when combined with others is housing stability. As indicated in the previously mentioned Congressional Research Service Report (James, 2015), housing remains a challenge for the justice-involved. This challenge is exacerbated by certain realities, such as the scarcity of affordable housing; legal barriers, to include the requirements of subsided housing; and the discrimination that exists in the housing market against offenders (James, 2015). Moreover, when housing instability includes periods of homelessness other problems may arise. Metraux and Culhane (2006) conducted a study of 7,022 homeless individuals in New York City public shelters and related the dependence on shelter housing (particularly on offenders released from jail) to deviance. The authors determined that “criminal justice issues, whether recognized or not, figure prominently among the homeless milieu" (p. 9). This is underscored by Kushel, Hahn, Evans, Bangsberg, and Moss (2005) in a study of 1,426 homeless and marginally housed adults. Using multivariate analysis the study showed high rates of homelessness among those released from incarceration, which proved even more problematic when combined with substance abuse, mental health issues, and unemployment.

To ameliorate homelessness among the offender population, placement of offenders in halfway houses is often used with mixed results on recidivism. In a study of 1,946 parolees released from incarceration between 2004 and 2008, Costanza, Cox, and Kilburn (2015) concluded that those transitioned to the community through a halfway house were almost two times more likely to complete their parole term successfully. The study found other characteristics, such as age, length of prison term, and vocational skill also significant to supervision outcomes (Costanza et al., 2015). Risk level appears to be another important predictor of success following halfway house placement, as indicated in a study of 7,306 offenders conducted by Lowenkamp and Latessa (2005). The study showed that placement in community-based halfway houses or residential reentry programs in Ohio was most effective for high-risk offenders, but significantly detrimental to the low/moderate risk population (Lowenkamp & Latessa, 2005). Findings suggest that unstable housing alone cannot be the sole criteria for halfway placements and that RNR should be part of the decision-making process to avoid harm (Lowenkamp & Latessa, 2005).

Along with housing instability, the effect of unemployment on recidivism has been explored in the literature with different effects touted. Liberton, Silverman, and

Blount (1992) concluded that stability indicators like housing, education, employment and financial status are correlated with successful completion of supervision. In an analysis of probation outcomes of 2,850 felony probationers, Sims and Jones (1997) countered this, finding that unemployment had less impact on recidivism than did fewer address changes, higher education, and some fiscal stability. Lockwood et al. (2012) identified employment as a major recidivism predictor in a five-year follow up study of over 6,500 released offenders in Indiana and Nally, Lockwood, Taiping, and Knutson (2014) supported this in their analysis of the same sample, concluding that ex-offenders were more likely to recidivate if they were unemployed after release regardless of risk classification. This latter study also found age and education to be important characteristics that impacted recidivism and concluded that ex-offenders experienced more difficulty securing jobs and following a traditional employment pattern (Nally et al., 2014).

Others argue that it is not the job itself that impacts recidivism, but factors related to employment. In data collected from a survey of successful parolees and those who violated their parole term, Bucklen and Zajac (2009) found that attitude toward employment was significant, with the parole violators exhibiting more cognitive distortions toward enjoying or maintaining a job. Uggen (1999) concluded that job quality was associated with less self-reported crime among a sample of employed ex-offenders and, in a subsequent study, also concluded that employment opportunity served as a significant turning point for offenders (Uggen, 2000). Given the literature thus far, the relationship between employment and crime, to include recidivism, can be described as complex as it varies by demographics and is sensitive to other factors. The same can also be said of all of the characteristics just discussed, especially as they relate to the lowest risk offender.

Summary of Literature Review

This review of literature details the principles of RNR with a focus on risk in community supervision. It includes research describing the harmful impact that misaligned interventions, inappropriate dosage and supervision, as well as EBP implementation barriers can have on offenders. It also includes a review of the different factors, offender characteristics, and combinations thereof that may impact recidivism, with emphasis given to the low-risk population whenever possible.

Because research specific to the low-risk offender is scant, the literature review is evidence that more is needed to understand what happens to this population. Questions remain unanswered, such as: Do low-risk offenders have low needs? Are they less criminal than others? What factors impact their supervision success? Is there a type of low-risk offender that performs better on supervision? Does low-risk supervision make sense? These questions warrant exploration, as interest in the low-risk offender should not begin and end solely on risk classification. Learning more about this population, to include who is likely to complete supervision successfully, can better inform policy and practice as well as provide the evidence-base for (or against) administrative management of low-risk offenders.

CHAPTER THREE: PURPOSE OF STUDY

The purpose of this study is to explore the characteristics of the low-risk offenders who benefited most from minimum supervision at the Court Services and Offender Supervision Agency, resulting in successful case closure. This is defined as any supervision closure that did not result from a negative action by the releasing authority (i.e., District of Columbia Superior Court [DCSC], United States Parole Commission [USPC], or Sending State Court [SSC]). This includes: early satisfactory termination from supervision, expiration of supervision (either successful or unsuccessful), and supervision transfers or returns to SSCs via Interstate Compact. An additional purpose of this study is to assess case outcomes and provide an evidence-base for recommendations related to minimum supervision.

Background of Mass Reporting in CSOSA

CSOSA is responsible for the community supervision of District of Columbia Code offenders, which can total approximately 13,000 individuals at any given time (The Court Services and Offender Supervision Agency [CSOSA], 2014). Although a federal agency, CSOSA serves a local purpose much like a State probation or parole entity ("CSOSA About Us," n.d.). Offenders are assigned to supervision units based on case type (i.e., interstate, behavioral health, domestic violence, general supervision, gender-specific/female, and sex offense) ("CSOSA About Us," n.d.). Contact standards and case management activities are established via the Autoscreener tool, an in-house comprehensive risk/needs assessment that determines an offender's supervision level and prescriptive supervision plan based on static and dynamic factors across several domains ("CSOSA About Us," n.d.). The supervision levels designated by the Autoscreener are Intensive, Maximum, Medium, and Minimum, each of which requires a set amount of contacts per month ("CSOSA About Us," n.d.).

In July 2011, CSOSA's Community Supervision Services (CSS) unit reassigned all non-sex offenders classified at the minimum level of supervision by the Autoscreener to specific Community Supervision Officers (CSOs) housed on individual supervision teams. This was in an effort to identify the lowest-risk offenders and remove them from caseloads comprised of higher risk supervisees. Although a step in the right direction, officers placed in these positions found it difficult to break from old habits and tended to rely on traditional or judgment-based supervision to keep track of their higher than average caseloads. This was primarily due to these officers remaining on teams that supervised non-minimum offenders, which contributed to low-risk offenders being seen without much regard to their risk classification.

In 2012, two minimum-classification officers assigned to an all-male mental health team (i.e., Team 54) began a mass-reporting concept for their combined minimum offender caseload of, approximately, 500 probationers and parolees/supervised releasees. This was done in an attempt to separate low-risk offenders from higher risk, gain better control of bimonthly contact standards for minimum offenders, and prevent from seeing them beyond their risk level. The concept worked well and, by March 2013, CSS implemented a team-based supervision process for minimum offenders with the creation of three teams (i.e., Team 54, Team 20, and Team 8) comprised of 6-8 CSOs assigned all-minimum caseloads. Shortly thereafter, two of the teams (i.e., Team 54 and Team 20) merged their respective mass reporting processes into one, week-long initiative on a bimonthly basis, which allowed for more time allocated to other administrative duties. The third team (i.e., Team 8) conducted its own mass reporting schedule for its domestic violence special designation within the same reporting week.

The mass reporting process allowed for minimum offenders to report at certain times in group format and touch bases with a supervising agent on a low-risk team. This format included: four reporting time frames (i.e., 9am, 11am, 2pm, and 5pm) across a designated week; a reporting location comprised of a large conference room inside the metro-accessible police headquarters in downtown District of Columbia, which allowed for a separate entry and exit; a reporting set up that consisted of a seating area for, approximately, 50 offenders as well as a face-to-face contact area where upwards of 13 officers were arranged at tables; a coverage schedule to ensure that all sessions across the five days was staffed appropriately; and a number system by which each offender reporting at each time frame was called in turn to be seen by the next available officer at the table. To date, the mass reporting process has remained intact and continues to allow for successful face-to-face contact with 700-900 offenders over the course of the designated week. Additionally, as of November 2015, the contact standard for the minimum offender population was further reduced to quarterly, setting the contact requirement for the process to 4 times per year.

Despite the relief of resources and expedited reporting process that resulted from this initiative, the shift from traditional to mass reporting was difficult for some officers and offenders to digest. Several CSOs required a great deal of coaching to accept the new process, as they were hesitant to allow any of their colleagues to see their offenders in their stead. Along the same lines, many offenders expressed their concern that they would no longer have unlimited access to their assigned officer nor the freedom to report when convenient. It was clear that the thought of offender reporting taking a form similar to that of a bank or motor vehicle department was a challenge for some to accept. However, after several rotations of the mass reporting concept, complaints from both sides dissipated and the new norm was embraced. As the mass reporting process has been in effect for, approximately, 36 months, an assessment of minimum supervision outcomes can be made.

CHAPTER FOUR: METHODS

Research Questions and Hypotheses

This study is an effort to explore the individual factors or characteristics that predict successful supervision outcomes for low-risk offenders. As such, the primary research question is: What case factors and offender characteristics best predict successful supervision outcomes for minimum risk offenders? The factors and characteristics of interest are: *Supervision Type, Gender, Race/Ethnicity, Age, Marital Status, Housing, City Quadrant (of residence), Employment, Education, Mental Health, Domestic Violence, Drug Use,* and *Rearrested.* I hypothesize that older (i.e., 51+) offenders with more favorable factors and characteristics (i.e., married, stable housing, employed, higher education, no history of domestic violence or mental health diagnosis, and no rearrest) will be more likely to have successful outcomes. A secondary research question is: What case factors and offender characteristics best predict an offender's removal from minimum supervision. I hypothesize that younger (i.e., 20-35) minimum offenders who have more unstable factors and characteristics (i.e., divorced, unstable housing, unemployed, low education, instances of domestic violence, mental health diagnosis, and rearrest) will be more likely to be removed from low-risk supervision.

Data

The data for this study was comprised of offenders who had been classified at the minimum level per CSOSA's Autoscreener and assigned to any one of CSOSA's Minimum Teams (i.e., Teams 8, 20, and 54). Those eligible for inclusion were District of Columbia residents placed on supervision in the year 2014 for a deferred sentencing agreement, civil protection order, probation, supervised release, and/or parole case originating from a District of Columbia Code Offense. For offenders who were on concurrent supervision in more than one of these case types, the one yielding the longest term of supervision was used as the primary case. This resulted in an original sample of 790 offenders (N=790).

In order to assess actual outcomes, offenders who remained on active supervision at the minimum level at the time of analysis were removed from the sample data, which totaled 240 removals (n=240). The remaining offenders had either reached supervision closure or entered a status change category that removed them from the minimum supervision trajectory between the 2014 entry year and October 2016, the month of data extraction. This resulted in a final sample of 550 offenders (n=550), comprised of 412 offenders who ended supervision successfully (n=412), 85 who ended supervision unsuccessfully (n=85), and 53 whose entered a non-minimum status either via supervision level increase or placement on monitored supervision (n=53). Figure 1 illustrates how the final sample was derived.

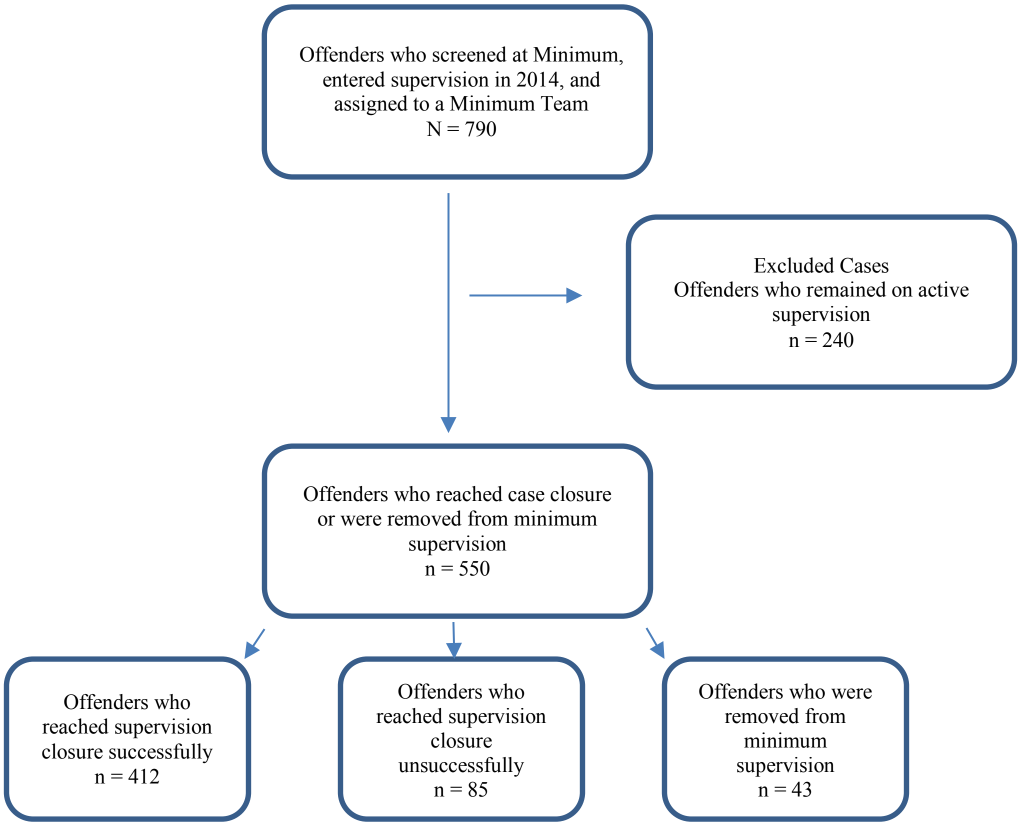

Figure 1 Data Selection Process.

Dependent Variables

Supervision outcomes that occurred between supervision onset at any point in calendar year 2014 and the month of data extraction (i.e., October 2016) are the dependent variables in this study, allowing for a time period up to 34 months. These are: *Successful, Unsuccessful,* and *Non-Min*. Successful is defined as any supervision closure that did not result from a negative action by the releasing authority (i.e., District of Columbia Superior Court [DCSC], United States Parole Commission [USPC], or Sending State Court [SSC]). This includes: early satisfactory termination from supervision, expiration of supervision (either successful or unsuccessful), and supervision transfers or returns to SSCs via Interstate Compact. Unsuccessful is defined as any supervision closure that resulted from a negative action by the releasing authority, to include supervision revocation, unsuccessful termination, and warrant issuance. The third outcome, Non-Min, captures all offenders who screened out of minimum level supervision during their term or were removed from active supervision and placed in a monitored status, two scenarios that would have ended their minimum supervision track.

Independent Variables

Offender demographics, continued criminal activity, and factors informed by the literature review serve as the independent variables. These categorical variables are: *Supervision Type, Gender, Race/Ethnicity, Age, Marital Status, Housing, City Quadrant, Employment, Education, Mental Health, Domestic Violence, Drug Use,* and *Rearrested.*

Supervision Type has two categories: Probation and Parole/Supervised Release. Probation includes all offenders who were on supervision for a deferred sentencing agreement, civil protection order, or probation matter before the DCSC. Such offenders may or may not have a confinement history related to the supervision case relevant to the study. Parole/Supervised Release includes all offenders who were under the jurisdiction of the USPC following a term of incarceration for the relevant supervision case.

Gender has two categories (i.e., Female and Male) as does Race/Ethnicity, which is comprised of African-American offenders (i.e., Black-Not Hispanic) or non-African-American (i.e., Non-Black).

Age is made up of three groups: 20-35, 36-50, and 51 or above. Marital Status is also comprised of three categories: Divorced, Married, and Single.

Housing indicates whether the offender had housing classified as Not Unstable or Unstable. Not Unstable housing is defined as not residing in a transitional home, shelter, or homeless in the District of Columbia. City Quadrant identifies whether the offender resided in the northern quadrants of Washington, D.C. (i.e., North) or the southern quadrants of the city (i.e., South).

Education level is comprised of 3 groups: Less than 12th Grade, General Equivalency Diploma [GED] or High School, and Some College or Above.

The Employment variable is comprised of two categories of offenders: Employed and Unemployed. The remaining variables indicate whether or not an offender ever received an Axis I diagnosis (Mental Health: Diagnosis or No Diagnosis), experienced an incident of domestic violence (Domestic Violence: Yes or No), whether or not they had a substance abuse history (Drug Use: Yes or No), and if they incurred a rearrest during the supervision term relevant to this study (Rearrested: Yes or No).

The independent variables were checked for multicollinearity using Pearson Correlation Coefficients. Table 1 shows the results from the correlation matrix for Successful v. Unsuccessful supervision outcomes (Model 1) and Table 2 shows the results from the correlation matrix for Successful v. Non-Min outcomes (Model 2).

Table 1. Pearson Correlation Coefficients of characteristics influencing supervision outcomes, Successful v. Unsuccessful (Model 1).

Characteristic	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Supervision Type													
2. Gender	.15 .0009												
3. Age	.27 <.0001	.25 <.0001											
4. Marital Status	.07 .1051	-.14 .0019	-15 .0006										
5. Race/Ethnicity	.16 .0005	-.03 .4966	.25 <.0001	.06 .1455									
6. Education	-.07 .1159	-.11 .0153	-.13 .0029	.05 .2700	.07 .0947								
7. Employment	-.21 <.0001	-.05 .2864	-.36 <.0001	-.02 .7006	-.26 <.0001	.08 .0764							
8. City Quadrant (North/South)	.03 .4813	-.07 .1018	.08 .0745	.03 .4726	.31 <.0001	.02 .6419	-.08 .0662						
9. Housing	-.08 .0576	-.07 .11	-.07 .1246	.01 .8893	-.06 .1665	-.03 .5084	.21 <.0001	.05 .2346					
10. Domestic Violence	-.31 <.0001	-.18 <.0001	-.21 <.0001	-.01 .8020	-.18 <.0001	.02 .6623	.17 .0001	-.10 .0308	.09 .0460				
11. Mental Health	.20 <.0001	.00 .9951	.14 .0017	.02 .6580	.11 .0110	.02 .6334	-.27 <.0001	.00 .9628	-.17 .0002	-.18 <.0001			
12. Drug History	.21 <.0001	.14 .0020	.26 <.0001	.04 .3844	.28 <.0001	.04 .3870	-.21 <.0001	.12 .0092	-.10 .0262	-.24 <.0001	.13 .0028		
13. Rearrest	.23 <.0001	.03 .5311	.13 .0025	-.00 .9747	.07 .1170	.00 .9528	-.22 <.0001	.04 .4027	-.06 .2125	-.09 .0389	.24 <.0001	.15 .0006	

Total number of minimum offenders who completed supervision either successfully or unsuccessfully, n=497.

Table 2. Pearson Correlation Coefficients of characteristics influencing supervision outcomes, Successful v. Non-Min (Model 2).

Characteristic	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Supervision Type													
2. Gender	.12 .0082												
3. Age	.13 .0064	.19 <.0001											
4. Marital Status	-.04 .3949	-.15 .0008	-.19 <.0001										
5. Race/Ethnicity	.12 .0075	-.06 .1756	.16 .0005	.06 .1801									
6. Education	-.10 .0268	-.08 .0685	-.09 .0407	.05 .3139	.12 .0114								
7. Employment	-.07 .1343	.00 .9465	-.31 <.0001	.02 .7149	-.25 <.0001	.04 .4371							
8. City Quadrant (North/South)	.03 .4534	-.11 .0166	.04 .3538	.08 .1005	.31 <.0001	.02 .6549	-.08 .0770						
9. Housing	-.05 .2350	-.01 .7404	-.04 .3873	.01 .8777	-.09 .0451	-.03 .5069	.15 .0008	.09 .0568					
10. Domestic Violence	-.24 <.0001	-.17 .0002	-.06 .1794	.01 .7567	-.16 .0003	.01 .8019	.09 .0500	-.12 .0099	.07 .1157				
11. Mental Health	.11 .0165	-.03 .4634	.08 .0692	-.04 .3300	.10 .0354	.06 .1820	-.23 <.0001	-.02 .6421	-.15 .0015	-.12 .0091			
12. Drug History	.11 .0189	.09 .0448	.20 <.0001	.04 .3539	.25 <.0001	.07 .1124	-.18 .0001	.09 .0566	-.03 .5639	-.17 .0002	.09 .0585		
13. Rearrest	-.01 .8825	.03 .5330	.06 .1823	-.03 .5172	-.01 .7439	-.04 .3908	-.18 <.0001	.05 .2353	-.02 .6632	.02 .6545	.09 .0510	.10 .0327	

Total number of minimum offenders who completed supervision successfully or were removed from the minimum track, n=465.

The highest statistically significant correlation reflected across both tables is between the variables of employment and offender age (-.36 in Model 1 and -.31 in Model 2, $p < .0001$), although the strength of the relationship is moderate. The next highest correlation that is statistically significant across both tables is Race/Ethnicity and City Quadrant (.31 in both Model 1 and Model 2, $p < .0001$). This relationship is also moderate. Multicollinearity does not appear to be at issue.

Statistical Method

Data analysis used SAS 9.4 for the computations of the statistical models. Each variable was explored through descriptive statistics. The chi-squared statistic was used to determine association between the independent variables and outcomes. Because the hypotheses being tested is based on relationships between a categorical outcome variable and categorical predictor variables, logistic regression was then used to further analyze the characteristics and factors that may have an impact on supervision outcome for minimum offenders as follows:

Model 1: OUTCOME = Successful (1) or Unsuccessful (0)

Model 2: OUTCOME = Successful (1) or Non-Min (0)

CHAPTER FIVE: FINDINGS

Descriptive Findings

Table 3 describes the study sample in detail and shows the association between the independent and dependent variables using the chi-squared statistic.

Table 3. Supervision outcomes of minimum offenders.

Characteristic	Category	Total n=550 N *(%)*	Successful n=412 N *(%)*	Unsuccessful n=85 N *(%)*	Non-Min n=53 N *(%)*	p-values*
Supervision Type	Probation	487 *(88.6)*	397 *(72.2)*	47 *(8.6)*	43 *(7.8)*	<.0001
	Parole or S.R.	63 *(11.4)*	15 *(2.7)*	38 (6.9)	10 *(1.8)*	
Gender	Male	449 *(81.6)*	323 *(58.7)*	81 *(14.7)*	45 *(8.2)*	.0010
	Female	101 *(18.4)*	89 *(16.2)*	4 *(.7)*	8 *(1.5)*	
Age	20-35	162 *(29.5)*	128 *(23.3)*	10 (1.8)	24 (4.4)	<.0001
	36-50	175 *(31.7)*	140 *(25.4)*	18 (3.3)	17 (3.0)	
	51+	213 *(38.8)*	144 *(26.2)*	57 (10.4)	12 (2.2)	
Race/Ethnicity	Black	416 *(75.7)*	294 *(53.5)*	77 *(1 4.0)*	45 *(8.2)*	.0002
	Non-Black	134 *(24.3)*	118 *(21.5)*	8 *(1.4)*	8 *(1.4)*	
Marital Status	Single	372 *(67.7)*	271 *(49.3)*	60 *(10.9)*	41 *(7.5)*	.2406
	Married	115 *(20.9)*	94 *(17.1)*	16 *(2.9)*	5 *(.9)*	
	Divorced	63 *(11.4)*	47 *(8.5)*	9 *(1.6)*	7 *(1.3)*	
Housing	Not Unstable	519 *(94.4)*	398 *(72.4)*	71 *(12.9)*	50 *(9.1)*	<.0001
	Unstable	31 (5.*6)*	14 *(2.5)*	14 *(2.5)*	3 *(.6)*	
City Quadrant	North	364 *(66.2)*	287 *(52.2)*	53 *(9.6)*	24 *(4.4)*	.0014
	South	186 *(33.8)*	125 *(22.7)*	32 *(5.8)*	29 *(5.3)*	
Employment	Employed	310 *(56.4)*	259 *(47.1)*	21 *(3.8)*	30 *(5.5)*	<.0001
	Unemployed	240 *(43.6)*	153 *(27.8)*	64 *(11.6)*	23 *(4.2)*	
Education	Some College+	214 *(39.0)*	172 *(31.3)*	29 *(5.3)*	13 *(2.4)*	.0538
	GED or HS	216 *(39.2)*	150 *(27.3)*	41 *(7.5)*	25 *(4.4)*	
	<12th grade	120 *(21.8)*	90 *(16.4)*	15 *(2.7)*	15 *(2.7)*	
Mental Health Status	Diagnosis	117 *(21.3)*	74 *(13.5)*	33 *(6.0)*	10 *(1.8)*	<.0001
	No Diagnosis	433 *(78.7)*	338 *(61.4)*	52 *(9.5)*	43 *(7.8)*	
Domestic Violence	History	360 *(65.4)*	300 *(54.5)*	34 *(6.2)*	26 *(4.7)*	<.0001
	No History	190 *(34.6)*	112 *(20.4)*	51 *(9.3)*	27 *(4.9)*	
Drug Use	History	342 *(62.1)*	235 *(42.7)*	75 *(13.6)*	32 *(5.8)*	<.0001
	No History	208 *(37.9)*	177 *(32.3)*	10 *(1.8)*	21 *(3.8)*	
Rearrested	Rearrest	61 *(11.0)*	20 *(3.6)*	20 *(3.6)*	21 *(3.8)*	<.0001
	No Rearrest	489 *(89.0)*	392 *(71.4)*	65 *(11.8)*	32 *(5.8)*	

*p-values are based on chi-squared tests.

The offenders included in the final sample were both males and females between the ages of 20 and 51+ years old. There were 101 females in the sample and 449 males. The majority of the offenders were Black-Not Hispanic at 75.7% (416), with the remaining 134 representing different races/ethnicities classified as Non-Black (24.3%). The majority of the sample at 88.6% was under the jurisdiction of the DCSC for a deferred sentencing agreement, civil protection order, or probation matter (487) while the remaining 63 (11.4%) were on parole or supervised release under the USPC, indicating they had served a period of incarceration prior to supervision.

The majority of those in the sample at 94.4% (519) reported having housing that was deemed not unstable (i.e., not residing in a transitional home, shelter, or homeless) in the District of Columbia. Over 5 ½% (31) were classified as living in unstable housing and either homeless or in transitional programming. The bulk of the sample, or 364 (66.2%), resided in the northern half of the District of Columbia (i.e., northwest or northeast) while 186 (33.8%) resided in the southwest or southeast quadrants.

Over 67% (372) of the sample was single while 115 (20.9%) reported being married and another 63 (11.4%) reported being separated or divorced. With respect to education, 216 (39.2%) offenders had a high school diploma or GED while 120 (21.8%) had less than a 12th grade education. Those with some college education or above yielded almost 40% of the sample, or 214. More offenders were employed at 56.4% (310) while the remaining 240 were unemployed (43.6%).

Over 78% of the sample (433) was identified as having no mental health diagnosis, while 21.3% (117) had been diagnosed with an Axis 1 clinical disorder at some point in their lives. Over 65% (360) were found to have had at least one domestic violence incident in their history compared to those who did not at nearly 35% (190). With respect to drug/alcohol use history, 342 (62.1%) were identified as having used illegal substances in their lives while 208 denied having such history (37.9%).

The vast majority of the sample remained arrest-free during their term of supervision at 89%, with the remaining 61 (11%) incurring at least one arrest following supervision onset in 2014. The average length of time spent on supervision for probationers was 1 year whereas parolees/supervised releasees averaged 2 years supervised. Those in the sample who ended supervision successfully averaged 1 year on supervision and those who were unsuccessful averaged 1.6 years. The minimum offenders who were removed from the track altogether averaged 1.7 years supervised.

Of all the variables, Marital Status is the only one that is *not* statistically significant in Table 3. Education shows borderline association with outcomes, while all other variables are significantly different across the three outcomes ($p < .05$).

Logistic Regression Findings

Two logistic regression models allowed for further probing into the associations between the variables and supervision outcome. Table 4 describes Model 1 (Successful v. Unsuccessful) and Model 2 (Successful v. Non-Min), and includes all predictor variables.

Table 4. Characteristics influencing supervision outcomes, logistic regression models 1 and 2.

	Model 1 Unsuccessful Supervision (ref. Successful)				**Model 2** Removal from Minimum (ref. Successful)			
Variable	Estimate	OR	95% CI	p-value	Estimate	OR	95% CI	p-value
Supervision Type								
Probation (ref.)								
Parole/S.R.	1.2210	11.496	5.131-25.756	<.0001	1.1075	9.162	2.675-31.383	.0004
Gender								
Female (ref.)								
Male	.5700	3.127	.977-10.007	.0548	.3900	2.181	.753-6.315	.1504
Age								
51+ (ref.)								
20-35	-.2415	.894	.360-2.223	.4094	-1.1146	.154	.054-.442	.0003
36-50	.3711	1.650	.779-3.496	.1382	.3606	.675	.248-1.835	.2154
Race/Ethnicity								
Black (ref.)								
Non-Black	-.1752	.704	.271-1.830	.4721	-0.4867	.378	.117-1.223	.1043
Marital Status								
Single (ref.)								
Divorced	.0891	.968	.388-2.412	.7744	-.3242	1.051	.316-3.499	.4532
Married	-.2108	.717	.336-1.532	.4394	.6982	2.922	.897-9.515	.1020
Housing								
Not Unstable (ref.)								
Unstable	.07561	4.537	1.655-12.440	.0033	.4085	2.264	.355-14.428	.3873
City Quadrant								
North (ref.)								
South	.1069	1.238	.659-2.329	.5070	.5367	2.926	1.363-6.279	.0059
Employment								
Employed (ref.)								
Unemployed	.4705	2.563	1.287-5.102	.0074	-.2034	.666	.276-1.603	.3642
Education								
Some College (ref.)								
GED H.S.	-.2165	.920	.463-1.826	.3133	-.1049	.455	.188-1.101	.6847
<12th Grade	.3493	1.620	.676-3.880	.1915	-.5771	.284	.100-.807	.0595
Mental Health								
Diagnosed (ref.)								
No Diagnosis	-.0104	.979	.492-1.949	.9526	.1194	1.270	.476-3.385	.6331
Domestic Violence								
No History (ref.)								
History	-.1799	.698	.373-1.306	.2606	-.4642	.395	.181-.860	.0194
Drug Use								
No History (ref.)								
History	.4061	2.253	1.016-4.995	.0456	-.2128	.653	.301-1.417	.2813
Rearrested								
No Rearrest (ref.)								
Rearrest	.5126	2.788	1.111-6.993	.0289	1.8834	43.244	14.931-125.251	<.0001

OR-Adjusted Odds Ratio; CI-Confidence Interval; -2 Log L: 303.858 (Model 1), 214.026 (Model 2)

The most significant variable reflected in Model 1 is Supervision Type. According to this model, low-risk parolees and supervised releasees were 11 times more likely to complete supervision unsuccessfully than probationers after adjusting for all other variables (i.e., Gender, Age, Race/Ethnicity, Marital Status, Housing, City Quadrant, Employment, Education, Mental Health, Domestic Violence, Drug Use, and Rearrest) (OR = 11.496, 95% CI = 5.131-25.756, $p < .0001$). Housing is the next significant predictor, indicating that offenders with unstable housing were 4.5 times more likely to complete supervision unsuccessfully (OR = 4.537, 95% CI = 1.655-12.440, $p = .0033$). Unemployed offenders as well as those who incurred a rearrest while on supervision were also less likely to complete supervision favorably at a rate of over 2 ½ times their employed and arrest-free counterparts (OR = 2.563, 95% CI = 1.287-5.102, $p = .0074$; OR = 2.788, 95% CI = 1.111-6.993, $p = .0289$). Lastly, minimum offenders with a history of substance abuse were 2 times more likely to be unsuccessful than those who did not have a drug history (OR = 2.253, 95% CI = 1.016-4.995, $p = .0456$).

Model 2 reflects the likelihood of removal of a minimum offender from the minimum supervision trajectory, either due to supervision level increase or placement in a status that suspended supervision (i.e., hospitalization, confinement). The most significant predictor of such removal from minimum supervision was whether or not an offender incurred a rearrest during supervision. If rearrested, the odds of an offender being removed from minimum supervision was 43 times higher than those without an arrest (OR = 43.244, 95% CI = 14.931-125.251, $p < .0001$). Also significant was Supervision Type with parolees and supervised releasees more likely to be removed from the minimum trajectory at a rate of 9 times higher than probationers (OR = 9.162, 95% CI = 2.675-31.383, $p = .0004$). Housing stability was not a significant predictor of minimum supervision removal, but residence location appeared to have some bearing, as offenders who resided in the southern quadrants of the city were nearly 3 times more likely to be removed from the low-risk track (OR = 2.926, 95% CI = 1.363-6.279, p = .0059).

Using the results of the correlations, another set of logistic regression sub-models were performed to include all variables except Employment, Age, and Race/Ethnicity, respectively. This was done as a precautionary measure to demonstrate that multicollinearity may not appear to be an issue. The focus here will be on the removal of Employment as a predictor variable, given that logistic regression conducted without the variables of Age and Race/Ethnicity produced even less change. Table 5 reflects the models excluding the variable Employment.

Table 5. Characteristics influencing supervision outcomes, logistic regression sub-models 1 and 2.

	Model 1 Unsuccessful Supervision (ref. Successful))				**Model 2** Removal from Minimum (ref. Successful)			
Variable	Estimate	OR	95% CI	p value	Estimate	OR	95% CI	p value
Supervision Type								
Probation (ref.)								
Parole/S.R.	1.1961	10.938	4.951-24.166	<.0001	1.0871	8.795	2.581-29.965	.0005
Gender								
Female (ref.)								
Male	.5541	3.029	.954-9.617	.0601	. 4071	2.257	.775-6.572	.1354
Age								
51+ (ref.)								
20-35	-.0966	1.231	.521-2.909	.7309	-1.1581	.138	.049-.387	.0001
36-50	.4011	2.025	.976-4.200	.1043	.3340	.613	.230-1.635	.2479
Race/Ethnicity								
Black (ref.)								
Non-Black	-.2178	.647	.254-1.650	.3617	-.4325	.421	.135-1.318	.1374
Marital Status								
Single (ref.)								
Divorced	.1414	.1.089	.431-2.751	.6549	-.3641	1.001	.306-3.267	.3932
Married	-.1975	.776	.370-1.629	.4659	.7287	2.984	.907-9.821	.0889
Housing								
Not Unstable (ref.)								
Unstable	.8805	5.818	2.176-15.553	.0004	.3417	1.980	.307-12.765	.4723
City Quadrant								
North (ref.)								
South	.1193	1.269	.681-2.367	.4531	.5327	2.902	1.355-6.215	.0061
Education								
Some College (ref.)								
GED H.S.	-.1929	.886	.450-1.744	.3650	-.1189	.450	.186-1.089	.6450
<12th Grade	.2642	1.399	.596-3.282	.3131	-.5607	.289	.102-.821	.0662
Mental Health								
Diagnosed (ref.)								
No Diagnosis	-.0944	0.828	.421-1.628	.5842	.1646	1.390	.530-3.648	.5038
Domestic Violence								
No History (ref.)								
History	-.1874	.687	.369-1.280	.2371	-.4580	.400	.184-.871	.0211
Drug Use								
No History (ref.)								
History	0.4169	2.302	1.058-5.008	.0355	-.2113	.655	.301-1.426	.2867
Rearrested								
No Rearrest (ref.)								
Rearrest	.6168	3.433	1.390-8.482	.0075	1.8041	36.899	13.740-99.092	<.0001

OR-Adjusted Odds Ratio; CI-Confidence Interval; -2 Log L: 311.215 (Model 1), 214.869 (Model 2)
Model does not include the variable *Employment*.

Despite removing Employment, Supervision Type remained a significant predictor variable for successful outcomes, indicating that parolees and supervised releasees were still nearly 11 times more likely to be unsuccessful on supervision than probationers (OR = 10.938, 95% CI = 4.951-24.166, $p < .0001$). This group was also over 8 times more likely to be removed from the minimum track (OR = 8.795, 95% CI = 2.581-29.965, p = .0005). Minimum offenders with unstable housing remained more likely to be unsuccessful at a rate of nearly 6 times higher than those with stable housing (OR = 5.818, 95% CI = 2.176-15.553, p = .0004) and those residing in the city's southern quadrants were still more likely to be removed from the minimum track at a rate of 3 times that of those in the north (OR = 2.902, 95% CI = 1.355-6.215, p = .0061). Drug history remained a significant predictor for success, as these minimum offenders were still more than 2 times likely to be unsuccessful (OR = 2.302, 95% CI = 1.058-5.008, p = .0355). Offenders who were rearrested during their supervision term were over 3 times more likely to be unsuccessful than those who were not (OR = 3.433, 95% CI = 1.390-8.482, p = .0075) and nearly 37 times more likely to be removed from minimum supervision altogether (OR = 36.899, 95% CI = 13.740-99.092, $p < .0001$).

Based on these results, removing the variable of Employment had a small impact on some of the significant variables. When logistic regression was conducted without the variables of Age and Race/Ethnicity, even less change resulted. A review of −2 Log L (with Intercept and Covariates) confirms that the models inclusive of all variables were either a better fit or unchanged when compared to the models excluding Employment (i.e., 303.858 v. 311.215 for Model 1; 214.026 v. 214.869 for Model 2).

CHAPTER SIX: DISCUSSION AND CONCLUSION

Discussion

This study explored the individual factors and characteristics of low-risk offenders in an effort to answer two research questions: Do case factors and offender characteristics predict successful supervision outcomes for minimum risk offenders? and Do they also impact the trajectory of minimum supervision? In other words, are there differences among the low-risk offender population that are important to consider or should community corrections agencies simply leave this population alone as the limited literature suggests?

Logistic regression models revealed that the type of case for which an offender is under supervision was an important predictor for both successful completion as well as removal from the low-risk track. Minimum offenders appeared to fare far worse if they were under the jurisdiction of the USPC, either on parole or supervised release, rather than under the DCSC on probation, deferred sentencing, or civil protection order. In fact, parolees and supervised releasees made up only 11% of the sample, but were 11 times more likely to end supervision unsuccessfully (Model 1, $p < .0001$). They were also 9 times more likely to be removed from minimum supervision than probationers (Model 2, p = .0004). These findings may not be surprising given the unprecedented challenges that plague prisoner reentry on a national level (Petersilia, 2009).

Focusing on unsuccessful outcomes, a possible explanation is the difference in supervision conditions between parolees/supervised releasees and probationers. The more extensive list of conditions imposed by the USPC on parolees/supervised releasees outweighs those imposed by the DCSC on probationers and may create more opportunities for offenders under its charge to incur technical violations that result in unsuccessful outcomes (Grattet & Lin, 2014). At present, the USPC imposes more than double the general conditions imposed by the DCSC, requiring parolees and supervised releasees to adhere to upwards of 20 different standard supervision requirements. This list does not include any special conditions that may also be added. Research tell us that imposing more supervision and/or intensive interventions on low-risk offenders leads to unfavorable results (Lowenkamp et al., 2006). As such, the amount and intensity of the conditions imposed by the USPC may be inherently more severe on low-risk offenders. This may also cause tension for the minimum parolee/supervised releasee as they may find themselves caught between the high expectations of their releasing authority and the low administrative management being conducted by the supervision agency.

Another possible explanation for the low rate of success among parolees and supervised releasees is the residual impact of incarceration. Those under the jurisdiction of the USPC have spent time confined for their offenses, many for lengthy sentences, whereas probationers are confined less (or not at all) by the DCSC. Research shows that prison experiences, and in particular those that are negative or involve victimization, are a factor leading to unsuccessful outcomes for formerly-incarcerated offenders (Listwan, Sullivan, Agnew, Cullen, & Colvin, 2013). Research speaks to the criminogenic effect of incarceration, although the strength of effect has been debated (Cullen, Jonson, & Nagin, 2011). Those at lowest risk to reoffend appear to be more vulnerable to the residual effects of confinement, as some evidence suggests they are more likely to recidivate due to incarceration (Cullen et al., 2011). The combination of higher supervision expectations as well as the incarceration experience certainly differentiates the parolee/supervised releasee from the probationer and could be contributing to worse outcomes for those who are low-risk.

Whether or not a low-risk offender was rearrested was the most significant predictor of removal from minimum supervision as well as significant for unsuccessful outcomes, albeit to a lesser degree. For the purpose of this study, a rearrest incurred while on supervision was treated as an event and not an outcome in and of itself. This was due to the fact that rearrests did not guarantee unsuccessful case closure, as minimum offenders who were rearrested in the sample were evenly distributed across the three outcomes. For example, an offender may have incurred a rearrest that was never papered or was quickly dismissed, hence not invoking action from the DCSC or USPC. He or she may have ultimately completed supervision successfully despite having incurred a new arrest. Taking this definition into account, the impact of a rearrest made minimum offenders nearly 3 times more likely to end supervision unsuccessfully (p = .0289) and, more significantly, predicted whether or not an offender remained on minimum supervision, making it 43% more likely that they were removed from the track ($p < .0001$). The latter scenario can be explained in one of two ways.

First, CSOSA policy requires a new Autoscreener for minimum and medium level offenders who are rearrested. A new criminal offense may have increased the minimum offender's criminogenic risk, resulting in the reassessment yielding an increased supervision level (Lopes, Krohn, Lizotte, Schmidt, Vásquez, & Bernburg, 2012). The second possible explanation involves assessment error. Those who incurred a rearrest while being supervised as a minimum offender may have been more reflective of a medium or higher risk level to begin with and placed on a minimum team due to a poorly completed initial Autoscreener (Sperber et al., 2013a; Bonta, 2002). Worse still, the offender's supervision level may have been overridden to minimum based on the judgement of the officer completing the assessment. The override capability of the Autoscreener is problematic in this vein, as it may allow officers who are unwilling to trust or use the instrument correctly an avenue to impose a supervision level based on their own opinion of the offender's risk (Viglione, Rudes, & Taxman, 2015).

Several other variables impacted low-risk case outcomes that are worth mention. Unstable housing, for example, was the second most significant predictor of unsuccessful outcome for the minimum population ($p = .0033$). Although not a criminogenic risk factor, housing may provide stability in the community that supports supervision engagement (Taxman, 2014). In addition, it is possible that minimum offenders with unstable housing may incur more instances of reporting violations or fall into lapses in contact with their officers, hence leading to an increase in unsuccessful supervision closures. Lack of stable housing may also point to other basic needs that may not be met in the community, regardless of risk to reoffend. Hence, the identification of housing as a destabilizer is supported by this analysis (Taxman & Caudy, 2015).

Drug use, given its impact on unsuccessful outcomes, and location of an offender residence's residence in the city (i.e., City Quadrant), given its impact on whether or not someone remained on minimum supervision, are also variables that appear important. However, of all the variables that show some predictive significance on supervision outcomes for the minimum offender, Employment is arguably the most amenable to intervention.

Analysis showed that those in the sample who were unemployed were 2 ½ times less successful than those who were employed. This result deserves attention as employment is the one variable that supervision can directly influence. CSOSA has dedicated extensive programming to address the employment and vocational needs of its offender population. The agency's Vocational Opportunities Training, Education and Employment (VOTEE) offices are located in each of CSOSA's field units and are staffed by specialists who engage referred offenders in either an education or vocation/employment track. The specialist identifies the track after performing assessments on a referred offender and, if employment is prioritized, extensive assistance with job placement takes place. Given the impact that employment had on the supervision success of minimum level offenders in this initial analysis, involving low-risk offenders in the aforementioned services may be worth considering, especially since over 40% of the sample was unemployed.

Employment assistance geared specifically for the low-risk population may shift more minimum offenders toward a successful versus unsuccessful closure. As indicated earlier, Employment is the one variable that proved significant in this study that is able to be readily acted on. Because securing a job is traditionally an important goal of supervision, corrections agencies likely already have programming in place to meet this end. However, an employment assistance strategy geared for low-risk offenders should be developed with research in mind. The manner in which this is done is critical since such a strategy should address the needs of the minimum offender outside of those geared toward higher risk (Lowenkamp & Latessa, 2004). It should also prioritize program evaluation so the agency does not engage in a practice that could worsen results for its lowest risk clients.

The idea of offering low-risk offenders employment programming should not be mistaken as a recommendation to directly address recidivism among this (or any) supervised population. There is a misguided belief in the field that employment is a panacea that deters reoffending. Although empirical studies have shown a relationship between employment and crime, it is not as direct as practitioners may assume (D. Huffer, personal communication, March 3, 2017). The relationship is mitigated by demographics such as age and race, criminogenic risk, and sensitive to the nature of the job market (D. Huffer, personal communication, March 3, 2017; Thornberry and Christenson, 1984; Laub & Sampson, 1993; Farrington, 1986). As indicated in the literature review for this project, perception of job quality has also been found to impact the relationship between employment and crime (Uggen, 1999). Without further analysis, it is not known if recommending employment services for the low-risk offender population will move the needle on successful outcomes, let alone recidivism. More research is needed to address this and other factors that impact this population.

In the end, the research questions posed have been successfully answered. The first question (i.e., Do case factors and offender characteristics predict successful supervision outcomes for minimum risk offenders?) has been answered as evidenced by the predictive variables found significant (i.e., Supervision Type, Housing, Employment, Rearrest, and Drug Use). The second research question (i.e., Do case factors and offender characteristics also impact the trajectory of minimum supervision?) was answered as evidenced by the variables that were most predicative of removal from the minimum trajectory (i.e., Rearrest, Supervision Type, and City Quadrant).

Part of the original hypothesis that certain factors and characteristics deemed more favorable (i.e., older, married, higher education, no domestic violence history, no mental health diagnosis) would impact successful outcomes is not supported by this study. Other favorable offender background factors noted in the original hypothesis (i.e., no drug use), stability factors (i.e. housing and employment), and continued criminality (i.e., no rearrest event while on supervision) are supported. The second hypothesis that the same characteristics and factors impact removal from the minimum supervision trajectory was also partially supported by the variables Rearrest and City Quadrant.

Conclusion

There is a lack of literature about the low-risk population, to include what impacts their supervision success. The analysis conducted for this thesis project explored the characteristics and factors that best predicted supervision outcomes for CSOSA's minimum supervision offenders. Of specific interest were those variables most responsible for successful case outcome and removal from the agency's more administrative minimum supervision trajectory. Through exploration across two logistic regression models and subsequent sub-models, it was discovered that certain characteristics and factors do appear more predictive of supervision outcome than others. This study showed that differences exist among the low-risk population that should be considered in its supervision. Some of these differences, such as supervision type, rearrest, and housing, appear to have a larger impact on a smaller subset. Others, such as employment, have the potential to improve outcomes if addressed.

Additional research could delve further into the differences between supervision case types and the way minimum offenders are managed by different releasing authorities. This could include the varying length of supervision terms imposed on low-risk offenders, given the potential limitation these differences may have had on the current study. More investigation into the types, frequency, and disposition of rearrests incurred by minimum level offenders could better inform outcomes, given that not all who are rearrested actually end supervision unsuccessfully. Research could also tackle the problem of housing, especially in the District of Columbia, and what challenges it poses to both offender and officer with respect to supervision strategies. And the extent to which substance abuse is best addressed among the low-risk population can also be investigated. Lastly, available programming that can be adjusted to accommodate the lower risk offender could be explored, beginning with those that may impact success more broadly, such as employment.

The findings of this project reveal that agencies may not be able to simply leave low-risk people alone. The minimum offender has needs that may not be well served with administrative case management. As indicated by Taxman and Caudy (2015), “lumping [the low-risk offender] into a global risk score or category” may not be the sole approach agencies should take. Instead, more creative responses that address risk without ignoring criminogenic need, destabilizers, and other factors should be considered.

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BIOGRAPHY

Reyna V. Cartagena received her Bachelor of Arts from The College of William & Mary in 1995. She has been employed in the criminal justice field ever since, first as a correctional officer then as a probation officer. She completed over twenty years in law enforcement, to include working as a Supervisory Community Supervision Officer with the Court Services and Offender Supervision Agency (CSOSA). She received several accolades and awards for her work in this role and has represented CSOSA both nationally and abroad. She is now a Social Science Analyst in CSOSA's Office of Research and Evaluation, where her experience and contributions are highly valued.