UNDERSTANDING RESOURCE DEPRIVATION: A MULTILEVEL EXAMINATION OF THE IMPACT COUNTY DEPRIVATION HAS ON COMMUNITY SUPERVISION AND TREATMENT OUTCOMES

By

LaToshia A. Butler
A Dissertation
Submitted to the
Graduate Faculty
Of
George Mason University
In Partial fulfillment of
The Requirements of the Degree
Of
Doctor of Philosophy
Criminology, Law and Society

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Spring Semester 2022
George Mason University
Fairfax, VA

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Dedication

I dedicate this dissertation to God, who is the Creator of the universe. Yahweh, you were with me every step of the way (Joshua 1:5). I struggled to get to this point in my life, but You kept me going by giving me supernatural strength that can only be found in You (2 Timothy 1:7). I thank You for Your sovereignty. You are supreme ruler of my life (Isaiah 55:8-9). No matter where I go, or how far I may stray, Your will, will be done (1 John 5:14). I thank You for Your ability to do any and all things (Ephesians 3:20). Nothing will be impossible for me as long as I walk with You (Luke 1:37). Your Word commands me to be strong and courageous and that is what has gotten me to this point (Joshua 1:9). I thank You for Your son, Jesus Christ, who died on the cross for my sins (John 3:16). I thank You for Your Word, which is living and sharper than any two-edge sword (Hebrews 4:12). Through Him, I am adopted into Your family, and I can preserve through any obstacles I may face. I thank You for Your Holy Spirit, which is my Paraclete who counsels, intercedes for, and guides me through my days (Romans 8:26). I'm in awe of everything You have done for me, and I just want to dedicate this accomplishment to You. You orchestrated every person, situation and occurrence to be brought into my life to bring me to this point (Romans 8:28). You knew all along that I would get here even when my fear was stronger than my faith. You armed me with strength, and you made my way perfect (Psalm 18:32). I give all my thanks to You (Psalm 136:1).

I would also like to dedicate this dissertation to my husband and daughter, Antwan and Amelia. Antwan, I thank you for being my ultimate support system since 2016 when I entered this doctoral program. I thank you for every time you took over all of the household tasks because I didn't have any energy to do it, tolerated my mood swings (smile), and was my shoulder to cry on. Your love is selfless, and I want to thank you publicly and proudly. I couldn't have accomplished this without you, and I share this accomplishment with you. I proudly wear your last name and I am honored to be Dr. LaToshia Austin. Amelia, right now you are just 23 weeks in mommy's tummy. Know that I did this for you and your siblings. I want each of you to know that while this was not easy, nothing is impossible with God (Luke 1:37). If mommy could complete her PhD, while pregnant, and working a full-time job, then know that strength and resilience is in your D.N.A. I promise when this is over I'm dedicating the rest of my pregnancy to eating anything you want.

Acknowledgements

I would like to acknowledge the following people who made this possible. First, I would like to acknowledge my family including my mother, father, godmother, Mr. Stan, sister, grandmother, and cousin. To my Mom (Saundra Womack), thank you for teaching me resilience and how to persevere through my obstacles. I could never repay you for the great foundation you laid before me or for all the sacrifices you've made. However, I promise to live my life in a way that reflects all of the hard work you put into molding me into the woman that I am. To my Dad (Leroy Butler, Jr.), thank you for our rekindled relationship and our conversations. I'm grateful that God restored us. To my godmother (Michelle), thank you for always being there. To Mr. Stan, thank you for being a great second Dad. To my sister (LaKellia Butler), thank you for being a butterfly in my heart. To my grandmother (Corrine Riddick), thank you for all of the wisdom and love you have given me over the years. To my cousin (Teressa Gardner), thank you for being an amazing big cousin and an awesome support system when I needed you the most.

Second, I would like to acknowledge my committee members, Dr. Danielle Rudes, Dr. Evan Lowder, Dr. Charlotte Gill, and Dr. Jill Viglione. Danielle, you have been an amazing Chair and Advisor. You encouraged me, molded me, and advocated for me every step of this program. I'm so grateful to have you and I can't wait to share more memories with you. Dr. Lowder, thank you for all the time you dedicated to molding me into a better statistician. I consider you my "Second Chair", as you were just as influential in this dissertation process. If I could share the moment that I'm hooded with you and Danielle, know that I would be honored to have you hood me. Dr. Gill and Dr. Viglione, thank you for the additional guidance, support, and feedback you provided me during this process. I am so grateful to have had you all here to mentor me.

Finally, I would like to acknowledge Mason and CLS faculty and staff who assisted me with this dissertation. First, Dr. Faye Taxman I would like to thank you for your mentorship and allowing me to use the RNR evaluation data for this dissertation. I believe, with your help, I was able to make a statement in community corrections literature. Dr. Allison Redlich and Brielle, thank you both for being so supportive of me completing this degree. Dr. James Willis and Dr Cynthia Lum, your classes were some of my most stimulating and exciting moments during my time here at Mason. I thank you all and I couldn't have made it to this point without you.

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Abstract

UNDERSTANDING RESOURCE DEPRIVATION: A MULTILEVEL EXAMINATION OF THE IMPACT COUNTY DEPRIVATION HAS ON COMMUNITY SUPERVISION AND TREATMENT OUTCOMES

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George Mason University, 2022

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Originally designed to serve as an alternative to incarceration, community corrections (i.e., probation, parole, and supervised release) is the largest component of the U.S. criminal justice system with approximately 4 million adults under some form of community supervision (Oudekerk & Kaeble, 2021). Decades of mass incarceration have led to unprecedented numbers of individuals returning home under community supervision (Chamberlain & Wallace, 2016). These last few decades, recidivism rates remain largely unchanged causing community-corrections scholars to question what needs are unaddressed amongst individuals under supervision. While evidence-based practices (EBPs), such as those modeled after risk-need-responsivity (RNR) principles, call for individuals to be referred to targeted rehabilitative treatments/services/programs, many individuals still return to disadvantaged neighborhoods with high crime and a heavy concentration of justice-involved individuals (Andrews et al., 1990; Chamberlain

& Wallace, 2016). Although research reveals that participation in programs that target criminogenic needs lower recidivisms (Andrews & Bonta, 2010), variation in effects across the quality of services (treatment type and quantity) and community corrections underlying philosophies (treatment vs. control and sanctions/violation practices) directly impact recidivism (Lowenkamp et al., 2006, 2010).

The RNR framework emphasizes that programs that adhere to these principles and effectively link individuals to treatment-oriented services overall reduce recidivism compared to programs with control-oriented approaches (Andrews & Bonta, 2010; Bonta & Andrews, 2017; Taxman, 2020). However, even cognitive-behavioral approached programs are only found to produce a reduction in recidivism ranging between 5% to 33%, suggesting that some individuals under supervision will still offend (Lipsey et al., 2001; Wilson et al., 2005). Thus, it is important for research to investigate other contributing factors in variation of recidivism rates, such as community or county-level factors and the inability to deliver these services, that may also be a contributing factor in unchanged recidivism and treatment outcomes.

This study seeks to extend social disorganization and resource deprivation theories to community corrections literature to provide insight on the variation seen when individuals supervised under certain conditions and within certain areas recidivate. More specifically, the current study uses data from 34 Oregon counties to examine how individual-level predictors (i.e., probationer demographics and specific type of treatment) and county-level conditions related to resource deprivation (i.e., county poverty, unemployment, and violent crime rates) and treatment capacity influence supervision outcomes of treatment program completion and reconviction. It is important to understand how and if individual probationer predictors *and* county-level conditions of deprivation affect the ability of the community and corrections agencies to be responsive to individual needs. It is hopeful that this research will begin to bridge the current knowledge gap and provide communities and corrections agencies sound recommendations for the development of improved probation and parole policies, practices, and resources.

Chapter 1: Introduction

1.1 Statement of the Problem

In 2020, about 1 in 66 adults was under some form of community supervision in the US (Kaeble, 2021). In fact, at that year-end, there were approximately 3,890,400 adults on either probation or parole in the United States (Kaeble, 2021). Additionally, the rate of adults placed on parole supervision at the end of 2020 increased by 1.3%, totaling 862,100. This problem intensifies when individuals under supervision have an increased likelihood of reengaging in offending behaviors, either by being rearrested, reconvicted, or re-incarcerated. Given these numbers, it is unclear how much of an effective alternative to incarceration or severe sanctions community supervision is actually serving (Langan & Levin, 2002; Phelps, 2020; Taxman et al., 2014). Hence, reducing recidivism has become an issue of national concern as parole and probation is now a “continuum of excessive penal control” impacting recidivism rates and causing the justice community to reevaluate current approaches (Phelps, 2020, p. 262).

Individuals under supervision[1] can be placed on various correctional supervision sanctions as an alternative to or post-imprisonment including probation, parole,

[1] Unless otherwise stated, the term “individual under supervision” or “justice-involved individuals” will be used interchangeably to account for individuals placed on all forms of community supervision.

supervised release, and/or mandatory release without supervision (James, 2011)[2]. While most probationers never serve a term of incarceration, parolees, on the other hand, serve the majority of their sentences in prisons before finishing the remainder of their sentence under community supervision. In addition, under parole and probation are several prison diversion options including problem-solving courts, global-positioning system (GPS or electronic monitoring), diversion programs, and home confinement (Latessa & Lovins, 2019). Each day, individuals under supervision need to connect with community and rehabilitative resources to assist them with the goal of deterring from crime (James, 2011). Several research studies suggest that access to employment and education are two of the most highly probable factors contributing to the ensuring those on community supervision do not recidivate (James, 2011, p. 10; Kethineni & Falcone, 2007; Petersilia, 2001). Understanding this, regardless of the type of community supervision placement, individuals need services to successfully navigate in the community. While research supports the importance of linking individuals to services while under community supervision, majority of the literature neglects to examine how community or county predictors can actually influence resource program allocation provided to individuals; which inherently impacts recidivism outcomes (Hipp et al., 2010).

The transition from prison to the community is difficult but must be addressed, and this function largely falls on the shoulders of community corrections agencies. Just as the cycle of individuals transitioning into the community or released from court and

[2] Although parole and probation are distinct components of the U.S. community corrections system, unless a distinction is necessary, for reader ease, this paper uses the term parole, PO, or community corrections to indicate both/either level(s) of community supervision.

placed on community supervision revolves each day, as the connecting institution, community corrections agencies must continuously provide resources and referrals to individuals as they monitor their behavior throughout the supervision period. An integral part of supervision success must include the access, enrollment, and completion of evidence-based treatment programs. An unaddressed area of concern considers how the availability and capacity for treatment resources and services within the community impacts an individual's progression on supervision.

The advancement of evidence-based practices (EBPs) has revealed that programs that adhere to effective rehabilitative interventions, particularly those that follow the risk-need-responsivity (RNR) framework, generally reduce recidivism and provide community corrections agencies the desired outcome of reduced recidivism (Andrews & Bonta, 2010; Bonta & Andrews, 2017). While it is critical to understand an individual's *risk* of reoffending and criminogenic *needs* relating to recidivism, *responsivity* — the second R — focuses on providing the appropriate targeted interventions and programing for effective outcomes (Andrews & Bonta, 2010). This "*R*" is directly related to correctional programming as it requires resources and rehabilitative services be available whether they are accessible intra-agency (via community corrections agencies), or community based (locally where the supervisee resides). Unfortunately, many individuals under supervision reside in disadvantaged neighborhoods lacking the resources needed to properly rehabilitate their criminogenic behaviors (Chamberlain & Wallace, 2016). In fact, studies detail the increasing challenges supervised populations face including, "housing, locating employment, and addressing unresolved substance abuse issues"

(Chamberlain, 2018; Chamberlain & Wallace, 2016, p. 913; Travis, 2005). Hence, individuals not only reside in disadvantaged communities with limited resources, but they also compete with others for housing, employment, and treatment services in neighborhoods already resource-deprived (Chamberlain & Wallace, 2016; Visher & Farrell, 2005). This shortcoming in *systemic* responsivity (discussed in a subsequent section) becomes increasingly important when seeking understand how individual and community-level predictors impact treatment and supervision outcomes.

Majority of the research on community supervision, has focused on how individual-level predictors (probationer demographics and risk factors) or treatment program effects (treatment quality or quantity) may influence the likelihood of recidivism. However, less attention has been paid to how community-level conditions of disadvantage may also influence the likelihood of recidivism amongst individuals under supervision. While multiple factors affect the overall success of community-based corrections, resource deprivation (i.e., community areas with limited quantity or capacity for resources/services) is critical because of its' direct connection to EBPs and the RNR framework/tool used by community corrections' practitioners. Community supervision can only be an effective alternative to incarceration if evidence-based probation practices, like RNR tool and treatment programming, are ability to connect individuals under supervision to the prescribed, targeted interventions in their communities. Macro-level theories such as social disorganization and resource deprivation propose that community or county-level factors may explain the seen variation in why some individuals supervised in these environments recidivate. Thus, this study sought to extend social disorganization and resource deprivation theory to community corrections literature by examining the impact county-level conditions of deprivation has on supervision outcomes of program completion and reconviction.

1.2 Purpose of the Study

The purpose of the present study is to undertake a comprehensive review of the literature in order to conduct a multilevel modeling (MLM) examining individual and county-level predictors that impact community supervision and treatment outcomes. This review seeks to understand where the current literature stands on aspects that impact parole and probation outcomes regarding evidence-based correctional programming, EBPs such as the RNR framework, and the macro- and micro-level predictors that effect recidivism focusing on reconviction and treatment success

As previously mentioned, little investigation has focused the role community or county-level conditions has on supervision outcomes (i.e., reconviction and program completion). In addition, little to no research has investigated how an individual under supervision's proximity to programming may also affect supervision outcomes and program participation. Individuals are placed on community supervision with the expectation that they will address deficits within their lives such as identified criminogenic risk and needs (Bonta & Andrews, 2017; Chamberlain & Wallace, 2016; Hipp et al., 2010; Lowenkamp et al., 2006). The understanding is that through rehabilitative programs/skills/trainings created to promote cognitive benefits and individual change, individuals under supervision should be able to foster prosocial bonds, address employment and/or educational limitations, and improve any moral decision-making skills (Bonta & Andrews, 2017; Lowenkamp et al., 2006). Most EBPs, such as those modeled after the RNR framework, focus on the individuals' need for adjustment and change, little attention has been focused on county-level conditions and treatment capacity for linking individuals to the appropriate services and programs to reduce recidivism (Bonta & Andrews, 2017). Thus, understanding how being placed on community supervision in a resource deprived community or county directly impacts recidivism helps identify systemic issues with the availability, capacity, and responsiveness to meet individual needs.

1.3 Research Questions

The research questions for this study seek to understand on how individual-level and county-level predictors of disadvantage or deprivation (county poverty, unemployment, and violent crime rates) may influence recidivism outcomes of program completion and reconviction. More specifically, it is important to understand how county-level conditions of treatment programming (i.e., specific type and capacity) impact supervision and treatment outcomes (Taxman, 2020). The following research questions guide this study:

1. What effect do individual-level demographics have on program success?
2. What effect do individual-level demographics have on reconviction?
3. What effect does treatment referral and initiation have on reconviction among probationers?
4. What effect does treatment initiation and success by specific program type have on reconviction among probationers controlling for individual demographics?

5. Is there an effect of county-level deprivation, county program quantity, and jurisdiction service gaps on probationer reconviction controlling for probationer demographics?

1.4 Theoretical Framework

For the last 30 years, the original RNR theoretical framework assisted with the promotion, growth, and use of evidence-based programming and treatments in corrections (Andrews et al., 1990; Bonta & Andrews, 2017; Taxman et al., 2013). Encompassing aspects of social learning theory regarding correctional programming, the RNR model is a theory of rehabilitation that does not have any origins toward any particular type of crime (Ward et al., 2007). The model emphasizes the importance of understanding how individual-level factors (such as risk level and criminogenic need) are influential in deciding the appropriate matched level of treatment needed for successful reentry. Ultimately, this approach to rehabilitative correctional programming seeks to achieve three main goals: 1) use the least restrictive sanctioning; 2) encourage cost-effective measures; and 3) reduce recidivism (Taxman et al., 2013). Unfortunately, some prevalent issues with community corrections remain unresolved. Empirical evidence supports that the basic principles of RNR result in a reduction of recidivism (Andrews et al., 1990; Andrews et al., 2006; Bonta & Andrews, 2017; Taxman, 2014; Taxman et al., 2013). However, with the size of the community supervision population totaling over 3 million within recent years, the demand placed on the use and use of community-based supervision continues to grow (Carson, 2018; Gill & Wilson, 2017; Hyatt & Barnes, 2018 Kaeble, 2021). In addition, unchanged recidivism rates forced policymakers, practitioners, and researchers to have an increased interest in addressing critical reentry needs (Carson, 2018; Gill & Wilson, 2017). Lastly, most of the existing recidivism literature has focused on individual-level factors that predict offending outcomes. Thus, with the new emergence of a more in-depth generation of RNR evaluation focusing on community conditions and macro-level factors, appears to likely yield recidivism reductions or overall better outcomes (Taxman, 2014).

Many judicial and correctional agencies actively pursue implementing the RNR model in trainings, policies, and practices of these justice settings (Taxman, 2013). A great deal of attention considers the risk and needs principles due to the control-oriented history of corrections. While the risk principle focuses on using criminal justice risk levels validated by assessment instruments to determine programming and surveillance, the needs (also referred to as criminogenic need) principle focuses on the factors that "drive criminal offending that are both dynamic and related to recidivism" (Bonta & Andrews, 2017; Taxman, 2014, p. 32). Bonta and Andrews (2017) identified eight criminological risk and need factors that directly correlate with criminal decision making and determine the level of intervention needed with offenders. These "central eight" dynamic risk factors include criminal history, antisocial personality, attitudes, cognition, employment, education, family, and substance abuse (Bonta & Andrews, 2017). Thus, correctional reentry programs aimed at reducing recidivism should directly target these offending behaviors. The second "R" — *responsivity* — is arguably where "the rubber meets the road" with reentry programming and where more attention should be directed (Taxman, 2014; Taxman, 2018). The responsivity principle "requires using evidence-based correctional and treatment programs, including tailoring programming to the risk, needs, psychosocial functioning, and strengths of the individual offender" (Taxman, 2014, p. 32). In other words, for the responsivity principle to function properly it cannot solely focus on reducing recidivism. It also must consider the receptivity and accessibility of individuals to treatment (Taxman, 2014).

Under the core construct of the responsivity principle are the two known components of *general* and *specific* responsivity. These key components address the type of programming (i.e., behavioral, social learning, or cognitive behavioral interventions) that should be offered (general) and matching the program to the individuals' characteristics (i.e., strengths, motivations, preferences, personality, age, gender, race, and ethnicity) best suited for the treatment (specific; Taxman, 2013; Taxman, 2014). However, a third area of responsivity — systemic or systematic responsivity — is important for understanding how organizational and community environments also an impact have on linking individuals to services. Taxman (2014) defined systemic responsivity as the system level (jurisdiction, community, organization, or agency) ability and capacity to provide programming that meets the individuals' needs. While "general" looks more into facilitating a quality type program and "specific" entails the capability of matching programs to the individual identified needs, both assume that programming is actually available (Taxman, 2014). The concept of systemic responsivity has not been fully explored but seeks to understand whether programming exists and if jurisdictions have the availability to provide treatment that matches the individuals' "risk-needs" profile (Taxman, 2014). This allows research to investigate the responsiveness of communities which hold the function of facilitating effective treatment needed at their geographical level.

While the RNR model is primarily an individual-level approach, systemic responsivity considers the important efforts that occur at the community-level. It asks the question "Do community environments have the components (i.e., What is the availability, participation, access, and responsivity?) needed to link individuals to treatment that can affect recidivism rates?" (Taxman, 2014). Systemic responsivity is an effort to literally "meet them [individuals under supervision] where they are" and directly connects to the effectiveness of correctional reentry programs. Community or county-level conditions and capacity becomes important for addressing recidivism as the community this where both practitioners and individuals under supervision must turn when there are limitations on treatment programs agency resources (Viglione, 2019). Thus, research must begin to question whether there are gaps in service at the community-level and to consider how to close these gaps are.

Understanding the community or county capacity for rehabilitative treatment programs and their impact on recidivism is a critical area of concern for two very important reasons. First, there is a collective understanding of the extreme difficulty returning citizens face transitioning back into the community (Gill & Wilson, 2017; Petersilia, 2004; Taxman et al., 2003). It is well-documented that successful reintegration requires individuals to connect to, bond with, or reestablish social networks that they may or may not have in their communities (Chamberlain, 2018; Petersilia, 2003; Taxman & Kras, 2016; Travis, 2005). These social bonds include family and/or social institutions that assist individuals with overcoming issues such as substance abuse, mental health, and negative peer influences (Bucklen & Zajac, 2009; Chamberlain & Wallace, 2016; Gunnison & Helfgott, 2007; Visher et al., 2017). These connections also assist with establishing housing, employment, vocational and other services (Chamberlain, 2018). Support provided to assist in the reentry process and promote prosocial activities has the ability to produce positive outcomes for the community (Gill & Wilson, 2017). Much of rebuilding social bonds occurs at the community-level, thus observing the effect of community conditions becomes increasingly important.

Secondly, there is evidence supporting the effectiveness of programs specifically designed to address criminological risk and needs (Bonta & Andrews, 2017). Programs that focus on employment, education, and substance abuse have had recidivism reduction (Costanza et al., 2015; Duwe, 2012; Lipsey & Cullen, 2007; MacKenzie, 2012; Wilson et al., 2000). Very few studies, however, have actually focused on community capacity for supervision success. What is known is that when individuals are referred for services, there are issues with participants receiving services that are needed, services actually being readily accessible, and availability or services being of sufficient quality (i.e., "risk-need" fit or evidence-based; Gill & Wilson, 2017; Hipp et al., 2010; Taxman, 2020; Taxman et al., 2014). Thus, in order for the RNR framework to produce promising results for reducing recidivism, agencies must correctly apply individual-level risk and needs while communities provide their level of capacity for effective services as a response (Taxman, 2013; Taxman et al., 2014). By extending research to examine community or county-level effects of resources, such as treatment capacity, we are better able to address community supervision concerns of recidivism and improve outcomes.

1.5 Definition of Terms

1.5.1 Definition of Community Corrections

Community corrections (also referred to as community-based corrections and/or community supervision) is the "supervision of criminal offenders in the resident population, as opposed to confining offenders in secure correctional facilities" (Bureau of Justice Statistics, 2020). The three types of community corrections supervision terms are probation, parole, and supervised release. While probation is a "court-ordered period of correctional supervision", parole and/or supervised release is a period of conditional release into the community after incarceration from prison (Bureau of Justice Statistics, 2020). Thus, community corrections populations are comprised of probationers, parolees or those placed in prison diversion programs (Bureau of Justice Statistics, 2020).

1.5.2 Definition of Probation

Probation refers to the court-ordered period of correctional supervision "in the community through a probation agency, generally in lieu of incarceration" (Bureau of Justice Statistics, 2020). When an individual is placed on probation (i.e., probationers), the releasing authority is often a state judicial court system. While some probationers have never served any term of imprisonment, others may be sanctioned to a "combined or split" sentence that includes a short-term of incarceration followed by community supervision (Bureau of Justice Statistics, 2020). Probation supervision may include various supervision reporting requirements which place probationers in either an active or inactive supervision status (Bureau of Justice Statistics, 2020). Active supervision can include but is not limited to regular reporting to a PO either in person, by kiosk, mail, or telephone. While inactive supervision may exclude probationers from regularly reporting, individuals are still required to complete court-ordered release conditions. Finally, in addition to being placed on probation, a probationer may be required to complete special conditions of release. Probationers must fulfill these release conditions, combined with reporting requirements to supervision, in order to be successfully terminated from community supervision. Conditions of release may include maintaining employment, obtaining vocational or educational training, obeying all laws, rules, and ordinances while in the community, abiding by GPS conditions, completion of treatment programs, payment of fines, restitution, or court expenses, etc. (Bureau of Justice Statistics, 2020). Consequently, failure to complete special conditions or abide by supervision reporting guidelines can result in unsuccessful termination of probation and/or further incarceration.

1.5.3 Definition of Parole

Parole refers to a criminal offender's conditional early release from prison to serve the remaining portion of their sentence as determined by the United States Parole Commission (USPC) in the community (Bureau of Justice Statistics, 2020). Individuals placed on parole (i.e., parolees) are released back into the community at the discretionary findings of a parole board decision, "according to provisions of a statute (mandatory release/mandatory parole), through other types of post-custody conditional supervision" (Bureau of Justice Statistics, 2020). Similar to probation, parole may include various supervision reporting requirements which place parolees in either an active, regular reporting to a PO either in person, by kiosk, mail, telephone, or inactive, exclusion from regularly reporting, supervision status (Bureau of Justice Statistics, 2020). Finally, in addition to being placed on parole, individuals may be required to complete special conditions of release. As with probation, releasing conditions for parole can range from strictly obeying all laws, rules, and ordinances while in the community to payment of fines, restitution, or court fees (Bureau of Justice Statistics, 2020). An additional violation of parole release is often failure to report to or absconding from community supervision. Failure to complete special conditions or abide by supervision reporting guidelines can result in unsuccessful termination of parole and reinstatement of incarceration.

1.5.4 Definition of Supervised Release

Supervised release is a term of community supervision served after an individual is released from federal prison. This form of supervision was created by the Sentencing Reform Act as a part of the Comprehensive Crime Act of 1984 intended to increase consistency and impartiality across U.S. federal sentencings (United States Sentencing Commission, 2019). Under the Sentencing Reform Act, not only was the United States Sentencing Commission established but parole supervision abolished except for those convicted before November 1987 (United States Sentencing Commission, 2019). Unlike parole, supervised release does not replace a portion of the individuals' sentence of incarceration, but is in addition to the time served in federal prison and begins only after at least 85% of the prison sentence is served (Bureau of Justice Statistics, 2020). As with probation and parole, an individual placed on supervised release is subject to special conditions of release that are intended to prevent the offender's return to incarceration (Bureau of Justice Statistics, 2020). Failure to complete special conditions or abide by supervision reporting guidelines can result in unsuccessful termination of supervised release and reinstatement of incarceration (Bureau of Justice Statistics, 2020).

1.6 Organization of the Dissertation

This study seeks to extend social disorganization and resource deprivation theory to provide further explanation in the variation of recidivism among individuals under supervision. While majority of research has been centered on how individual-level predictors influence the likelihood of recidivism, less consideration has been paid to the role that community or county-level factors may contribute as either a modest or larger factors in the success or reconviction of an individual. More specifically, this study uses data from 34 Oregon counties to examine how county-level factors influence individuals under supervision odds of recidivism with two outcome variables: reconviction within 3 years and treatment program completion. This study will employ a two-level nested data analysis with corresponding research questions focusing on 1) individual-level predictors and 2) county-level factors. Table 1 highlights this analysis:

Table 1

Multilevel Model, Research Questions and Predicting Variables

		Research Questions	Predicting Variables
Level 2 County	RQ5	Does the effect of initiation or completion on reconviction differ depending on whether an individual lives in a resource deprived county or not?	**County Level Variables:** County Deprivation Index Jurisdiction Program Capacity Program Quantity
	RQ4	What effect does treatment initiation and success by specific program type have on reconviction among probationers controlling for individual demographics?	
Level 1 Individual	RQ3	What effect does treatment initiation and completion have on reconviction among probationers?	**Individual Level Variables:** Age Gender Race Level of Supervision Treatment Utilization
	RQ2	What effect do individual demographics have on reconviction?	
	RQ1	What effect do individual demographics have on program success?	**Outcome Measures:** Reconviction – 3-year Program Completion

This dissertation is organized as follows: Chapter 2 includes an in-depth review of the literature including parole and probation, social disorganization, and resource deprivation theories. Chapter 3 discuss the macro- and micro-level predictors that impact community supervision outcomes. Chapter 4 details the methodology used to investigate the research questions and the analysis plan. Chapter 4 discusses the results of the MLM analysis for each identified research question. Chapter 5 includes a reviewing the findings presented in the previous chapter. Chapter 6 concludes with discussing the limitations identified in the study, discussion on future research, and recommendations for community corrections policy.

Chapter 2: Review of the Literature

2.1 Parole and Probation in the United States

2.1.1 A Brief Overview

Prisoners returning to the community from incarceration or justice-involved individuals sentenced to community supervision in lieu of incarceration may be placed on varying terms of community corrections (Alexander, 2017; James, 2011). These periods of monitoring may include terms of probation, parole, and/or supervised release (Bureau of Justice Statistics, 2022). While probation supervises "adult offenders who courts place on supervision in the community through a probation agency, generally in lieu of incarceration", parole and supervised release mandates offenders "who are conditionally released from prison to serve the remaining portion of their sentence in the community" (Bureau of Justice Statistics, 2022). As a result, parole and probation agencies play a critical role in the rehabilitation process through monitoring individuals as they reintegrate back into society, attempting to equip them with pro-social skills while also maintaining public safety. Historically, parole and probation agencies operated as institutions primarily focused on rehabilitating individuals (Alexander, 2017). However, this focus shifted in the 1970s during a movement that created more control-oriented and punitive policies as a response to crime (Alexander, 2017; Feeley & Simon, 1992). As a result, more emphasis was placed on community corrections agencies to adhere to the surveillance and monitoring of individual behaviors rather than the more social service-oriented tasks as before (Alexander, 2017). In addition, probation became a "net-widener" as a variety of offenses, mostly non-violent, resulted in its use with successful termination a likely outcome (Phelps, 2018). Consequently, community supervision is presently the most common sentence facing justice-involved individuals in the US with increasingly high supervision populations and recidivism rates unchanged. An examination of the recent parole and probation trends and practices, including incarceration rates, best illustrates this point.

2.1.2 Probation & Parole Supervision Trend and Practices

Although crime rates dropped significantly, over the last three decades the US has incarcerated more individuals than any other country with similar crime levels at a rate five times higher, reaching historic numbers (Schmitt et al., 2010). In fact, the imprisonment rate has rosed to being 427 per 100,000 by year 2019 (Carson, 2020; Leverentz et al., 2020). Every year more than 700,000 previously incarcerated persons are released from prison and returned to the community, and the number of individuals who enter and leave jails (including pretrial detainees) has been estimated to reach approximately 9 million per year (Carson, 2018; Durose et al., 2014; Leverentz et al., 2020). With the combined U.S. prison and jail population just over 1.4 million, adults under community supervision total over 3 million (Kaeble, 2021; Wagner & Rabuy, 2017). In fact, the adult probation population makes up the majority (79 %) of the overall persons on community supervision. In comparison to probation, the parole population has increased by nearly 10% since 2005 (Kaeble, 2021). Finally, the parole population increased in 30 states during 2020, except for the District of Columbia and the U.S. federal system's term of supervised release (Kaeble, 2021).

In addition to the rate that the US incarcerates individuals, the continuum cycle of those placed on community supervision only to recidivate and be reincarcerated presents alarming numbers. Data from 34 states revealed that of the prisoners released in 2012 from incarceration to community supervision, 62% were re-arrested in 3 years and 71% were arrested within 5 years (Antenangeli & Durose, 2021). Likewise, those placed on supervision are required to satisfy a multitude of release conditions and, when conditions are left incomplete, they face revocation (Phelps, 2018). Consequently, probation or parole violations account for nearly half of percentages for those individuals under supervision who are eventually returned to prison (Antenangeli & Durose, 2021). Among those released from incarceration in 2012 across 21 states, 39% had a parole or probation violation or an arrest for a new offense within 3 years post-release (Antenangeli & Durose, 2021). Almost half (46%) of that same population had a parole or probation violation or new arrest within 5 years post-release (Antenangeli & Durose, 2021). As expected, these number give concern to the policies and practices in place to address recidivism. To improve outcomes, the criminal justice system has placed immense pressure on community corrections agencies to implement evidenced-informed decisions and rehabilitative interventions (Viglione, 2017; Viglione et al., 2018). Hence EBPs, such as developing risk assessment tools and interventions focused on attitudinal and behavioral altering techniques, like those highlighted by the RNR framework, now add to the efforts undertaken by many justice organizations to reduce recidivism (Bonta &

Andrews, 2017; Viglione, 2017; Viglione, 2018). Thus, for the last 20 years, community corrections have emphasized EBPs that are scientifically proven to reduce recidivism (Viglione, 2019), in ways the ideological shift of risk actuarial models (New Penology) could not to encompass (Feeley & Simon, 1992).

2.2 Evidence-based Practices

"What works" or EBP ideologies emphasize the need for community corrections agencies to use the most relevant, effective rehabilitative practices to change supervision outcomes (Bonta & Andrews, 2017; Taxman, 2018; Viglione, 2019). Evidence-based practices are the "objective, balanced, and the responsible use of current research and the best available data to guide policy and practice decisions, such that outcomes for consumers are improved" (Viglione, 2017, p. 1356). These scientifically proven and client-centered approaches to supervision offer researchers, practitioners, and policymakers the opportunity to identify the policies, practices, treatments, and interventions directed connected with better outcomes (Taxman, 2018). This focus also creates the impetus for community corrections agencies to take a uniquely situated stance amongst criminal justice organizations where they aid offender populations in both a social work (e.g., assistance) and law enforcement (e.g., authority) role performed simultaneously (DeMichele & Payne, 2018). The implementation of EBPs has resulted in a culture shift within community corrections' work as front-line practitioners, such as POs and case managers, core ideologies must change from the control-oriented strategies of the 1970s (New Penology) toward rehabilitative approaches that emphasize motivating individuals to choose lawful behavior (Viglione, 2018, p. 1332).

During the 1990s, studies and systematic reviews defined EBPs and created a list of "what works" in reducing recidivism within corrections (Sherman et al., 1997; Taxman, 2018). Though nearly 30 years old, the approved list of EBPs effective in addressing recidivism has remained generally consistent. These include: 1) cognitive-behavioral interventions/therapy (CBI/CBT) programs that address criminogenic needs; 2) graduated, swift and certain sanctions as a response to offending; and 3) standardized assessment tools that follow the RNR framework, particularly for practitioner case planning and referrals (Taxman, 2018). Several studies find support for the effectiveness of EBPs with robust focus on how implementation works within community corrections (Andrews et al., 1990; Bonta & Andrews, 2017; Sherman et al., 1997; Taxman, 2018).

While most community corrections agencies now regularly use EBPs, there are still issues within parole and probation impacting its success. Majority of research devoted to understanding the issues surrounding EBP use in parole and probation has focused on the implementation issues at program-level or individual-level predictors of recidivism based on individual demographics (Aos et al., 2006; Lowenkamp et al., 2006, 2010; Smith et al., 2009). Rarely has research attempted to expand to community-level effects that may also impact the use of EBPs, such as treatment programming capacity based on RNR tool recommendations. Perhaps, two of the most important PO functions involve assessing individual risk/needs and monitoring an individual under supervision's behavior while residing in the communities (Taxman & Kras, 2016; Viglione, 2019). While viewed separately, both functions result in POs referring their clients to corrective interventions/correctional programming that assist with resisting criminal behaviors.

Correctional programming within community corrections calls for the use of rehabilitative and learning techniques aimed at changing the behaviors and thinking patterns (justifications and beliefs) that lead to criminal offending. Often POs must use their discretion to refer individuals to the needed treatment programming that addresses maladaptive behaviors. This programming should be based on EBP-reformed principles, specifically those modeled after RNR. The RNR model — also known as a theory of offender rehabilitation or a theory of correctional intervention (Gendreau et al., 2006; Ward et al., 2007) — addresses how learning and rehabilitation techniques should be applied in correctional settings for the best outcomes (Bonta & Andrews, 2017). RNR encompasses the guidelines for which treatment programming should focus on such as how much programming is needed, and what type of programming is best suited for targeted populations. All these factors of correctional programming (identify risks, characteristics/behaviors needing intervention, and responding by target programming) are aspects to consider when examining the importance of how certain circumstances (such as community conditions and treatment capacity) effect EBP implementation. The risk principle is further explored.

2.2.1 Risk

The risk principle is used to guide supervision planning and correctional programming as it defines the behaviors, beliefs, or attributes most directly related to the likelihood of offending. There are two important components of this principle include: 1) the use of a validated risk assessment for predicting criminal behavior and 2) appropriately assigning the level of service to its matched, assessed risk level (Viglione, 2019). When an individual is placed on community supervision, they are then assessed for their likelihood or "risk" of reoffending (Andrews et al., 1990). The RNR model demonstrates that certain attributes or demographics increase the likelihood to reoffend including age (young), gender (male), criminal thinking (impulsivity), antisocial behavior, and criminal associations/antisocial peers. Thus, the level of supervision, the assigning of appropriate programs, and the intensity of these programs should all be determined by the individuals' risk for reoffending (Andrews & Bonta, 2010). As a result, individuals under supervision denoted as high risk should be placed in the most intensive programming and, likewise low risk individuals under supervision should be placed in very little to no programming. Research studies have found that inappropriately mismatching placing individuals in programs designed for differing risk levels can actually increase recidivism. For example, Bonta and Andrews (2017) found that programs provided to high-risk individuals under supervision are five times more effective at reducing recidivism than those who are low risk. Likewise, Bonta et al. (2000) found that low risk clients placed in the appropriate minimal treatment programming saw a recidivism reduction of 15% and, oppositely, those low-risk clients placed in more intensive programming witnessed a 32% recidivism increase. The link between risk level and program effectiveness is strongly supported with the overall conclusion that correctional programs fair better when more attention is placed on high-risk individuals (Andrews et al., 1990; Bonta & Andrews, 2017; Dowden & Andrews, 1999; Lowenkamp & Latessa, 2002; Lowenkamp et al., 2006).

The existing literature highlights the importance of correctly placing individuals in the appropriately matched programs. It also highlights the importance of focusing the most intensive efforts on high-risk individuals as there is greater return in reducing recidivism. Thus, when examining correctional programming in communities, it is important to make sure that high risk individuals are not only placed in intensive programing (i.e., dosage and implementation) but also that programming support is actually available in the individual's community. Next, the needs principle is discussed.

2.2.2 Needs

The needs principle is used to guide practitioners to determine what an individual's criminogenic "needs" are and which of those factors correlate to increased criminal behavior. While the risk principle focuses on whom should receive programming (and how much), the needs principle seeks to identify what behaviors should be targeted. Following the RNR framework, while an individual may have additional needs, the "needs" principle suggest that we target the specific offender risk factors that are dynamic (amenable to change) versus static (unable to change; Dowden & Andrews, 1999). As previously mentioned, Andrews and Bonta (2010) identified the "central eight" dynamic factors (i.e., antisocial cognition, criminal peers, substance abuse, mental health, etc.) that treatment programs should target as these actors are most related to recidivism. Static factors, however, are attributes such as age that cannot be changed, are not appropriate targets for programming (Bonta & Andrews, 2017). Unfortunately, many communities' supervision and prison division programs have solely focused on the premise of providing individuals under supervision with employment or financial achievements as a target criminogenic need to address. However, some studies have found that employment programs alone do not meet the desired effects of recidivism reduction (Bushway & Reuter, 2002; Visher et al., 2005). Likewise, Bucklen and Zajac (2009) conducted a study on the correlates of parole success and failures from a parolee population from the Pennsylvania Department of Corrections. Results from the study found that little evidence that having employment was a significant predictor of success or failure on parole (Bucklen & Zajac, 2009). In fact, more statistical significance was found for supporting the need for improving antisocial attitudes and peer groups as having a prosocial support network of peers and/or family members significantly reduced recidivism (Bucklen & Zajac, 2009). Thus, correctional programming should focus on changing antisocial attitudes, promoting prosocial familial and peer relationships, and addressing substance abuse and/or mental health issues — all of which should be accessible and available within community environments. To successfully implement the needs principle, the appropriate rehabilitative services need to be available and have the capacity to address individuals under supervision criminogenic factors.

2.2.3 Responsivity

While the risk principle focuses on whom should receive treatment and the needs principle focuses on what characteristics should be treated, the responsivity principle seeks to provide guidance on treatment delivery and style. Responsivity concentrates on how to provide treatment programs that meet the cognitive-behavioral learning style based on the individual's characteristics (Viglione, 2019). It is broken into two components: general and specific responsivity. As previously stated, general suggests that programming should provide be personalized to the individuals learning style, taking into consideration the person's abilities and skills when determining treatment mode and delivery (Bonta & Andrews, 2017). Specific responsivity focuses on matching the program to the individuals' characteristics (i.e., biological, social, and psychological) best suited for the treatment (Bonta & Andrews, 2017). Critics of the responsivity principle have argued that limiting its definition to only general and specific neglects to consider 1) the constraints on the criminal justice system to meet the learning style and capacity of individuals and 2) the limited availability of treatment programs accessible to individuals on supervision (Crites & Taxman, 2013). Thus, a new emergence of *systemic* responsivity considers the capacity of communities, organizations, and jurisdictions to provide programming that meets the individuals' needs at that systems level (Taxman, 2014).

Research on the responsivity principle has primarily centered around which specific responsivity characteristics (such as gender and low intelligence) were important to focus on for treatment completion. Hubbard (2007) conducted a study of mixed-gender of over 400 individuals under supervision who were receiving cognitive-behavioral treatment from multiple treatment facilities. Results showed that gender (male more likely to be arrested compared to female) and level of risk (high-risk individuals need intensive treatment) were statistically significance predictors of recidivism and treatment completion, respectively (Hubbard, 2007). In addition, specific characteristics such as IQ, sexual assault history, personality require more research (Hubbard, 2007).

All things considered, it is critical that correctional programming follows all the principles outlined by RNR for the greatest reduction in recidivism. Andrews et al. (1990) findings found support that programs that adhere to the RNR principles are more likely to witness greater reductions of recidivism than those with less adherence. Other meta-analytic studies have supported these findings (Andrews et al., 2010; Gendreau et al., 2006; Prendergast et al., 2013).

As the responsivity component of RNR primarily focuses on program delivery and technique approach, this principle is directly connected to critical aspects of correctional programming and treatment. Effectively delivered programs must consider critical delivery elements such as treatment time, location, teaching techniques and learning style. However, practical considerations such as the distance individuals would have to travel to programs, the significance in recidivism caused by in program initiation (entry) and completion, and program availability should also be incorporated in this principle (e.g., systemic responsivity; Taxman, 2014), some of which this dissertation seeks to uncover. Supervision success is not just dependent upon accurately implementing RNR or EBPs but also must encompass other broader aspects that impact an individual’s supervision such as community resources, programming, and services. Understanding the influence disadvantaged community conditions and treatment program capacity may have on an individual’s inability to achieve goals, such as entering, attending, and completing treatment programs or supervision, may also explain variations in offending behaviors.

2.2.4 The Responsiveness of Communities and Correctional Programming

With proper implementation, the RNR framework should effectively improve supervision outcomes (Bonta & Andrews, 2017), however, there may be underlying issues at the community or county-level that impact design implementation. Implementing this model in communities that are concentrated with disadvantage (or resource deprived) as well as the lack the availability and capacity to provide the appropriate correctional programming directly connects to unaddressed recidivism (D'Amato et al., 2021). Many individuals under supervision return to resource deprived or disadvantaged neighborhoods and, consequently, re-engage in offending (Chamberlain & Wallace, 2016; Hipp et al., 2010; Kubrin & Stewart, 2006; Mears et al., 2008). For example, Kubrin and Stewart (2006) found that individuals supervised in areas with higher concentrated disadvantage were more likely to recidivate than those supervised in more stable neighborhoods. The issue connected to these neighborhoods is that they are often reduced in prosocial opportunities, access to resources, and service providers (characteristics of social disorganization). Few very studies have examined the connection between community-level effects of resource providers and recidivism outcomes. The most notable study, Hipp et al. (2010) found that parolees who returned to communities that were geographically assessable to treatment service providers fared better on community supervision. Unfortunately, far less consideration has been given to the importance of understanding how community-level factors, including resource and service availability, plays in recidivism of those on supervision.

The connection between community disadvantage, treatment programming and individual-level differences must be further explored in order to further understand the variation, if any, in offending behavior. What is known is that in order for individuals under supervision to refrain from recidivating, some aspect of correctional rehabilitative programming should be implemented (Bonta & Andrews, 2017). Research supports that high-risk individuals should receive the most intensive programming, while low risk clients need little to none (Bonta & Andrews, 2017). In addition, supervised populations also must overcome various obstacles or “needs” as they reintegrate in their communities. The responsivity component of RNR model stresses that attention must be paid to individual’s specific characteristics in order to anticipate program completion. Along with level of risk and criminogenic needs, importance should be given to more practical concerns such as issues that may impact treatment and supervision completion.

While the connection between community disadvantage and program availability still lacks adequate research, social disorganization, and subsequent theories such as resource deprivation suggest that communities with limited resources could be a contributing factor to poor supervision outcomes. Disorganized communities, such as those experiencing high levels of poverty, unemployment, family disruption, residential mobility, violent crime, and resource-limited means are more likely to experience weak social controls and lack community support (Kornhauser, 1978). Research suggests that individuals supervised in disorganized communities have an increased likelihood of recidivating due to the lack of community supports (Hipp et al., 2010; Kubrin & Stewart, 2006). Poor community conditions are indicative of a multitude of obstacles for supervised populations face during supervision including inadequate employment opportunities, transportation, educational/vocational systems, housing, and support programs. Thus, an obvious concern of responsivity (i.e., systemic responsivity) would be how and if resource-deprived environments meet the needs of individuals under supervision when they lack the capacity to provide adequate programs.

Evidence suggests that neighborhood characteristics and proximity to community resources (i.e., substance abuse and mental health treatment) can impact recidivism for individuals under supervision (Hipp et al., 2010; Hipp & Yates, 2009; Kubrin & Stewart, 2006). For this reason, additional research should investigate how variation in community conditions and treatment capacity may predict supervision outcomes like reconviction and program completion. A further examination into social disorganization theory and corresponding theories is examined.

2.3 Social Disorganization Theory

While the explanation of how neighborhood location and program availability may explain variation in recidivism has not been fully explored, theoretical arguments have attempted to examine the relationship between community, city, and county features of disadvantage and recidivism. Marco-level theories such as social disorganization attempt to explain the influence community or county-level mechanisms have on crime. Social disorganization theory suggests that poor neighborhood conditions (i.e., increased poverty levels, ethnic heterogeneity, residential mobility, and transiency) create opportunities for an increased presence of criminal behavior due to a lack of social control. A brief overview of social disorganization theory, arguments of resource deprivation and the interplay between community conditions and offending behavior is further explained.

2.3.1 A Brief History

In an attempt to explain the variation of delinquency rates across neighborhoods in Chicago, Shaw and McKay (1969) hypothesized that higher rates of delinquency would be found in inner city areas. Shaw and McKay (1969) proposed that heavy rates of delinquency would present itself inner city areas as these neighborhoods were characterized by high levels of social disorganization including increased poverty, rapid population growth, ethnic heterogeneity, and transiency (i.e., residents moving out of neighborhoods within 5 years). Since these characteristics were considered contributors to neighborhood decline, it was argued that these communities would remain “disorganized” if issues were left unchanged. In addition, these communities were seen as having “differential value systems” from that of communities demonstrating stability and uniformed community support which produced lawful, behaved residents (Shaw & McKay, 1969). To test this hypothesis, Shaw and McKay (1969) hand mapped addresses of each delinquent and created matched area zones to correlate rates of crime by area which remained consistent regardless of the ethnic makeup of the communities. Areas found to be most disadvantaged were those with high rates of delinquency and offered conflicting moral values such as opportunities for legitimate employment, educational outlets, prosocial leisure activities, and collective efficacy amongst neighbors.

As hypothesized, social disorganization found that a variety of macro-level conditions influence individuals’ likelihood to recidivate (Shaw & McKay, 1969). Social disorganization creates a concrete stance that structural conditions of communities or counties can be a contributor to crime. The condition of a neighborhood sends a message about the values of the community in areas that lacked social control also experience a decline in strong social networks, limited opportunities for growth, and encompass values that promote crime.

While not fully explored, the recidivism witnessed in community corrections may vary by community or county based on the structural features of the area in which the individual under supervision returns. The macro-level features of an area that are associated with social disorganization also may influence an individual's likelihood of recidivating (D'Amato et al., 2021; Sampson & Groves, 1989; Shaw & McKay, 1969). More modernly, social disorganization theory speaks directly to community corrections and the importance of having collective efficacy in a community as this may affect service provision and reentry success. Strong social capital becomes important for building intangible resources such as "relations among persons that facilitate action" for mutual benefit (Kubrin, 2009; Rose & Clear, 1998). If collectively, neighbors perceive those on supervision are returning to the community without resources, then collectively the community will work together to advocate for itself. In addition, social structures such as social bonds and networks are also impacted when incarceration and community supervision influence the disorganization of communities. Incarceration impacts the social bonds of a community by altering its socio-economic status (SES) due to removing vital resources for labor, residential mobility in the increased presence of residents who are consistently removed and returned to a neighborhood, and family disruption in the increase of single-headed households or loss of a male figures. (Kubrin, 2009; Rose & Clear, 1998). Thus, when individuals placed on community supervision reside in disadvantaged communities, because of these effects, they experience an inability to develop prosocial interpersonal networks, conform to meaningful social controls, and establish stabilization factors that are positive for community outcomes.

Lastly, social disorganization connects directly to the variation in recidivism experienced by individuals under supervised as the neighborhoods they return to are often characterized with higher rates of poverty and resource deprivation. Communities or counties with high poverty may be indicative of "reduced access to money, resources and residential participation in formal social controls" (D'Amato et al., 2021, p. 1075; Shaw & McKay, 1969). In addition, these communities or counties characterized most often demonstrate having lower economic status in homeownership or property value, median income, and increased unemployment. Combined with higher levels of violent crime and reduced resources, all these factors lessen the social controls in these communities and create mechanisms that influence crime. Thus, individuals under supervision who return to these less socially organized areas, are at an increased likelihood of recidivating due to experiencing a reduced collective efficacy in a community's inability to advocate for stabilizing resources, lack of informal and formal social controls.

In summary, social disorganization theory supports the argument that community or county conditions are a contributing factor in recidivism as these neighborhoods encompass elements of disadvantage that contribute to the weakening of social controls. Neighborhoods of weakened social controls create openings for crime to thrive as they lead to inadequate opportunities for residents, especially those on community supervision, to be placed in areas that promote interpersonal skills, legitimate job markets, funding for community revitalizations and organizational supports. Thus, the issue of resource-limited or deprived communities creates obstacles for community supervision populations as these are the areas they are likely returned (Hipp et al., 2011). Additional theories such as resource or economic deprivation also lends support to the argument that deprived communities or counties contribute variation to crime.

2.3.2 Resource Deprivation

Resource (also known as relative or economic) deprivation is defined as an "actors' perceptions of the discrepancy between their value expectations (the goods and conditions of the life to which they believe they are justifiably entitled) and their value capabilities (the amounts of those goods and conditions that they think they are able to get and keep)" (Gurr, 1968, p. 1104). In other words, it is "what one has" versus "what one should have or expects to have" as it relates to resources and social circumstances (Brush, 1996, p. 524). Within criminology, resource deprivation is "frequently viewed through a social disorganization lens" as it is linked to community-level ecological outcomes including urban violence, homelessness, and poverty (Mears & Bhati, 2006, p. 510, 514). It is the combination of factors including weak, ineffective, or inadequate economic conditions including high levels of poverty, residential mobility, unemployment, lack of community resources/services and/or conventional opportunities for support. While other competing hypotheses argue resource deprivation is not the primary cause of collective violence and recidivism, when combined with the lack of mobilization of resources, resource deprivation is a significant contributing factor (Brush, 1996). Resource deprivation is also correlated with increased urban disorder, homicide rates, and lack of collective efficacy in communities (Mears & Bhati, 2006). Research suggests that community-level conditions of deprivation affect social behaviors in and across communities especially those in similar race and SES (Mears & Bhati, 2006). Directly related to community corrections literature, some studies examine the impact resource deprivation has on parolee supervision outcomes and PO perceptions of the resources used/needed for supervision success (Chamberlain & Wallace, 2016; Hipp et al., 2010; Mears et al., 2008; Seiter, 2002).

Attempting to understand parolee supervision progress, Bucklen and Zajac (2009) examined how neighborhood disadvantage impacts parolee revocation. Using mixed methods, the authors surveyed over 500 successfully terminated and violated parolees within the last three years of release to understand their perspectives on their supervision outcomes (Bucklen & Zajac, 2009). Parolees identified antisocial attitudes and poor peer groups (i.e., clustering offender populations) as a main cause of recidivism (Bucklen & Zajac, 2009). Parolees also had their supervision periods revoked for substance abuse relapse violations (Bucklen & Zajac, 2009). These findings highlight the importance of continuing to provide CBT-based treatment and substance abuse programing for individuals under supervision (Bucklen & Zajac, 2009). In addition, although neither parole violators nor successors indicated finding employment as problematic, both groups noted difficulties with staying employed and dissatisfaction with the quality of jobs available upon release (Bucklen & Zajac, 2009). Negative attitudes toward employment, life skills, and workplace behaviors may actually hinder employment stability more than actually finding employment (Bucklen & Zajac, 2009). The need for CBT resources that provide parolees with prosocial skills and coping mechanisms may indirectly improve other reentry domains including reemployment, peer relations, and compliance with supervision (Bucklen & Zajac, 2009). Similar studies have examined absconded parolee perspectives noting the largest predictors of recidivism were limited substance abuse and education resources (Powers et al., 2018). In addition, Hipp et al. (2010) examined neighborhood context to determine if the physical closeness of social service providers have an impact on parolee supervision success. Findings suggest that individuals on supervision perceive resources that address criminogenic needs as impactful and those residing in these communities where resources are scare have higher rates of recidivism (Hipp et al., 2010). Parolees who returned to stable neighborhoods with greater accessibility to services recidivated less often with more successful supervision outcomes (Chamberlain & Wallace, 2016; Hipp et al., 2010).

Likewise, Seiter (2002) studied the State of Missouri Department of Corrections' PO perceptions of reentry program availability and key programming aspects that improve the chances of successful reintegration. Of the 104 total responses received, most (55%) POs cited either job training/vocational skills or substance abuse treatment (54%) as the program(s) of consistent awareness, current use, or formerly used in supervision planning (Seiter, 2002). Other cited programs were residential facilities, work release programs, and employment assistance outlets (Seiter, 2002). In addition, POs also identified consistent employment (34%) and substance abuse treatment/ sobriety maintenance (21%) as the most important aspect of reentry programming that likely improves supervision success (Seiter, 2002). Similar studies bridge the gap between how PO and parolee perceptions differ on reentry resource needs and challenges (Gunnison & Helfgott, 2007; Gunnison & Helfgott, 2011; Helfgott, 1997). Studies continue to examine themes of perception and the physical closeness of intervention services; however, this insight only partially addresses the issues currently facing community corrections regarding resource deprived neighborhoods.

Collectively, these findings highlight how resource deprived communities' impacts supervision and treatment outcomes in community corrections. Existing research reports on which resources POs and individuals under supervision perceive as essential. Much less is understood about how treatment capacity of and quantity for interventions is also impacted in these environments. While informative, most of the information relating to resources available for reentry services is dated, some being nearly 10 years old. Resource availability and effectiveness are key components of reintegration with both likely leading to improved recidivism rates and other positive outcomes. While PO perceptions are valuable, perceptual data is limited on several levels. First, POs are not required to track the recidivism and/or success of individuals under supervision after case termination. Thus, PO perception is not likely credible data for evaluating reentry resources in that they simply do not know what worked and for whom. Moreover, current research does not adequately detail the quantity or capacity of treatment programs/resources within community (i.e., the number of treatment programs available and if these programs have the volume to meet the needs of the probation population).

Finally, while POs offer some insight over the availability of programs and services, they can likely only do so for the services they know of and/or have used. That is, the information they possess is bounded by what they know to be available and use. While the RNR framework provides clear guidance for case planning based on assessing risk and determining needs this information depends on steady, effective, and available programs/services (resources). Thus, future research must provide a standard methodological approach to how and in what ways are resource services measured, matched, and what types of services are available for individuals under supervision upon release. In addition, research must further extend to examining the neighborhood structural aspects of communities to assess the capacity to provide treatment programming, understand the gap analysis of capacity and need, and advocate for efficient allocation of resources for supervised populations (Taxman, 2020). Since EBP implementation is only as fruitful as the availability to provide services, then a critical component to improving outcomes within probation and parole agencies is understanding how and if community condition and treatment capacity influence community supervision success.

2.3.3 The Impact of Community Conditions on Criminal Offending

Although a substantial amount of research has investigated the relationship between community conditions and crime (Browning et al., 2004; Kubrin & Herting, 2003; Mears & Bhati, 2006; Messner & Rosenfeld, 2004; Sampson & Groves, 1989; Sampson & Raudenbush, 1999; Shaw & McKay, 1969; Warner & Pierce, 1993), very little is known about how these conditions impact supervision outcomes. While social disorganization theory argues that certain characteristics of neighborhoods (aspects of resource deprivation) increase offending behaviors, more evidence is needed in understanding how these conditions impact certain populations, specifically those placed on community supervision. Previously incarcerated persons placed on community supervision must overcome many obstacles in order to successfully complete supervision and reintegrate back into society. Research has noted that previously incarcerated individuals often return to disadvantaged neighborhoods (Chamberlain & Wallace, 2016; Hipp & Yates, 2009; Hipp et al., 2011). Knowing these circumstances, it is critical for parole and probation agencies to understand the limitations individuals face while under community supervision in resource deprived neighborhoods with the expectation to resist re-offending.

Very few studies have actually attempted to investigate the effect that community conditions have on community supervision outcomes. One of the earliest examinations of this relationship was undertaken by Kubrin and Stewart (2006). Using data obtained from 4,630 probationer residing across 156 neighborhoods, this study sought to examine the effects neighborhood disadvantage had on offender outcomes (Kubrin & Stewart, 2006). Disadvantage variables (poverty-level, public assistance, and unemployment) as well as Massey's (2001) index of concentration at the extremes (ICE) was used to calculate the Census tract variables for neighborhood-level conditions. Individual-level variables including race, age, offense type (property or drug) and supervision-level were all relevant predictors of recidivism. Both disadvantage and ICE variables were also strong recidivism predictors. Study finding showed that the probability of recidivism was increased in more disadvantaged neighborhoods (60 %) than those of less disadvantage (42%).

Likewise, Morenoff and Harding (2011) sought to expand this research by examining how neighborhood effects including unemployment rates also predicted recidivism amongst parolees. This research investigated the supervision outcomes from a sample of 11,000 parolees (sample size 1,848) released to supervision from Michigan in 2003. Recidivism (dependent variable) used five supervision outcome variables including absconding, new offense arrest, revocation from technical violations, revocation from new conviction and new felony conviction without incarceration. U.S. Census tract variables (including employment rates) were used to measure neighborhood conditions. Findings suggest, using the Cox regression method, that more affluent neighborhood experienced a decrease in technical violations and absconding. In addition, residential stability was found to be a predictor of recidivism for both new offense convictions and absconding.

Moreover, Chamberlain and Wallace (2016) conducted a study on over 31,000 persons released from incarceration in Ohio and found that disadvantage had no effect on recidivism outcomes such as re-arrest, re-incarceration, and reconviction. However, residential stability was a significant predictors of outcome variables (Chamberlain & Wallace, 2016). Other studies have also reported mixed findings (Tillyer & Vose, 2011) or no significant effects (Stahler et al., 2013; Wehrman, 2010) that concentrated disadvantage has on recidivism outcomes while specifically observing residential stability.

Finally, more recently Galouzis et al. (2020) conducted a three-layered multilevel analysis examining the effects that individual-level, supervision officer and supervision office location variables would have on supervision outcomes in Australia. The outcome variable for recidivism was re-imprisonment within 1 year. While the supervision officer-level variable focused on the how many supervision officers the parolee had during each supervision term, supervision office variables included Australian Bureau of Statistics (2016) Socio-Economic Indices factors such as SES indexes, regional status (metro, regional, or remote) and rehabilitation programming delivered per office. Findings suggest a relatively small effect supervision officer and office measures had on recidivism with most of the variance in parole outcomes predicted by individual-level factors (Galouzis et al., 2020). Parolees supervised in a metropolitan area were more likely to be re-imprisoned as these areas were more disadvantaged, these effects did not explain a significant portion of variation in supervision outcomes (Galouzis et al., 2020).

While the research presented has found mixed findings to support community conditions effect on supervision outcomes, most of the relevant research has neglected to include program quantity, capacity, and completion aspects in these investigations. In addition, some studies have reported community conditions have no effect (Chamberlain & Wallace, 2016; Stahler et al., 2013; Wehrman, 2010) on supervision outcomes, other studies (Galouzis et al., 2020; Kubrin & Stewart, 2006; Morenoff & Harding, 2011; Tillyer & Vose, 2011) present promising findings and, thus, lend support that further investigation is needed in hopes of resolving this gap in the literature on how community conditions cause variation in community supervision outcomes.

2.4 Chapter Summary

It is important to recognize the current state of parole and probation in the United States is due to the rapid expansion of its use (Phelps, 2017). This led to an increased need for standardized assessments and client-centered approaches toward behavioral change, much of which were developed from the “New Penology” of community corrections and evidence-informed practices/policies (Phelps, 2017; Viglione, 2018). This includes the guiding principles of the RNR theoretical framework, which show a positive effect from correctional programming on supervision outcomes. Empirical research suggests that when applied correctly, RNR principles should result in a reduction of recidivism. Despite the implementation of RNR in community corrections, recidivism rates remain unchanged, and the correctional population is historical larger than ever before. Outside factors such as socially disorganized neighborhoods provide a possible explanation to the significant variation in offending outcomes. Still under investigated, empirical research been able to examine the relationship effects of macro- and micro-level predictors of supervision offending behaviors. For example, social disorganization theory and studies of community resource deprivation have been linked to causes of recidivism and crime. The following section seeks to examine the current state of the literature on the predicting variables of supervision outcomes. These predictors are directly linked to the variables examined in the present study.

Chapter 3: Predictors of Supervision Outcomes

3.1 Macro-level Predictors of Offending

While the majority of the community supervision literature on recidivism has primarily focused on examining individual-level predictors, more recently studies have attempted to expand this knowledge and investigate how macro-level factors (i.e., at the neighborhood, community, and county-level) also can influence supervision outcomes (Chamberlain & Wallace, 2016; Hipp et al., 2010; Kubrin & Stewart, 2006; Mears et al., 2008). Macro-level theories such as social disorganization suggests that neighborhood disadvantage (i.e., high levels of poverty, resource deprivation, residential turnover, unemployment, and violent crime) increases the likelihood of criminal offending (Sampson & Groves, 1989; Shaw & McKay, 1969). Declining neighborhood conditions produce a lack of informal social control in communities which creates opportunities for criminal behavior to thrive (Shaw & McKay, 1969). When the previously incarcerated return to the community, they are faced with navigating these obstacles while attempting to abide by their supervision conditions. Empirical evidence has found a positive relationship between increased presence of individuals released to supervision and neighborhood crime (Chamberlain, 2018; Chamberlain & Boggess, 2019; Hipp & Yates; 2009; Kovandzic et al., 2004). In addition, research suggests that macro-level conditions may have a greater impact, at least modestly, on supervisee recidivism rather than individual-level predictors and that these factors may moderate the relationship, if any, that exist (Hipp et al., 2010; Kubrin & Stewart, 2006). Consequently, it is important to understand how macro-level community/neighborhood context may provide a causal relationship to offending. Macro-level predictors of supervision outcomes are further discussed.

3.1.1 Socioeconomic Disadvantage and Related Factors

Disadvantaged communities often house greater populations of previously incarcerated persons (Kubrin & Stewart, 2006; Lynch & Sabol, 2004). There are many reasons why these areas have higher concentrated numbers of supervised populations and increased offending. First, poor neighborhoods often experience higher rates of police patrol and surveillance, which leads to greater likelihoods of arrests/re-arrest, violation detection and supervision revocation (Gottfredson & Taylor, 1986). In addition, prior to release, incarcerated individuals are allowed to select which residence they will return to, which often is the neighborhood from where they have familiarity (formerly lived in or have familial relations; Bensel et al., 2015). Unfortunately, individuals under supervision most often return to communities that are not only disadvantaged, but also lack positive prosocial support from either the community, social support networks, family, or peer associations which prevents them from returning to criminality (Chamberlain & Wallace, 2016). Lastly, because individuals under supervision have several deficits against them, (lack of education, employment history, substance abuse issues, criminal record, etc.) the housing options available are restricted (Petersilia, 2003). Thus, returning to these neighborhoods is often the only option available (Hipp et al., 2009; Petersilia, 2003;

Visher & Travis, 2003) which makes addressing recidivism among supervised populations important to understand. Several studies have examined the effect such socioeconomically disadvantaged neighborhoods and its related factors have on recidivism among individuals under supervision (Hipp et al., 2010; Kubrin & Stewart, 2006). Community or county-level characteristics, such poverty and unemployment create an environment where individuals under supervision have more difficulty abstaining from offending behaviors due to the lack of formal social controls and reduced access to resources in the community. This consequently impedes on the effectiveness of community supervision due to the limited resources available to assist individuals with treatment services and cohesive prosocial networks.

3.1.2 Poverty & Unemployment

Macro-level predictors such as neighborhood context can impact offending behaviors. Several studies have examined the relationship between community conditions, such as poverty and unemployment, with supervisee recidivism. Overall, research suggests that individuals under supervision residing in disadvantaged communities generally lack the economic, resource and network support provided to those of more stable neighborhoods (Fagan et al., 2003; Hipp et al., 2009; Hipp et al., 2010; Kubrin & Stewart, 2006). One of the first and most notable studies of neighborhood disadvantage and supervision outcomes was conducted by Kubrin and Stewart (2006). Using Census tract data from Oregon, Kubrin and Stewart (2006) examined how neighborhood disadvantage effects parolee outcomes and rates of recidivism (defined as arrest within 2 years). Neighborhood disadvantage was measured using percentage variables of poverty, public assistance, median household income, and unemployment. Overall, the findings suggest that concentrated disadvantage was positively associated with negative parole outcomes such as re-arrest. In addition, using ICE indexes, affluence served as a protective factor against recidivism which produces a (52%) reduction in the odds of re-arrest. Although the study suggest that individual-level predictors accounted for a greater amount of variation in outcomes, macro-level factors such as neighborhood conditions help alleviate this disparity gap.

Likewise, Mears et al. (2008) conducted a study investigating the effect resource deprivation and racial segregation may have on recidivism outcomes. Using county-level data from Florida, resource deprivation (a combined index variable of unemployment, poverty, median household income, public assistance, and female-headed household percentages) was used to conduct a multi-level analysis in hopes of understanding how and which macro and individual-level predictors explained a greater variation in recidivism. Recidivism, comparatively, was defined as felony re-incarceration within two years of release. Findings suggest that resource deprivation was positively associated with recidivism of violent crime, however negatively associated with re-incarceration of drug offenses (Mears et al., 2008).

Other studies have also examined the effect macro-level conditions of disadvantage has on recidivism outcomes. While some studies note that there is a positive relationship (Bensel et al., 2015; Chamberlain, 2018; Chamberlain & Boggess, 2019; Hipp et al., 2010; Kubrin & Stewart, 2006) others have noted no effect at all (Stahler et al., 2013). In either case, these studies highlight significant considerations regarding socioeconomic disadvantage and supervision outcomes evaluations. First, each study used measurements of poverty and unemployment (as well as other related factors) to appropriately define concentrated disadvantage and/or resource deprivation. In addition, while each study defined recidivism differently (i.e., either re-arrest, re-conviction, felony re-conviction, re-incarceration, or supervision revocation) the overall consensus is that there is an understood relationship between the stability of the community in which a supervisee resides and offending behaviors. Lastly, each study used similar measurements to track economic disadvantage — Census tract community/county-level data and percentage measures of concentrated disadvantage — showing that the clustering of individuals under supervision and how these variables interact is appropriate and consistent predictors of recidivism across the literature. Thus, it is important that additional research focus on the relationship between macro-level conditions of disadvantage and crime/recidivism/supervision outcomes.

3.2.3 Violent Crime

In addition to poverty and unemployment, studies have found that neighborhood context, such a violent crime, is also linked to being a predictor of recidivism. Majority of the research conducted has appropriately linked the increased presence of supervised populations and neighborhood crime (Hipp & Yates, 2009; Raphael & Stoll, 2004), however, less is known about the characteristics of such neighborhoods and the recently released. Indeed, it is quite understandable how violent crime and recidivism/supervision outcomes correlate. First, disadvantaged communities generally experience higher rates of crime as individuals under supervision who return to these neighborhoods are likely to recidivate due to being placed back in an unstable and resource deprived environment (Chamberlain & Boggess, 2019; Kubrin & Stewart, 2006; Kubrin & Weitzer, 2003; Pratt & Cullen, 2005). As previously stated, these disadvantaged areas lack significant resources needed to rehabilitate individuals under supervision including housing, employment, educational opportunities, and social support networks (Hipp et al., 2009; Visher & Farrell, 2005). Due to the lack of social services and strong support networks, these neighborhoods become a breeding ground for higher rates of illegal activity. Second, disadvantaged neighborhoods with a larger presence of supervised populations have a higher likelihood of experiencing recidivating behaviors. Two noted predictors of parolee recidivism are: 1) conviction offense and 2) level of supervision. Research has found that individuals under supervision convicted of property and drug offenses have the highest rates of recidivism once released from incarceration (Langan & Levin, 2002; Chamberlain, 2012). This is likely due to there being more opportunities to engage in property offenses and unaddressed substance issues compared to other types of crime (Chamberlain & Boggess, 2019). In addition, the level of supervision one is placed under is also a noted predictor of recidivism as the intensity of this supervision suggests that there are significant criminogenic risks and needs that need to be addressed. Likewise, a heightened supervision-level equates to greater contact with parole and probation agencies for drug testing, routine office visits, increased sanctions and monitoring which puts individuals under supervision under increased surveillance from POs, likely to produce violation detection.

However, the clustered effect that the presence of individuals under supervision has on neighborhood crime, specifically understanding violent crime, still requires investigation. Some studies have noted the positive effect of this relationship. For example, Hipp and Yates (2009) conducted a study on neighborhood crime rate and the presence of parolees in Sacramento, CA, over the course of 2003 to 2006 time period. The study found that neighborhoods with increased rates of parolees convicted on violent crimes also experience significant increases in burglaries and murder (Hipp & Yates, 2009). Conversely, the study found no evidence that parolees convicted of non-violent offenses (such as property and drug crimes) impacted neighborhood crime. Building off this research, Chamberlain and Boggess (2019) examined a population of parolees from Cleveland, Ohio to determine whether there was a relationship between parolee characteristics and neighborhood crime, specifically types of parolee supervision traits (level of supervision and offense type) with property and violent crime offenses. Results suggest that there is a positive relationship between parolees convicted of violent offenses and both violent and property crime. In addition, Chamberlain and Boggess (2019) found that "highly disadvantaged neighborhoods with a greater concentration of parolees convicted of violent offenses are more vulnerable to increases in violent crime rate than more advantaged neighborhoods with similarly high concentration of violent parolees" (pg. 1535). Lastly, evidence from this study states that as violent crime increases, so does the level of concentrated disadvantage (Chamberlain & Boggess, 2019). These findings highlight that while there is an association between individual-level risk factors and recidivism, there also appears to be a greater explanation of recidivism of individuals under supervision happening at the neighborhood-level (macro-level).

3.1.4 Resources and Services

Several studies have noted providing resources and social service support to the previously incarcerated as an integral part of the reintegration process (Chamberlain, 2018; Chamberlain & Wallace, 2016; Hipp et al., 2010; Kubrin & Stewart, 2006; Petersilia, 2001; Petersilia, 2003; Travis, 2005). Studies have investigated how the relationship that service provider proximity and/or availability serves as a predicting outcome of recidivism. One of the first studies to examine the impact of neighborhood context with the social service agency characteristics effect on parolee recidivism was conducted by Hipp et al. (2010). Hipp et al. (2010) examined whether service provider proximity predicts the recidivism rates of parolees residing near these areas. The hypothesis being that parolees in closer proximity to resources and services should witness a reduction in recidivism due to readily accessible social support. As expected, Hipp et al. (2010) actually found that more service providers located near parolees reduces the likelihood of offending by 26.8 %.

More recently, Konkel (2019) examined the effect service provider locations have on recidivism, specifically focusing on general and technical violations of parolees. Parolee data was obtained from Pennsylvania Department of Corrections (DOC). Konkel (2019) conducted an MLM analysis with U.S. Census block units of neighborhood context variables to examine the effect of service provider locations on the supervision outcomes of over 3,000 parolees released between 2010 until 2012. Findings suggest that neighborhood context was found to increase parolee re-incarceration, however, service providers located in more disadvantaged neighborhoods successfully decreased the odds of reoffending. More specifically, DOC service providers located in extremely disadvantaged neighborhoods were found to have an 18.1% reduction in general re-incarceration over the presence of general service providers. On the other hand, DOC service providers in disadvantaged areas produced only a 13.3% reduction in technical violations. Conversely, each additional general service provider located in disadvantaged areas produces a 20.7% increase in the odds of re-incarceration. Konkel (2019) aligned these findings with theoretical arguments supporting the greater the presence of DOC service providers located in disadvantage neighborhoods, the more likely parolees would participate in this type of programming due treatment to being a condition of released and the fear of revocation (Taxman & Bouffard, 2005).

3.1.5 Quantity

Although evidence suggests that recidivism rates among supervised populations decreases when community service providers are present (Hipp et al., 2010; Hipp et al., 2011; Visher & Courtney, 2007), in order for communities and the justice system to see the proper reinvestment of treatment services there must be an increase in the number and type of programs offered within community correctional settings (Taxman et al., 2014). During the mass incarceration era, rehabilitative treatment programming lacked significantly as many of the criminal justice system policies supported the use of incarceration over rehabilitation. Now, with the well-recognized ineffectiveness of these policies, reinvestment back into rehabilitative programming in correctional and community correctional settings calls for a comprehensive evaluation of the services available to support these individuals under supervision.

Very few studies identify the quantity or availability of correctional/treatment programming and its impact on supervised populations. Two of the most notable studies that address the number of programs and programming availability are Phelps (2011) and Taxman et al. (2014). Using national data from U.S. state prisons before 1990 (1979 and 1984) and after (1990, 1995, 2000, and 2005), considering the impact of the mass incarceration era, Phelps (2011) conducted a longitudinal review of the correctional programs available in prisons to determine the difference in patterns, if any, in inmate reentry services. Findings demonstrate that, despite the rapid increase in imprisonment, availability for programming in prisons remained consistent during this time period. However, Phelps (2011) noted during this time that the access to programs was limited as most programs allowed only a limited number of participants (between 10–100; Phelps, 2011). That is, as the prison population grew, the number of programs available were still limited in capacity for participation. While prisons have been able to maintain the availability and access to participation in programs, the size of the programs has not met the need of the growing population (Phelps, 2011; Taxman et al., 2014).

Likewise, Taxman et al. (2014) used the developed RNR simulation model to conduct two simulation tests on the effect of recidivism if treatment outcomes were improved. The first model used a hypothetical population of 10,000 offenders to see if the population would be impacted by expanding the “access to treatment and improving treatment effectiveness through adherence to the RNR principles” (Taxman et al., 2014,

p. 60). The second simulation examined the effect of implementing RNR principles in state prisons at a national-level on recidivism over the course of a 9-year period (Taxman et al., 2014). Overall, the simulation models showed that increasing the number and type of programming in correctional and community correctional settings does have a positive impact on recidivism. With the first simulation model, findings show that when the proportion of the population receiving treatment increases to 50%, the recidivism rate can be reduced by 8% (Taxman et al., 2014). This equates to increasing treatment by 50% which would "prevent approximately 475 recidivism events in one year for a population of 10,000 offenders" (Taxman et al., 2014, p. 62). Additional findings from both simulation models supported implementing RNR programming within prisons and including expanding RNR- informed treatment matching as both strategies of recidivism reduction. Overall, the concluded findings from the project supported the expansion of programs to a greater percentage of inmates/individuals under supervision and advancement of evidence-based programming in order to witness a reduction in recidivism and proper reinvestment in justice-oriented funding.

3.1.6 Capacity

New developments in the community corrections literature examines the responsiveness of communities and their capacity to link probationers and parolees to the appropriate need and service programs. Taxman (2020) expands the RNR theoretical framework by investigating the systematic responsivity of St. Louis, Missouri, one of the highest homicide cities in the US, to identify treatment and service provider gaps allocated to address violence and/or crime risk factors. The RNR tool is an online database developed by Taxman to survey organizations to determine the availability of programs and services, categorize these programs by treatment type, and target the offending behaviors each programs seeks to address. Overall, the findings suggest that nearly all resource and service provider needs were significantly under capacity (Taxman, 2020). More specifically, programs serving in the following needs were under capacity to provide service: 1) severe substance abuse, 2) decision making, 3) self-management, and 4) interpersonal skills (Taxman, 2020). On the other hand, programming for life skills and restorative justice efforts (listed as other) were above capacity by 9% and 49%, respectively (Taxman, 2020). This innovative research highlights the importance of resources and services not only being available in communities to reduce recidivism, but also have the sufficient capacity needed to address targeted behaviors (Taxman, 2020). Insufficient capacity and low-quality programming are just as detrimental to the public safety as the lack of treatment presence in disadvantaged communities. Due to the limited amount of research in this areas, future studies should consider expanding macro-level predictors to encompasses treatment quantity and capacity of service providers within community environments that house higher rates of supervised populations.

3.2 Micro-level Predictors of Offending

As previously noted, the majority of the recidivism literature has focused on examining the individual-level predictors of supervision outcomes and offending. Various studies have identified individuals under supervision characteristics and individual-level risk factors that increase the likelihood of recidivism. The following review of the literature on micro-level predictors of offending is heavily supported with consistent findings. While other individual- level predictors exist (i.e., criminal history, education, mental health, substance abuse history, familial status, and housing), for the purposes of this dissertation only the individual-level variables used in the present study are discussed. Micro-level predictors of age, gender, race/ethnicity, level of supervision and treatment utilization are reviewed below.

3.2.1 Age

Research has consistently supported the relationship between age and criminal offending. Specifically, juvenile and/or young adult under supervision are more likely to recidivate and be revoked from community supervision than their older counterparts (Chamberlain & Wallace, 2016; Durose et al., 2014; Hipp et al., 2010; Kubrin & Stewart, 2006; Lloyd et al., 2019). Consistent with the literature, Hipp et al. (2010) found that young parolees (age 37 years and less) were 10 times more likely to recidivate than older parolees. Likewise, Albonetti and Hepbrun (1997) found that age and gender significantly affected the risk of probation revocation amongst disadvantaged probationers. Other studies have continued to note that as age increases the likelihood of recidivism decreases (Hoffman & Beck, 1984; Listwan et al., 2013).

Research has also examined the impact that age has on revocation of supervision. For example, Tapia and Harris (2006) found that young, males from historically oppressed groups were more likely to receive harsher penalties and revocation of supervision compared to their Whites. Similarly, Chamberlain and Wallace (2016) found that older parolees were less likely to recidivate than young parolees regardless of neighborhood disadvantage and high concentration of parole populations. Overall, the research is generally consistent with the findings that young adults under supervision are more likely to recidivate and that as age increases, the issue of reoffending lessens.

3.2.2 Gender

As with age, research has consistently supported the fact that males are more likely to recidivate than females. Most notably, the criminal justice system is heavily populated and overrepresented by men regardless of demographic factors including age, race, criminal history, and behavioral health diagnosis. In regards offending behaviors, men are more likely to be arrested, commit violent offenses (Beesley & McGuire, 2009; Collins, 2010; Felson, 1996) and receive harsher sentences for the same offenses than women (Blackwell et al., 2008; Demuth & Steffensmeier, 2004; Doerner & Demuth, 2010; Embry & Lyons, Jr., 2012). The review of corrections literature suggests the same patterns can be seen comparing gender-based recidivism rates. The likelihood that an individual would recidivate decreases substantially (by 33%) if they are female (Hipp et al., 2013; Kubrin & Stewart, 2006; Stahler et al., 2013; Steen & Opsal, 2007). While offending behaviors and history of victimization may impact these findings, overall gender is a reliable predictor of offending.

3.2.3 Race/Ethnicity

Comparative to gender, the criminal justice system is disproportionally overrepresented by racial/ethnic individuals from historically oppressed groups specifically African Americans and Hispanics. Black males account for approximately 37% of the total male prison population, while White and Hispanic males represent 26.5% and 32.3%, respectively (Bureau of Justice Statistics, 2021). The imprisonment rate of Black females is 1.8 times as high as White females whereas the rate for Black males is 5.8 times as high as their White counterparts (Bureau of Justice Statistics, 2021). Although African Americans, Hispanics, and Native Americans makeup the highest incarcerated groups in the country, Blacks are still the largest portion and most incarcerated persons in the U.S. correctional system (i.e., prison and jail; Bureau of Justices Statistics, 2021).

Regarding race and recidivism, Blacks are scored more likely to recidivate based on predictive risk assessment factors (Skeem & Lowenkamp, 2016). Likewise, in predicting the recidivism relationship of structural community characteristics such as concentrated disadvantage, race (i.e., Black minorities) is noted to be one of the strongest predictors of recidivism (Wehrman, 2010). As it relates to parole revocations, Black parolees are 19% more likely to have their supervision revoked for a new offense and face a 50% likelihood of revocation for technical violations (Hipp et al. 2010; Steen & Opsal, 2007). Lastly, compared to White and Hispanic parolees, Black parolees are more likely to receive harsher parole sanctioning, re-arrest for a new offense, arrest for a violent offense and reconvicted of drug and property crime (Durose et al., 2014; Kubrin & Stewart, 2006; Orrick et al., 2011; Steen & Opsal, 2007). Thus, there is a strong predicting relationship between an individual's race and recidivism.

3.2.4 Level of Supervision

Following the RNR theoretical framework, an individual under supervision-level of risk for reoffending is a predominate predictor of offending behavior. Within most community correction agencies, POs are required to administer the risk assessment tool during the beginning of an individual's supervision period in order to predetermine reoffending risk. The most commonly used risk assessment tool is the Level of Service Inventory-Revised (LSI-R) and/or Level of Service – Case Management Inventory (LS/CMI), its revised version (Andrews & Bonta, 1995; Andrews et al., 2008). This tool requires practitioners to complete a semi-structured assessment with the supervisee, capturing much of the variation mentioned in the previously discussed micro-level predictors. In addition, the tool seeks to capture both static and dynamic criminogenic factors (i.e., the central eight) in order to encompass the individuals under supervision total characteristic makeup and compute risk of recidivating (Andrews & Bonta, 1995; Andrews et al., 2008). The level of risk score is then divided into categorical scorings (a variation of low, medium, and high) where the highest percentages indicate a stronger likelihood of recidivism (Andrews & Bonta, 1995). Empirical evidence supports the accuracy of level of risk scoring as research has found that individuals under supervision provided a low risk level have a decreased likelihood of offending, and an inverse effect for high risk levels. (Andrews & Bonta, 1995; Andrews et al., 2006; Austin et al., 2003; Bonta & Andrews, 2017).

Coinciding with level of risk, level of supervision is also a predictor of individual offending behavior. The assessed risk level provides the supervisee the associated level of monitoring/surveillance/supervision they will receive throughout the community supervision period. This entails the frequency and intensity of office visits with assigned Pos, urine analysis scheduling, treatment programming, supervision conditions (either court ordered, or assessment referred), and added surveillance techniques (i.e., GPS monitoring, gun and sex offender registration, home confinement, etc.). Studies have found that intensive monitoring results in a greater likelihood of recidivism and thus, require the most attention and should receive more intensive correctional programming (Pearson, 1988; Petersilia & Turner, 1993). Likewise, low-risk individuals under supervision have a low risk of recidivating and, consequently require little to no programming at all (Bonta & Andrews, 2017; Lowenkamp & Latessa, 2005). This relationship is supported by research as studies have found that individuals placed on more intensive supervision have an increased odd of re-arrest, re-incarceration, and revocation (Chamberlain & Wallace, 2016; Hipp et al., 2010; Kubrin & Stewart, 2006).

3.2.5 Treatment Utilization

The financial costs of the mass incarceration era and how its outcomes proved to make already disadvantaged communities worse, supported the notion that correctional and community correctional rehabilitative programming was needed to alter these consequences and reduce recidivism. (Taxman et al., 2014). Efforts to reduce recidivism without the use of rehabilitative programming are only an illusion to fixing the problem (Petersilia, 2011; Taxman et al., 2014). More importantly, rehabilitative treatment programming cannot just occur in prisons and jails, but also must extend to probation, parole, and community social service environments because its effectiveness diminishes when treatment is solely left to correctional facilities and not provided in the community (Taxman et al., 2014). Research suggests that recidivism rates amongst supervised populations decrease with the utilization of treatment programming/community-based service support (Chamberlain & Boggess, 2019; Hipp et al., 2010; Hipp et al., 2011;

Wallace & Papachristos, 2014). Several studies have noted the impact of treatment referral, initiation and completion has on recidivism. Further examination into treatment and recidivism research is listed below.

3.2.6 Referrals and Initiation

Throughout community corrections, POs navigate the “movement of cases from one institution to another, with movement typically effected by means of a referral” (Emerson, 1991, p. 198). This movement can be inter-organizational (i.e., Bureau of Prisons or court system) or community/service oriented based (i.e., substance abuse treatment, mental health services, employment, etc.) In the RNR model, after the assessment tool is completed and a supervision case plan is developed, the next step in the supervision process involves submitting referrals to community correctional rehabilitative services and programs that are both appropriate and responsive to the individuals’ risk and needs. Some studies examined the impact of implementing rehabilitative treatment (through observing the effects of referrals, participation, and completion) on probationer recidivism.

For example, Huebner and Cobbina (2007) conducted a study to examine the effect of drug use and drug treatment on recidivism amongst a sample of over 3,017 probationers from the 2000 Illinois Probation Outcome Project (data period from October 30 through November 30, 2000). More specifically, the study sought to understand the relationship between probationers’ characteristics, participating in and completing drug treatment and its impact on recidivism. Findings are consistent with prior research that drug treatment can reduce recidivism (Visher & Courtney, 2007; Wexler et al., 1999).

However, while entering treatment is important, the actual completion of treatment is where the most positive outcomes are found. Huebner and Cobbina (2007) found that while 37% of probationers who completed treatment had a new arrest, 67% who dropped out and 53% of non-treatment probationers were rearrested in the same period (p. 629). In addition, 28% of dropouts and 25% of non-treatment probationers had arrests for drug-related offenses while only 12% of completers had drug re-arrests. Overall, probationers who failed to complete treatment were the most likely to be arrested overall whether it was for a drug-related offense (Huebner & Cobbina, 2007).

In addition, Sheeran and Heideman (2021) sought to examine the effect of the Milwaukee County Adult Drug Treatment Court (MCADTC) to see the impact that race and ethnicity of participants had on referral admittance, likelihood of graduation and likelihood of recidivism (new charge/ re-arrest). Overall, findings show that more than half of all referrals and graduations to the MCADTC program were White (59.7%), followed by Black (30.2%) and then Hispanic (10.1%) participants (Sheeran & Heideman, 2021). Regarding treatment completion and recidivism, participants who had been revoked from the MCADTC program were more likely to have received a new charge within 12 months of post program release than those who successfully completed (p. 10). Lastly, findings support prior research that participating in treatment reduces the likelihood of recidivism. Sheeran and Heideman (2021) found that participants who successfully graduated from drug court were 60% less likely to receive a new charge within 12 months of program completion compared to those who were revoked.

Across various probationer demographics and characteristics, the presence of treatment greatly influences the decrease in recidivism and the lack thereof comes with opposite consequences. For example, mental health court participants are more likely to be associated with reduced recidivism with participation in community treatment than otherwise (Han & Redlich, 2016). Similar to adult offenses, studies have found that juveniles who are expelled from community-based treatment are more likely to recidivate to violent crime or return to drug or property offending due to voluntarily dropping out (Lockwood & Harris, 2015). With respect to female parolees, Morash et al. (2019) found that, depending on the risk level, a violation response of treatment over punitive measures can result in favorable (decrease in recidivism) outcomes for high-risk supervision. Thus, not connecting probationers and parolees to community-based social services/treatment programming, regardless of demographics, magnifies the likelihood of recidivating as treatment effectiveness can reduce offending behaviors.

3.3 Chapter Summary

The previous chapter highlighted some of the empirically supported literature on macro- and micro-level predictors of supervision offending. Although other predictors exist, these factors were selected for their significance in the present study. This study encompasses measurement of recidivism outcomes not only supported by RNR research, but also measures that determine the presence of social disorganized neighborhoods and economically neglected communities. There appears to be a connection in the literature surrounding the influence that community or county factors and existing resources or support programming) may have on recidivism, which is highlighted in the previous chapter. Regarding macro-level predictors, social disorganization theory has found support that disadvantaged communities breed the presence of crime and produce several obstacles that may hinder supervision success. Disadvantaged communities that are characterized by increased economic deprivation (e.g., poverty, violent crime, unemployment) and lacking community resources have an increased likelihood of recidivism. Likewise, majority of research has found empirical support that for the micro-level predictors of offending including an individual's age, gender, race/ethnicity, level of supervision and treatment utilization (program initiation/entry and completion). Even with the present empirical support, the link between individual-level predictors, capacity for treatment programming and community factors still remains limited. Thus, this dissertation project seeks to extend the social disorganization and resource deprivation literature to community corrections in order to examine how county-level conditions influence individuals under supervision odds of recidivism regarding program completion and reconviction. The following chapter presents the methodology of the study.

Chapter 4: Methodology

4.1 Overview

The present study is a secondary analysis of the data obtained from the RNR simulation tool (PI: Dr. Faye S. Taxman) that was applied in all 36 counties of Oregon in the spring of 2015 by the Center for Advancing Correctional Excellence (ACE!) at George Mason University (GMU; Taxman & Murphy, 2016). One of the primary goals of the RNR evaluation in Oregon was to assist the Oregon Department of Corrections (ODOC) with identifying systemic issues surrounding resource referrals and inform gap analysis for programming capacity (Taxman & Murphy, 2016). Thus, individual-level probationer demographics and treatment type are analyzed by comparing the impact county-level factors may have on recidivism and treatment completion. The present study seeks to provide a more in-depth understanding on how county conditions of deprivation inform the ability for community corrections agencies to address supervisee needs.

The aim of the present study is to use the available data to conduct a MLM analysis on the various factors at the individual and county-level that impact treatment programming and supervision outcomes in Oregon. While empirical evidence has found support for macro- and micro-level predictors of supervision outcomes and the need for targeted rehabilitative programming, the literature largely does not provide a full understanding of the connection between community conditions (i.e., poverty, unemployment, violent crime, and treatment utilization) and its impact on supervision outcomes (reconviction) and program completion (treatment success). Using the MLM approach, a two-level analysis will be conducted examining cluster variables observing how individual (i.e., probationer) and county-level factors interact and influence recidivism probationer reconvictions within three years and treatment completion.

The methodology used to investigate the noted research questions is explained in this chapter. This chapter will include the following sections; 1) overview; 2) research questions; 3) quantitative research design; 4) RNR in Oregon: Study Context; 5) data; 6) sample; 7) measures and data collection; 8) assumptions testing and imputations process; and 9) ethical considerations.

4.2 Research Questions

The following research questions guided this study:

1. What effect do individual demographics have on program success?
2. What effect do individual demographics have on reconviction?
3. What effect does treatment initiation and success have on reconviction among probationers?
4. What effect does treatment initiation and success by specific program type have on reconviction among probationers controlling for individual demographics?
5. Does the effect of initiation of completion on reconviction differ depending on whether an individual lives in a resource deprived county or not?

4.3 Quantitative Research Design

This study used a quantitative research design method of MLM to explore the relationship, if any, between individual-level and county-level factors to understand their ability to predict the supervision outcomes of reconviction and treatment completion. Within the quantitative methodological approach, researchers must use theoretical-based cause and effect thinking in the selections of specific variables, research questions, measurement, and observations (Creswell, 2003, p. 18). For this reason, this study attempted to select specific variables that are supported by the literature and has developed research questions (reference above) to conduct an exploratory investigation regarding reconviction and treatment completion.

This current study also utilized a secondary analysis of the data collected as this information was obtained from the RNR tool developed by ACE! at GMU. While the principal investigator (Dr. Faye Taxman) collected and analyzed the data for another primary purpose, this secondary data analysis adds further contributions to the investigation by not only reviewing the previously collected data, but also additional data sources and exploring what remains to be learned about recidivism and treatment outcomes (Johnson, 2014).

Finally, this research design will utilize MLM to answer the presented research questions. Woltman et al. (2012) define HLM as "a complex form of ordinary least squares (OLS) regression that is used to analyze variance in the outcome variables when the predictor variables are at varying hierarchical levels" (p. 52). The MLM method seeks to investigate relationships that lie when levels of data are nested/layered within and between each level that, all too often, may not be properly examined using other statistical methods (Woltman et. al, 2012). This current study used MLM to conduct a two-level analysis examining individuals (level 1), located within respective counties (level 2) and the observed impact on recidivism and program completion. Concluding sections will interpret the results and discuss how community corrections agencies can progress policy recommendations surrounding the extent programming is available and completed as well as community responsiveness to individual needs.

4.4 The RNR Study in Oregon: Study Context

The RNR simulation tool is an online survey database developed by ACE! at GMU to assist practitioners, administrators, case managers, and treatment providers who assist correctional populations with delivering the appropriate treatment services and interventions geared toward recidivism reduction. The tool follows the RNR framework intended to offer the best reentry outcomes for individuals through linkage to programming based on criminological risk and needs factors (Andrews & Bonta, 2010). The tool is comprised of three methodological components:

1. The **RNR Program Tool for Adults:** which examines program quality and implementation based on available information on effective interventions;
2. **Assess the individual** which recommends and matches the appropriate programming to the individual based on the risk-needs profile; and
3. **Assess Jurisdiction Capacity** which aggregates available programming and services in given jurisdiction based on the risk-needs profiles and identifies service gaps (Taxman & Murphy, 2016).

In addition, the RNR simulation tool classifies identified programs into six categorical groupings: 1) severe substance abuse; 2) criminal lifestyle and thinking; 3) self-improvement and management; 4) social and interpersonal skill development; 5) life skills development; and 6) punitive supervision interventions (Taxman & Murphy, 2016). Each program is assessed for its adherence to EBPs and overall domains of RNR dosage and implementation (Taxman & Murphy, 2016). Altogether these components are designed to evaluate of how well correctional agencies use EBPs efforts, link individuals to EBPs validated programs and whether these programs/services operate in a capacity to manage these populations. The RNR simulation tool was the primary data source for the RNR study of Oregon correctional programming. This study is further explained below.

4.4.1 Implementation in Oregon

From 2000 until 2014, Oregon witnessed an expansion in incarceration rates and spending on preventive correctional efforts. In order to improve the quality and quantity of community corrections efforts, the Oregon Criminal Justice Commission (CJC) contracted GMU's ACE! in the spring of 2015 to conduct a review on the existing resources available for community supervision referral. The research project goals were intended to: 1) identify the needs for services and programs geared to reducing recidivism; 2) inform gap analysis of effective allocation of resources; 3) address low treatment completion rates; and 4) identify systemic issues to improve referrals and collaboration across agencies (Taxman & Murphy, 2016, p. 5). With the combined efforts of the Oregon CJC and ODOC, researchers at ACE! were able to implement the noted goals using the RNR simulation tool which evaluates community capacity for treatment resources/services by examining program quality, matching programming to client needs and identifying service gaps and needs in given counties.

Several combined data sources were used in the evaluation of Oregon counties and their capacity for programming resources and matching profiles of the needs of those on supervision. First, ODOC provided ACE! the “admissions to community supervision” dataset which consisted of over 100,000 admissions in Oregon beginning in January 2009. From this data ACE! identified 70,786 individuals who were most recently admitted onto supervision (those who were already serving supervision, parole violators, detained inmates and those placed on a new supervision period while still incarcerated were excluded). In addition, this dataset included data from the LS/CMI, which is the risk-needs assessment tool used in Oregon Community Corrections to assess their correctional population. As with similar risk assessments, the LS/CMI screens individuals for dynamic and static factors such as age, employment, criminal history, substance abuse and other patterns. Of the 70,786 individuals identified, only 34,332 had a full assessment completed as Oregon probation agencies are not required to complete full assessments on low-risk or sex offenders. The LS/CMI was identified needs factors that are related to recidivism (criteria discussed in a subsequent section).

In addition, ODOC provided ACE! treatment participation, sanctions, and recidivism data. From the treatment program data, ACE! was able to receive individual-level data regarding treatment participation, referral date, program name, entry/exit dates and completion status from 2009 to 2011. Comparisons were drawn between individuals served by each program with available treatment capacity. Sanctions and services data were provided for each Oregon county displaying the custodial and non-custodial monthly enrollment average of clients who were provided varying supervision services (i.e., community service, Day Reporting Center, outpatient substance abuse, intensive supervision, etc.). ACE! compared the number of non-custody data reported programs with reported treatment enrollment and participation. Recidivism data covered corrections admissions from 2009 to 2011 for reconviction. This dataset was recoded as Oregon defines recidivism as reconviction of a new crime or arrest within three-years of release. Finally, ACE! and community corrections directors invited over 400 treatment providers in all Oregon counties to complete the RNR program tool, an online self-administered assessment of community corrections treatment programs and their ability to provide EBPs that reduce recidivism. Of this, 115 of the programs completed the online program tool. To increase response rate, GMU developed a shortened version of the tool that included more critical elements of the original RNR program tool. An additional 200 (55%) programs were assessed with this tool either by phone or email. Only two (< 1%) programs declined to participate and 44 (12%) of the programs did not complete either the full or shortened survey. In total, it was averaged that at least 461 programs exist in Oregon.

Overall, the study findings suggest that Oregon Community Corrections population has an abundance of programming that addresses substance abuse needs (an excess of 12%), however, there were significant program capacity gaps in all other treatment areas (i.e., criminal lifestyle and thinking, supervision/punishment, interpersonal skills, etc.). Several recommendations were provided including the need for

Oregon to refer their correctional population to the programs that target their risk-needs profile as determined by the LS/CMI. Lastly, ACE! suggested that Oregon expand its funding to increase programming in the deficient areas and increase communication between community corrections and treatment providers in order to improve program completion rates.

4.5 Data

Data from this study was gathered from three separate sources. The first source of data included information from those individuals who were placed on community supervision, including demographic data and the treatment utilization programming variables (referral, entry/initiation, and exit dates, program names, and completion status). This data was provided from the was derived from the ODOC and was provided to ACE! for the RNR evaluation in Oregon. In addition, the ODOC provided recidivism data (reconviction within 1 and 3 years of release) which was obtained from the ODOC but provided through the RNR evaluation conducted by ACE!. In addition, Oregon Community Corrections provided information about individuals on supervision level and risk from the LS/CMI risk-needs assessment. Oregon Community Corrections conducts risk/needs assessments on all individuals under supervision except for very-low risk and sex offenders. This data provides risk/needs scores for dynamic and static criminogenic needs. The RNR program tool developed by ACE! is the third database, which provided treatment program capacity data needed to deliver programming to individuals on supervision. From this database county/jurisdiction program capacity data was developed. Finally, county-level data was acquired from the 2010 American Community Survey from the United Census Bureau – Five Year Estimates.

4.6 Sample

The sample used in this study is a subset of individuals under supervision originally studied in the RNR evaluation in Oregon. The RNR dataset includes probationer population data of over 70,000 admissions to Oregon community supervision from January 2009 until December 2011. This data was filtered so that individuals who were already serving their sentences at the start of the sampling period, parole violators, inmates serving a detainer warrant, and those who rolled over to a new commitment while incarcerated were excluded. Individuals under supervision resided in 36 Oregon counties, however three counties (Gilliam, Sherman, and Wheeler) share treatment resources and services which require those under supervision to be collapsed into "Tri-County" cluster. This made the level 2 sample consist of 34 Oregon counties.

Prior to any analysis or data reductions, three data files were merged to create the final sample for this study. The outcome variables for "Reconviction within 3-years" and "Reconviction 1-year" were merged with the RNR tool data containing treatment variables. From this data merge, the original population began at $N = 77,847$. Due to data missing data and the selected outcome variable (selected to better explain variation), the final sample was reduced from the original population. The final sample consisted of 9,874 individuals placed on community supervision across 34 Oregon counties. The reduction in population sample is further explained.

The population sample was significantly reduced by more than half due to missing data and inconsistencies in these data, (e.g., missing dependent variables, independent variables, and LS/CMI assessment data for level of risk). First, outcome variables of "Reconviction within 3-years" and "Reconviction 1-year" were merged into one dataset with the RNR tool data containing treatment variables. The original population sample started with 77,847 individuals under supervision. The outcome variable of "*Reconviction within 1-year*", included 70,786 individuals under supervision (missing sample of *N* = 7,061 did not have this data). Of the "Reconviction within 1-year" population, majority (*N* = 64,628 or 91.3%) individuals did not experience reconviction within 1 year. Only 8.7% (or *N* = 6,158) of probationers were found to be reconvicted within the first year of supervision. The outcome variable "Reconviction within 3-years" included 16,845 individuals under supervision (missing sample of *N* = 61,002 did not have this data). Of the "Reconviction within 3-years" population, majority (*N* = 10,140 or 60.2%) individuals did not experience reconviction within 3 years. However, a greater sample than that found in the "Reconviction within 1-year" variable did experience reconviction within 3-years (*N* = 6,705 or 39.8%).

Since probation terms are typically shorter sentencing terms of supervision (often less than 12 months), there is less variation that would be explained with using the "Reconviction 1-year" outcome variable. In addition, research suggest that tracking individuals under supervision for as little as a year may miss a significant proportion of offending behaviors (Durose et al., 2014). Comparatively, observing individuals under supervision using the "Reconviction within 3-years", a greater percentage (39.8% or *N* =

6,705) of these individuals had experienced reconviction within 3 years of release. Thus, the outcome variable "Reconviction within 3-years" was selected for the study which reduced the sample to 16,845.

From the 16,845, a portion of the sample population (N = 7,061 or 41.9%) did not have treatment-level data from the RNR tool and, thus was considered missing. More specifically, Oregon Community Corrections does not require LS/CMI assessments be completed on low-risk individuals and sex offenders receive a specialized assessment tool. Thus, absence of such data creates an inability to identify the risk levels and treatment program needs as well as provide individuals on supervision level of risk data. At the completion of the assessment tool, individuals on supervision are provided a risk score which also determines the level of supervision or monitoring while in the community. In addition, based on an individual's level of risk and level of supervision (an evaluation of risk and needs to determine supervision monitoring), individuals are referred to treatment services while in the community to rehabilitate themselves. Treatment data that was provided to the RNR tool to understand the gap analysis of jurisdiction capacity over the overall correctional population need. For this reason, the final sample excludes all missing data where individuals had no treatment data (N = 7,061). Due to the limited number of variables and what would have been a large proportion of missing data, there was not enough observed sample to conduct an accurate imputation.

The selection of the "Reconviction within 3-year" outcome variable and data merge inconsistencies with the RNR tool data reduced the sample to its final sample population. With the removal of all data missingness, this brought the final sample to 9,874 individuals under supervision. Additional efforts to address the missing data issue with this study are discussed in the subsequent imputation process section.

4.7 Measures

Table 2

Study Variable Descriptions

Variable	Role	Level	Measurement
Conviction after 3 years	DV	1st	Coded 1 = reconvicted after 3 years, 0 = not reconvicted
Program success	DV	1st	Coded 1 = treatment success, 0 = No success
Age	Demo	1st	Age groups: ages 16-27, ages 28-35, ages 36–42, and ages 43 or older
Race	Demo	1st	Coded 1 = not white, 0 = white
Gender	Demo	1st	Coded 1 = male, 0 = female
Level of supervision	Demo	1st	Supervision groups: low, low/medium, medium, and high supervision levels
Total program initiation	IV	1st	A count variable of the number of treatment program initiations for a probationer
Total program completion	IV	1st	A count variable of the number of treatment program completions for a probationer
Anger treatment	IV	1st	A count variable of the number of anger treatment programs a probationer has initiated or completed
Cognitive treatment	IV	1st	A count variable of the number of cognitive treatment programs a probationer has initiated or completed
Domestic violence treatment	IV	1st	A count variable of the number of domestic violence treatment programs a probationer has initiated or completed
Education treatment	IV	1st	A count variable of the number of education treatment programs a probationer has initiated or completed
Vocational Training treatment	IV	1st	A count variable of the number of employment treatment programs a probationer has initiated or completed

Mental health treatment	IV	1st	A count variable of the number of mental health treatment programs a probationer has initiated or completed
Parenting skills treatment	IV	1st	A count variable of the number of parenting skills treatment programs a probationer has initiated or completed
Supervision treatment	IV	1st	A count variable of the number of supervision treatment programs a probationer has initiated or completed
Substance abuse treatment	IV	1st	A count variable of the number of substance abuse treatment programs a probationer has initiated or completed
Sex offender treatment	IV	1st	A count variable of the number of sex offender treatment programs a probationer has initiated or completed
Transitional housing treatment	IV	1st	A count variable of the number of transitional housing treatment programs a probationer has initiated or completed
Program quantity	IV	2nd	A count variable of the number of treatment program a county has in place to serve its probationer population
County deprivation	IV/M	2nd	A z-score composite of a county's violent crime, poverty, and unemployment rates, higher values indicate greater deprivation
Jurisdiction program capacity index	IV/M	2nd	A ratio that varies between 0 and 1 that measures whether a county's capacity meets its need, higher values indicate greater capacity

Note. DV is dependent variable, IV is independent variable, M is moderator variable, and Demo is a probationer demographic variable. The level column indicates on what level the variable was measured, 1st indicating the probationer level and 2nd indicating the county-level.

4.7.1 Dependent Variables

Outcome measures. The two outcome measures for this study were provided from the RNR evaluation which included: 1) Recidivism – Conviction 3 year and 2) Program completion. Both variables are coded dichotomously indicating whether an incident occurred (1 if the incident occurred during the supervision period, 0 if it did not occur). Along with recidivism measures re-arrest and revocation, reconviction while on supervision is a significant measure of compliance and adherence to supervision success. While re-arrest or re-incarceration data can be useful, it can be difficult to draw accurate conclusions on the effects resources have on recidivism with these measures when they often can result with the individual receiving a continuance of supervision once released from custody (Ostermann et al., 2015). In addition, using re-conviction as a recidivism variable is consistent with the literature approach as an individual must be convicted of a crime to be placed on probation (Hipp et al., 2010). Thus, using captured reoffending behavior (reconviction) as an outcome measurement is an accurate measure for recidivism. In addition, observing the relationship between recidivating behaviors, such as reconviction, and community disadvantage/deprivation may provide new highlights on risk prediction amongst supervised populations by identifying community or county-level factors that lead to recidivism (Hipp et al., 2010; Kubrin & Stewart, 2006). Likewise, program completion is also considered to be a critical component of achieving supervision success as completion of treatment addresses criminogenic needs which reduces odd of recidivating (Bonta & Andrews, 2017). The next section further describes these two variables.

Reconviction. The first outcome variable used for this study is "Recidivism – Conviction 3 year" (1 = *yes*, 0 = *no*). For this study, recidivism is measured in terms of reconviction within 3 years of being placed on supervision. While the measure of recidivism can be operationalized as re-arrest, re-incarceration, or re-conviction, for this study, reconviction will be the measure. The current analysis seeks to understand how individual characteristics and treatment programming, or lack thereof has an impact on reconviction. This variable is a reported measure that ODOC provided to ACE! in 2015. Recidivism data included the individuals who entered and exited corrections agencies from 2009 to 2011 by reconviction. This data will be used to assess which individual-level and county-level factors predict recidivism. Reconviction is a dichotomous variable and is coded so that those probationers who were not reconvicted within 3 years of supervision coded as 0 = *no* and probationer who experiences reconviction will be coded as 1 = *yes*. Of the final sample, majority (N = 5,546 or 56.7%) of the probationer did not experience reconviction within 3 years compared to those who did experience reconviction (N = 4,238 or 43.3%).

Program success. The second outcome variable observed is program completion of any type of treatment including: substance abuse, criminal cognitions, self-improvement, interpersonal skills, life skills and supervision monitoring. Program success variable will be operationalized to define program completion of any treatment as a "success" (1 = *yes*, 0 = *no*) outcome component during the supervision period. This variable also indicates that an individual was not only referred to treatment, but also initiated/entered treatment and successfully completed the program once engaged. Program success is a dichotomous variable and identified as a successful completion (coded as 1) or unsuccessful termination (coded as 0). This variable is important to the study as it indicates whether the individual completed a rehabilitative treatment program. Ideally, for an individual to successfully reintegrate back into society, they not only need to be referred to the appropriate interventions but also successfully complete the program(s) during the course of supervision. Of the final sample, majority of the population has no treatment success (*N* = 6,397 or 65.4%) compared to those who had treatment success (*N* = 3,387 or 34.6%).

Interaction terms. One of the research questions in this study propose cross-level moderating effects that use and interaction terms of an individual-level covariate with a county-level covariate on the outcome of interest. Research Question 5 seeks to observe whether the effect of program utilization (initiation and completion, both individual-level) is moderated by levels of county deprivation on reconviction. The individual-level measures for program initiation and completion are two count variables indicating the number of times a program was initiated (entered) or completed. This research question seeks to understand if different levels of program initiation or completion predicts the likelihood of reconviction at differing levels of county deprivation. Before the interaction term was created, each variable was mean centered with all individual-level variables group mean centered and all county-level variables grand mean centered (Bauer & Curran 2005). Thus, level 1 variables of treatment initiation and completion were group-mean centered removing any between-county variance. Level 2 variables of county deprivation were grand-mean centered allowing for the effect of the variable to influence variance at the county-level. Level 1 variables of treatment initiation and completion were multiplied by the level 2 variable of county deprivation to create the interaction term. The main effects and the interaction effects were included in the model to determine if these cross-level moderating effects had an impact on reconviction.

4.7.2 Individual-level Variables

Level 1

Individual-level (level 1) variables in this study include probationer demographics from the assessment tool and program referral, entry, and completion data for each specific treatment type. These variables were selected based on the review of the literature that supports the RNR framework and risk assessment prediction. While several individual-level predictors can be used, the selected variables were those best supported by the literature and appropriate for this study. The level 1 individual predictors include age, gender, race, level of supervision, and treatment utilization.

Individual Demographics

Age. Research has consistently found supporting evidence of the relationship between age and criminal offending (Hoffman & Beck, 1984; Listwan et al., 2013; Tapia & Harris, 2006). This variable is included to understand if individual-level differences, such as age, have an influence in predicting the odds of reconviction. The *age* individual-level predictor was obtained from the RNR evaluation in Oregon. This variable is coded as follows: 1 =*ages 16–27*, 2 = *ages 28–35*, 3 = *ages 36–42*, and 4 = *ages 43-older*. Majority of the population were categorized as being between the ages of 16–27 (N = 3753 or 38.4%).

Gender. The gender individual-level predictor was obtained from the RNR evaluation in Oregon. This variable will be recoded into a dichotomous variable where 1 will indicate the probationer is Male and 0 will indicate the probationer is Female. Of this sample, majority (N = 7,310 or 74.7%) identified as being male compared to female (N =

2,474 or 25.3%). Empirical literature has found support that males are overrepresented in the correctional system and more likely to recidivate than females (Hipp et al., 2013; Kubrin & Stewart, 2006; Stahler et al., 2013; Steen & Opsal, 2007). This variable is included to understand if individual-level differences, such as gender, have an influence in predicting the odds of reconviction.

Race. The race individual-level predictor was obtained from the RNR evaluation in Oregon. This variable will be recoded into a dichotomous variable where 1 will indicate that the probationer is non-White and 0 will indicate that the probationer is White. In addition, majority of the sample identified with being While (N = 8,281 or 84.6%) compared to non-White (N = 1,503 or 15.4%). Other races included as "non-White" include African American, Hispanic, American Indian, Asian/ Pacific Islander and "other". Research has consistently found supporting evidence of the relationship between race/ethnicity and recidivism (Hipp et al. 2010; Skeem & Lowenkamp, 2016; Steen & Opsal, 2007). In particular, research has found support that racial/ethnic minorities have an increased likelihood to recidivate on supervision and reside in disadvantaged areas (Kubrin & Stewart, 2006). For the purposes of this study, the observation will focus on the relationship between racial minority, supervision, and treatment outcomes. This variable is included to understand if individual-level differences, such as non-White, have an influence in predicting the odds of reconviction.

Level of supervision. The level of supervision an individual-level predictor was obtained from LS/CMI data provided to the RNR evaluation conducted in Oregon. The criminal justice risk level variable is the assigned level of risk given to probationers based on their risk assessment score (i.e., LS/CMI score). Within community corrections, once the structured assessment instrument produces a recidivism risk level, this score places the individual on a supervision monitoring level which provides the proper identification of criminogenic needs and informs supervision recommendations regarding interventions (Guay & Parent, 2018, p. 82). Research has consistently found supporting evidence of the relationship between intensive monitoring, or high levels of supervision, and an increased likelihood of recidivism (Pearson, 1988; Petersilia & Turner, 1993). This variable is coded as follows: 1 = *low risk*, 2 = *low/medium risk*, 3 = *medium risk*, and 4 = *high risk*. Of the population, majority (*N* = 4,141 or 42.3%) were placed as low/medium supervision. Of the other supervision levels there are low supervision (22.5%), medium supervision (19.4%) and high supervision (12.3%).

Treatment utilization. In addition to the demographic and individual characteristic variables, level 1 variables will also include treatment utilization data. These variables will include total program initiated and program completed variables by program type. All treatment program utilization data (treatment referral, entry, exit dates, specific type, and completion) was obtained from the ODOC but provided through the RNR evaluation conducted by ACE!. As program referral and initiation are important to supervision success, it is critical for the current study to gauge how resources and services are allocated across counties. The RNR simulation tool includes program data from across Oregon counties to include program type, location, referral date, entry date, completion date, program category type and program facility name. The RNR simulation tool accounted for 11 program types across Oregon. Each program was divided into 6 program categories by the following treatment type: 1) substance abuse; 2) criminal lifestyle; 3) self-improvement; 4) interpersonal skills; 5) life skills; and 6) punishment/supervision. For the purposes of this study, punishment and/or supervision resources were excluded as being considered “treatment” as these services are geared toward restricting behaviors and have little to do with addressing criminogenic needs. Types of programming included in punishment/supervision programs are electronic monitoring, community service and sanctions conferencing. Thus, the final sample of treatment utilization services only includes the five other treatment categories (substance abuse, criminal lifestyle, self-improvement, interpersonal skills, and life skills).

Total program initiation. The program initiation variable is a count variable derived from the original RNR tool. The RNR tool identified program initiation variables by a one-time count of the recorded date that an individual entered a treatment program/service (i.e., entry date). The program initiation date indicates the date that the individual on supervision began attending the treatment program/service. This variable indicates that a probationer was not only referred to a program, but that the individual entered treatment program and began attendance. This variable was recoded so that each entry date will be used to account for each entry occurrence as a mean to account for the attendance of multiple treatment programs and additional first-time initiation of the same program. an entered individual under supervision treatment. In addition, this variable will observe the type of program that an individual was initiated into (e.g., substance abuse, cognitive behavior treatment, domestic violence treatment, vocational training, anger management, education, sex offender treatment, transitional housing, and supervision monitoring). Each entry count will be operationalization as 1 = *yes* or 0 = *no.* In the final sample, each program initiated (N = 9,784) ranged from 0 to 19. The average number of programs initiated by individuals under supervision per county is 10. All total program treatment initiation variables by treatment type are also presented in Table 4.

Total programs completed. The original RNR tool identified the program completion variable as the recorded date that the probationer completed a treatment program/service. This variable was recoded as a count variable so that each completion date can be used as a program completion count for each time a probationer successfully completed treatment. In addition, this variable will observe the type of program that a probationer completed (e.g., substance abuse, cognitive behavior treatment, domestic violence treatment, vocational training, anger management, education, sex offender treatment, transitional housing, and supervision monitoring). Each completion count will be operationalization as 1 = *yes* or 0 = *no.* In the final sample, probationer completion (N = 9,784) ranged from 0 to 10. All total program treatment completion variables by treatment type are also presented in Table 4.

4.7.3 County-level Variables

Level 2

Three variables were selected to investigate the relationship that level 2 county-level conditions of resource deprivation, program quantity, and jurisdiction capacity have on program success and reconviction outcomes. The present study examined the following county-level variables: 1) county deprivation index variable, 2) program quantity, and 3) jurisdiction program capacity. Finally, the jurisdiction capacity variable was created using RNR simulation tool and risk assessment data.

County deprivation index. Consistent to what is known in social disorganization and community supervision recidivism literature, variables for socioeconomic disadvantage factors were created using various data sources for all 36 Oregon counties (Hipp et al., 2010, Kubrin & Stewart, 2006; Konkel, 2019). Data from the 2010 U.S. Census Bureau American Community Survey (5-year estimates) is used to create the level 2 county deprivation index variable. Specifically, measures of poverty and unemployment by county were exacted and used to create a county deprivation variable. Likewise, violent crime rates per county were taken from the Uniform Crime Reporting data and also used to be the third measure to create the county deprivation index**.** The selected measures are consistently used variables/measures found in community corrections and recidivism literature to examine county/community/neighborhood conditions (Kubrin & Stewart, 2006). In order to determine county resource deprivation levels, a county deprivation index variable was created using the measures for violent crime, poverty, and unemployment rates for each of the Oregon counties. The use of an index score to understand the relationship concentrated disadvantage or deprivation has on recidivism has been used in previous studies (Hipp et al., 2010; Mears et al., 2008). Likewise, based on the literature, the conceptualized meaning of deprivation has components of violent crime, poverty, and unemployment. Income, or lack thereof, and poverty are key constructs of the social disorganization theory and are often studied as being characteristics of the area's probationers reside. Likewise, the link between resource deprivation and urban violence has long been explored in criminological literature specifically related to recidivism. Thus, these measures were selected to develop the deprivation index variable.

As previously stated, although Oregon is separated into 36 counties, two counties (Sherman and Wheeler Counties) are dropped from the county-level as they share resources with Gilliam County. Combined, these counties are identified as tri-county for Oregon Community Corrections, Oregon Department of Corrections, and treatment services. Thus, all measures and index variable were created with the exclusion of these two counties (Sherman and Wheeler) and the final sample of second-level units consisted of 34 counties. Nonparametric correlations for the three composite item variables (violent crime rates, below poverty rates, and unemployment rates) were conducted to understand their strength and the correlations were all low and insignificant (all $\rho s < .281$, and all ps $>.102$. Next, histograms for all the indicators were produced, and each measure was fairly normally distributed (all skewness and kurtosis measures were $< \pm 2$) with no extreme outliers. Using the standard deviation and mean of the 34 counties at the county-level, the three variables were converted into z-scores to standardize their measures. Finally, the deprivation index variable was created using the average of the three z-scores where the higher levels of each variable (positive range) indicate a greater amount of deprivation for the county and lower levels (negative range) indicate more resourceful or advantageous. Of the county deprivation variable, the mean deprivation index was .008 (SD = .668). The deprivation score for counties ranged from Hood River County as the least resource deprived (-1.24) while Baker County was the most deprived (1.16). Each of the unstandardized component items (violent crime rate, under poverty rate, and unemployment rate) correlated with the composite deprivation index (all *ρs* > .617 and *ps* < .001).

Program quantity. The program quantity variable was obtained from ODOC but provided through the RNR evaluation conducted by ACE!. This variable refers to the number of program types per county. The program quantity variable was calculated as a count variable for the diverse number of different types of programs within each county. As program referral, engagement and program completion are important to supervision success, it is critical for the current study to gauge the number of resources and services are allocated in each county and whether this influences recidivism. Descriptive of this variable indicate that counties diversity in programming ranges from five to 11 different types of programs. The average number of programs available per county were eight. Since the RNR simulation tool includes program data identified by county, this variable assisted with counting the number of programs provided across all Oregon counties.

Jurisdiction program capacity. The jurisdiction capacity variable was developed combining data from two sources: LS/CMI risk assessment data and county treatment program capacity data (assessments of programs' ability to deliver services to probationers) through the RNR program tool. While risk assessment data was used to determine the risk/need profiles of the correctional population, treatment capacity data was pulled to understand each counties' ability to deliver treatment services and programs to individuals under supervision. By combining the information from these two datasets, a county program capacity variable was created assessing each counties' ability to have the capacity (treatment program space/availability for a probationer) by the county need (number of probationers in that county that needed the specific treatment). First, the primary program need variable was used from the LS/CMI risk assessment data. Then, using the RNR Program Tool, program capacity data was extracted from each county by five treatment types (i.e., substance abuse, criminal lifestyle, self-improvement, interpersonal skills, and life skills). Using both the jurisdiction capacity and program need totals, a program capacity/need variable was calculated (dividing the numerator county program capacity by the denominator population need) excluding any county that did not report capacity and capping program capacity if it exceeded the need. For example, Baker County had a substance abuse county capacity of 97 treatments available, however the population need for this treatment in Baker County was only 11. Capping the capacity (97) at the need (11) for Baker County substance abuse treatment was measured at capacity, or 1 (11/11), fully meeting this need. This calculation was completed for all 34 Oregon counties with each treatment type.

The primary program need variable was obtained from the LS/CMI risk assessment to identify which "primary" need an individual should be referred depending on the five treatment categories (i.e., substance abuse, criminal lifestyle, self-improvement, interpersonal skills, and life skills). Following the RNR framework, while an individual under supervision may have several needs, the "needs" principle suggest that community corrections target the specific offender risk factors that are dynamic (amenable to change) such as substance abuse, versus static (unable to change) such as age (Andrews et al., 1990; Andrews & Bonta, 2010; Taxman et al., 2013). The RNR model refers to the predictors of recidivism as the "Central 8" and argues that we focus on dynamic factors most related to recidivism (Andrews & Bonta, 2010). Thus, the primary program need variable focuses on this most primary dynamic need (e.g., substance abuse or criminal associations) and the LS/CMI risk assessment selects this variable for supervision rehabilitative treatments to focus on. Of the final sample size, out of 9,784 probationers, 4,885 probationers were identified as having a primary program need. The most prominent primary need was interpersonal development (18.3%). This missing data is the result the LS/CMI not being fully completed to identify a program need. More specifically, low-risk/sex offenders not being required to complete the LS/CMI which therefore creates the inability to identify the program needs. All issues of missing data are further addressed in that subsequent section.

Table 3

Descriptive Table Showing Program Need Variable Frequencies and Percentages

Program Primary Need	*Frequency*	*%*
Substance Abuse Dependency	579	5.9
Criminal Cognition	491	5.0
Self-Improvement	333	3.4
Interpersonal Development	1787	18.3
Education/Life Skills	1695	17.3
Total	4885	49.9
Missing Program Need	4899	50.1

Note. Frequencies sum to 9784 reflect missing data. Missing data is the result the LS/CMI not being fully completed to identify a program need.

4.8 Assumptions Testing

Multicollinearity testing was conducted using variance inflation factors testing for the first-level predictors. Originally, both program referrals and program initiation had very high variance inflation (> 5) indicating they were multi-collinear. This likely due to the high correlation treatment referrals have with treatment initiation, as an individual cannot initiate into treatment without a referral first being placed. Because program referrals and program initiation were multicollinear (r = .946 and VIF > .5), program referrals were removed and Research Question 3 will focus on program initiation and completion counts instead.

The second-level variables were assessed using correlation at first and found that jurisdiction capacity and the program quantity were correlated and significant (r = .548, p < .001), however in VIF testing they did not exceed a VIF of 2. When including the counts by all the program types for initiation and completion, there was a significant correlation in some cases, but no evidence of multicollinearity in multivariate testing (VIF < 5).

4.9 Imputation Process

A preliminary missing value analysis was conducted to determine whether the structure of missingness in the data might bias the results of the analysis. There were four variables that had missing data: 1) level of supervision, 2) program quantity, 3) county deprivation, and 4) the jurisdiction program capacity index and missingness comprised approximately 1% of the total number of values in the dataset. Accordingly, Little's MCAR test was conducted to assess whether the data was missing completely at random

(MCAR; Little, 1988). The null hypothesis of Little's MCAR test assumes that the pattern of the data is MCAR and the test follows a χ^2 distribution. All study variables were included in the test simultaneously and the results of the test revealed that the pattern of missing values in the data was not missing completely at random (MCAR), χ^2 (149) = 1109.92, $p < .001$ and is either missing at random (MAR) or not missing at random (NMAR). To check for the possibility of MAR or NMAR status, variables with missing data were recoded 1 for missing values and 0 for observed values. Then these missingness variables were used as dependent variables and all observed variables as predictors to observe if there was statistically significant association between study variables in the dataset and missingness in the variables with missing data. Many of the other study variables (e.g., race, gender, age, program success, and reconviction) were significant predictors of the missingness in these variables (*ps* < .05), suggesting the data was MAR. Missing not at random (MNAR) status would suggest that none of the observed data could predict missingness in the data (Little & Rubin, 2002).

Due to the MAR structure and the amount of missingness in the data, a multilevel multiple imputation missing replacement procedure was conducted in Mplus using 10 imputed datasets to replace missing values for the following variables that had missing data: 1) level of supervision, 2) program quantity, 3) county deprivation, and 4) jurisdiction program capacity index. Multiple imputation process was conducted using 10 imputed datasets. The Mplus default of the chained equations algorithm was used to estimate and impute the datasets. All the key study variables were used in the imputation process to help estimate the missing values. After the imputation process was complete, descriptive statistics were conducted to assess differences in means between the original variables and the selected imputed variables. The original and imputed table shows very little difference in terms of the sample mean with low standard errors for the imputed data. These are encouraging results. The analysis used Rubin's rules to analyze the imputed datasets which pool the parameter estimates for each imputed dataset to derive confidence intervals and *p*-values (Rubin, 2004). Finally, Mplus was used for the MLM in the final analysis (Muthén & Muthén, 2011).

Table 4

Imputation Process of Original Data and Imputed Data

	Original Data		Imputed Data		
Imputed Study Variable	*N*	*M*	*N*	*M*	*SE*
Level of supervision	9446	2.22	9784	2.30	.010
Program quantity	9152	10.08	9784	10.06	.019
County deprivation	9152	.21	9784	.22	.008
Jurisdiction program capacity index	9152	.52	9784	.52	.003

4.10 Ethical Considerations

Since the current study is a secondary analysis of the data collected from the RNR evaluation from Oregon, many of the ethical considerations required for data collection were addressed in the initial study. First, there are no issues with presence of harm caused to participants. The unit of analysis for the present study are the individuals placed on Oregon community supervision from January 2009 until December 2011. The ODOC provided the probationer dataset of supervision admissions data. From this, only 70,786 individuals were analyzed in the RNR evaluation in which LS/CMI data could be obtained from half (N = 34, 332) the population to identify the risk-needs profiles used moving forward. All data obtained consisted of demographic data provided from the assessment instrument on containing only probation characteristics (i.e., gender, race/ethnicity, age, etc.), risk category (LS/CMI data) and needs factors (i.e., substance abuse, criminal peers, education, etc.). None of the information received required or presented any harm to the population as all data obtained is provided through self-disclosure or assessments conducted during supervision entry processing. In addition, since all the data provided to/by ACE! contained admissions to community supervision variables, there is no expectation of informed consent or that voluntary participation be required of the individuals identified as their demographic information is public record and accessible through the ODOC. Likewise, except for date of birth data, all probationer variables were previously de-identified so that there was no issues of confidentiality or anonymity. Probationers have a numerical corrections system identifier (“reckey”) in the dataset which is their only known label. Furthermore, to ensure all ethical standards are being upheld, only the relevant components of the probationer data was used and accessed. For the present study, only the probationer demographic data that was needed for final analysis was used. For example, individual-level data needed for the present study included age, race, gender, and level of supervision. All other probationer variables (i.e., education, criminal charge, date of birth, family stabilization factors, level of risk, etc.) were excluded as this information as not needed based on the review of the literature and development of the research questions needed for the current analysis was excluded. Lastly, to maintain the integrity of ODOC and respect of the intellectual community, all data received and used for this present study was only analyzed for research purposes and to support the advancement of knowledge for community corrections. None of the data received was shared or distributed unless for academic purposes.

4.11 Analytic Strategy

To examine this study, the current study employs MLM to account for the two-level nested structure of data (Raudenbush & Bryk, 2002). The dichotomous dependent variables will be used to examined community supervision outcomes. Using MLM allows for the estimation of the variation effects of county-level factors of recidivism. MLM techniques are necessary due to this dissertation seeking to understand if the recidivism odds of individuals under supervision may partly be impacted by social disorganization and resource deprivation theories. The models for the county-level sample only included individual from 34 counties, as two counties (Sherman and Wheeler) were collapsed into another (Gilliam) on due to the sharing of county resources.

This this analysis was conducted with the notion that multilevel models would be ran and would control for county variation throughout all models. The ICC variation for all models ranged between 5.5% to 10.7% between-county variation explained by the outcome variables program success and reconviction. However, the interpretation of what constitutes a substantive amount of cluster variation (ICC) for MLM varies across research fields (Raudenbush & Bryk, 2002; Raykov & Marcoulides, 2015; Trevethan, 2017).

MLM was used to determine each research question in the study. All level 1 individual level variables were group-mean centered, where the variable was centered around the county mean for the county. All level 2 county-level variables were grand-mean centered, where the variable was centered around the entire sample mean allowing for variable effects to influence level 2 variations. Across all research questions, each model included a fixed effects model where level 1 variables were fixed. In addition, all research questions included a random effect of specific level 1 variables where slopes were allowed to vary across counties based on exploratory analysis and theoretical justification.

To conduct the random intercept fixed slope models (RIFS) in Mplus, the function TWOLEVEL RANDOM was used with the individual level outcomes and predictors specified on the WITHIN level of the Mplus syntax to denote fixed effects. The dependent variable intercept was then specified on the BETWEEN level of the Mplus syntax to denote the random intercept. To conduct the random intercept random slope models (RIRS) in Mplus, the function TWOLEVEL RANDOM in addition to MONTECARLO integration was used to handle the complexity of estimating the random slope means and variances. Relationships between predictors and the outcome that were allowed to vary across clusters were specified using a ***random#*** title and the **|** syntax conventions in Mplus to designate a random slope in the WITHIN level of the Mplus syntax. These commands and conventions in the syntax allowed the effects to vary across clusters. The dependent variable intercept was then specified on the BETWEEN level of the Mplus syntax to denote the random intercept. The resulting output of these models produced a summary of the variables used in the analysis, the N, number of clusters, number of imputed datasets, sample statistics, number of free parameters, model fit statistics, and the model results. The number of free parameters was used to calculate the degrees of freedom. The analytical structure of each research question is described further.

For Research Question 1, the researcher conducted multilevel models to examine individuals under supervision demographic characteristics as predictors of treatment program success. The first model includes all level 1 variables were modeled as fixed effects. The second model included random effects as the researcher allowed the random slope for level of supervision to vary across counties to understand the relationship between level of supervision and recidivism across counties. Prior research has shown that some jurisdictions are more successful at supervising individuals than others (Galouzis et al., 2020; Taxman, 2008).

To address Research Question 2, the researcher conducted multi-level models to examine individuals under supervision demographic characteristics as predictors of reconviction within three years. In this first model, all level 1 variables were modeled as fixed effects. The second model included random slopes for all demographic predictors to vary level counties via a random effect. The researcher allowed random slopes to vary across counties as prior research has shown variability in the age-recidivism relationship (Chamberlain & Wallace, 2016; Males, 2015; Tapia & Harris, 2006), race-recidivism relationship (Reisig et al., 2007), gender-recidivism relationship, and level of supervision varying in some jurisdictions (Galouzis et al., 2020; Taxman, 2008).

To address Research Question 3A, the researcher conducted multilevel models to examine the relationship between treatment initiation and success and reconviction within 3 years with individual demographics. In this first model, all level 1 variables were modeled as fixed effects. In this second model (RIRS), the researcher allowed the random slopes for age, level of supervision and total program initiation predictors to vary level counties via a random effect. The researcher allowed random slopes to vary across counties as prior research has shown variability in the age-recidivism relationship (Chamberlain & Wallace, 2016; Males, 2015; Tapia & Harris, 2006), level of supervision to variation shown in some jurisdictions (Galouzis et al., 2020; Taxman, 2008), and program initiation to vary as prior research has shown that (Hipp et al., 2010; Konkel, 2019).

To address Research Question 3B, the researcher conducted multilevel model to examine the relationship between individual demographics and reconviction within three years controlling for total program initiation by specific program types. Only a fixed effect model was conducted due to the number of predictors and the multiple imputation process. A second fixed effect multilevel model was conducted to examine the relationship between individual demographics and reconviction within 3 years controlling for total program completion by specific program types where only fixed effects were conducted as well.

Finally, to address Research Question 4, the researcher conducted multilevel models to examine the relationship between whether treatment initiation or completion in resourced-deprived counties influences reconviction within 3 years. The first model

(RIFS) all level 1 variables were modeled as fixed effects. In this second model, the researcher allowed the random slopes for age and level of supervision to vary level counties via a random effect. Age was allowed to vary across counties based on prior research showing variability (Chamberlain & Wallace, 2016; Males, 2015; Tapia & Harris, 2006) and level of supervision varied based on as prior research has showing variability in some jurisdictions (Galouzis et al., 2020; Taxman, 2008). In addition, the researcher conducted multilevel models to examine the relationship between whether treatment completion in resourced-deprived counties influences reconviction within 3 years. The research question is seeking to understand if different levels of program completion predict the likelihood of reconviction at differing levels of county deprivation. The first model had all level 1 variables were modeled as fixed effects. In the second model, allowed the random slopes for age and level of supervision to vary level counties via a random effect based on prior research (Chamberlain & Wallace, 2016; Galouzis et al., 2020; Males, 2015; Tapia & Harris, 2006).

Level 2 variables used in the final analysis were program quantity, jurisdiction program capacity and county deprivation variables. As previously stated, these variables were selected to measure social disorganization and resource deprivation mechanism. In addition, the interaction term for total program initiation/completion and county deprivation were created and added to the study to examine if different levels of program initiation or completion predicted the likelihood of reconviction at differing levels of county deprivation.

The final results of this analysis are presented in multilevel regression tables in the next chapter. Each table reports the fixed slopes and random slopes models that were conducted for each question, except for Research Question 3B which only conducted fixed slopes. The results are interpreted used odds ratios to represent the statistically significance of the likelihood of the outcome variable. Summary of results are provided in the next chapter.

4.12 Chapter Summary

This chapter began its discussion by providing an overview of the purpose of the present study, research questions, and the quantitative research design. Since the present study is a secondary analysis of data, this chapter also explained the original study's purpose, data collection methods from the RNR tool and overall findings (i.e., the RNR Oregon study) from the initial analysis. Next, the chapter discussed the data collection methods, the research population, and measures (dependent variables, individual-level predictors, county-level predictions). The chapter concluded by discussing the analytic strategy including merging data, data preparation techniques, and preliminary analysis prior to final analysis and summarization of results. The following chapter will discuss the summary of results by answering each research questions identified.

Chapter 5: Results

5.1 Overview

This chapter statistically explores the variables used in this study, reviews each research questions findings, and reports the results of the analytical tests investigating the effects of county deprivation, treatment utilization, and individuals under supervision risk factors has on the supervision outcomes of reconviction and program completion. First, descriptive statistics for each categorical and continuous variable are discussed. Next, each research question and its findings are reviewed along with the corresponding table of analysis. Finally, a brief summary of findings for each of the research questions concludes the chapter.

5.2 Description of Sample

Table 5 displays frequencies and percentages for the descriptor variables in this study. The majority of individuals under supervision in the sample did not have a reconviction within 3 years (56.7%). However, a majority of the sample did not receive treatment program success (65.4%). The sample was primarily 16 to 27 years of age (38.4%), White-Caucasian (84.6%), male (74.7%), and categorized as low to medium level of supervision (42.3%).

Table 5

Frequencies and Percentages of Categorical Study Variables

Variables	*n*	%
Reconviction within 3 years		
No reconviction within 3 years	5546	56.7
Reconvicted within 3 years	4238	43.3
Program success		
No treatment success	6397	65.4
Treatment success	3387	34.6
Age categories		
16 to 27 years	3753	38.4
28 to 35 years	2483	25.4
36 to 42 years	1428	14.6
43 years old or older	2120	21.7
Race		
White-Caucasian	8281	84.6
Minority	1503	15.4
Sex		
Female	2474	25.3
Male	7310	74.7
Level of supervision		
Low supervision	2203	22.5
Low to medium supervision	4141	42.3
Medium supervision	1894	19.4
High supervision	1208	12.3

Note. Frequencies not summing to 9784 reflect missing data.

Table 6 displays descriptive statistics for the remaining variables in this study. The variables capture individual-level and county-level variables in this study. For the individual-level variables, total program initiation refers to a count of the number of treatment programs an individual initiated that ranged from 0 to 19 (M = 1.16, SD =

1.67). Total program completion is a count of the number of treatment programs an individual successfully completed ranging from 0 to 10 ($M = .55$, $SD = .97$). All total program treatment initiation and completion variables by treatment type are also presented in Table 4. These variables capture a count of the number of treatment programs an individual initiated or successfully completed by the type of program they were assigned to.

Table 6

Means and Standard Deviations of Continuous Study Variables

Variables	*N*	*M*	*SD*	*Min*	*Max*
Individual-level variables (number of for the following variables)					
Total program initiation	9784	1.16	1.67	0	19
Total program completion	9784	.55	.97	0	10
Anger management treatment initiation	9784	.02	.14	0	3
Anger management treatment completion	9784	.01	.10	0	2
Domestic violence treatment initiation	9784	.07	.31	0	4
Domestic violence treatment completion	9784	.03	.19	0	3
Vocational training treatment initiation	9784	.02	.14	0	4
Vocational training treatment completion	9784	.01	.09	0	2
Parenting skills treatment initiation	9784	.02	.21	0	9
Parenting skills treatment completion	9784	.01	.11	0	2
Substance abuse treatment initiation	9784	.70	1.12	0	12
Substance abuse treatment completion	9784	.32	.65	0	7
Transitional housing initiation	9784	.01	.13	0	3
Transitional housing completion	9784	.01	.08	0	2
Cognitive treatment initiation	9784	.20	.69	0	9
Cognitive treatment completion	9784	.10	.41	0	6
Education treatment initiation	9784	.04	.24	0	7
Education treatment completion	9784	.03	.18	0	4
Mental health treatment initiation	9784	.06	.29	0	5
Mental health treatment completion	9784	.02	.14	0	3
Supervision treatment initiation	9784	.01	.09	0	2

Supervision treatment completion	9784	.00	.05	0	2
Sex offender treatment initiation	9784	.03	.19	0	4
Sex offender treatment completion	9784	.01	.09	0	1
County-level variables					
Number of programs (quantity)	34	8.62	1.74	5	11
County deprivation	34	.01	.67	-1.24	1.16
Jurisdiction program capacity index	33	.24	.15	.03	.527

Note. *N* not equal to 9,784 reflects missing data

For the county-level variables, the program quantity variable captures the number of treatment programs in a county available to individuals involved in the justice system within its jurisdiction, ranging from 5 to 11 (*M* = 8.62, *SD* = 1.74). County deprivation is a composite index of county unemployment, violent crime, and poverty rates that was standardized to z-score metric and ranged from -1.24 to 1.16 (*M* = .01, *SD* = .67). Higher values on this scale indicate greater deprivation or higher rates of unemployment, poverty, and violent crime. For example, Hood River County is the least resource deprived (-1.24) while Baker County is the most deprived (1.16). Jurisdiction program capacity index is a metric that captures a county's treatment program capacity relative to its program need of the community supervision population which ranged from .03 to .56 (*M* = .24, *SD* = .15). Higher values on this scale indicate greater capacity to provide treatment for individuals under supervision. For example, Clackamas County is the county with the greatest program capacity (.527) and Malheur County is the county with the least program capacity (.032). Clackamas County is one of the least deprived counties in Oregon which and also has the greatest program capacity to meet individuals under supervision needs. No county was able to provide the required capacity (measured at 1) to meet the community supervision population need.

Table 7

Descriptive Table Showing Oregon Counties and Jurisdiction Capacity and County Deprivation Values

County	County Deprivation	Jurisdiction Capacity
Baker	1.160	.242
Benton	-.100	.112
Clackamas	-1.080	.527
Clatsop	-.580	.515
Columbia	-.100	.372
Coos	.260	.423
Crook	.000	.110
Curry	-.060	.077
Deschutes	-.380	.203
Douglas	.530	.256
Gilliam	-1.210	.143
Grant	-.620	.158
Harney	-.350	
Hood River	-1.240	.151
Jackson	.580	.416
Jefferson	.620	.429
Josephine	.920	.311
Klamath	.520	.075
Lake	.790	.143
Lane	.570	.434
Lincoln	.680	.232
Linn	-.480	.389
Malheur	1.150	.032
Marion	.410	.174
Morrow	-.490	.044
Multnomah	1.110	.445
Polk	-.110	.125
Tillamook	-.500	.134
Umatilla	.190	.190
Union	-.160	.115

Wallowa	-.250	.241
Wasco	-.170	.169
Washington	-.920	.514
Yamhill	-.410	.169

Note. Jurisdiction capacity is a ration from 0 to 1 that measures whether a county's capacity meets its need, where higher values indicate greater capacity. Harney County did not provide treatment program capacity data for the RNR evaluation in Oregon. County deprivation is measured as a z-score composite of violent crime rates, poverty rates, and unemployment rates, where higher values indicate greater deprivation.

5.3 Primary Analysis

For the primary analyses, multilevel logistic regression analyses were conducted to test and answer the study research questions. The multilevel approach consisted of a mixed effects model that tested both a random intercept with fixed slopes (RIFS) and a random intercept and random slopes (RIRS) models for each research question. The RIRS model was conducted to establish whether individual-level effects varied across counties. The fixed slopes and variance components are reported to model statistics in the tables. A likelihood ratio test (LRT) was conducted to test improvement in model fit between the RIFS and RIRS models using the difference in loglikelihood to calculate the χ^2 statistic and the number of parameters difference as degrees of freedom to associated *p*-value. Based on the multiple-imputation methods conducted, full-information was provided for all analyses (N = 9,784 and all 34 counties).

5.4 What Effect Do Individual Demographics Have on Program Success?

To address Research Question 1, the researcher conducted multilevel models to examine individuals under supervision demographic characteristics as predictors of treatment program success. With this research question, the researcher sought to understand if probationers' demographics predict the likelihood of treatment success. In this first model (RIFS) all level 1 variables were modeled as fixed effects. The results of this analysis are shown in Table 8. The RIFS model had the following model fit statistics, *AIC* = 12185.471, *BIC* = 12228.602, loglikelihood = -6086.736. The intra-class correlation (*ICC*) for this model was calculated as .099, suggesting that 9.9% of program success is explained by between-county variation. The results of the fixed effects indicate that the effects of being a minority (β = -.390, *OR* = .677, $p < .001$) and the effect of being a male (β = -.276, *OR* = .759, $p < .001$) were statistically significant. This suggests that minorities are 1.477 times less likely to complete a treatment compared to White/Caucasian individuals. Similarly, males are 1.317 times less likely to complete treatment compared to females.

In this second model (RIRS), the researcher allowed the random slope for level of supervision to vary across counties via a random effect. The varying of this slope for Research Question 1 sought to understand the relationship between level of supervision and recidivism across counties. Prior research has shown that some jurisdictions are more successful at supervising individuals, either by geographic location (Galouzis et al., 2020) or proactive supervision efforts (Taxman, 2008). The results of this analysis are shown in Table 5. The RIRS model had the following model fit statistics, *AIC* = 12107.828, *BIC* = 12158.147, loglikelihood = -6046.914. The intra-class correlation (ICC) for this model was calculated as .107, suggesting that approximately 10.7% of the chances of program success are explained by between-county variation. The results indicate that the effects of age (β = -.036, *OR* = .965, $p = .029$), being a minority (β = -.412, *OR* = .622, $p < .001$)

and the effect of being a male (β = -.283, *OR* = .754, p < .001), and level of supervision (β = -.141, *OR* = .868, p = .004) were all statistically significant. These findings indicate that as age categories increases, individuals are 1.037 times less likely to complete a treatment program. In addition, minorities are 1.50 times less likely to complete a treatment compared to White/Caucasian individuals. Males are 1.33 times less likely to complete treatment compared to females. Lastly, as level of supervision categories increase, individuals are 1.15 times less likely to complete a treatment program. In addition, the slope variance of the level of supervision was statistically significant (γ = .044, p < .001), indicating that the effect of level of supervision on program success varies by county.

An LRT was conducted comparing the log likelihood criteria and difference in parameters to determine if the random slopes model was an improvement over the fixed slopes (nested) model. The LRT produced the following chi-square statistic and p-value, $\chi^2(1) = 79.644$, $p < .001$. This suggests that the RIRS model was an improvement over the RIFS model.

Table 8

Multilevel Logistic Regression of Individual Demographics Predicting Program Success

	DV: Program Success					
	Random Intercept and Fixed Slopes			Random Intercept and Random Slopes		
Level and Covariates	*β*	*OR*	*p*	*β*	*OR*	*p*
Level 1 Fixed						
Age	-.028	.972	.123	-.036	.965	.029

Race (Minority)	-.390	.677	.001	-.412	.662	.001
Sex (Male)	-.276	.759	.001	-.283	.754	.001
Level of supervision	-.032	.969	.727	-.141	.868	.004
Variance components						
Intercept variance		.362***			.395***	
Slope variance of:						
Level of supervision					.044*	
Model statistics						
N		9784			9784	
J		34			34	
ICC		.099			.107	
AIC		12185.471			12107.828	
BIC		12228.602			12158.147	
Loglikelihood		-6086.736			-6046.914	
Likelihood ratio test					$\chi^2(1) = 79.644$, $p < .001$	

Note. *β* is the beta coefficient, *OR* is the odds ratio, *p* is the *p*-value, *N* is the sample size, *J* is the number of clusters (counties), ICC is the intra-class correlation coefficient, AIC is the Akaike Information Criteria, and BIC is the Bayesian Information Criteria. *$p < .05$, **$p < .01$, ***$p < .001$.

5.5 What Effect Do Individual Demographics Have on Reconviction?

To address Research Question 2, the researcher conducted multilevel models to examine individuals under supervision demographic characteristics as predictors of reconviction within 3 years. With this research question, the researcher sought to understand if probationers' demographics predict the likelihood of reconviction. In this first model (RIFS) all level 1 variables were modeled as fixed effects. The results of this analysis are shown in Table 9. The RIFS model had the following model fit statistics, *AIC* = 12062.749, *BIC* = 12105.880, loglikelihood = -6025.375. The ICC for this model was calculated as .063, suggesting that 6.3% of the chances of reconviction is explained by between-county variation. The results of the fixed effects indicate that the effects of age ($\beta = -.147$, $OR = .863$ $p < .001$) and the effect of being placed on high supervision (β

= .688, *OR* = 1.990, $p < .001$) were statistically significant. This suggests that as age increases the likelihood of reconviction decreases by 1.159 units. Similarly, with every one-unit increase in supervision-level, the likelihood of reconviction increases by 1.990.

In this second model (RIRS), the researcher allowed the random slope for all demographic predictors to vary level counties via a random effect. The researcher allowed age to vary across counties via a random effect as prior research has shown variability in the age-recidivism relationship (Chamberlain & Wallace, 2016; Males, 2015; Tapia & Harris, 2006). The researcher allowed race to vary across counties via a random effect as prior research has shown the variability in the race-recidivism relationship (Reisig et al., 2007). The researcher allowed gender to vary across counties via a random effect as prior research has attempted to find variability in the gender-recidivism relationship, though unsuccessful (Fearn, 2007). The researcher allowed level of supervision to vary as prior research has shown that some jurisdictions are more successful at supervising individuals, either by geographic location (Galouzis et al., 2020) or proactive supervision efforts (Taxman, 2008). The RIRS model had the following model fit statistics, *AIC* = 12060.929, *BIC* = 12132.814, loglikelihood = -6020.464. The intra-class correlation (*ICC*) for this model was calculated as .095, suggesting that approximately 9.5% of the chances of reconviction are explained by between-county variation. The results indicate that the effects of level of supervision (β = -.677, *OR* = 1.968, p = <.003) is statistically significant. These findings indicate that as level of supervision categories increase, individuals are 1.968 more likely to reconvicted. Finally, none of the random variances of the predictor slopes were statistically significant, indicating that there is no variation by county.

An LRT was conducted comparing the loglikelihood criteria and difference in parameters to determine if the random slopes model was an improvement over the fixed slopes (nested) model. The LRT produced the following chi-square statistic and *p*-value, $\chi^2(4) = 9.822$, $p < .001$. This suggests that the RIRS model was an improvement over the RIFS model.

Table 9

Multilevel Logistic Regression of Individual Demographics Predicting Reconviction Within 3 Years

	DV: Reconviction					
	Random Intercept and Fixed Slopes			Random Intercept and Random Slopes		
Level and Covariates	*β*	*OR*	*p*	*β*	*OR*	*p*
Level 1 Fixed						
Age	-.147	.863	.001	-.139	.870	.75
Race (Minority)	-.126	.882	.102	-.125	.882	.177
Sex (Male)	-.085	.919	.112	-0.1	.905	.936
Level of supervision	.688	1.990	.001	.677	1.968	.003
Variance components						
Intercept variance		.222			.348	
Slope variance of:						
Age					0	
Race (Minority)					.01	
Sex (Male)					.013	
Level of supervision					.022	
Model statistics						
N		9784			9784	
J		34			34	
ICC		.063			.095	
AIC		12062.749			12060.929	

BIC	12105.880	12132.814
Loglikelihood	-6025.375	-6020.464
Likelihood ratio test		$\chi^2(4) = 9.822$, $p < .001$

Note. β is the beta coefficient, *OR* is the odds ratio, *p* is the *p*-value, *N* is the sample size, *J* is the number of clusters (counties), *ICC* is the intra-class correlation coefficient, *AIC* is the Akaike Information Criteria, and *BIC* is the Bayesian Information Criteria. **p* < .05, ***p* < .01, ****p* < .001.

5.6 What Effect Does Treatment Initiation and Success with Individual Demographics Have on Reconviction Among Probationers?

To address Research Question 3A, the researcher conducted multilevel models to examine the relationship between treatment initiation and success and reconviction within 3 years with individual demographics. With this research question, the researcher sought to understand if program initiation or completion predicts likelihood reconviction. This research question included probationer demographics (such as age, race, gender, and level of supervision) as covariates. In this first model (RIFS) all level 1 variables were modeled as fixed effects. The results of this analysis are shown in Table 10. The RIFS model had the following model fit statistics, *AIC* = 11873.934, *BIC* = 11931.442, loglikelihood = -5928.967. The ICC for this model was calculated as .06534, suggesting that 6.5% of the chances of reconviction is explained by between-county variation. The results of the fixed effects indicate that program initiation (β = .238, *OR* = 1.269 *p* < .001), program success (β = -.341, *OR* = .711, *p* < .001), the effect of age (β = -.124, *OR* = .883, *p* < .001) and level of supervision (β = .655, *OR* = 1.925, *p* < .001) were statistically significant. This suggests that as program initiation increases the likelihood of reconviction increases by 1.269 units. Similarly, with every one-unit increase in program success, the likelihood of reconviction decreases by 1.406. In addition, as age increases, the likelihood of reconviction decreases by 1.132. Finally, a one unit increase in level of supervision increases the likelihood of reconviction by 1.925.

In this second model (RIRS), the researcher allowed the random slopes for age, level of supervision and total program initiation predictors to vary level counties via a random effect. The researcher allowed age to vary across counties via a random effect as prior research has shown variability in the age-recidivism relationship (Chamberlain & Wallace, 2016; Males, 2015; Tapia & Harris, 2006). The researcher allowed level of supervision to vary as prior research has shown that some jurisdictions are more successful at supervising individuals, either by geographic location (Galouzis et al., 2020) or proactive supervision efforts (Taxman, 2008). The researcher allowed program initiation to vary as prior research has shown that program initiation can vary across jurisdictions due to areas being disadvantaged (Hipp et al., 2010; Konkel, 2019). The RIRS model had the following model fit statistics, *AIC* = 11848.217, *BIC* = 11934.479, loglikelihood = -5912.109. The ICC for this model was calculated as .079, suggesting that approximately 7.9% of reconviction is explained by between-county variation. The results indicate that the effects of program initiation (β = .298, *OR* = 1.347 p < .001) and level of supervision (β = .649, *OR* = 1.914, p < .001) were statistically significant. These findings indicate that as program initiation increase, individuals are 1.347 times more likely to reconvicted. A one unit increase in level of supervision increases the likelihood of reconviction by 1.914. Finally, none of the random variances of the predictor slopes were statistically significant, indicating that there is no variation by county.

An LRT was conducted comparing the loglikelihood criteria and difference in parameters to determine if the random slopes model was an improvement over the fixed slopes (nested) model. The LRT produced the following chi-square statistic and *p*-value, $\chi^2(4) = 33.716, p < .001$. This suggests that the RIRS model was an improvement, and the null model was rejected.

Table 10

Multilevel Logistic Regression of Treatment Initiation and Success with Individual Demographics Predicting Reconviction Within 3 Years

	DV: Reconviction					
	Random Intercept and Fixed Slopes			Random Intercept and Random Slopes		
Level and Covariates	*β*	*OR*	*p*	*β*	*OR*	*p*
Level 1 Fixed						
Total program initiation	.238	1.269	.001	.298	1.347	.001
Total program success	-.341	.711	.001	-.401	.670	.2
Age	-.124	.883	.001	-.123	.884	.112
Race (Minority)	-.104		.205	-.104	.901	.23
Sex (Male)	-.036		.513	-.033	.968	.56
Level of supervision	.655	1.925	.001	.649	1.914	.001
Variance components						
Intercept variance		.23			.415	
Slope variance of:						
Total Program Initiation					.286	
Age					.00	
Level of supervision					.017	
Model statistics						
N		9784			9784	
J		34			34	
ICC		.065			.079	
AIC		11873.934			11848.217	
BIC		11931.442			11934.479	
Loglikelihood		-5928.967			-5912.109	
Likelihood ratio test					$\chi^2(4) = 33.716, p < .001$	

Note. β is the beta coefficient, *OR* is the odds ratio, p is the p-value, N is the sample size, J is the number of clusters (counties), ICC is the intra-class correlation coefficient, AIC is the Akaike Information Criteria, and BIC is the Bayesian Information Criteria. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

5.7 What Effect Does Treatment Initiation and Success by Specific Program Type Have on Reconviction Among Probationers Controlling for Individual Demographics?

To address Research Question 4, the researcher conducted multilevel model to examine the relationship between individual demographics and reconviction within three years controlling for total program initiation by specific program types. With this research question, the researcher sought to understand if initiated into a specific type of treatment (such as parenting skills or mental health treatment) predicts likelihood of reconviction. Only a RIFS model was conducted due to the number of predictors and the multiple imputation process. The results of this analysis are shown in Table 11. The RIFS model had the following model fit statistics, *AIC* = 5990.920, *BIC* = 6107.836, loglikelihood = -2977.460. The ICC for this model was calculated as .022, suggesting that 2.2 % of the chances of reconviction being explained by between-county variation. The results of the fixed effects indicate that age (β = -.163, *OR* = .850, $p < .001$), level of supervision (β = .636, *OR* = 1.889, $p < .001$), entering anger management program (β = -.767, *OR* = .464, $p < .001$), entering vocational training program (β = .294, *OR* = 1.342, $p < .028$) , entering mental health treatment (β = .31, *OR* = 1.363, $p < .001$), entering parenting classes (β = -.189, *OR* = .828, $p < .001$), entering supervision monitoring (β = .469, *OR* = 1.598, $p < .001$), entering substance abuse treatment (β = .227, *OR* = 1.255, p

< .001) and entering transitional housing (β = .811, *OR* = 2.250, $p < .001$) were statistically significant. These finding suggests that as age increases, individuals are 1.176 times less likely to be reconvicted. As supervision level increases, individuals are 1.889 times more likely to be reconvicted. As anger management increases, the likelihood of reconviction decreases 2.155. As the vocational training program type increases, the likelihood of reconviction increases by 1.342. As mental health treatment type increases, the likelihood of reconviction increases by 1.363. As the parenting class program type increases, the likelihood of reconviction decreases by 1.208. As the supervision monitoring program type increases, the likelihood of reconviction increases by 1.598. As substance abuse program type increases, the likelihood of reconviction increases by 1.255. Finally, as transitional housing increases, the likelihood of reconviction increases by 2.250.

An LRT was not conducted due to the number of predictors in the model. As previously stated, due to the multiple imputation process, there were too many imputed datasets to run a RIRS mode to compare the loglikelihood criteria and difference in parameters to determine if an RIRS model would have been an improvement over the RIFS model.

Table 11

Multilevel Logistic Regression of Treatment Initiation by Specific Types Predicting Reconviction Within 3 Years

	Random Intercept and Fixed Slopes		
Level and Covariates	β	*OR*	*p*

Level 1 fixed			
Age	-.163	.850	.001
Race (Minority)	-.033	.968	.511
Sex (Male)	.054	1.055	.208
Level of supervision	.636	1.889	.001
Total program completion	.011	1.011	.261
Anger management	-.767	.464	.001
Cognitive behavior	.184	1.202	.099
Domestic violence	-.088	.916	.265
Education	.075	1.078	.688
Vocational training	.294	1.342	.028
Mental health	.31	1.363	.001
Parenting skills	-.189	.828	.001
Supervision	.469	1.598	.001
Substance abuse	.227	1.255	.001
Sex offender TX	-.319	.727	.111
Transitional housing	.811	2.250	.001
Model statistics			
N		9784	
J		34	
ICC		.022	
AIC		5990.920	
BIC		6107.836	
Loglikelihood		-2977.460	
Likelihood ratio test			

Note. β is the beta coefficient, *OR* is the odds ratio, *p* is the *p*-value, *N* is the sample size, *J* is the number of clusters (counties), ICC is the intra-class correlation coefficient, AIC is the Akaike Information Criteria, and BIC is the Bayesian Information Criteria. *$p < .05$, **$p < .01$, ***$p < .001$.

In addition, the researcher conducted multilevel model to examine the relationship between individual demographics and reconviction within 3 years controlling for total program completion by specific program types. With this research question, the researcher sought to understand if completing a specific type of treatment (such as anger management or domestic violence classes) predicts likelihood of reconviction. Only a RIFS model was conducted due to the number of predictors and the multiple imputation process. The RIFS model in Table 12 had the following model fit statistics, *AIC* = 5948.651, *BIC* = 6065.568, loglikelihood = -2956.326. The ICC for this model was calculated as .022, suggesting that approximately 2.2% of program success are explained by between-county variation. The results indicate that age (β = -.148, *OR* = .862, *p* = .001), level of supervision (β = .631, *OR* = 1.879, $p < .001$), program initiation (β = .352, *OR* = 1.422, $p < .001$), completing anger management (β = -1.239, *OR* = .290, $p < .001$), completing cognitive behavioral intervention (β = -.435, *OR* = .647, $p < .001$), completing domestic violence class (β = -.747, *OR* = .474, $p < .001$), completing vocational training (β = -.428, *OR* = .652, $p < .001$) , completing parenting class (β = -1.24, *OR* = .289, $p < .001$), completing substance abuse treatment (β = - .325, *OR* = .723, $p < .001$), completing sex offender treatment (β = -1.746 *OR* = .174, $p < .001$), and completing transitional housing (β = .678, *OR* = 1.970, $p < .001$), were statistically significant.

These findings suggest that as age increases, individuals are 1.160 times less likely to be reconvicted. As supervision-level increases, individuals are 1.879 times more likely to be reconvicted. As program initiation increases, individuals are 1.422 time more likely to be reconvicted. As the anger management program type increases, the likelihood of reconviction increases by 3.406. As cognitive behavioral intervention increases, the likelihood of reconviction decreases by 1.545. As domestic violence treatment increases, the likelihood of reconviction decreases by 2.109. As vocational training increases, the likelihood of reconviction decreases by 1.533. As parenting skills class increases, the likelihood of reconviction decreases by 3.460. As substance abuse program type increases, the likelihood of reconviction increases by 1.383. As sex offender treatment program type increase, the likelihood of reconviction decreases by 5.747. Finally, as transitional housing increases, the likelihood of reconviction increases by 1.970.

An LRT was not conducted due to the number of predictors in the model. In addition, due to the multiple imputation process, there were too many imputed datasets to run a RIRS mode to compare the loglikelihood criteria and difference in parameters to determine if an RIRS model would have been an improvement over the RIFS model.

Table 12

Multilevel Logistic Regression of Treatment Completion by Specific Types Predicting Reconviction Within 3 Years

	Random Intercept and Fixed Slopes		
Level and Covariates	*β*	*OR*	*p*
Level 1 fixed			
Age	-.148	.862	.001
Race (Minority)	-.029	.971	.59
Sex (Male)	.031	1.031	.457
Level of supervision	.631	1.879	.001
Total program initiation	.352	1.422	.001
Anger management	-1.239	.290	.001
Cognitive behavior	-.435	.647	.001
Domestic violence	-.747	.474	.001
Education	-.342	.710	.109
Vocational training	-.428	.652	.001
Mental health	-.06	.942	.569
Parenting skills	-1.24	.289	.001
Supervision	.395	1.484	.411
Substance abuse	-.325	.723	.001
Sex offender TX	-1.746	.174	.001
Transitional housing	.678	1.970	.001
Model statistics			
N		9784	

J	34
ICC	.022
AIC	5948.651
BIC	6065.568
Loglikelihood	-2956.326
Likelihood ratio test	

Note. β is the beta coefficient, *OR* is the odds ratio, p is the p-value, N is the sample size, J is the number of clusters (counties), ICC is the intra-class correlation coefficient, AIC is the Akaike Information Criteria, and BIC is the Bayesian Information Criteria. $*p < .05$, $**p < .01$, $***p < .001$.

5.8 Does the Effect of Initiation or Completion Differ Depending on Whether an Individual Lives in a Resource Deprived County or Not?

To address Research Question 5, the researcher conducted multilevel models to examine the relationship between whether treatment initiation or completion in resourced-deprived counties influences reconviction within 3 years. The research question is seeking to understand if different levels of program initiation predict the likelihood of reconviction at differing levels of county deprivation. In this first model (RIFS) all level 1 variables were modeled as fixed effects. The results of this program initiation analysis are shown in Table 13. The RIFS model had the following model fit statistics, $AIC = 11947.715$, $BIC = 12026.789$, loglikelihood = -5962.858. The ICC for this model was calculated as .057, suggesting that 5.7% of reconviction is explained by between-county variation. The results of the fixed effects indicate that age ($\beta = -.132$, $OR = .876$, $p < .001$), level of supervision ($\beta = .652$, $OR = 1.919$, $p < .001$), program initiation ($\beta = .179$, $OR = 1.196$, $p < .001$) were statistically significant. These findings suggest as age increases, the likelihood of reconviction decreases by 1.141. As level of supervision increases, the likelihood of reconviction increases by 1.919. As program initiation increases, the likelihood of reconviction increases by 1.196. The interaction term of program initiation and county deprivation was not statistically significant in this model.

In this second model (RIRS), the researcher allowed the random slopes for age and level of supervision to vary level counties via a random effect. The researcher allowed age to vary across counties via a random effect as prior research has shown variability in the age-recidivism relationship (Chamberlain & Wallace, 2016; Males, 2015; Tapia & Harris, 2006). The researcher allowed level of supervision to vary as prior research has shown that some jurisdictions are more successful at supervising individuals, either by geographic location (Galouzis et al., 2020) or proactive supervision efforts (Taxman, 2008). The RIRS model had the following model fit statistics, *AIC* = 11940.023, *BIC* = 12033.473, loglikelihood = -5957.011. The intra-class correlation (*ICC*) for this model was calculated as .073, suggesting that approximately 7.3% of the chances of program success are explained by between-county variation. The results of the fixed effects indicate that the effects of age (β = -.13, *OR* = .878, $p < .001$), level of supervision (β = .656, *OR* = 1.927, $p < .001$), program initiation (β = .179, *OR* = 1.196, $p < .001$) were statistically significant. These findings suggest every 1-year increase in age decreases the likelihood of reconviction decreases by 1.139. As level of supervision increases, the likelihood of reconviction increases by 1.927. As program initiation increases, the likelihood of reconviction increases by 1.196. The interaction term of program initiation and county deprivation was not statistically significant in this model. In addition, the slope variances indicate that there is no variation by county.

An LRT was conducted comparing the loglikelihood criteria and difference in parameters to determine if the random slopes model was an improvement over the fixed slopes (nested) model. The LRT produced the following chi-square statistic and *p*-value, $\chi^2(2) = 11.148$, $p < .001$. This suggests that the RIRS model was an improvement over the RIFS model.

Table 13

Multilevel Logistic Regression of Treatment Program Initiation in Resource Deprived Counties Ability to Predict Reconviction Within 3 Years

	DV: Reconviction					
	Random Intercept and Fixed Slopes			Random Intercept and Random Slopes		
Level and Covariates	*β*	*OR*	*p*	*β*	*OR*	*p*
Level 1 Fixed						
Age	-.132	.874	.001	-.13	.878	.001
Race (Minority)	-.087	.917	.29	-.087	.969	.281
Sex (Male)	-.029	.971	.594	-.032	.996	.555
Level of supervision	.652	1.919	.001	.656	1.927	.001
Total program initiation	.179	1.196	.001	-.011	.989	.394
Initiation*CDEP	-.013	.987	.31	.02	1.020	.734
Level 2						
Program quantity	.051	1.052	.476	.056	1.058	.421
County deprivation	.036	1.037	.795	-.001	.999	.993
Jurisdiction capacity	.19	1.209	.769	.229	1.257	.738
Variance components						
Intercept variance		.2				
Slope variance of:						
Age						
Level of supervision						
Model statistics						

N	9784	9784
J	34	34
ICC	.057	.073
AIC	11947.715	11940.023
BIC	12026.789	12033.473
Loglikelihood	-5962.858	-5957.011
Likelihood ratio test		$\chi^2(2) = 11.148$, $p < .001$

Note. β is the beta coefficient, *OR* is the odds ratio, *p* is the *p*-value, *N* is the sample size, *J* is the number of clusters (counties), ICC is the intra-class correlation coefficient, AIC is the Akaike Information Criteria, and BIC is the Bayesian Information Criteria. *$p < .05$, **$p < .01$, ***$p < .001$.

In addition, the researcher conducted multilevel models to examine the relationship between whether treatment completion in resourced-deprived counties influences reconviction within 3 years. The research question is seeking to understand if different levels of program completion predict the likelihood of reconviction at differing levels of county deprivation. In this first model (RIFS), all level 1 variables were modeled as fixed effects. The results of this analysis are shown in Table 14. The RIFS model had the following model fit statistics, *AIC* = 12095.907, *BIC* = 12174.981, loglikelihood = -6036.953. The ICC for this model was calculated as .055, suggesting that 5.6% of reconviction is explained by between-county variation. The results of the fixed effects indicate that age (β = -.149, *OR* = .862, $p < .001$), level of supervision (β = .673, *OR* = 1.960, $p < .001$), and program completion (β = .065, *OR* = 1.067, $p < .048$) were statistically significant. These findings suggest as age increases, the likelihood of reconviction decreases by 1.160. As level of supervision increases, the likelihood of reconviction increases by 1.960. As program completion increases, the likelihood of reconviction increases by 1.067.

In the second model (RIRS), the researcher allowed the random slopes for age and level of supervision to vary level counties via a random effect. The researcher allowed age to vary across counties via a random effect as prior research has shown variability in the age-recidivism relationship (Chamberlain & Wallace, 2016; Males, 2015; Tapia & Harris, 2006). The researcher allowed level of supervision to vary as prior research has shown that some jurisdictions are more successful at supervising individuals, either by geographic location (Galouzis et al., 2020) or proactive supervision efforts (Taxman, 2008). The RIRS model had the following model fit statistics, $AIC = 12085.919$, $BIC = 12179.370$, loglikelihood = -6029.96. The ICC for this model was calculated as .067, suggesting that approximately 6.7% of program success are explained by between-county variation. The results of the fixed effects indicate that age ($\beta = -.146$, $OR = .864$, $p < .009$) and level of supervision ($\beta = .671$, $OR = 1.956$, $p < .001$), and program completion ($\beta = .066$, $OR = 1.067$, $p < .048$) were statistically significant. These findings suggest as every 1-year increase age, decreases the likelihood of reconviction by 1.157. As level of supervision increases, the likelihood of reconviction increases by 1.956. As program completion increases, the likelihood of reconviction increases by 1.068. The interaction term of program completion and county deprivation was not statistically significant in this model. In addition, the slope variances indicate that there is no variation by county.

An LRT was conducted comparing the loglikelihood criteria and difference in parameters to determine if the random slopes model was an improvement over the fixed slopes (nested) model. The LRT produced the following chi-square statistic and *p*-value,

$\chi^2(2) = 13.986$, $p < .001$. This suggests that the RIRS model was an improvement over the RIFS model.

Table 14

Multilevel Logistic Regression of Treatment Program Completion in Resource Deprived Counties Ability to Predict Reconviction Within 3 Years

	DV: Reconviction					
	Random Intercept and Fixed Slopes			Random Intercept and Random Slopes		
Level and Covariates	*β*	*OR*	*p*	*β*	*OR*	*p*
Level 1 fixed						
Age	-.149	.862	.001	-.146	.864	.009
Race (Minority)	-.117	.890	.144	-.117	.890	.143
Sex (Male)	-.076	.927	.156	-.079	.924	.14
Level of supervision	.673	1.960	.001	.671	1.956	.001
Total program completion	.065	1.067	.048	.066	1.068	.048
Completion*CDEP	.044	1.045	.068	.041	1.042	.1
Level 2						
Program quantity	.051	1.052	.473	.058	1.051	.527
County deprivation	.032	1.033	.817	.026	1.026	.981
Jurisdiction capacity	.182	1.200	.775	.304	1.540	.925
Variance components						
Intercept variance		.195			.237	
Slope variance of:						
Age					.001	
Level of supervision					.024	
Model statistics						
N		9784			9784	
J		34			34	
ICC		.055			.067	
AIC		12095.907			12085.919	
BIC		12174.981			12179.370	
Loglikelihood		-6036.953			-6029.96	
Likelihood ratio test					$\chi^2(2) = 13.986$, $p < .001$	

Note. *β* is the beta coefficient, *OR* is the odds ratio, *p* is the *p*-value, *N* is the sample size, *J* is the number of clusters (counties), ICC is the intra-class correlation coefficient, AIC is the Akaike Information Criteria, and BIC is the Bayesian Information Criteria. $*p < .05$, $**p < .01$, $***p < .001$.

5.9 Summary of Chapter Findings

This chapter statistically explores the variables used in the analysis, reviews each research question, and reports the results of the analytical tests investigating the effects of county deprivation on individual treatment and supervision outcomes.

First, the sample descriptive for categorical variables are examined. From the sample descriptive analysis, it can be seen that majority of the sample is White-Caucasian, male, and between the ages of 16 and 27. In addition, the majority of the sample were not reconvicted within 3 years but also did not have treatment success. Compared to the overall characteristics of the non-study sample, the sample statistics are generalizable to the overall Oregon probation population.

The results from each analytical test report effects from how each research question examines the impact of county deprivation on community supervision outcomes. For example, Research Question 1 findings show that age, race (non-White), and gender (male) are all indicators of treatment program success. More specifically, as age increases the likelihood of treatment program success decreases. In addition, race and sex are predictors of treatment success as minorities and males are less likely to complete treatment programs compared to Whites and females. Finally, the results from RIRS model indicate that level of supervision is statistically significant in predicting treatment program success and this effect varies across counties.

The findings from Research Question 2 show that age and level of supervision are both predictors of reconviction. More specifically, every 1-year increase in age decreases the likelihood of reconviction. In addition, level or supervision is an indicator of reconviction. More specifically, as level of supervision increases, the likelihood of reconviction increases.

Results from Research Question 3 show that program initiation and success are indicators of reconviction within 3 years. Since program initiation is a count variable, this measure indicates that the more individuals are initiated into programs the increases likelihood of reconviction within 3 years. Likewise, program success is a count variable, showing that as program success increases, the likelihood of reconviction decreases. In addition, individual demographics are examined in this research question. Similarly, age and level of supervision are predictors of reconviction. As age increases the likelihood of reconviction decreases. In addition, as level of supervision increases, the likelihood of reconviction increases. The model included reduced random effects to account for county variation. Random effects were observed for program initiation, age, and level of supervision. However, no variation was found across counties.

The findings from Research Question 4 examine the relationship between specific treatment program type and reconviction within 3 years while controlling for probationer demographics. The results show that treatment program type for both initiation and completion can predict reconviction. More specifically, an increase in treatment initiation for anger management and parenting skills decreases the likelihood of reconviction within 3 years. Likewise, an increase in program initiation for vocational training, mental health treatment, supervision monitoring, substance abuse and transitional housing increases the likelihood of reconviction. Following this, an increase in treatment completion for anger management, cognitive behavioral therapy, domestic violence, vocational training, parenting skills, substance abuse, and sex offender treatment decreases the likelihood of reconviction within 3 years. An increase in transitional housing completion increases the likelihood of reconviction. While controlling for individual demographics, age and level of supervision remain as significant predictors of reconviction within 3 years. Finally, program initiation was found to be a significant predictor of reconviction in the RIFS program completion model of Research Question 3B. Program completion was not found to be significant in the RIFS program initiation model of Research Question 3B.

Lastly, the findings from Research Question 5 explore the relationship between whether treatment initiation or completion in resourced-deprived counties influences reconviction within 3 years. As previously reported, age and level of supervision are predictors of reconviction for both program initiation and completion. As age increases the likelihood of reconviction decreases. In addition, as level of supervision increases, the likelihood of reconviction increases. The results also illustrate that both treatment program initiation and completion are significant predictors of reconviction. Finally, as program initiation and completion increase, the likelihood of reconviction increases. The model included reduced random effects to account for county variation. However, no variation was found across counties. In addition, none of the county-level variables of program quantity, jurisdiction capacity, or county deprivation were statistically significant. How these results can be interpreted in light of theory will be discussed in Chapter 6.

Chapter 6: Discussion and Conclusion

6.1 Overview

This chapter provides summary analysis for the research questions and variables used in this study. First, this chapter discusses the current state of the literature and how the results of this study can be interpreted in light of theory. Next, study limitations are addressed in order to accurately report the findings in light of the study restrictions. Finally, the chapter concludes with a call for future research and policy implications from the present study.

6.2 Discussion

Although the community corrections population has slowly declined in recent years, United States correctional system currently supervises over 3 million individuals in the community making it the largest component of the criminal justice system (Kaeble, 2021). Justice- involved individuals are sentenced to terms of imprisonment, jail confinement, or community sanctions but are often deferred from incarceration into community-based supervision. While diverting individuals from incarceration into community supervision is intended to serve as an alternative to confinement, recidivism rates of these individuals tell an opposing narrative. Probation or parole violations account for nearly half of percentages (46%) for those individuals under supervision who are eventually returned to prison just 5 years post-release (Antenangeli & Durose, 2021).

Additionally, the percentage of probation and parole violations increases the longer individuals remain in the community as 61% of those released from prison in 2008 were violated within 10 years (Antenangeli & Durose, 2021). The ultimate goal of community supervision is to reduce recidivism; however, recidivism rates demonstrate that community supervision is struggling to fulfill this purpose. In addition, majority of the literature on recidivism variation has focused primarily on individual-level differences that influence supervision outcomes. While this may explain a portion of variation in recidivism, it neglects to address macro-level issues that can explain a substantial amount of variation as well (Hipp et al., 2010, Kubrin & Stewart, 2006; Lowenkamp et al., 2010). Little investigation has focused on how and if macro-level conditions of a community influence the outcomes of those residents placed on supervision. Social disorganization and subsequent theories argue that community or county-level factors may also have influence on the recidivism of individuals under supervision. Key elements of social disorganization theory argue that lack of social bonds, prosocial networks and neighborhood collective efficacy prevent individuals under supervision from having access to the needed correctional and rehabilitative services in the community. Thus, the current study sought to extend the literature and investigate how elements of social disorganization and resource deprivation factors explain variation in recidivism rates of individuals under supervision.

The results of this current study did not find that elements of social disorganization and resource deprivation influence recidivism outcomes for those under supervision. More specifically, the level 2 county-level variables of jurisdiction program capacity, program quantity and county deprivation (index variable of violent crime, poverty, and unemployment rates) were not found to be statistically significant in influencing the supervision outcomes of reconviction within 3-years. In addition, the interaction between program initiation/completion and county deprivation was not statistically significant in this study. However, the current study did report significant findings regarding individual-level differences and treatment program-level differences (e.g., variation in outcomes by treatment type and level of supervision programming) that are critical for the improvement of community supervision for policy and practice considerations.

First, variation is found at the individual-level and highlights the variability of individuals under supervision demographics with the outcome's variables. As supported by the literature, the study found that individual-level differences can predict supervision outcomes of reconviction and program success. Findings show support that age, race, and gender are all significant indicators of treatment program completion. More specifically, as age increases the likelihood of treatment program success decreases. In addition, race and sex are predictors of treatment success as minorities and males are less likely to complete treatment programs compared to Whites and females. The findings that age (youth), race (non-White), and sex (males) are significant predictors in supervision outcomes such as treatment is supported by the literature (Chamberlain & Boggess, 2019; Durose et al., 2014; Galouzis et al., 2020; Konkel, 2020; Hipp et al., 2010; Hipp et al., 2011; Hipp et al., 2013; Kubrin & Stewart, 2006; Prevost, 2019; Steen & Opsal, 2007; Wallace & Papachristos, 2014). This issue compounds when examining the descriptive characteristics of the current study's sample in that majority (84.6%) of the sample is White-Caucasian and majority (65.4%) did not have treatment success. These findings suggest that this is a decline in program success for older, male, minority individuals under supervisions even though they represent a smaller sample size of the population.

In addition, the study found that individual-level predictors of age and level of supervision are both predictors of reconviction within 3 years. With every 1-year increase in age, decreases the likelihood of reconviction. In addition, level or supervision is an indicator of reconviction. More specifically, as level of supervision increases, the likelihood of reconviction increases. The findings that age and level of supervision are significant predictors in reconviction is supported by the literature (Chamberlain & Wallace, 2016; Hipp et al., 2010; Hipp et al., 2013; Kubrin & Stewart, 2006; Skeem & Lowenkamp, 2016; Stahler et al., 2013; Steen & Opsal, 2007). This finding was consistent found across all models in this study. Since a majority of the sample is between the ages of 16 and 27 (38.4%) but an even smaller percentage is placed on a high level of supervision (12.3%), this highlights a smaller size of the population is more likely to produce the greater instances of recidivism and be reconvicted with three years. Surprisingly, younger justice-involved individuals placed on high levels of supervision produce most of the recidivism while representing a smaller portion of the supervision population. Juvenile and/or young adult individuals under supervisions are more likely to recidivate and be revoked from community supervision than their older counterparts (Hipp et al., 2010; Kubrin & Stewart, 2006). Likewise, young parolees (age 37 years and less) were 10 times more likely to recidivate than older parolees (Hipp et al., 2010). Level of supervision is a predictor of individuals offending behavior as the higher the supervision level, the greater the likelihood of risk for reoffending (Andrews & Bonta, 2010; Andrews et al., 2006; Austin et al., 2003; Bonta & Andrews, 2017). These findings suggest that the most intensive programming should be targeted to younger and more high-risk individuals under supervisions as this sample size has the greatest risk of reconviction. Focusing on this specific group of individuals on supervision could provide promising results for producing supervision outcomes.

Higher levels of supervision were found to be one of the most significant and compelling individual-level predictors from the study's findings. Level of supervision was found to not only be a predictor of program success but also a predictor of recidivism. The study found that as supervision-level increases, the likelihood of program success decreases. In addition, to being a predictor of program success, the increase in level of supervision also increases the likelihood of reconviction within 3-years. More importantly, the study found that the effect of level of supervision on program success varies across counties. In fact, this finding was the only across county variation effect found in the study, indicating that in some counties' supervision-level is a stronger or weaker predictor of program success. In terms of probation practice, this supports that certain counties are producing better outcomes from supervision over others, either by location or practices. The notion that the geographic location in which community supervision occurs may influence supervision outcomes has not been thoroughly investigated, but does have little support (Galouzis et al., 2020). One explanation of this is that the location in which community supervision occurs may provide more relevant support services for needs (e.g., housing, mental health treatment, vocational training, community-based rehabilitation) and produce a better quality of resources and social networks for individuals under supervision. For example, the distribution of the jurisdiction capacity with the county deprivation variables indicates that some counties had higher levels of deprivation and lower levels of treatment capacity (e.g., Baker and Malheur Counties). In addition, the jurisdiction capacity variable provided that there were other counties that were the least deprived (or more stable conditions) and had the greatest capacity for treatment (e.g., Clackamas and Clatsop Counties). However, there were counties that experienced both high levels of deprivation and high capacity (e.g., Multnomah County) or low levels of deprivation and low capacity (e.g., Hood River County). This relationship varies across counties as not all deprived counties lack treatment capacity nor did all stable counties provide had high treatment capacity, and this deserves future investigation. In addition, as this finding shows that there is variation in the level of supervision (either high or low) and the likelihood of reconviction, some supervision should re-evaluate their supervision practices. If individuals on higher levels of supervision are not recidivating (either by reconviction or program success) at a rate as those on lower levels of supervision then intensive monitoring should be adjusted and treatment resources reallocated so that the individuals who need these services are actually being addressed (Petersilia & Turner, 1990; Petersilia & Turner, 1993; Taxman, 2008). Finally, future investigation of this finding should be considered as supporting evidence can show support for social disorganization theory and evidenced of county-level variation in supervision outcomes.

Lastly, the study found that program-level variables for treatment matter significantly in predicting recidivism. The findings support that initiation or entry into and completion of specific treatment program types can predict reconviction. While the increase in program initiation signifies that critical “needs” should be addressed focusing on intensive criminogenic needs, the completion programs increase the likelihood of supervision success and produces the desired outcomes of community supervision. This finding supports RNR theory to address high-risk individuals with greater access to treatment for success (Bonta & Andrews, 2017) and that systemic responsivity is important in effectively implementing the RNR model (Taxman, 2014). All in all, treatment programming matters significantly in community supervision and neglecting placing individuals into treatment can be detrimental in seeking to reduce recidivism.

First, focusing on program initiation, an increase in initiation for anger management and parenting skills decreases the likelihood of reconviction within 3 years. However, program initiation for vocational training, mental health treatment, supervision monitoring, substance abuse and transitional housing increases the likelihood of reconviction. The inclusion of individuals under supervision demographics covariates in this finding for program initiation type may serve as a moderating effect on the relationship program type has on reconviction. For example, increased initiation into both anger management and parenting classes decreases the likelihood of reconviction. Every 1-year increase in age decreases the likelihood of reconviction. As an individual under supervision ages, their likelihood for needing anger management and parenting classes may subside due to maturity. In addition, higher levels of supervision are correlated with age. Thus, older individuals under supervisions would likely be on lower levels of supervision and have a decreased need for anger management and parenting classes. In addition, the presence of increased program initiation predicting the likelihood of reconviction can serve as a signal to community corrections that individual need certain types of services should be monitored, not as a mean for inspecting violating behaviors but as a target to provide proactive support for the individual to complete the desired treatment.

Regarding program completion, an overall increase in completion decreases the likelihood of individuals under supervision recidivating. Increases in specific program completion such as anger management, cognitive behavioral therapy, domestic violence, vocational training, parenting skills, substance abuse, or sex offender decreases the likelihood of reconviction within 3 years. This finding shows support that while entering treatment is important, in order for community supervision to receive the desired outcome of reduced recidivism, the actual completion of treatment is what is most beneficial. These findings are consistent with research that shows increased treatment completion, such as substance abuse and mental health, can have an impact on supervision and reduce offending behaviors (Huebner & Cobbina; 2007; Visher & Courtney, 2007; Wexler et al., 1999). As previously mentioned, the RNR model requires community supervision to include the proper assessment of an individuals under supervision's risks and needs, followed by a referral to the rehabilitative services or programs that is responsive to the individual's criminogenic needs (Bonta & Andrews, 2017). Accordingly, increased presence of treatment program completion greatly influences the decrease in recidivism and as treatment effectiveness can reduce offending behaviors by providing individuals under supervisions stabilizing needs.

On the contrary, certain programs were found to be counterproductive to the goals of community supervision. An increase of placement in transitional housing, supervision monitoring (e.g., Global Positioning System monitoring or GPS, community service, and conference sanctioning) and substance abuse initiation increase also have an increase in reconviction. Specifically, regarding supervision monitoring, these programs focus more on punishment and addressing violating behaviors rather than rehabilitation. The moderating effect here is that relationship between level of supervision and these types of programming. The connection between level of supervision, supervision monitoring and transitional housing is that individuals under supervisions enter these programs to address non-compliant or violating behaviors as well as address significant stabilization needs. When an individual is placed on higher levels of supervision, their behavior is monitored with more scrutiny. This increases their likelihood of being referred to supervision monitoring for violating behaviors. While supervision monitoring is intended to address violating behaviors, it is counterproductive as it increases likelihood of revocation and takes a more control-oriented position of supervision. Research shows that high intensity supervision increases the likelihood of violation detection (Petersilia & Turner, 1990; Petersilia & Turner, 1993). As an individual under supervision's supervision-level increases, so does their risk of reoffending and likelihood for engaging in supervision monitoring. In addition, transitional housing and substance abuse treatment program types are corelated with more intensive supervision-levels and criminogenic needs also resulting in increased violations. Transitional housing is a significant stabilization factor found to effect younger individuals under supervisions than older ones more dramatically. In addition, treatment such substance abuse is criminogenic needs that requires intensive and prolonged treatment over the course of supervision. Individuals under supervisions seeking to maintain their sobriety do so throughout the course of their terms of supervision and lives. Program initiation and completing into this type of program will require repeat attendance.

Finally, while increased program completion is an encouraging supervision activity, the findings suggest that consistently referring individuals under supervision to monitoring programs and services increase the likelihood of recidivism. While these programs are intended to address violations and reprimand behavior (such as technical violations) while on supervision, increased participating and completions of supervision monitoring leads the individuals under supervision's supervision being revoked. Statistics show that probation or parole violations account for nearly half of percentages (46%) of those returned to prison within 5 years post-release (Antenangeli & Durose, 2021). Thus, this problem is impacting a significant portion of the supervision population as violations, not new arrests, are incarcerating individuals at alarming rates. Community supervision should focus more attention assisting individuals with initiating and completing program promote prosocial skills and resources such as vocational training and cognitive-behavioral therapy as these programs will decrease reduce recidivism.

6.3 Implications

In order to alleviate the concern of recidivism rates of returning citizens, community corrections must address internal and external policies that impact supervision performance. Recidivism is not just harmful to those under supervision, it also impacts the greater community at large including families, victims, treatment providers, rehabilitation and reform advocates, and criminal justice stakeholders. Findings from this study lend larger support for the need to evaluate treatment programming to ensure success, further investigate the effect level of supervision has on program success across counties, and continue to address individual demographics that are consistently found to be a predictor of recidivism.

One of the most important findings of this study is the positive association of treatment initiation and completion on reconviction. Although findings showed that increased program initiation increases the likelihood to reconviction, it also highlights that program completion significantly reduces reconviction within 3-years. This provides community corrections agencies the opportunity for early intervention in the supervision process and to closely monitor those under supervision who require intensive treatment programming. The increased placement into certain programs, such as vocational training, is not a negative indicator as the completion of these same programs can lead to positive supervision outcomes. On the contrary, increased placement into control-oriented programs (e.g., supervision monitoring and transitional housing) increase the likelihood of reconviction. Community supervision should consider altering practices to better address this fluctuation of results. For example, instead of violating or reprimanding individuals for failing to complete treatment, better alternatives could be swiftly re-initiating individuals back into treatment or contacting releasing authorities (e.g., courts or parole commissions) to intervene before revocation occurs. In addition, community corrections could implement contingency management (CM) approaches to supervision such as providing less emphasis on sanctions over rewards and enacting positive reinforcement to produce evidence-based outcomes (Rudes et al., 2012).

Findings from the study also found support that level of supervision was a consistent and significant predictor of reconviction and program success. This finding is supported by the literature that individuals placed on higher levels of supervision monitoring are more likely to experience parole and probation violations (Petersilia & Turner, 1990). Community supervision agencies should implement more proactive supervision policies and practices supported by EBPs and RNR (Bonta & Andrews, 2017; Taxman, 2008) that address the issues found supervising those on higher levels of supervision and/or risk level. For example, risk-needs assessment could be implemented during incarceration and prior to release to indicate the level of risk and supervision before individuals are returned back to the community. This not only provides community corrections notice of high-risk, high-supervision individuals that will be reporting to supervision, but also the ability to ensure services can be readily available to individuals once released. In addition, since studies have found that individuals under supervision more often return to concentrated disadvantaged neighborhoods (Chamberlain & Wallace, 2016), corrections agencies should consider the community or county-level factors when supervising individuals under supervision. For example, parole and probation agencies can focus their supervision practices and policies on targeting the needs of high-risk, high-level supervision individuals such as ensuring access to vocational training, social supports and rehabilitating programs are available in the community. In addition, parole and probation officers could be required to do pre-release home verifications on the individuals designated home address to ensure the neighborhood is suitable for supervision needs. This practice can, inherently, address concerns on whether communities have the capacity to meet the needs of the correctional population. Likewise, “responsivity” resource guides can be developed as supervision “handouts” to assist newly released individuals with locating the treatment providers and services located within near distances to home addresses. Direct engagement with the individuals home environment can provide proactive insight into the access to resources available to the individual and, if needed, a directive to relocate to another address or placement in transitional housing. Since successfully completing programs leads to reductions of recidivism (Kroner & Takahashi, 2012), then addressing the needs prior to release and at the introduction of supervision helps ensure individuals have the opportunity to successfully complete supervision.

Likewise, parole and probation officers should be required to collaborate with treatment providers to prepare supervision plans with rehabilitation. Community corrections should consider contracting treatment providers to work internally with agencies so that supervision staff has access to these services and can focus their attentions on monitoring the progression of an individual’s supervision and less on searching for networks and resources. Equally important is ensuring that the development of supervision plans follow the foundations of RNR for a reduction of recidivism (Bonta & Andrews, 2017).

Lastly, this study did not report definitive findings that county-level characteristics (violent crime, unemployment, and poverty) were associated with increased likelihood of reconviction. However, other studies have found positive associations between neighborhood or community-level disadvantage and recidivism (Konkel, 2020 Hipp et al., 2010; Konkel et al., 2019; Kubrin & Stewart, 2006; Prevost, 2019). Due to the success of other findings, future research implications can include further studying how and if macro-level factors influence supervision outcomes such as the likelihood of arrest, incarceration, and conviction. In addition, future research should investigate other county-level characteristics that also link to increased reconviction such as single-headed households, education level, income level, residential stability, receiving public assistance. Depending on the geographic area being investigated (urban, suburban, or rural) different characteristics may be more appropriate to observe than others. Limitations of this study are further explained.

6.4 Limitations and Future Research

There are two major areas of limitations in this study that could be addressed in future research that may produce different findings. These areas are separated as either being issues presented from the original (or master) files of the full probation population dataset from Oregon or issues with the study design and methodology. Both of which present opportunities for future research to address these concerns.

Issues with the study's original file include the areas of missingness, the exclusion of certain variables that would have benefited the findings, limitations of a two-level analysis, and the creation of a jurisdiction capacity variable. First, the original Oregon community corrections probationer dataset contained over 70,000 individuals under supervision. However, significant missingness was found across variables including the level of supervision, program quantity, county deprivation, and jurisdiction program capacity variables. In addition, treatment variables were also missing data. Due to the large number of missingness in the sample, and to alleviate this limitation, a multilevel multiple imputations in Mplus was conducted using 10 imputed datasets to ensure complete datasets created results from the analysis were interpretable from the overall population. While many of the study variables were significant predictors of the missingness, the multiple imputation process provided imputed descriptive statistics that, when compared to the original variables, there was very little difference in terms of means differences with low standard errors. However, if future research intends to address community corrections issues with probationer data, having fuller datasets, conducting a longitudinal study, and having access of data that contains outcome variables with longer effect timeframes would be beneficial. In addition, securing adequate amount of treatment data for the entire population helps to produce interpretable findings.

In addition, the original file had limitations in availability of the variables selected for the two-level analysis from the study. The current study conducted a two-level multilevel analysis examining individual-level and county-level predictors of recidivism outcomes. Procedurally, once an individual under supervision is released from incarceration, they are placed on supervision with a parole and probation office. This parole and probation office serves as a valuable level of analysis for several reasons. Within this office, parole and probation officers refer individuals under supervisions to treatment programming that is preferably on-site, agency affiliated, and within easy access of the supervision office. However, if treatment programming within the parole and probation office is unavailable (i.e., lack of capacity, close proximity, or inadequate quality), then an individual under supervision is referred to treatment services within the community. The value of variables that explain parole and probation office treatment programming referral, initiation, and completion provides promising outcomes for future research. However, Oregon Community Corrections is organizationally structured differently than most supervision settings. First, Oregon Community Corrections is divided by its counties, not probation offices. Thus, the original file assigns individuals under supervisions to their respective counties of residence, which is where they are supervised. For the present study, while there are 36 Oregon counties, probationers were assigned to 34 counties as three counties (Sherman, Wheeler, and Gilliam) share probation resources. Treatment providers and the allocation of community corrections programs are separated by counties. Thus, regardless of how many probation offices are located within a county, which varies depending on county size, all individuals under supervisions are referred to services based on the county they reside and not on supervision office resources. In the terms of MLM, this structure omits a major element of the supervision process which is the presence of and referral to services within and available to supervision offices. In addition, this structure neglects to include the value of discretionary decision-making process and rational behind treatment referrals, initiation, and completion that practitioner expertise can only provide (Viglione, 2019). Unfortunately, because of the structure of Oregon Community Corrections, nothing could be done to resolve this issue only to proceed with a two-level analysis that investigates individuals and county-level factors. Future research should extend by selecting a different state where individuals under supervision are assigned to a supervision office and receive office-level treatment services before community or county-level resources are exhausted. In addition, future research could also select a state or jurisdiction where an additional level of analysis can occur including the individual, community/neighborhood, and then county-level variation are considered for a more detailed approach. Either option provides the possibility of a three-level analysis and the availability of having increased observations at the level 2 for more interpretable results.

In addition, variables that detail the discretionary decision-making processes of parole and probation officers would be valuable for understand the perceptions behinds treatment resource availability. Additional variables that would benefit this analysis include average number of treatment programs per office, average number of programs offered per year, average number of programs referred to per year, probation officer to probationer caseload averages, number of supervision officers (e.g., referring to individuals under supervision officer reassignment), and office location (Galouzis et al., 2020). Likewise, the county deprivation variable used in this study was an index variable of county unemployment, poverty, and violent crime. These variables are identified more with urban or metropolitan disadvantage and are not necessarily associated with the economic hardships of Oregon. As Oregon is a rural state, more relevant variables that address rural poverty should be selected in future research such as family size, education level, occupation, and residential mobility. These variables may provide more insight into the concerns of rural economic disadvantage (Galouzis et al., 2020). The lack of presence of these variables in this study limited the extent of the analysis and overall interpretability of the findings. Future research should address this issue of variable selection in order to accurate account for variation across counties.

Additional issues with current study methodology's include issues with generalizability of findings, insufficient sample size in the level 2 variables for statistical measurements, and issues with data collection and research design. First, while the current study findings have internal validity, true within the setting of Oregon Community Corrections, the findings lack generalizability as they unlikely to be interpretable to other community corrections agencies. As previously noted, Oregon's structure of community supervision is one that is unique to its state. Oregon Community Corrections is divided by counties, not probation offices, and this is how its corrections treatment programs are separated. However, while there may be other states may follow this model, most states have parole and probation offices that provide designated resources to individuals under supervisions before or in addition to state/county/community-based treatment. In addition, majority of the population sample was White/Caucasian (84.6%) and only 15.4% was minority probationers. These numbers do not accurately reflect the current state of community corrections populations statistics. While U.S. Parole and Probation still maintains a majority of the population is White/Caucasian (38%), the minority population is much larger in size (32 %) and, thus, may provide different findings when supervision and treatment outcomes are analyzed.

In addition, the study had insufficient sample size in the level 2 variables for statistical measurements. Since the current study uses MLM analysis, the strength of the analysis should contain a large sample size at level 2. The ICC is used to ensure that the analysis has sufficient variation at the level 2. For majority of the research questions, the ICC ranged from 2.2% variability to 10.7% in level 2 variability. The importance of ICC variability varies from research fields, however, the small sample size at the level 2 plays an important factor in the small variability found in the ICC. The level 2 sample size includes only 34 counties, which is a very small sample for MLM. Likewise, any observations made at the level 2 may lead to unreliable estimation of the findings. Since MLM is generally used to determine how level 2 effects determine level 1 outcomes, a larger level 2 sample helps provide more accurate variation across counties.

Lastly, issues with the original data collection and research design hinders the study findings. The RNR tool reported treatment provider reported variables including treatment program data, completion, specific type, and outcomes from this dataset. All the individual-level variables relating to individuals under supervision demographics, recidivism and treatment participation was reported from Oregon Community Corrections. Unfortunately, treatment data was collected from the Oregon treatment providers themselves whose answers for accuracy and response rate relied dependently upon the providers. This is also the data that was used to develop the jurisdiction capacity variable, which majority of the treatment providers reported inaccurate capacity relative to the correctional need. More specifically, many of the providers overestimated their capacity to be greater than it was based on the nature of their programs and the service organization (Murphy et al., 2016). Likewise, treatment providers have no accurate measurement for determining whether the programming being offered to individuals under supervision was evidence-based or adequate to serve criminal justice population. However, future research can address these issues in a more comprehensive study that evaluated where programs being offered are evidence-based in order to ensure findings are interpretable and accurately assess the current state of parole and probation.

6.5 Conclusion

The findings from this study continue to support the literature regarding individual-level differences in variation of recidivism. Results showed that an individual under supervisions age (youth) and level of supervision (high) are strong predictors of reconviction. Likewise, an individual under supervisions race (minority) and gender (male) are strong predictors of treatment unsuccess. In addition, the study found support of the literature that engagement in treatment programming can influence the outcomes of supervision. While program initiation is important for treatment programming, completion of treatment displays overwhelming results for the reduced likelihood of recidivism. In addition, while increased completion of rehabilitative treatments can reduce recidivism, the specific type of treatment an individual engages in is a predictive factor for recidivism that agencies should monitor closely. Community corrections agencies should take caution in over supervising individuals and addressing violating behaviors with sanctions as this can be counterproductive to supervision and lead to reconviction.

The study found no support that county-level variables relating to social disorganization and resource deprivation theories were predictors of recidivism variation across counties. The only county variation effect found was level of supervision on program success. This finding highlights that certain supervision agencies produce better outcomes of program success as fluctuating levels of supervision (either high or low) may achieve treatment success or not. This highlights the need for closer examination of supervision practices regarding the monitoring levels of individuals.

Finally, while this study found no support for county-level variation in social disorganization factors, and other studies have found support and have provided valuable insight. Nevertheless, future research should continue to focus on macro-level factors (i.e., neighborhood, community, or county-level factors) of recidivism and if this plays a role in the variation effect seen in individual supervision outcomes. The variation in recidivism among supervised populations receives little investigation and is worthy of further explanation. As community corrections continues to remain the largest component of the criminal justice system, its success hinders solely on the completion of supervision which can only occur when recidivism is reduced, and rehabilitative needs are met.

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Biography

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