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Examining the Influence of Individual and Neighborhood Characteristics on Jail Recidivism

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by

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ABSTRACT

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Under the Supervision of Professor Tina L. Freiburger

This study examined how various individual and neighborhood characteristics influenced the likelihood for individuals to recidivate following release from a local jail. Using data from various sources, this study contributed to the understanding of jail recidivism by addressing several gaps in the literature. First, little attention has been directed towards the study of jail reentry and, instead, concentrates on prison reentry. Next, using a social disorganization perspective, neighborhood context was examined for a sample of jail ex-inmates. Individual characteristics were simultaneously examined for the current sample, using theoretical underpinnings from the Risk-Needs-Responsivity (RNR) model. Finally, recidivism was measured using multiple indicators, including subsequent charges, convictions, and incarceration terms.

Analyses were conducted on a sample of 6,482 individuals who were released from the House of Corrections in Milwaukee County, Wisconsin in 2013 and 2014. Results of the study revealed that neighborhood context was not a significant influence on the current sample of jail ex-inmates. Instead, results indicated that recidivism was largely a matter of individual risk. Gender, race, ethnicity, age at release, criminal record, risk score, and time served were found to significantly influence an individual's likelihood of receiving a new charge, conviction, or incarceration term within three years post-release. The findings of this study demonstrated a lack of support for the relationship between neighborhood context and jail reentry. However, empirical support was found for the relationship between individual characteristics and jail reentry and confirm the importance of individual risk factors for predicting recidivism.

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CHAPTER 1

INTRODUCTION

Following several decades of “get tough on crime” policies and practices and a more than 300% increase in prison and jail populations since the 1980s, the United States today incarcerates roughly 2.3 million individuals (Fagan, West, & Holland, 2002; Glaze & Bonczar, 2008; Glaze & Kaeble, 2014; Raphael & Stoll, 2007). Accordingly, jail inmates represent a majority of the overall incarcerated population, with an estimated 12 million individuals cycling in and out of U.S. jails each year (Beck, 2006; Lyman & LoBuglio, 2006; Sawyer & Wagner, 2019; Solomon, Osborne, LoBuglio, Mellow, & Mukamal, 2008; Subramanian, Delaney, Roberts, Fishman, & McGarry, 2015). The magnitude of these numbers has created many obstacles for administration and policymakers, and criminal justice reform has emerged in the United States following the get-tough-on-crime movement. Scholars in the criminal justice field have made significant contributions towards understanding the influences of recidivism post-prison, yet there is a lack of understanding of how these factors influence recidivism for persons released from jail. The present research addressed these concerns and examined the impact of individual and neighborhood characteristics on the likelihood for individuals to recidivate following release from jail. As such, the current study was able to offer an in-depth and holistic understanding of jail recidivism.

Past Empirical Investigations

In many ways, the challenges of reentry from local jails mirror that of reentry from state or federal prisons. Yet, additional unique challenges of jail reentry influence the likelihood of successful reintegration. While the literature on jail reentry is limited, research that is available has revealed that certain individual and neighborhood characteristics have a significant impact on recidivism for jail ex-inmates. The Risk-Needs-Responsivity (RNR) model has identified various individual-level risk factors that are significantly associated with an individual's odds of recidivism. Demographic characteristics, such as gender, age, race and ethnicity represent static risk factors examined in jail recidivism research to understand differences among those individuals who recidivate post-release and those who remain crime-free. Studies typically reveal that males, as well as younger individuals, have a significantly higher likelihood of recidivism when compared to their respective counterparts (Caudy, Tillyer, & Tillyer, 2018; Folk, et al., 2018; Freudenberg, Daniels, Crum, Perkins, & Richie, 2005; Fritsche, 2019; Jung, Spjeldnes, & Yamatani, 2010; Olson, 2011; Verheek, 2015; Weller, 2012). Race and ethnicity has often been considered one of the strongest predictors of recidivism, indicating that individuals who are Black or Hispanic have the highest likelihoods of recidivism compared to individuals who are White (Gendreau, Little, & Goggin, 1996; Olson, 2011; Verheek, 2015; Weller, 2012; Yamatani, 2008).

Several additional individual-level characteristics have been noted in the literature on jail reentry to significantly affect the likelihood of recidivism. Following the RNR model, criminal history, such as prior charges or convictions, typically reveals a positive and significant relationship with recidivism, where a more extensive criminal history is associated with increased odds of recidivating post-release (Caudy, et al., 2018; Lyman, 2017; Miller & Miller, 2010). Additionally, an individual's current criminal record presents some interesting findings related to the likelihood of jail recidivism. Analyses have revealed that individuals who were initially convicted and imprisoned for a violent offense have the lowest odds of recidivism, compared to those with a current property, drug, or public order offense (Lyman & LoBuglio, 2006; Olson, 2011; Sawyer & Wagner, 2017).

The length of stay in jail and the risk level of an individual have been employed in jail recidivism research to determine their impact on the recidivism process. Although individuals in jail will spend significantly shorter periods of time incarcerated compared to prison, it remains important to investigate the potential impact that confinement of any length may have on the likelihood to recidivate post-release. Furthermore, the risk level of an individual remains an important predictor of recidivism for jail ex-inmates. The RNR model proposes that individuals with more extensive criminogenic risk factors present a higher likelihood for future criminal behavior (Andrews & Bonta, 1994). Scholars investigating this relationship between risk level and recidivism have supported the RNR framework and revealed a positive association, with those individuals identified as high-risk receiving the highest rates of recidivism, followed by medium-risk and low-risk (Caudy, et al., 2018; Lyman, 2017; Lyman & LoBuglio, 2006).

The literature on individual-level associations of jail reentry have produced various findings related to recidivism patterns, yet it may offer an incomplete understanding. Neighborhood context is frequently suggested as a necessary component of offender reentry because many individual characteristics are largely determined to some extent by social forces within one's immediate environment (Kubrin & Weitzer, 2003). Yet, the research on neighborhood context and jail recidivism remains significantly limited. Further, the use of macro-level theory to examine the role of neighborhoods and jails in criminal justice is restricted and incomplete. Verheek (2015) examined the role of social disorganization theory on jail reentry and determined that higher levels of concentrated disadvantage and racial and ethnic heterogeneity were significantly associated with higher rates of recidivism. The study also revealed that higher levels of neighborhood affluence and residential stability significantly decreased rates of recidivism (Verheek, 2015). These findings lend support to social disorganization theory in that various neighborhood characteristics can significantly influence the likelihood of recidivism within communities that house jail ex-inmates. On the contrary, Fritsche (2019) did not find support that neighborhood context significantly impacted the odds of recidivism. Investigating the effect of neighborhood policing practices and concentrated disadvantage on the likelihood of recidivism, she found that only neighborhood policing practices were significantly related to recidivism rates. Instead, recidivism was largely due to individual-level factors (Fritshe, 2019). Inconsistencies with empirical support for social disorganization theory and the impact that neighborhood context may have on jail recidivism creates a need for future research.

Purpose of the Study

The research thus far on jail reentry offers some insight into the correlates that influence recidivism patterns, yet several gaps in the literature remain that need to be addressed. Therefore, the purpose of the current study was to examine how various individual and neighborhood characteristics influence the likelihood for individuals to recidivate following release from jail. Exploring jail reentry, while also addressing some of the gaps in the literature, allowed for a more comprehensive understanding of who recidivates, which factors drove that recidivism, and what policy implications can be offered to better prevent future criminal activity within local communities (Janetta, 2009).

To accomplish this goal, the present research examined a sample of individuals who served a sentence at the House of Corrections in Milwaukee County, Wisconsin and were released in 2013 and 2014[1]. Using a three-year recidivism window, the current study determined

[1] The years 2013 and 2014 were used in the current study to provide the most recent data that would allow for a three-year recidivism window to be examined (i.e., 2013-2016; 2014-2017). These years would also increase the likelihood that more recent cases (i.e., in 2016 or 2017) would be closed.

whether individual and neighborhood characteristics were associated with a jail ex-inmate's likelihood of receiving a subsequent charge, conviction, or incarceration term.

Using the present sample of individuals, this study addressed several gaps in the current literature on jail reentry. First, considerable research is available on the reentry of individuals released from state or federal prisons, yet much less attention has been directed towards individuals who are released from local jails. Prisons typically house individuals who have been convicted, are serving longer sentences, and have a more organized release date and reentry plan (Lyman & LoBuglio, 2006; Yamatani, 2008). As such, analyses on recidivism following prison tend to be more straightforward and abundant within the literature. Jails, however, present unique challenges such as rapid turnover and various legal statuses, which make it difficult to conduct empirical investigations on recidivism (Solomon, et al., 2008). The current study presented an opportunity to undertake these challenges and conduct an empirical investigation on the potential factors that influence a jail ex-inmate's likelihood to recidivate following their release from local corrections in Milwaukee County.

Next, research that is available on jail recidivism tends to focus more on the various individual-level factors that influence the likelihood of recidivism. Fewer studies incorporate neighborhood context and the impact that environment may have on recidivism. Even more so, the use of theory to explore the role of jails in criminal justice remains scarce (Klofas, 1990). Social disorganization theory offers an important framework to understand how various neighborhood characteristics may contribute to the rates of recidivism for individuals who are released from local jails. Yet, there are only two studies that have utilized social disorganization theory as a framework for examining the relationship between neighborhood context and jail recidivism (Fritsche, 2019; Verheek, 2015). Thus, the current study used social disorganization theory as a theoretical framework to test several neighborhood characteristics that are hypothesized to influence recidivism rates. The current study also sought to better understand how both individual and neighborhood characteristics may impact the likelihood of recidivism.

Finally, research on jail reentry routinely uses recidivism as the outcome measure of interest, examining only a single indicator to gauge success upon release (Fritsche, 2019; Miller & Miller, 2010). Employing re-arrest as the sole measure produces the highest rates of recidivism, while using reincarceration produces the lowest rates of recidivism (Durose, Cooper, & Synder, 2014; James, 2015). Considering that each measure produces a different rate of recidivism, analyses become misleading and are limited in their understanding of the recidivism process (King & Elderbroom, 2014). To address this gap in the literature, the current study incorporated multiple measures of recidivism that gauged the full spectrum of the recidivism process. Recidivism was operationalized through subsequent charges, convictions, and incarceration terms.

Summary

The literature on jail reentry is limited, yet those studies that have examined this phenomenon have found some evidence that various individual characteristics, such as demographics or legal factors, have a significant influence on the likelihood for someone to remain crime-free following their release from jail. As discussed, these studies remain incomplete since they typically employ only one measure of recidivism (Fritsche, 2019; Miller & Miller, 2010). Examinations of neighborhood context and its relation to jail reentry also remains scant; and the few studies that have tested this phenomenon have produced mixed findings. Further, the use of theory to examine the influences of jail reentry has been lacking. A deficiency of adequate research on the effect of individual and neighborhood characteristics on jail recidivism creates a need for further examinations. Therefore, the current study addressed several gaps in the literature to provide a comprehensive understanding of the potential influences on jail recidivism.

The inclusion of both individual- and neighborhood-level factors allowed the current study to extensively examine the impact of variables at both levels. Using both the Risk-Needs-Responsivity model and social disorganization theory as underlying theoretical perspectives, along with the inclusion of multiple measures of recidivism, the present research was able to offer an in-depth and holistic understanding of jail recidivism. The next chapter provides a review of existing theory on offender reentry and their potential applications to jail reentry. This chapter also includes a further discussion on jails and their unique challenges, as well as using recidivism as an outcome measure of interest. Finally, Chapter 2 provides a dialogue on empirical investigations of jail reentry and the impact of both individual and neighborhood characteristics on the likelihood to recidivate. Chapter 3 then outlines the methodology that was used for the current study. Chapter 4 presents the analysis and findings of the data used in the present research. Finally, Chapter 5 provides a discussion of the results, as well as offer conclusions related to potential policy implications and future research.

CHAPTER 2

LITERATURE REVIEW

The purpose of the current study was to examine how various individual and neighborhood characteristics influence the likelihood for an individual to recidivate following release from jail. This literature review first provides a theoretical summary of the Risk-Need-Responsivity model and social disorganization theory and their potential applications to jail reentry. Next, a dialogue is provided on jails and their unique challenges to the reentry process, followed by a discussion on recidivism as an outcome measure. The literature review also provides a discussion of the empirical research on jail reentry, including the impact of both individual and neighborhood characteristics on the likelihood to recidivate. Finally, a summary of the current study is provided that portrays the purpose of the research and the proposed hypotheses that were examined.

Theoretical Framework

Risk-Needs-Responsivity Model

The psychology of criminal conduct today plays a major role in criminal justice and criminology (Andrews, Bonta, & Wormith, 2006). Concerns such as the likelihood of recidivism and potential interventions to decrease the chances of criminal conduct remain at the forefront of corrections. However, crime cannot be understood without first investigating whether the personal, interpersonal, and community supports for human behavior are favorable or unfavorable to crime (Andrews, Bonta, & Wormith, 2011; Ogloff & Davis, 2004). Developed in the late 1980s, Andrews and colleagues established the Risk-Needs-Responsivity (RNR) model by identifying various criminogenic risk factors from a meta-analysis of prior research used to predict the likelihood of recidivism (Andrews & Bonta, 1990, 2006; Christensen, Jannetta, & Willison, 2012; James, 2018; Weller, 2012). Borrowing theoretical positions of general personality and social psychology of crime, with a special focus on social learning and social cognition theory, the RNR model is now one of the few comprehensive frameworks for guiding offender risk and assessment (Andrews & Bonta, 2003, 2007, 2010; Andrews, et al., 2006, 2011; James, 2018; Ward & Stewart, 2003).

The RNR model at its core encompasses three basic principles: (1) assessing risk, (2) addressing criminogenic needs, and (3) providing responsive treatment (Andrews & Bonta, 1994, 2003, 2007; Andrews, et al., 2011; Casey, et al., 2014). The *risk principle* concentrates on the influence of various dynamic and static risk factors on the likelihood of recidivism. Dynamic risk factors can change over time (e.g., substance abuse, education, employment, housing), while static risk factors cannot change (e.g., criminal history, age at first arrest or time of release, race and ethnicity) (Andrews & Bonta, 1994; James, 2018). The *needs principle* stresses the importance of considering criminogenic needs (i.e., dynamic risk factors) in the delivery of treatment and programming. The *responsivity principle* dictates how responsive an individual will be to various treatments or services based on their abilities and learning styles (Andrews & Bonta, 1994, 2003, 2007; Andrews, et al., 2011; Casey, et al., 2014). Specifically, the RNR model postulates eight central factors for predicting recidivism, including a history of antisocial behaviors, antisocial personality patterns, antisocial cognition, antisocial associates/peers, family and marital status, education and employment, leisure and recreation, and substance abuse (Andrews & Bonta, 1990, Andrews, et al., 2006; James, 2018). These "central eight" factors have been validated to predict general recidivism in a variety of populations (Brennen, Dietrich, & Ehret, 2009; Gendreau, et al., 1996; Smith, Cullen, Latessa, 2009), and have been accepted as a foundation of evidence-based correctional practice in the United States (Andrews & Bonta, 2010; Cullen & Jonson, 2011; Rempel, 2014).

Empirical investigations of the RNR model. Due to high rates of recidivism and the effects it can have on offenders, victims, families, and the community research has focused on which factors influence the likelihood of recidivism. Several studies and meta-analyses have examined the impact of various risk factors and, more specifically, programming that adheres directly to the RNR principles to examine their association with recidivism. Singh and Frazel's (2010) meta-analysis revealed several static risk factors that significantly increased the risk of recidivism, including prior arrests and incarcerations, being African American, younger, male, and having a current property or drug offense (see also, Stahler, et al., 2013). Time served was also identified as a strong predictor of recidivism, with the risk of recidivating significantly decreasing over time. Gendreau and colleagues (1996) further revealed several static risk factors (e.g., race and ethnicity, age, criminal history) and dynamic risk factors (e.g., antisocial attitudes and substance abuse) that were significantly associated with the likelihood of recidivism. Another meta-analysis of 80 studies examined the effectiveness of correctional programming that specifically adhered to the RNR principles and found that these interventions were associated with significantly larger effect sizes (Andrews, et al., 1990). These findings have also been supported by other scholars who have indicated that treatment and programs adhering to all three RNR principles were associated with the greatest reduction in recidivism rates (Andrews & Bonta, 2006; Dowden & Andrews, 1999, 2000).

Fristche (2019) also used the RNR framework to investigate the influence of individual risk on recidivism for a sample of individuals released from New York jails in 2015. Using risk factors of age, gender, criminal history, employment, education, housing, and substance abuse, Fritsche (2019) combined these into one cumulative risk score to analyze the association with recidivism odds. Results of the study revealed a strong positive relationship between individual risk score and the probability of re-arrest, where a one-point increase in risk score led to a 24-28% increase in the odds of being rearrested. Additionally, the author examined each individual-level factor separately to determine their influence on recidivism and found that homelessness, younger age, being male, longer criminal history, and substance abuse had the strongest individual-level influences on the odds of re-arrest (Fritsche, 2019). Even after examining the impact of neighborhood-level factors on the risk of recidivism, results determined that recidivism was largely a matter of individual risk.

Rempel and colleagues (2018) also tested the RNR model in a New York misdemeanor population by examining various risk factors and their influence on recidivism. A comprehensive risk and needs assessment were administered to 964 misdemeanor defendants in New York City. Recidivism was then collected through official criminal records. The authors found several significant predictors of re-arrest, including a history of gang involvement, problems in an intimate relationship, lack of a HSED/GED, criminal attitudes, current unemployment, and substance abuse (Rempel, Lambson, Picard-Fritsche, Adler, & Reich, 2018). A lack of prosocial leisure activities and measures of antisocial temperment (i.e., impulsivity) were not found to significnatly predict re-arrest. Additionally, the authors determined that several static factors were significnatly more likely to predict re-arrest than dynamic factors. In fact, criminal history, younger age, and male sex explained more than twice as much variation in the likelihood of re-arrest than the other 14 factors that were analyzed in the study (Rempel, et al., 2018).

Social Disorganization Theory

The contributions provided by Robert Park and Ernest Burgess on concentric zone theory paved the way for the development of social disorganization theory. During the 1920s and 1930s Park and Burgess were concerned with the influence that urbanization, industrialization, and immigration patterns had on the social organization of Chicago neighborhoods (Kubrin, 2009). A *neighborhood* was described as a collection of both people and institutions occupying a spatially defined area that could be influenced by ecological, cultural, and political forces (Park, 1916). Accordingly, they set out to study these drastic changes and the potential effects that neighborhood patterns had on the city. Borrowing concepts from plant ecology, where animals and plants compete for space and existence, the authors applied this reasoning to social ecology in that humans would also compete for scarce and desirable space within Chicago neighborhoods (Kubrin, 2009; Park & Burgess, 1925). These notions ultimately led to the emergence of the concentric zone theory, emphasizing the process of invasion, dominance, and succession to better understand city life. Park and Burgess mapped out Chicago's neighborhoods into five concentric zones that emanated from the city's center and corresponded to areas of social disorganization: Zone I (central business district), Zone II (zone in transition), Zone III (zone of workingmen's homes), Zone IV (residential zone), and Zone V (commuter's zone) (Park & Burgess, 1925). It was theorized that urban areas grew through the process of continual expansion from their inner core towards outer areas (Burgess, 1967). Thus, as the central business district grew, affluent residents would begin to move outwards, leaving an unstable zone more conducive to social disorder (i.e., zone in transition) (Kubrin, 2009; Park & Burgess, 1925).

The focus within this study was not on crime, but rather the explanation of urban social structures. Then, in 1942 Shaw and McKay's *Juvenile Delinquency and Urban Areas* brought social ecology and social disorganization theory to the forefront of criminal justice. It was here that Shaw and McKay first tested concentric zone theory and the effects of neighborhood characteristics on crime. More specifically, the authors wanted to understand the extent that differences in economic and social characteristics paralleled variations in rates of juvenile delinquency (Kubrin, 2009; Shaw & McKay, 1942). Shaw and McKay (1942) examined the geographical distribution of juvenile delinquency through court case files in 1900, 1920, and 1930, as well as collected fieldwork data for Chicago neighborhoods. They found that crime rates were concentrated within certain areas, particularly within Zone II (zone in transition). The zone in transition, which was closest to the central business district, was at the highest risk of being exposed to ecological factors that would best influence the emergence of criminal behavior, including “slum-like” conditions of deteriorating housing, high rates of poverty, and increased economic insecurities (Park & Burgess, 1925; Shaw & McKay, 1942). As one moved further away from the center of the city, economic conditions improved, and crime rates decreased (Sampson, 2012; Shaw & McKay, 1942). These findings led to the conclusion that crime was not evenly dispersed throughout the city and that crime remained relatively stable within certain areas despite changes in the racial and ethnic populations of that area (Shaw & McKay, 1942). Crime was likely a function of various neighborhood characteristics (i.e., high rates of poverty, residential mobility, and racial/ethnic heterogeneity) rather than a function of individuals within that neighborhood.

Basic tenants of social disorganization theory. The central element of social disorganization theory is that communities are characterized along a dimension of *organization*. A socially organized community, such as those found in Zones III, IV, and V, consists of cohesion and solidarity on essential norms and values, as well as social interaction and trust among residents. These qualities subsequently lead to greater informal social control and ultimately lower crime rates (Bellair & Browning, 2010; Kubrin, 2009; Kubrin & Wo, 2016)[2]. On the contrary, socially disorganized communities lack the above elements and are unable to realize shared goals and values, including the goal of local control over crime and deviance (Bursik, 1988; Sampson, 2012; Shaw & McKay, 1942). These communities, therefore, have limited informal social control and higher rates of crime (Kubrin & Stewart, 2006; Kubrin & Wo, 2016; Shaw & McKay, 1969).

[2] Informal social control can be defined as the scope of collective intervention that the community directs towards local problems, such as crime (Kornhauser, 1978; Shaw & McKay, 1942).

It is important to understand that neighborhood characteristics do not directly cause crime, but instead indirectly affect the level of crime within communities. Factors such as high rates of poverty, racial and ethnic heterogeneity, and residential mobility affect the formation of social ties among residents and the ability of residents to have informal social control (Kubrin, 2009; Kubrin & Wo, 2016; Shaw & McKay, 1942). The level of informal social control then influences the ability to regulate behavior, including local crime and deviance within those areas (Kubrin, 2009; Kubrin & Wo, 2016; Shaw & McKay, 1942).

Empirical tests of social disorganization theory and jail reentry. The central questions posed by social disorganization theory are (1) why do some neighborhoods have higher crime rates than others? and (2) what is it about certain communities that generate higher crime rates? Scholars who have sought to examine these research questions have employed various indicators to test the effect they may have on criminal activity within communities. Variables of concentrated disadvantage, residential stability, racial and ethnic heterogeneity, and family disruption represent some of the most common indicators used to test social disorganization theory. Each of these variables are operationalized differently, indicating a need to better understand which indicators are contributing the most to predicting criminal activity. Pratt and Cullen (2005) sought to achieve this by conducting a meta-analysis that examined macro-level predictors of crime. They determined that some of the strongest predictors included the percentage of non-white residents, percentage of Black-only residents, rates of incarceration, level of collective efficacy, family disruption, and poverty (Pratt & Cullen, 2005). Thus, the top tier predictive factors of crime represented social disorganization theory concepts of concentrated disadvantage, racial and ethnic heterogeneity, and family disruption (Pratt & Cullen, 2005).

Social disorganization theory has frequently been used as a theoretical framework for understanding prisoner reentry, however, there is a lack of application to jail reentry. There are only two studies that have used social disorganization as a theoretical underpinning for jail reentry. Fritsche (2019) examined the effect of both neighborhood policing practices and concentrated disadvantage on the likelihood of recidivism for individuals released from New York jails in 2015. Police enforcement tactics included indicators of historical and current rates of stop-and-frisk activity in each precinct, as well as historical and current rates of "proactive" misdemeanor arrest activity in each precinct. Concentrated disadvantage was operationalized as the percent unemployment rates, percentage of the population under 18 years of age, percent female-headed households, and the median household income. It was determined that neighborhood policing practices significantly increased odds of re-arrest for individuals, however, concentrated disadvantage had no significant effect on an individual's odds for a new arrest (Fritsche, 2019). Finding only minor support for the social disorganization theory, this study suggested that recidivism was largely a matter of individual risk rather than the product of neighborhood context.

Another study, conducted by Verheek (2015), utilized social disorganization theory as a theoretical underpinning to study jail reentry. Using a sample of inmates who were released from Kent County Correctional Facility in Michigan between 2010-2011, the author incorporated measures of concentrated disadvantage, neighborhood affluence, racial and ethnic heterogeneity, and residential stability to predict odds of new arrests and new incarceration terms within two years following release. An index was created for concentrated disadvantage and incorporated the percentage of individuals receiving public assistance, the percentage of persons living below the poverty level, the percentage unemployed, the median family income, and the percentage of households headed by a single parent (Kubrin & Stewart, 2006; Verheek, 2015). Neighborhood affluence was operationalized using the index of concentration at the extremes (ICE) offered by Massey (2001). This measure includes values related to the number of affluent families in relation to the number of poor families. Racial and ethnic heterogeneity examined the chance that two randomly selected individuals would be from different races or ethnic groups, including (1) black and non-black, and (2) Hispanic and non-Hispanic. Finally, residential stability represented an index that consisted of the percentage of housing units that were currently vacant (inverse), the average length of residence, and the percentage of residents who moved into their residence during the past five years (Verheek, 2015). The results of the study determined that higher levels of concentrated disadvantage and Black and Hispanic heterogeneity were significantly associated with increased rates of re-arrest and reincarceration (Verheek, 2015). In addition, higher levels of neighborhood affluence and residential stability significantly decreased rates of re-arrest or reincarceration within two years following an individual's release (Verheek, 2015). Compared to the first study conducted by Fritsche (2019) there was evidence that neighborhood context had an effect on the likelihood for individuals to recidivate following release from jail, supporting the basic tenants of social disorganization theory.

Summary

The use of theory, in general, to examine the role of jails in criminal justice has been sparse (Klofas, 1990). More often than not, literature investigating the role of jails report on individual-level factors that influence recidivism, as offered by the RNR model. But, there is a lack of examination related specifically to social disorganization theory and jail reentry. Instead, most studies that focus on neighborhood context and reentry tend to rely on samples of released prisoners (Kubrin & Stewart, 2006; Tillyer & Vose, 2011). The few studies that have examined the role of social disorganization theory and jail recidivism have produced mixed findings and warrant further investigations. As Hallett (2012) states, it is important to continue moving beyond individual-level research and additionally focus on macro-level theory that may impact former offenders.

Jails and Their Unique Challenges

The past several decades have seen a surge in incarceration rates, largely due to the "get tough on crime" shift in policy and enforcement practices. In 1985, 108 out of every 100,000 residents were incarcerated in jail; and in 2007, 259 out of every 100,000 residents were incarcerated in jail. This rate declined slightly in 2016, with 229 out of every 100,000 residents incarcerated in jail yet remains significantly higher than rates represented during the early 1980s (Zeng, 2018). In any given month, jails have contact with as many offenders as prisons do in a year (Beck, 2006); and more individuals will experience jail incarceration than prison incarceration (Wagner & Rabuy, 2017). It is estimated that 12 million people cycle in and out of 3,500 U.S. jails (compared to 50 state prison systems) each year, representing about 9 million unique individuals (Beck, 2006; Lyman & LoBuglio, 2006; Sawyer & Wagner, 2019; Solomon, et al., 2008; Subramanian, et al., 2015). This translates into 34,000 individuals released from U.S. jails each day and 230,000 released each week (Solomon, et al., 2008). In 2008, the turnover rate for jail populations represented 66.5% per week (Minton & Sabol, 2009), and in 2016 the turnover rate was 55% (Zeng, 2018)[3]. The majority of inmates in jail have not yet been convicted, as scholars estimate that about 60% of inmates are awaiting court action on a current charge, while 40% were actually sentenced offenders or convicted offenders awaiting sentencing (Minton & Golinelli, 2014; Minton & Zeng, 2015; Minton & Zeng, 2016; Sawyer & Wagner,

[3] The Bureau of Justice Statistics calculates the weekly turnover rate by adding jail admissions and releases, dividing by the average daily population and multiplying by 100.

2019). This rate remained unchanged since 2005, until increasing slightly in 2016 to 65% and 35% respectively (Zeng, 2018). Further, from 2000-2014 the jail inmate population increased roughly 1% each year due solely to the increase in the un-convicted population (Minton & Zeng, 2015, 2016).

Jails represent short-term incarceration facilities that are operated by local governments. They are a point of entry into the criminal justice system following arrest, as well as a point of release and return to the community (Beck; 2006; Subramanian, et al., 2015; Turney & Connor, 2018). Compared to prisons, jails primarily hold offenders of less serious crimes for one year or less (Jung, et al., 2010). In fact, it is estimated that about 75% of the jail population are confined for non-violent traffic, property, drug, or public order offenses (James, 2004; Subramanian, et al., 2015). Additionally, unlike prisons, jails confine individuals for a variety of circumstances, including those awaiting trial, sentencing or transfer to state facilities, those convicted and serving a sentence of one year or less, and those who have violated the conditions of their parole, probation, bond, or community-based programs (e.g., electronic monitoring, day reporting, work programs, etc.) (Crayton, Ressler, Mukamal, Jannetta, & Warwick 2010; Freudenberg, et al., 2005; Lyman & LoBuglio, 2006; Minton & Golinelli, 2014; Minton & Zeng, 2016; Sawyer & Wagner, 2019; Solomon, et al., 2008; Subramanian, et al., 2015).

Unique Challenges

In many ways, the challenges of reentry from local jails mirror that of reentry from state or federal prisons, however, there are several differences between the jail and prison population that present unique challenges to successful reintegration. First, jails have heterogeneous populations that house individuals who are detained for pretrial, awaiting transfer, serving a sentence, or have violated their parole, probation, or bond among others. In addition, the jail population contains both low- and high-risk offenders. Prisons, on the other hand, house offenders who are serving a sentence and are generally medium-to-high risk (Lyman & LoBuglio, 2006; Turney & Connor, 2018; Zeng, 2018). The diverse populations in jails create unknown release dates and variations in the length of stay, which make reentry planning challenging (Solomon, et al., 2008). Second, the majority of individuals who cycle through jails have significant issues related to substance abuse, mental health, housing, and employment (Solomon, et al., 2008). However, a jail's first priority is to ensure the safety and security of those who are inside the jail, including both inmates and staff. Consequently, security takes precedence over programming and individuals' criminogenic needs are often not addressed prior to reentry (Crayton, et al., 2010). Third, jails represent short-term incarceration facilities, compared to prisons. It is estimated that more than 80% of individuals in jail will be confined for less than one month (Beck, 2006). These shorter confinement periods create instability and limit the opportunity for programming and intervention (Mellow, Mukamal, LuBuglio, Solomon, & Osborne, 2008; Turney & Connor, 2018). Finally, each of the challenges presented so far influence the ability for effective transition processes. Shorter lengths of stay and unpredictable release dates make planning for reentry difficult. Unlike prisons, most individuals who are released from jail are not under some form of post-release supervision. This creates a lack of ongoing support and assistance once someone is released back into the community, ultimately increasing the chance for recidivism (Solomon, et al., 2008).

These challenges present a view that jail incarceration can serve as a more punitive form of punishment than prison incarceration (May, Applegate, Ruddell, & Wood, 2014). Even more so, a lack of intervention and transitional planning creates potential issues. While a small percentage of individuals will be housed for life in prison, all individuals who are sentenced to jail terms will eventually return home (Travis, 2005). Typically, these individuals return to the same economically disadvantaged neighborhoods from which they left (Freudenberg, et al., 2007; Miller & Miller, 2010; Subramanian, et al., 2015). In fact, Verheek (2015) found that the majority of his sample of released jail inmates in Michigan returned to just eight zip codes that had some of the highest levels of concentrated disadvantage and lowest levels of neighborhood affluence. Returning to neighborhoods with lower levels of affluence indicates heightened barriers to successful reentry. For example, Wilson and colleagues (2011) found that 75% of their sample were readmitted to jail within four years of their release; and Folk and colleagues (2018) found that 63% of released inmates from county jails in the District of Columbia were rearrested within the first year of release. Furthermore, Olson (2011) examined individuals who were convicted, sentenced, and released from Cook County Jail in Illinois and found that 52.3% were rearrested and returned to jail within three years post-release. Lyman and LoBuglio (2006) additionally determined the proportion of sentenced inmates who were released and rearraigned within one year in Hampden County, MA varied between 48% and 58% between 2000-2004.

Summary

Despite the number of individuals who are affected by the jail system, there is a lack of literature on jail reentry and the correlates that influence recidivism. Instead, most scholars focus on former prisoners to understand the reentry process. Prison inmates typically come into an institution post-conviction, serve a longer sentence, and have a more orderly and planned departure (Lyman & LoBuglio, 2006; Yamatani, 2008). Jails, on the other hand, have rapid turnover and contain various legal statuses (e.g., pretrial, sentenced, transferred, etc.) that present challenges to measuring jail recidivism (Solomon, et al., 2008).

Difficulties in the ability to measure jail recidivism should not discourage researchers. Rapid turnover and high recidivism rates of the jail population indicate a need to better understand how offenders are flowing through the criminal justice system and what factors are influencing their return to incarceration. Using local data to assess these characteristics of the correctional population represent a critical first step in identifying who recidivates, which factors drive that recidivism, and ultimately how resources can be allocated to better prevent criminal activity (Janetta, 2009). Jail recidivism research acts as a valuable tool to inform decisions within the community that affect security, classification, movement, programs and release planning, and population trends (Lyman & LoBuglio, 2006).

Recidivism as an Outcome Measure

Recidivism should be, and often is, a key outcome in modeling reintegration since it is the most visible indicator of correctional impact, can be defined as limiting or as broadly as needed, and illustrates problems related to criminal activity and public safety (Urban Institute, n.d.; Wright & Cesar, 2013). Recidivism analyses can track population trends, inform policy change, and develop recidivism rates by offender characteristics to help develop future planning and programs (Solomon, et al., 2008). The flexibility of examining recidivism, however, often means there is no consistent definition found within the literature. For instance, some scholars use a broad view of recidivism through the "falling back or relapse into prior criminal habits, especially after punishment" (Solomon, et al., 2008, p. 53); or simply "reengaging in criminal behavior after receiving a sanction or intervention" (King & Elderbroom, 2014, p. 2). Others may define a recidivist as "one who, after release from custody for having committed a new crime, is not rehabilitated and instead falls back into former criminal behavior and commits a new crime" (Maltz, 1984, p. 18).

Scholars also commonly operationalize recidivism through one or more of the following measures: re-arrest, recharge, reconviction, or reincarceration (James, 2015; Lyman & LoBuglio, 2006; Solomon, et al., 2008; Urban Institute, n.d.). Rates of recidivism can then be calculated to measure the frequency with which individuals reengage with the criminal justice system (Urban Institute, n.d.). Researchers typically operationalize recidivism based on the overall purpose of their study or the data that is available. First, re-arrest indicates that an individual has officially recidivated and represents the initial point of entry into the criminal justice system (Subramanian, et al., 2015). Re-arrest captures the broadest view of new offenses and interactions with the criminal justice system and results in the highest rates of recidivism (Fritsche, 2019; Sawyer & Wagner, 2019; Urban Institute, n.d.). The use of re-arrest can present issues though when it is used as the only indicator of recidivism. Many individuals who are arrested are subsequently released because they were found to not have been involved in the crime. Including these cases could potentially result in recidivism rates that are overestimated, leading to a greater Type I error rate (Maltz, 1984).

Nonetheless, re-arrest represents one of the most common measures in jail recidivism research. Yamatani (2008), for instance, found a re-arrest rate of 33.1% for male ex-jail inmates within a 12-month period. Miller and Miller (2010) further indicated a 46.9% rate of re-arrest during the first year for a sample of inmates released from a rural county jail in Ohio. Finally, it also has been found that individuals released from New York City jails have re-arrest rates of about 40% within one-year following release (New York City Independent Budget Office, 2009), with Fritsche (2019) specifically illustrating that 49% of individuals who were arrested and detained in 2015 were subsequently arrested within 12-months post-release.

Second, subsequent charges can be used as a reliable indicator of recidivism. This indicator is often counted as a failure event if prosecutorial action is taken against the arrest in the form of charges filed, indictment, or a grand jury presentation (Maltz, 1984). This typically includes dispositions that are recorded as either guilty or not guilty (James, 2015). Unfortunately, this measure is seldom used throughout the literature, as an analysis showed that only one out of the 99 studies examined used subsequent charges as a measure of recidivism (The Sentencing Project, 2010).

Third, reconviction represents another indicator of recidivism that only measures charges which have resulted in a guilty disposition (Lyman, 2017; Maltz, 1984; Ruggero, Dougherty, & Klofas, 2015). Thus, cases where the charges were dropped, an individual was acquitted, or did not result in custody time are often eliminated from the sample (Lyman & LoBuglio, 2006; Urban Institute, n.d.). Lyman and LoBuglio (2006) used this definition in their study of sentenced and released offenders in a Massachusetts county jail. The authors found that individuals who were released between 2000-2004 had a reconviction rate between 25.5% and 34.7% within one-year post-release. Further, Lyman (2017) conducted an additional study examining individuals who were released from a Massachusetts county jail in 2013 and determined that 44.9% of individuals were reconvicted within three years following their release.

Lastly, reincarceration signifies another measure of recidivism used in jail reentry and is sometimes thought of as the most relevant indicator because it examines offenses that were serious enough to warrant a sentence of incarceration (Sawyer & Wagner, 2019). Re-incarceration is defined as a violation resulting in subsequent incarceration and sentence of any length. This can be further defined as either a new criminal offense or return-to-custody for a technical violation (Chamberlain & Wallace, 2016; Lyman, 2017; Lyman & LoBuglio, 2006;

Ruggero, et al., 2015). Lyman and LoBuglio (2006) conducted an examination of individuals released from a county jail in Massachusetts between 2000-2004 and found that reincarceration rates for a one-year follow-up period varied between 21.1% and 30.9%. Further, Lyman (2017) found that jail ex-inmates released in 2013 had a total reincarceration rate of 37.7% three years post-release, with 32.7% incarcerated for a new criminal offense and 5% incarcerated for a technical violation. Further, the author found that individuals who were released in 2015 had a total reincarceration rate of 15.8% within one year following release, with 12.5% incarcerated for a new criminal offense and 3.7% incarcerated for a technical violation.

While scholars have employed a variety of recidivism measures, there does seem to be consistency in the definitions of the start and failure event associated with measuring that recidivism. When examining recidivism, the time-period of analysis begins on the date an individual is released from jail (Urban Institute, n.d.). The failure event (i.e., the point at which an offender has failed to remain crime-free following release from incarceration) is often measured as either the date that the new criminal offense occurred or the date of arrest for the new criminal offense. Ordinarily, the date of arrest is the only indicator that is available to researchers, however, the offense date is regarded as a superior indicator because it accurately distinguishes when the crime occurred and represents recidivism in its purest form (Maltz, 1984). An arrest, on the other hand, could potentially occur sometime after the initial crime transpired. Yet, Greenwood and colleagues (1977) argue that arrest dates are still reliable measures to use because, in most cases, the arrest date occurs within a few days of the actual offense date. In fact, they revealed in their study that about 90% of all cases examined were closed by law enforcement within one week of the occurrence of the crime.

Furthermore, examinations on reentry research typically consider recidivism in six-month, one-year, or three-year time frames (Lyman & LoBuglio, 2006). It is suggested that tracking individuals for at least three years following their release from jail is ideal. A longer observation period produces a comprehensive picture of recidivism patterns, as well as sustained effects on the link between reentry and recidivism (King & Elderbroom, 2014). Additionally, it allows for researchers to capture the majority of the population who may recidivate. Jung and colleagues (2010), for example, revealed the greatest surge in recidivism rates occurred during the first year (36.7%) following release from a county jail in Pennsylvania. An additional 12.5% were rearrested during the second year post-release (49.3%) and another 6% were rearrested during year-three (55.9%). Had the authors restricted their analyses to a 12-month follow-up period they would have missed nearly 20% of the sample who eventually recidivated, leaving out critical information on recidivism patterns and sustained effects.

Summary

The measure of recidivism employed for a particular study should correlate with the interests of the overall research and the intended "measure of success" that one wishes to achieve. It is suggested that researchers employ more than one indicator of recidivism to capture a comprehensive picture of reentry and patterns of recidivism (King & Elderbroom, 2014; Urban Institute, n.d.). Yet, recidivism is commonly reported as a single measure and may be imprecise to draw meaningful conclusions or fully assess the impact of changes in policy or practice (King & Elderbroom, 2014). The choice of measure will also likely influence the significance of the recidivism rate achieved. Using re-arrest as an indicator of recidivism tends to produce the highest rates of recidivism, followed by reconviction and reincarceration which produce lower rates (Durose, et al.; James, 2015). A simple arrest produces a failure event, yet not all cases will result in a charge, conviction, or new incarceration term. Further, cases that move forward through the criminal justice system may take months or even years to reach a full disposition of conviction and sentencing (Lyman & LoBuglio, 2006). Scholars who have incorporated multiple measures of recidivism into their analyses have produced different rates of recidivism for the same sample. For example, Lyman and LoBuglio (2006) determined that 47.8% of their sample had been rearraigned, 25.5% had been reconvicted, and 21.1% had been reincarcerated within one-year following their release. Lyman (2017) also found that 44.9% of her sample in Massachusetts were reconvicted within three years post-release, while only 37.7% were reincarcerated. Hence, using one indicator of recidivism portrays only a portion of the recidivism process. It remains crucial in recidivism research to capture a comprehensive picture of recidivism patterns to offer the most reliable and effective implications (Erdahl, 2015).

Empirical Research on Jail Reentry

Examining the influence of individual-level factors on recidivism is perhaps one of the most well-known and well-studied components of research on offender reentry (Wright & Cesar, 2013). Yet, research in the past several decades has begun to examine how various neighborhood-level factors may also contribute to the likelihood of recidivism. Understanding the characteristics that influence individual offenders to engage in crime provides a necessary component for reducing recidivism, however, it-alone offers an incomplete understanding of the reentry process (Wright & Cesar, 2013). As Currie (1998) states, “even the best efforts at rehabilitation of offenders will be undermined unless they are linked to a broader strategy to improve conditions in the communities in which offenders will return”. To date though, much of this research on offender reentry has focused on those individuals released from prisons. To examine jail reentry in the current study, it becomes important to investigate the brief literature that is available on jail recidivism to determine whether former jail inmates have a unique profile and risk upon release.

Individual-level Influences

Gender. Gender represents one such characteristic frequently analyzed in jail recidivism research. Examining the demographics of jails nationwide, males are significantly overrepresented, comprising about 85 – 87% of the jail population (Beck, 2006; Bronson & Berzofsky, 2017; Minton & Golinelli, 2014; Minton & Zeng, 2015; Minton & Zeng, 2016; Zeng, 2018). Males tend to be incarcerated for more serious offenses, while females are typically confined in jail for non-violent offenses such as property, drug, or public order crimes (Harlow, 1998; Swavola, Riley, & Subramanian, 2016). Further, males are incarcerated at rates six times that of females (Zeng, 2018), however, the incarceration rate for females over the past several decades have seen a dramatic increase. The number of females incarcerated has risen nearly 50% from 68,468 in 1995 to 101,179 in 2003. Further, since 1995 the average annual growth rate of female imprisonment has increased 5% each year, compared to 3.4% for males; and from 2010-2013 this rate increased to 10.9%, while the rate for the male population declined 4.2% (Beck, 2006; Harrison & Karberg, 2004; Minton & Golinelli, 2014; Minton & Zeng, 2016). These drastic differences between males and females is likely due to changes in policy and shifts in law enforcement practices nationwide during the 1980s that contributed to the escalation of arrests (and in particular, drug arrests) for women (Swalova, et al., 2016). In fact, while the arrest rate for drug-related offenses doubled for men between 1980-2009, this rate nearly tripled for women (Swalova, et al., 2016).

Empirical investigations of gender and the likelihood of recidivism frequently conclude that males have a significantly higher likelihood to recidivate. Olson (2011) conducted a study of individuals who were convicted, sentenced, and later released in 2007 from Cook County Jail in Illinois. The study revealed that males had a significantly higher rate of re-arrest than females within three years post-release. Similar results were also discovered by Fritsche (2019), who concluded that males had significantly higher odds of re-arrest compared to females. Folk and colleagues (2018) conducted another study in the District of Columbia examining correlates of recidivism for inmates released from a county jail. Based on interviews with subjects, they determined that males recidivated at significantly higher rates than females during the first year of release. A study led by Caudy and colleagues (2018) found new arrest rates of 31% for females and 42% for males, while Freudenberg and colleagues (2005) found that 39% of females were rearrested within one year following release from New York City jails. Further, Verheek (2015) studied inmates who were released from Kent County Correctional Facility in Michigan between 2010-2011 and revealed that being female reduced odds of re-arrest by 30.9% and the odds of reincarceration by 40.9%. Finally, Weller (2012) produced an examination of three county jails in Florida, concluding that females were less likely than males to be rearrested in one of the counties, yet just as likely as males to be rearrested in the remaining two counties.

Scholars who have tried to understand why females are less likely to recidivate often look at the extent of their criminal history. Men are more likely to have extensive criminal histories related to increased prior arrests and incarceration terms. Additionally, men are more likely to be incarcerated for a violent or weapons-related offense, while females are more likely to have an offense that is drug-related (Freudenberg, et al., 2007). Incorporating social disorganization literature into the understanding of recidivism, it is also possible that neighborhood context matters for males more than it does for females. Gender socialization shares that females are more likely to spend time in the home and less time out in the community, while the opposite is true for males. This, in turn, may give females less exposure to the criminogenic neighborhood conditions that may increase their chances for recidivism (Beyers, Bates, Pettit, & Dodge, 2003; Steffensmeier & Haynie, 2000).

Race/Ethnicity. Another strong predictor of jail reentry is race and ethnicity. The risk of incarceration is higher for people of color, specifically for Black individuals. In 2003, the risk of incarceration for Black individuals was five times than that for White individuals; and Hispanics were almost two times higher than for Whites (Harrison & Karberg, 2004). In 2016, Black individuals were incarcerated in jail at a rate of 3.5 times than that for White individuals (Zeng, 2018). Wisconsin, in particular, is at the forefront of racial disparity for Black male incarceration rates, representing a rate that is 12 times the rate for White males (Levine, 2019). When examining the overall incarcerated population by racial and ethnic makeup, the disparity becomes even more evident. Black, non-Hispanic inmates make up about 40% of the incarcerated population, even though they represent only 13% of the general United States population. On the other hand, White, non-Hispanic inmates signify roughly 39% of the incarcerated population and about 64% of the U.S. make-up. Hispanic inmates represent 19% of the incarcerated population, but 16% of the U.S. population (Beck, 2006; Bronson & Berzofsky, 2017; Minton & Golinelli, 2014; Minton & Zeng, 2015, 2016; Sawyer & Wagner, 2019; Zeng, 2018).

Disparities in the incarcerated population often warrant further analysis on the likelihood of recidivism following release from incarceration. A meta-analysis of over 130 studies on the influences of recidivism revealed that race and ethnicity was one of the strongest predictors of recidivism (Gendreau, et al., 1996). Although this study analyzed empirical investigations of prisoner reentry, it would be expected to find similar results when examining jail reentry. In fact, several studies that have examined the impact of race and ethnicity on jail reentry have determined that people of color have significantly higher odds of recidivism. Weller (2012) revealed that both Black and Hispanic individuals were significantly more likely than White individuals to be rearrested in three separate counties in Florida; and Yamatani (2008) found that Black individuals had significantly higher rates of re-arrest compared to their White counterparts. Additionally, Verheek (2015) determined that Black individuals were over two times more likely than other races to be rearrested and 76.9% more likely to be reincarcerated within two years following their release from a Michigan facility. Finally, Olson (2011) revealed that, within three years post-release from Cook County Jail in Illinois, Black individuals had a re-arrest rate of 59.2%, White individuals had an arrest rate of 43.4%, and Hispanic individuals had an arrest rate of 36.8%.

Age. While gender, race and ethnicity represent some of the most common factors examined on jail reentry, the age of an inmate is another indicator frequently discovered as an important influence in the likelihood of recidivism. Statistics on the incarcerated jail population illustrate that the majority of individuals who are confined are under the age of 40 years (Harrison & Beck, 2006; James, 2004). It is estimated that about 26% are between 18-24 years and 35% are between 25-34 years of age (Bronson & Berzofsky, 2017). Minton and Zeng (2016) report that the adult incarceration rate for individuals who are 18 years of age and older has started to decline slowly from 2006-2013, however, the rate still remains significant and the majority of the population still contains individuals who are younger.

An offender's age has routinely been identified as one of the most consistent predictors of recidivism. A meta-analysis conducted on offender reentry concluded that age was a significant predictor of adult recidivism, indicating that age was negatively correlated with recidivism

(Gendreau, et al., 1996). This conclusion between age and criminal behavior is often attributed to the age-crime curve offered by Gottfredson and Hirschi (Gottredson & Hirschi, 1990). The relationship suggests a curvilinear relationship between age and criminal activity, revealing a sharp incline in offending behavior during early adolescence, followed by a steep decline into the mid-20s, and thereafter more steadily (Farrington, 1986; Gottfredson & Hirschi, 1990). In essence, as individuals become older they tend to "age out" of their criminal careers (Hanson, 2002; Laub & Sampson, 2003).

Empirical research on jail reentry supports these theoretical underpinnings that age is negatively corelated with the likelihood of recidivism. For example, Weller (2012) revealed in their study that age was negatively correlated with re-arrest rates in three separate counties in Florida. Jung and colleagues (2010) conducted a study in Pennsylvania and found that older age at the time of release was associated with a significantly lower risk of re-arrest, as well as longer survival time. A one-year increase in age was related to a 1.6% decrease in the risk of recidivism (Jung, et al., 2010). In addition, Olson (2011) revealed in a sample of individuals released from Cook County Jail that inmates who were 25 years or younger at the time of their release had the highest rate of new arrests (60.3%), followed by those who were 36-50 years (51.7%), 26-35 years (49.3%), and over 50 years of age (40.9%). Finally, Verheek (2015) examined individuals released from a correctional facility between 2010-2011 and concluded that age significantly decreased the odds of re-arrest by 2.3% each year, as well as reduced the odds of reincarceration by 1.6% each year.

Interaction effects of gender, race, ethnicity, and age. Scholars frequently examine the interaction effects of gender, race, ethnicity, and age on the likelihood of recidivism, although investigations tend to focus on male populations. Caudy and colleagues (2018) investigated the effects of race, ethnicity, and gender on jail reentry for a sample of individuals who were sentenced to jail in a large urban county between 2011-2013 and subsequently released. They concluded that both Black and Hispanic males were significantly more likely to receive a new arrest compared to White males (Caudy, et al., 2018). Jung and colleagues (2010) conducted an additional study in Pennsylvania that analyzed the interaction of age, gender, race and ethnicity on the likelihood to recidivate. They first examined the interaction of age and gender on recidivism patterns and found a gradual decrease in re-arrest rates as the age of release increased. More specifically, there was a 65.5% rate of new arrests for men who were 20 years of age and younger, compared to only 37.2% for men who were 50 years of age and older. The authors next examined the interaction effects of gender, race, and ethnicity and determined that about 12.0% more Black males, compared to White males, were re-arrested within one-year following release (43.0% and 31.1%). Further, at two-years post-release 57.6% Black males and 41.9% White males were re-arrested, and at three-years post-release there were 65.2% Black males and 47.6% White males re-arrested and jailed. This indicates recidivism rates that are roughly 1.6 times higher for Black males than for White males (Jung, et al., 2010). The authors also conducted a survival analysis to examine the time to failure and whether this varied along dimensions of individual-level factors. They found that Black males were rearrested earlier than White males, indicating an average survival time of 596 days for Black males and 732 days for White males (Jung, et al., 2010). Finally, the authors analyzed the interaction of age, gender, race and ethnicity on the likelihood to recidivate and concluded that age at release served as a stronger protective factor for Black males than White males. More specifically, younger Black males had an average of 651 survival days compared to 534 days for older Black males (difference of 117 survival days). Younger White males had an average of 746 survival days compared to older

White males who received an average of 712 survival days (difference of 34 survival days) (Jung, et al., 2010).

Risk level. The risk level of an offender is typically used for assessment and classification, as well as predicting the likelihood of recidivism. Multipurpose screens provide administration a description of the needs of inmates at reentry by measuring dimensions of mental health, employment, substance abuse, and criminal history among others (Mellow, Mukamal, LoBuglio, Solomon, & Osborne, 2008). These characteristics are then scored and combined to form a scale that can assist in providing appropriate services and programming while incarcerated (Miller, Caplan, & Ostermann, 2016). Additionally, assessment tools can identify not only the risk of recidivating but also specific areas that are most likely to impact recidivism, such as substance abuse, education, prior criminal history, and criminal thinking (Mellow, et al., 2008).

Gendreau and colleagues' (1996) meta-analysis on the strength of various predictors of adult recidivism concluded that an individual's risk score produced one of the highest values for predicting the odds of recidivating. Further, scholars who have examined the association between risk level and recidivism have found support that risk score and recidivism are significantly associated. A study of sentenced and released offenders in 2004 from a county jail in Massachusetts revealed that inmates identified as low-risk were the least likely to be rearraigned, reconvicted, and reincarcerated within one year. Those identified as medium-risk received higher rates of recidivism than low-risk, and offenders who were high-risk revealed the highest rates of recidivism on all three outcome measures (Lyman & LoBuglio, 2006). Another study involving inmates released from jail in 2015 determined that high-risk individuals received the highest rates of reincarceration within one-year post-release, followed by those identified as medium-risk and low-risk (Lyman, 2017). Finally, Caudy and colleagues (2018) concluded in their examination of individuals who were sentenced to jail between 2011-2013 that risk score was positively associated with increased odds of re-arrest. That is, as an individual's risk level increased, so did their chances of recidivism after release from jail.

Prior criminal record. It is estimated that 73% of inmates in jail have been previously sentenced to either probation or to an incarceration term (Solomon, et al., 2008). As such, prior criminal history has long been suggested as a significant predictor of future criminal behavior. Several scholars have supported this in their studies of offender reentry, where adult criminal history is consistently reported as a major risk factor for predicting recidivism (Andrews & Bonta, 1998a; Brennan, et al., 2009; Gendreau, et al., 1996). An empirical investigation by Miller and Miller (2010) revealed a positive correlation between prior criminal record and recidivism, demonstrating that an increased number of previous charges significantly increased individuals' likelihoods of re-arrest within 12 months post-release. Additional studies have examined the impact of prior convictions on the likelihood to recidivate following release from jail, concluding a similar positive and significant association (Caudy, et al., 2018). Lyman (2017) further indicated that two or more prior convictions had the strongest correlation with an inmate's likelihood of receiving a new incarceration term within one-year post-release.

Current criminal record. Not only does the prior history of an inmate influence their likelihood to recidivate in the future, but their current offense also has a significant impact on reentry. In 2015, it was estimated that 68 - 70% of jail inmates were being held for a felony offense, while 27% were held for a misdemeanor or other criminal offense (5%) (Minton & Zeng, 2016; Zeng, 2018). Investigating the effect current offense may have on recidivism after release, Fritsche (2019) concluded that individuals with a current misdemeanor charge were more likely to be rearrested within 12-months than those with a felony charge. Scholars support the finding that more serious offenses tend to be associated with a lower risk of recidivism (Fritsche, 2019; Sawyer & Wagner, 2017). Looking specifically at the type of current offense, Lyman and LuBuglio (2006) determined that violent offenses were associated with the lowest rates of both reconviction and reincarceration. For reconviction, individuals with a current public order offense received the highest rates of recidivism (45.7%), followed by property offenses (22.7%), drug-related offenses (16.7%), and then violent offenses (14.8%). Similarly, reincarceration rates were the highest for individuals with a current public order offense (39.4%), followed by property offenses (19.2%), drug-related offenses (15.1%), and violent offenses (12.3%). Other studies have revealed that having a current property or drug-related offense presents the highest risk of recidivism (Singh & Frazel, 2010; Stahler, et al., 2013).

Time served. An individual's length of stay in jail also has been investigated as a potential influence on post-release offending. Time served is important to examine because the average daily jail population is largely driven by the changes in admissions, releases, and lengths of stay (Olson, 2011). Compared to prison, individuals in jail spend significantly shorter periods of time in confinement. In 1983, the average length of stay in jail for *both* convicted and un-convicted offenders was 14 days (Subramanian, et al., 2015). This increased slightly in 2013 to 23 days on average, and to 25 days in 2016 (Subramanian, et al., 2015; Zeng, 2018). For offenders who are convicted and sentenced to serve time in jail, it is estimated that individuals will serve an average of nine months behind bars (Solomon, et al., 2008).

Empirical research on time served has presented some inconsistent findings. For instance, Jung and colleagues (2010) conducted an analysis that examined the effect of time served and likelihood of re-arrest for individuals released from jail. They determined a positive association between the two variables, signifying that longer time served in jail was significantly related to a higher risk of re-arrest. Further, a survival analysis revealed that longer time served was correlated with a shorter survival time. For each additional day in jail, there was a 0.1% increase in the risk of re-arrest for individuals (Jung, et al., 2010). However, other studies have determined that *shorter* periods of confinement are associated with increased odds of recidivism (Tartar & Jones, 2016). Even more, some research has indicated that time served is not significantly related to the risk of recidivism (Bahr, et al., 2010; Huebner, DeJong, & Cobbina, 2010).

Neighborhood Context

Identifying the individual-level factors associated with recidivism patterns provides a necessary component for reducing recidivism, however, it may offer an incomplete understanding (Wright & Cesar, 2013). Many individual characteristics are largely influenced by the social forces within one's immediate environment (Kubrin & Weitzer, 2003). As such, the inclusion of neighborhood context in reentry research is necessary to gain a more holistic understanding of the recidivism process (Clear, 2007; La Vigne & Thomson, 2003; Wright, Pratt, Lowenkamp, & Latessa, 2012). Focusing exclusively on individual characteristics fails to recognize the potential importance of certain neighborhood factors on recidivism (Wright, et al., 2012).

Concentrated disadvantage. One such variable commonly found to have a significant impact on the likelihood to recidivate following release from incarceration is concentrated disadvantage (Pratt & Cullen, 2005; Verheek, 2015). This is a broad term for neighborhoods with higher proportions of residents of lower socioeconomic status (Kubrin, 2009). Research on reentry has focused almost exclusively on prisoner reentry and operationalizes the concept of concentrated disadvantage slightly different. Chamberlain and Wallace (2016) utilized indicators related to the percent of residents living below poverty, percent unemployed, percent of single-parent households, median income level, and the median home value. Alternatively, Morenoff and colleagues (2001) created a “concentrated disadvantage index” through the combined *z*-scores related to the percentage of families receiving public assistance, percent unemployed, percentage of female-headed households with children, and the percentage of Black residents. Finally, Pratt and Cullen (2005) conducted a meta-analysis that, in part, tested concepts of social disorganization theory related to racial heterogeneity, socioeconomic status, residential mobility, family structure and disruption, and collective efficacy. They concluded that neighborhood-level social disorganization, specifically high levels of concentrated disadvantage, was a significantly stable predictor of crime (Pratt & Cullen, 2005).

While concentrated disadvantage has gained empirical support with prisoner reentry, there is a dire lack of examinations regarding the impact it may have on individuals released from jail. Further, analyses that have examined this relationship present mixed findings. Verheek (2015) investigated the relationship between concentrated disadvantage and jail reentry for a correctional facility in Michigan between 2010-2011. Concentrated disadvantage was operationalized through the percentage of individuals receiving public assistance, the percentage of persons living below the poverty level, the percent unemployed, median family income, and the percentage of households headed by a single parent. The author revealed similar findings to that of prisoner reentry, where higher levels of concentrated disadvantage were associated with higher rates of re-arrest and reincarceration (Verheek, 2015). Fritsche (2019), on the other hand, came to a different conclusion in the association between concentrated disadvantage and recidivism. The author conducted a study examining various individual and neighborhood characteristics on the likelihood of recidivism for individuals released from New York jails in 2015. To operationalize concentrated disadvantage, she employed indicators of the percent unemployment rates, percentage of the population under 18 years of age, percentage of female-headed households, and median household income. Analyses revealed that concentrated disadvantage was not significantly related to the odds of recidivism, but instead individual-level factors played a larger role in the likelihood of receiving a new arrest (Fritsche, 2019). It becomes apparent then that additional research is needed to better understand the role that concentrated disadvantage may play on jail reentry.

Concentrated affluence. It is frequently suggested that measures of concentrated disadvantage only tell part of the story and neglects the phenomenon of concentrated affluence. Affluence should be accounted for in neighborhood-level research because it can provide protective factors in areas that have additional contextual factors that would otherwise produce higher rates of crime (Morenoff, et al., 2001). To account for this, Massey (2001) offers the Index of Concentration at the Extremes (ICE) measure. This measure captures the level of concentrated affluence relative to the concentration of poverty within an area. In essence, ICE examines the degree to which persons with various levels of poverty and affluence coexist in a neighborhood, representing relative inequality rather than absolute levels of disadvantage (Massey, 2001). Scholars have created the following formula to analyze concentrated affluence:

$$\frac{\text{(number of affluent households– number of poor households)}}{\text{(total number of households)}}$$

“Affluent” generally refers to households with annual incomes that are two standard deviations above the mean, while “poor” households are those with annual incomes below the poverty line. The resulting formula produces a value between +1 and -1, where +1 indicates that all households are affluent, -1 indicates that all households are poor, and 0 indicates an equal balance of both (Massey, 2001; Morenoff, et al., 2001).

The only study found that has examined the relationship between concentrated affluence and jail recidivism was conducted by Verheek (2015). In his study of jail ex-inmates in Michigan, he found that higher levels of concentrated affluence (as measured through ICE) were significantly related to lower rates of both new arrests and incarceration terms within two years post-release. This suggests that neighborhoods with higher proportions of families who were wealthy may have had the ability to exercise informal social control and thus direct community efforts towards local problems, such as crime (Kornhauser, 1978; Shaw & McKay, 1942).

Racial and ethnic heterogeneity. Aside from concentrated disadvantage and affluence within a neighborhood, many scholars have argued that reentry research would not be complete without the consideration of race and ethnicity in a macro-level framework (Hallett, 2012; Lyles-Chockley, 2009; Nixon, et al., 2008; Olusanva & Cancino, 2012). Communities with diverse racial groups who live in close proximity to each other are likely to have fewer interactions between residents compared to racially homogeneous communities (Gans, 1968). In addition, heterogeneous neighborhoods are more likely to have cultural differences, which could impact their ability to agree on a common set of goals and values to solve regularly experienced problems. As a result, individuals will be less likely to have concern for one another or take interest in neighborhood activities, thus limiting the level of informal social control and increasing the chance for higher rates of crime (Bursik, 1988; Kornhauser, 1978).

Operationalizing racial and ethnic heterogeneity typically includes one or more of the following indicators: percentage of residents who are Black, non-Hispanic, percentage of residents who are Hispanic/Latino, or percentage of residents who are foreign-born

(Rhineberger-Dunn & Carlson, 2009; Verheek, 2015). These measures provide an indication of the diversity found within a given community and the potential impact this may have on the rates of crime in that area. Verheek (2015) incorporated this in his analysis of jail ex-inmates by investigating the influence of racial and ethnic heterogeneity separately through the examination that two randomly selected individuals would be from different racial groups (black and non-black; Hispanic and non-Hispanic). It was revealed that higher levels of Black heterogeneity significantly increased the odds of both re-arrest and reincarceration; and higher levels of Hispanic heterogeneity were also associated with higher rates of re-arrest and reincarceration within two years post-release (Verheek, 2015). These findings suggest, and in alignment with social disorganization theory, that heterogeneous areas may be less likely to share common goals, thus limiting informal social control and increasing recidivism.

Residential stability. Residential mobility habitually serves as a neighborhood characteristic that may influence the jail reentry process. Defined as the frequency with which people move in and out of a neighborhood, this measure has significant connections to social disorganization theory (Kubrin, 2009). Some communities experience high turnover rates, with residents continually moving in and out of an area. Consequently, this makes it more difficult for residents to know, trust, and interact with one another, which disrupts and limits a community's network of social integration and cohesion (Crutchfield, 1989; Crutchfield, Geerken, & Gove, 1982). Lower levels of interaction and cohesion further limit a community's ability for informal social control, ultimately increasing the chances for crime to occur (Kubrin, 2009; Sampson & Groves, 1989).

Scholars that have used residential mobility in their examinations of offender reentry have operationalized their concept using various indicators. Typically, the average length of residence, percentage of households that have moved into their residence during the past five years, percentage of housing units that are currently vacant, and percent homeowners are used to gain a sense of turnover within an area (Chamberlain & Wallace, 2016; Morenoff, et al., 2001; Sampson, et al., 1997; Verheek, 2015). Analyses then tend to reveal that violence is often associated with residential instability of a neighborhood (Sampson, et al., 1997). Verheek (2015) indicated that residential instability was significantly associated with the recidivism level for jail ex-inmates. In his study of offenders who were released between 2010-2011 from Kent County Correctional Facility in Michigan, results indicated that 74.5% of those who were released returned to zip codes that held the lowest levels of residential stability. Furthermore, he found that higher levels of residential stability within a given zip code significantly decreased the odds of both re-arrest and reincarceration (Verheek, 2015). This leads to the indication that residentially stable neighborhoods are likely characterized by residents who have lived there for a sufficient amount of time. Accordingly, these residents have a higher likelihood to interact, know, and trust one another and collectively work together to solve local issues, such as crime (Kubrin, 2009; Sampson & Groves, 1989).

Summary

The reentry process can be complex since there are potentially multiple individual- and neighborhood-level factors at work in influencing an individual's likelihood to recidivate following release from incarceration. Individual characteristics, such as demographics, risk level, criminal record, and time served have been found to significantly influence the risk of recidivism (Fritsche, 2019; Jung, et al., 2010; Verheek, 2015; & Cesar, 2013). Additionally, neighborhood context is regarded as a needed inclusion in recidivism research because it provides a holistic understanding of the reentry process. Concentrated disadvantage and affluence, racial and ethnic heterogeneity, and residential stability are among some of the most reliable predictors of recidivism (Fritsche, 2019; Gendreau, et al., 1996; Verheek, 2015). Yet, the research on offender reentry remains significantly limited to examinations of prisoners. It becomes imperative then to offer additional research on the jail reentry process to better understand the influence that various individual and neighborhood characteristics may have on the likelihood to recidivate. It can then be determined whether former jail inmates have unique profiles and needs upon release, and whether they differ from former prisoners with regards to the nature and severity of recidivism and reentry risks.

Current Study

Research on the influences of jail recidivism remains an important topic of investigation. Considerable research is available on the reentry of individuals released from state or federal prisons, yet little attention has been directed towards those released from jails. This is largely due to the unique challenges that jails present. Jails are located in the center of communities, with an estimated 12 million individuals cycling in and out each year (Beck, 2006; Solomon, et al., 2008). As such, jails consist of heterogeneous populations (i.e., both convicted and un-convicted offenders, and both low- and high-risk offenders), shorter confinement periods, and unpredictable release dates, making it more difficult to track offenders following release (Jung, et al., 2010; Lyman & LoBuglio, 2006; Solomon, et al., 2008). Additionally, compared to prisons, *every* offender sentenced to incarceration in jail will eventually be released and will likely return to the same economically disadvantaged neighborhood from which they left (Freudenberg, et al., 2007; Miller & Miller, 2010; Subramanian, et al., 2015; Travis, 2005). Using local data to assess various characteristics of the jail population represents the critical first step in identifying who recidivates, which factors impact that recidivism, and how resources can be allocated in communities to better prevent criminal activity and enhance public safety (Janetta, 2009).

Furthermore, not only is there an overall lack of research on jail recidivism, but the use of theory to explore the role of jails in criminal justice remains sparse (Klofas, 1990). There are only two studies that employed social disorganization theory as a framework for understanding the relationship between neighborhood context and jail recidivism; and these studies present mixed findings. Fritsche (2019) employed police precinct level as the proxy for neighborhood context, finding only minor support for social disorganization theory and instead suggesting that individual risk played a larger role in jail recidivism. Verheek (2015) employed zip codes as the proxy for neighborhood context and found evidence that neighborhood-level factors were significantly related to the likelihood for individuals to recidivate post-release from jail. It is possible that differences found in the association of neighborhood context and recidivism was due to the choice of the neighborhood-level unit of analysis, but further investigations are warranted to better understand the relationship between neighborhood characteristics and jail recidivism.

Finally, employing recidivism as an outcome measure can be a valuable indicator of correctional impact and problems related to criminal activity and public safety (Urban Institute, n.d., Wright & Cesar, 2013). Yet, much of research incorporates only a single measure of recidivism, revealing limited conclusions of recidivism processes and the full impact of various changes in policy and practice (King & Elderbroom, 2014). Additionally, the choice of indicator influences the level of recidivism that will be observed. Using re-arrest as the sole indicator produces the highest rates of recidivism, followed by reconviction and reincarceration (Durose, et al., 2014; James, 2015). Incorporating multiple measures of recidivism provides a more comprehensive picture of recidivism patterns (Erdahl, 2015). This can then produce more reliable and effective implications for practice and policy.

Taking into account the challenges and gaps in the current literature, several questions remain regarding the impacts of jail reentry. Specifically, what individual characteristics affect the likelihood that an ex-jail inmate will recidivate following release from incarceration? What neighborhood characteristics impact the odds of recidivism for former jail inmates? Are there cross-level interactions between individual- and neighborhood-level factors that work together to significantly influence the likelihood of recidivism?

The present dissertation sought to address these gaps in the literature on jail recidivism by examining a sample of individuals who served at sentence at the House of Corrections in Milwaukee County, Wisconsin, and were released in 2013 and 2014. Using a three-year recidivism window, it was examined whether individual and neighborhood characteristics were associated with a jail ex-inmate's likelihood of receiving a subsequent charge, conviction, or incarceration term.

Hypotheses

The current dissertation examined the influence of individual- and neighborhood-level factors on the likelihood for individuals to recidivate following release from jail. To assess the impact of these variables on recidivism risk, two theoretical models were used to explore both individual and neighborhood characteristics. The Risk-Needs-Responsivity (RNR) model has offered several individual-level risk factors that are shown to influence the likelihood of recidivism (Andrews & Bonta, 1990, 2006; Christensen, Jannetta, & Willison, 2012; Fritsche, 2019; James, 2018; Weller, 2012). This analysis examined several of those criminogenic risk factors and tested the following individual-level hypotheses:

(H.1) Individuals who are younger, male, and Black will have higher odds of recidivism than their counterparts.

(H.2) Individuals with a more extensive prior criminal record and a higher LSI-R:SV total risk score will have higher odds of recidivism than individuals with a less extensive prior criminal record and lower LSI-R:SV total risk score.

(H.3) Individuals who were initially convicted of a property offense will have the highest odds of recidivism compared to their counterparts.

(H.4) Time served will be significantly associated with an individual's likelihood of recidivism[4].

Social disorganization theory also offers several neighborhood-level variables that are shown to significantly influence the likelihood of recidivism (Fritsche, 2019; Pratt & Cullen, 2005; Verheek, 2015). Using this framework as a theoretical underpinning, the current analysis tested the following neighborhood-level hypotheses:

(H.5) Neighborhoods with higher levels of concentrated disadvantage, concentrated immigration, and racial and ethnic heterogeneity will have increased rates of recidivism compared to their counterparts.

(H.6) Neighborhoods with higher levels of neighborhood affluence and residential stability will have decreased rates of recidivism compared to their counterparts.

Finally, prior literature has also examined cross-level interactions between individual- and neighborhood-level variables and their influence on recidivism (Caudy, et al., 2018; Jung, et al., 2008; Verheek, 2015). Following these examples and the basic tenants of the RNR model and social disorganization theory, the present analysis sought to test a cross-level interaction

[4] Time served has presented inconsistent findings throughout prior literature and, therefore, a non-directional hypothesis was used in the current research.

hypothesis between individual- and neighborhood-level variables of certain demographic characteristics and concentrated disadvantage. Specifically,

(H.7) Younger Black males who reside in neighborhoods with higher levels of concentrated disadvantage will have the highest odds of recidivism compared to their counterparts.

CHAPTER 3

METHODOLOGY

The present research examined the influence of individual- and neighborhood-level factors on the likelihood for individuals to recidivate following release from local corrections in Milwaukee County, WI. To assess the hypotheses put forth in Chapter 2, the current research examined data from a sample of individuals who served a sentence at the House of Corrections in Milwaukee County and were released in 2013 and 2014. A three-year recidivism window was then evaluated to determine whether any individual or neighborhood characteristics were significantly associated with a jail ex-inmate's likelihood of receiving a subsequent (1) charge, (2) conviction, or (3) incarceration term. The present study sought to address gaps in prior literature and provide a comprehensive understanding of recidivism and what factors may drive that recidivism for a jail-specific sample of individuals.

Study Setting

Milwaukee County is the most populous county in the state of Wisconsin, with an estimated population of 948,201 individuals (U.S. Census Bureau, 2018, July 1). The population in the county is 51.6% female and 48.4% male. The majority of the county is also White (51.5%), followed by Black (27.2%) and Hispanic/Latino (15.1%) (U.S. Census Bureau, 2018, July 1). Roughly 19.1% of the population lives in poverty, yet the unemployment rate in 2018 was around 3% (U.S. Bureau of Labor Statistics, 2019, May 1; U.S. Census Bureau, 2018, July 1). Further, Milwaukee is often recognized as the most segregated city in the country. Results of the American Community Survey released from the U.S. Census Bureau for 2013-2017 revealed that Milwaukee received the highest segregation index in the country (79.6)[5], ahead of New York, Chicago, and Detroit (Frey, 2018). Wisconsin has also been at the forefront for incarceration rates among black males, with zip code 53206 gaining special attention as the "zip code that incarcerates the highest percentage of black men in America" (Levine, 2019).

The Wisconsin Department of Corrections has statutory authority over two main local correctional centers, including the Milwaukee County Jail (MCJ) and the Milwaukee County House of Corrections (HOC) (Clark, 2010; Dietz, 2018; Henken, 2011). The HOC, which remained the focus of the current study, is a 2,000-bed secure detention facility that typically houses offenders who have been sentenced to an incarceration term of one year or less (Henken, 2011). It was estimated in 2017 that about 1,250 inmates were currently being housed in the HOC (Behm & Diedrich, 2017).

An analysis was conducted by the Pretrial Justice Institute that examined the county's jail population, including trends in both the MCJ and the HOC. Findings indicated that in 2003 the majority of adults were arrested in Milwaukee County for a criminal traffic offense, followed by a criminal misdemeanor and a criminal felony offense. This changed slightly in 2008 when the majority of adults were being arrested for a criminal misdemeanor offense (Clark, 2010). Further, the number of overall jail bookings decreased from 2003-2008, however the average length of stay increased from about 24 days in 2003 to roughly 28 days in 2008. Examinations of jail inmate profiles reveal similar findings to those of national statistics. In 2008, the majority of

[5] The segregation index varies from values of 0 (i.e., complete integration) to 100 (i.e., complete segregation), and represents the percent of Blacks that would need to relocate to be fully integrated with Whites across metropolitan neighborhoods (Frey, 2018).

adults who were booked into local corrections were younger Black males. Additionally, 45.2% were booked with a felony offense as the most serious charge, followed by 35.2% for misdemeanors and 7.7% for an ordinance or traffic offense; and 47.9% of adults were booked on only one charge (Clark, 2010). Finally, a further investigation on the number of prior bookings for individuals in Milwaukee County illustrate that only one in five adults were booked in Milwaukee County local corrections for the first time, while about half of the population had five or more previous bookings in Milwaukee County (Clark, 2010). These findings present a dire need for further investigations of local corrections in Milwaukee County and the potential influences that are leading to repeated returns to jail.

Data Collection

The current research merged several existing data sources. This study relied in part on individual-level data collected by the Office of African American Affairs and Comcentia for individuals who were released from local corrections in Milwaukee County. Additionally, neighborhood-level data was collected from the U.S. Census Bureau to operationalize variables of concentrated disadvantage, concentrated affluence, concentrated immigration, racial and ethnic heterogeneity, population density, and residential stability.

Level-One Data Sources

Individual-level data was initially obtained from the Office of African American Affairs (OAAA) and Comcentia[6] in Milwaukee County, WI. These data included information on individuals who were completing a sentence at the Milwaukee County House of Corrections (HOC) and were subsequently released in 2013 and 2014. Further, these sources contained information on demographics (e.g., gender, race and ethnicity, and age), booking and release

[6] Comcentia is an IT company that provides support to the Office of African American Affairs in obtaining and managing data.

date, type of custody (i.e., un-convicted or convicted), risk score, and the severity and type of current offense[7]. Information provided from OAAA and Comcentia was also used to determine each individual's prior criminal record (e.g., prior charges, prior jail incarcerations, prior prison incarcerations). Additional data was obtained from the ProPhoenix corrections management system (CJIS) for Milwaukee County local corrections and the Wisconsin Circuit Court Access (CCAP)[8]. These data contained information on recidivism for local correctional populations. In an effort to link these data sets, a "unique identifier" was created that incorporated defendants' first three letters of their first name, first three letters of their last name, and their date of birth[9] (Milwaukee Community Justice Council, 2014). This ensured that information from CJIS and CCAP could be accurately linked to the initial information contained on all individuals who were completing a sentence at the HOC. Once linked, the final data set contained complete information on all individuals who were completing a sentence at the HOC and whether they recidivated. The data set was then examined to determine eligibility within a three-year time period following release.

Level-Two Data Sources.

Initial data obtained from the Office of African American Affairs and Comcentia on individuals who completed a sentence at the HOC also contained information on the home address reported by offenders upon their initial release. Prior research that has examined neighborhood context in relation to recidivism frequently employs the address that is first

[7] If an individual had multiple charges related to the current case, the most serious charge was kept for analysis.
[8] The ProPhoenix corrections management system is a software that allows for inmate tracking, including booking and release information (ProPhoenix, 2019). The Wisconsin Circuit Court Access is a "website that provides public access to the records of Wisconsin circuit courts for counties using the Consolidated Court Automation Programs (CCAP) Case Management system (Wisconsin Court System, 2012).
[9] Example of a unique identifier: (first name) John, (last name) Smith, (date of birth) 01/01/1987 = JohSmi01011987. The match success rate for the current sample was 99.75%. There were 20 cases where the unique identifier was the same and the data could not be accurately matched. These data were excluded from the data set.

reported upon release as a sole measure since that is typically the only data that is available (Bensel, Gibbs, & Lytle, 2015; Kubrin & Stewart, 2006; Kubrin, Squires, Stewart, 2007; McNeeley, 2017; Stahler, Mennis, Belenko, Welsh, & Hiller, 2013). As such, these studies have been criticized because the measure that is self-reported to administration upon release may not actually represent the location at which the offender most frequently resides (Bensel, Gibbs, & Lytle, 2015; Petersilia, 2003). While this is certainly a possibility, several studies have found that individuals' residences remain stable over time. For example, La Vigne and Parthasarathy (2005) determined that 88% of their sample were residing in the same residence approximately two-to-three months following their release from incarceration, and 72.4% were still residing in the same place one-to-two years following their release. For those individuals who did move, they generally moved to areas that had similar socioeconomic factors (La Vigne & Parthasarathy, 2005). Another study found similar results, where only 35% of their sample had changed residences eight months following their release from incarceration (Visher, Yahner, & La Vigne, 2010). Therefore, while cautious, the present study utilized the first known address that was reported to administration following their release from the HOC in 2013 or 2014.

Defining the appropriate unit of analysis for recidivism remains important to effectively examine empirical relationships. Prior literature has employed a variety of geographical areas to capture neighborhood-level processes, including zip codes, census tracts, and census block groups (Hipp, 2007; Krieger, et al., 2002). Zip codes represent administrative units established by the United States Postal Service (USPS) and are a popular geographic unit because of their ease for collecting information at the zip code level (Grubesic, 2008; Krieger, et al., 2002). Several issues transpire though when employing zip codes as the level of aggregation. First, rather than geographical space, zip codes are attributed to roads and post offices. Thus, if an area does not have a recognized address range it will not be assigned a zip code (Grubesic, 2008; Grubesic & Matisziw, 2006). Second, the USPS makes updates to their zip code boundaries which could change the boundary that an individual is placed in over time (Grubesic & Matisziw, 2006; Krieger, et al., 2002). Third, compared to census tracts and census block groups, zip codes contain a larger population size and researchers could run the risk of capturing a unit that contains several neighborhoods (Hipp, 2007). In comparison to zip codes, census tracts are defined by the U.S. Census Bureau as relatively small and permanent statistical subdivisions of a county. Census tracts generally contain between 1,500 and 8,00 people and are designed to be homogeneous with respect to population characteristics (e.g., socioeconomic status, living conditions, etc.) (Hipp, 2007; Krieger, et al., 2002; U.S. Census Bureau, n.d.). Census block groups are characterized by even smaller geographic boundaries, containing between 600 and 3,000 people. These entities are the smallest geographic unit for which census data is published and are identified by a five-digit zip code tabulation area (ZCTA) to overcome the difficulties of defining areas covered by each zip code (Grubesic, 2008; Krieger, et al., 2002; U.S. Census Bureau, n.d.b).

When considering each of these geographical areas, the choice of geographic aggregation used for analysis ultimately depends on the spatial component of the relationships being studied. Employing zip codes as the unit of analysis for recidivism is likely too great a level of aggregation since several neighborhoods, each with their own amount of heterogeneity, will likely be captured in one unit (Hipp, 2007). As such, census tracts or census block groups become the ideal units of analysis to estimate relationships between neighborhood context and recidivism. Hipp (2007) found in his analysis of crime and disorder that aggregating the geographic unit to the block-level provided the best approach to estimating the true conditions in a neighborhood. In alignment with these findings, the current study employed census block groups as the unit of analysis. This allowed the analysis to accurately estimate the true relationship between neighborhood context and recidivism by employing the data at the smallest geographic unit available by the Census Bureau.

Sample

As illustrated above, the data contained information on individuals who were completing a sentence at the HOC in Milwaukee County and were released in 2013 or 2014. The original data set yielded 15,435 cases. When examining jail recidivism, it remains important to clearly define the portion of the jail population that is released to the community and "at risk" of recidivating. Including offenders who are being released for transfer to another correctional facility would underestimate the true recidivism rate of the population (Lyman & LoBuglio, 2006). Therefore, the current study considered an individual to be "at risk" of recidivating if they were under the custody of the HOC, had a release reason code of "time served/sentence completed", and were initially booked under one of the statuses that has been deemed suitable[10] (Milwaukee Community Justice Council, 2014). All other individuals who did not meet the criteria were removed from the sample (n=7,455). In addition, if an individual, upon release, reported a home address that was outside of the City of Milwaukee, WI[11] they were excluded from the study (n=1,498)[12]. Thus, the final data set used for analysis contained 6,482 cases.

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[10] Individuals were considered eligible if they had one of the following initial booking status codes: awaiting sentencing, felon pretrial, felon sentenced Huber employed, felon sentenced Huber unemployed, felon sentenced state charge, felon sentenced work release employed, felon sentenced work release student, felon sentenced work release unemployed, misdemeanor other county Huber employed, misdemeanor pretrial, misdemeanor sentence Huber employed, misdemeanor sentenced Huber student, misdemeanor sentenced Huber unemployed, misdemeanor sentenced on probation, misdemeanor sentenced state charge, misdemeanor sentenced work release child care, misdemeanor sentenced work release employed, misdemeanor sentenced work release unemployed (Milwaukee Community Justice Council, 2014).

[11] The City of Milwaukee was chosen over the county of Milwaukee because the cell sizes within each block group for Milwaukee County were too small to conduct an analysis.

[12] Chi-square tests and independent samples t tests were conducted to determine if the two sets of groups (City of Milwaukee vs. Milwaukee County) differed significantly on any variables. The results revealed significant differences on gender, race (White, Black, other), current offense type (violent, public order, OWI-related, traffic-related), age at release, prior charges and prison incarcerations, new charges, new convictions, new incarceration terms, and all neighborhood-level variables [see Appendices A-C for full tables].

Dependent Variables

Recidivism, in general terms, occurs when an individual commits a crime, engages in a period of criminal justice system intervention, and is subsequently charged, convicted, or reincarcerated for a new crime within a certain period of time (Milwaukee Community Justice Council, 2014). The current research employed three measures of recidivism to better capture a comprehensive picture of reentry, including recharge, reconviction, and reincarceration. Each dependent variable was measured as a binary outcome (yes/no). To provide a longitudinal understanding of recidivism patterns among the current sample, a follow-up period of three years was used. Thus, individuals who were released from the HOC in 2013 were followed through 2016; and individuals who were released from the HOC in 2014 were followed through 2017. The initial starting point represented the date the individual was released from the HOC and, in the case of recidivism, the failure event represented a subsequent *offense date* [within a three-year period] that was contained in the CCAP entry.

New charges. A new charge was considered eligible if an individual received a subsequent offense post-release that was either a criminal traffic (CT), criminal misdemeanor (CM), or criminal felony (CF) offense with a severity greater than a forfeiture. Further, the new charge needed to occur during the designated recidivism window employed for the current study (i.e., three years). For analysis, new charges were defined as a binary outcome coded as “0” for no new charge and “1” for one or more subsequent charges.

New convictions. A new conviction was considered eligible if an individual received a post-release CT, CM, or CF charge that had a severity greater than a forfeiture and resulted in a guilty disposition during the designated recidivism window. Any cases that were dismissed, deferred prosecution, or open were not counted as a guilty disposition. For analysis, new convictions were defined as a binary outcome coded as “0” for no new conviction and “1” for one or more subsequent convictions.

New incarceration terms. A new incarceration term was considered eligible if an individual met any of the following criteria following their release from jail: had an offense date occurring during the designated recidivism window, was found guilty on a new CT, CM, or CF charge with a severity greater than a forfeiture and was sentenced to a term of incarceration in either jail or prison. For analysis, a new incarceration term was defined as a binary outcome coded as “0” for no reincarceration and “1” for one or more subsequent incarceration terms.

Independent Variables

Prior research has offered various individual and neighborhood factors that significantly influence an individual’s likelihood of recidivating following release from jail. As such, the present study employed several individual-level and neighborhood-level independent variables, as grounded in theory, to determine the impact they had on recidivism for the current sample. Table 1 illustrates each of the independent measures (both individual- and neighborhood-level) and the coding values that were used.

Table 1: Coding of Independent Variables

Individual-level

Gender
- Male = 1
- Female = 0

Race/Ethnicity
- White, non-Hispanic, no = 0 yes = 1
- Black, non-Hispanic, no = 0 yes = 1
- Hispanic or Latino, no = 0 yes = 1
- Other, no = 0 yes = 1

Age at time of release (years)

LSI-R:SV total risk score (ranging from 0-8)

Prior criminal record
- Number of prior charges
- Number of prior jail incarcerations
- Number of prior prison incarcerations

Current offense type
- Violent, no = 0 yes = 1
- Property, no = 0 yes = 1
- Drug, no = 0 yes = 1
- Public order, no = 0 yes = 1
- OWI-related, no = 0 yes = 1
- Traffic-related, no = 0 yes = 1
- Other, no = 0 yes = 1

Time served
- Number of days individual was incarcerated for current conviction

Year of release
- 2013 = 0
- 2014 = 1

Neighborhood-level

Concentrated disadvantage
- Households receiving SSI (%)
- Persons in poverty (%)
- Persons 16+ years unemployed (%)
- Households receiving public assistance (%)
- Female single-parent households with children under 18 years (%)

Concentrated affluence
Families with income < $25,000
Families with income > $75,000
Total households
Concentrated immigration
Foreign-born persons (%)
Hispanic or Latino (%)
Racial/ethnic heterogeneity
White-alone (%)
Black or African American alone (%)
American Indian or Alaskan Native (%)
Asian (%)
Native Hawaiian or Pacific Islander (%)
Other (%)
Population density of neighborhood (total population/area size in square miles)
Residential stability
Owner-occupied housing unit rate (%)
Living in same house 1 years ago (%)

Individual-level Independent Variables

Gender. Prior research frequently employs various demographic characteristics in their analyses of recidivism, including the potential differences that may arise between males and females. It is often revealed that males have a significantly higher likelihood of recidivating post-release when compared to their female counterparts (Caudy, et al., 2018; Folk, et al., 2018; Fritsche, 2019; Olson, 2011; Verheek, 2015). Therefore, in the current research gender was examined as a dichotomous variable and was represented as either male (=1) or female (=0).

Race/ethnicity. An individual's race and ethnicity are viewed as one of the strongest predictors of recidivism, typically indicating that Black or Hispanic/Latino individuals have the highest risk for recidivating (Harrison & Karberg, 2004; Olson, 2011; Verheek, 2015; Weller, 2012; Yamatani, 2008). Four dichotomous variables were created for race and ethnicity, including White, Black, Hispanic/Latino, and other. Black was used as the reference category.

Age at release. Prior literature has also habitually examined the age of an offender in relation to their likelihood of recidivism, revealing a consistent positive correlation (Gendreau, et al., 1996; June, et al., 2010; Weller, 2012; Verheek, 2015). The present research followed this trend and examined an individual's age at the time of release from the HOC. This was represented as a continuous variable measured in years[13].

Risk score. The risk level of an offender represents another predictor of adult recidivism and has been found to produce one of the highest values for predicting the odds of recidivism (Gendreau, et al., 1996). In Wisconsin, officials frequently employ the Level of Service Inventory – Revised (LSI-R), which is a quantitative assessment tool that incorporates various offender attributes on criminal history, education and employment, financial, family and marital status, accommodation, leisure and recreation, companions, alcohol and substance issues, emotional and personal health, and various attitudes (Andrews & Bonta, 1995, 1998b). The LSI-R aids in predicting the risk of recidivism, as well as providing appropriate services and programming for individuals (Mellow, et al., 2008).

In addition to the LSI-R, there is a shorter version available (LSI-R: SV) that still incorporates the same assessment categories as the full version. Research conducted on the LSI-R:SV indicates that it is predictive of the same outcomes that are shown through the LSI-R (Andrews & Bonta, 1998b). The LSI-R:SV consists of eight items that are selected from the LSI-R: prior adult convictions, arrests under the age of 16, current unemployment, criminal associates, alcohol/drug problems, psychological problems, parental/intimate relationships, and

[13] Age was rounded to the nearest whole number.

attitudes supportive of crime. The first six items on the LSI-R:SV are scored on a “yes” or “no” assessment, and the last two items are rated on a “0-3” scale (very unsatisfactory, relatively unsatisfactory, relatively satisfactory, satisfactory) (Andrews & Bonta, 1998b). Responses are then summated to create the LSI-R:SV total, ranging from zero to eight (Andrews & Bonta, 1998b, Mellow, et al., 2008; Solomon, et al., 2008).

The current study examined risk score based on responses received from the LSI-R:SV[14] and were measured as a continuous variable. Risk level for the shortened assessment can vary from zero to eight, with a total score of “0-2” indicating minimum-risk, “3-5” indicating medium-risk, and “6-8” indicating maximum-risk.

Prior criminal record. Previous research that examines an individual’s prior criminal history and their subsequent likelihood of recidivism habitually reveal a positive correlation (Caudy, et al., 2018; Lyman, 2017; Miller & Miller, 2010). The current analysis investigated prior criminal record with three continuous variables: the number of prior charges, the number of prior jail incarcerations, and the number of prior prison incarcerations.

Current criminal record. In concurrence with an individual’s prior criminal history, their current criminal record frequently reveals a significant influence in their likelihood to recidivate once released. In the present study, current offense type represented the offense for which an individual was initially put under HOC custody. Seven dichotomous variables were created, including violent, property, drug, public order, OWI-related[15], traffic-related, and other. Property offenses was used as the reference category.

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[14] Efforts were made to use the full LSIR in the current study, however, 95.2% of the cases had missing data. For the LSIR:SV, there were 19.3% of the cases with missing data. Therefore, the LSIR:SV was used in the current study and multiple imputation was executed for the missing cases.

[15] Wisconsin classifies a drinking and driving offense as an OWI, while other states refer to this as driving while under the influence of an intoxicant (DUI) or driving while intoxicated (DWI). The largest difference between these cataloging is that in Wisconsin, a person can be prosecuted for driving while intoxicated even if they have not driven the vehicle since all that is needed is to either operate or turn the vehicle on (Bayer, 2017).

Time served. While jails represent short-term confinement facilities, the length of stay can potentially impact the likelihood of success post-release. In the present analysis, time served was incorporated as a continuous variable, representing the total number of days an offender served for their current conviction under HOC custody.

Year of release. Finally, a control variable was created to represent the year that an individual was released from the House of Corrections in Milwaukee County. One dichotomous variable was created for the year of release and was represented as either 2013 (=0) or 2014 (=1).

Neighborhood-level Independent Variables

The present data included information on the home address reported by offenders upon their initial release. Post-release addresses were geocoded using ArcView GIS for individuals within the City of Milwaukee. The initial data set containing 6,482 cases produced a 96% match (4% of the cases were not able to be matched, N=234). The geocoded addresses were then joined with census block groups in the City of Milwaukee. This produced 859 centroids within the city limits. Following, each of the neighborhood-level variables were created using publicly available data from the U.S. Census American Community Survey (2014, 5-year estimates). A principle components factor analysis using varimax rotation was used to produce indices for concentrated disadvantage, concentrated immigration, and residential stability (Table 2). Concentrated affluence was created using the Index of Concentration at the Extremes (ICE) measure, and racial/ethnic heterogeneity was created using the Herfindahl-Hirschman index (HHI). Population density was produced once the initial data was imported into ArcView GIS. This data was then imported into ArcView GIS and joined, along with individual-level data, to create a final data set that included complete information for each individual and their assigned census block group.

Concentrated disadvantage. Drawing on data from the U.S. Census American Community Survey, an index was constructed to represent neighborhood concentrated disadvantage for each census block group. The use of a single index to represent concentrated disadvantage reduced the threat of multicollinearity between related variables in the neighborhood-level research (Kubrin & Weitzer, 2003). Five indicators were used to reflect concentrated disadvantage: the proportion of persons receiving SSI, the proportion of persons in poverty, the proportion of persons unemployed, the proportion of households receiving public assistance, and the proportion of female single-parent households with children under 18 years. To create the index, factor analysis was employed to distill multiple indicators into one concentrated disadvantage index (Fritsche, 2019; Verheek, 2015). All five indicators had factor loadings above 0.69[16] (Table 2). Thus, an unweighted factor score was produced and was used as the independent variable for concentrated disadvantage in all subsequent analyses. Cronbach's alpha was further calculated to examine the reliability of the concentrated disadvantage measure and produced a value of .683, indicating good reliability.

Concentrated affluence. Concentrated affluence is another measure that was employed in the current research to account for the degree that persons with poverty and affluence coexist within a given area (Massey, 2001). The Index of Concentration at the Extremes (ICE) measure was created for each census block group and utilized the following formula:

$$\frac{\text{(number of affluent households – number of poor households)}}{\text{(total number of households)}}$$

[16] As shown in Table 2, the rotated component matrix indicated some relation between poverty and owner-occupied housing, however owner-occupied housing had the strongest factor loading on the third component (i.e., residential stability).

Data was collected from the U.S. Census American Community Survey (2014, 5-year estimate) to compute the ICE measure (U.S Census Bureau, 2018, October 11). Households were considered "poor" if they had an income less than or equal to the federal poverty line of $25,000; and households were considered "affluent" if they had an income greater than or equal to $75,000 (U.S. Census Bureau, 2019, January 24). The total number of households for a given unit was also included to compute the above formula. The resulting index produced a value between -1 and +1, where -1 indicates that all households in a given census block group are poor, 0 indicates a balance of both poor and affluent, and +1 indicates that all households are affluent (Massey, 2001; Morenoff, et al., 2001).

Concentrated immigration. The current study also captured the level of concentrated immigration in each census block group. Similar to the work of Sampson and colleagues (1997), the current study used two measures to create a concentrated immigration index: the proportion of foreign-born persons and the proportion of persons who are Hispanic or Latino. To create the index, factor analysis was employed to distill multiple indicators into one concentrated immigration index. Each of the two indicators had factor loadings above 0.9 and thus, an unweighted factor score was produced and used as the independent variable for concentrated immigration in all subsequent analyses (Table 2). Cronbach's alpha was also calculated to examine the reliability of concentrated immigration and produced a value of .708, indicating good reliability.

Racial/ethnic heterogeneity. The current study also examined the degree of racial and ethnic diversity in each census block group using the Herfindahl-Hirschman index (HHI):

$$\text{HHI} = 1 - (\text{White}^2 + \text{African American}^2 + \text{American Indian/Alaska Native}^2 + \text{Asian}^2 + \text{Hawaiian/Other Pacific Islander}^2 + \text{Other}^2)$$

The HHI examines the degree of heterogeneity by calculating the proportions of persons who are White, African American, American Indian or Alaska Native, Asian, Hawaiian or Pacific Islander, and of other racial/ethnic make-up. The resulting index represented the racial and ethnic heterogeneity for each census block group, with higher index scores representing greater diversity within an area (Hirschman, 1964).

Population density. The population density for a neighborhood was also included as a neighborhood characteristic for the present study. Information on the total population was gathered from the U.S. Census American Community Survey. Once data was imported into ArcView GIS the index for population density was created. To do so, the area size (in square miles) was produced and then used to calculate an index for population density (total population / area size). The resulting value was then used as the independent variable for population density in all subsequent analyses.

Residential stability. Another variable that is important to understanding the influence of neighborhood context and recidivism is residential stability. Prior literature that employs this measure typically reveals that higher levels of residential stability significantly decrease the odds of recidivism (Verheek, 2015). The present study sought to examine the impact of this context by including two indicators: the proportion of owner-occupied housing units and the proportion of persons living in the same household one year ago. Similar to other measures of neighborhood context, factor analysis was employed to distill multiple indicators into one residential stability index. Each of the two indicators had factor loadings above 0.8[17] (Table 2). An unweighted factor score was then produced and used as the independent variable for residential stability in all

[17] As shown in Table 2, the rotated component matrix indicated some relation between poverty and owner-occupied housing, however owner-occupied housing had the strongest factor loading on the third component (i.e., residential stability).

subsequent analyses. Cronbach's alpha was further calculated to examine the reliability of the residential stability measure and produced a value of .649, indicating adequate reliability.

Table 2: Varimax Rotated Matrix using Principle Component Factor Analysis

Indicators	*Factor 1*	*Factor 2*	*Factor 3*
Concentrated disadvantage			
Households receiving SSI	.815		
Persons in poverty	.711		-.350
Persons 16+ years unemployed	.699		
Households receiving public assistance	.690		
Female single-parent households	.716		
Concentrated immigration			
Foreign-born persons		.928	
Hispanic or Latino		.925	
Residential stability			
Owner-occupied housing units	-.373		.905
Living in same house 1 year ago			.801

Data Analysis

Multilevel modeling was originally proposed to test the hypotheses around individual risk, neighborhood context, and jail recidivism. Multilevel modeling was considered appropriate since the current study was examining the effects of individual-level variables being "nested" within neighborhood structure (Johnson, 2010; Luke, 2002, 2004). It recognizes that individuals in a given area may be more similar to one another than individuals who reside in another area (Kubrin & Stewart, 2006). If the current study were to implement a traditional one-level regression analysis it would violate the assumption of independence of standard errors because the standard errors are also correlated within the neighborhood-level (Fritsche, 2019; Guo & Zhao, 2000; Luke, 2002, 2004). Multilevel modeling could, therefore, allow the current study to accurately control for the influence of neighborhood clustering by separately estimating the intercepts and slopes of the individual-level data within the neighborhood-level data. This would also correct for any potential biases in the parameter estimates of the model and provide correct standard errors, ultimately allowing the possibility to examine which neighborhood factors affect recidivism rates (Guo & Zhao, 2000).

An initial series of two-level logistic regression models were employed using HLM7 to measure three binary outcomes (recharge, reconviction, reincarceration)[18]. In a preliminary set of analyses, unconditional models (i.e., models only including the random intercept) were conducted on all three dependent variables. The variance component for the random slope on all three outcome measures were not significant, indicating there was not sufficient variation in recidivism across census block groups (Table 3). The results of the unconditional models suggest that multilevel modeling was not necessary; and a single-level logistic regression analysis was appropriate to analyze the influence of individual-level variables on jail recidivism. Logistic regression analyses would allow for the measurement of how dichotomous and continuous independent variables influence binary dependent variables (e.g., recharge, reconviction, reincarceration).

Table 3: Results of the Unconditional Models[19]

	Standard Deviation	Variance Component	Degrees of Freedom	χ^2	p-value
New Charge	.120	.015	544	570.55	.208
New Conviction	.141	.020	544	577.62	.154
New Incarceration Term	.190	.036	544	582.88	.121

[18] The current analysis follows that of prior literature in measuring the dependent variable as a binary outcome (Fritsche, 2019; Horney, et al., 1995; Kubrin, et al., 2007; Kubrin & Stewart, 2006; McNeely, 2017; Verheek, 2015).
[19] Unconditional models were also run using census tracts as the unit of analysis. The results were also not significant.

CHAPTER 4

RESULTS

This chapter presents the results of the quantitative analyses employed to test the overall hypotheses offered in Chapter 2. First, descriptive statistics are presented for all independent (individual-level) and dependent variables in the current sample of individuals from the House of Corrections in Milwaukee County. Dichotomous variables were examined through frequencies, represented as percentages. Continuous variables were examined by calculating the mean and the standard deviation for each measure. Next, bivariate correlations are presented to illustrate significant relationships among the variables and to detect the presence of multicollinearity among the independent variables. Finally, results of the binary logistic regression models are presented. These models estimated the influence of various individual characteristics on the likelihood to receive a new charge, conviction, or incarceration term. Additionally, interaction effects were analyzed using logistic regression analyses to examine the influence of race, ethnicity, gender, and age on the likelihood of recidivism.

Descriptive Statistics

Table 4 presents the descriptive statistics for each of the three dependent variables. The rates of recidivism for the entire sample overall indicated 41.7% for new charges, 37.4% for new convictions, and 30.3% for new incarceration terms. Individuals who were released in 2013 received a higher rate on all three measures of recidivism, including new charges (45.1% vs. 36.9%), new convictions (39.6% vs. 34.2%), and new incarceration terms (34.8% vs. 24.0%).

Table 4: Descriptive Statistics for Dependent Variables Delineated by Year of Release

	2013 (N=3,807)	2014 (N=2,675)	Total (N=6,482)
New Eligible Charge	45.1%	36.9%	41.7%
New Eligible Conviction	39.6%	34.2%	37.4%
New Eligible Incarceration	34.8%	24.0%	30.3%

Table 5 presents the descriptive statistics for all individual-level variables, as delineated by year of release from the HOC. Overall, the majority of the sample were Black, non-Hispanic males. The mean age did not differ among the year of release, indicating an average age of 31.9 years at the time of release from the HOC. The average LSI-R:SV total score for the overall population was 3.6, indicating a medium risk-level. Prior criminal history illustrated a mean of 1.4 prior charges, 0.6 prior jail incarcerations, and 0.1 prior prison incarcerations. Individuals who were released in 2013 revealed a more extensive criminal history than those who were released from the HOC in 2014. As for the current type of offense, a higher percentage of individuals overall were convicted of a public order offense, followed by property, drug, violent, traffic-related, OWI-related, and other. Finally, the current sample of individuals spent an average of 86 days (2.8 months) incarcerated at the HOC. Those individuals who were released in 2014, on average, were incarcerated longer than individuals who were released from the HOC in 2013 (93.2 vs. 80.9 days).

Table 5: Descriptive Statistics for Individual-level Variables Delineated by Year of Release

	2013 (n=3,807)	2014 (n=2,675)	Total (n=6,482)
Gender			
Male	86.2%	87.2%	86.6%
Female	13.8%	12.8%	13.4%
Race/Ethnicity			
White, non-Hispanic	17.3%	16.3%	16.9%
Black, non-Hispanic	74.2%	75.4%	74.7%
Hispanic/Latino	7.7%	7.5%	7.6%
Other	0.8%	0.8	0.8%
Age at release (years)	31.9(11.3)	31.9(11.4)	31.9(11.3)
LSI-R:SV total score*	3.6(1.5)	3.5(1.6)	3.6(1.5)
Prior criminal record			
Prior charges	2.4(2.8)	0.0(0.1)	1.4(2.4)
Prior jail incarcerations	1.1(1.5)	0.0(0.01)	0.6(1.3)
Prior prison incarcerations	0.2(0.5)	0.0(0.01	0.1(0.4)
Current offense type			
Violent	11.3%	12.7%	11.9%
Property	20.4%	18.8%	19.8%
Drug	13.8%	11.4%	12.8%
Public order	28.2%	29.5%	28.7%
OWI-related	12.6%	9.3%	11.2%
Traffic-related	10.0%	13.0%	11.3%
Other	3.8%	5.2%	4.4%
Time served (days)	80.9(92)	93.2(97.9)	86(94.7)

*Multiple imputation was conducted for the LSI-R:SV total score since 19.3% of the initial cases contained missing data.

Bivariate Correlations

The bivariate correlation matrix in Appendix D presents the bivariate correlations between the independent and dependent variables. Bivariate correlations were examined to identify significant relationships among the variables and to detect the presence of multicollinearity among the independent variables. None of the correlations among the independent variables were above .7, indicating that multicollinearity was not an issue.

When examining correlations between the dependent variable of new charges and the independent variables, several significant variables appeared. There was a significant negative correlation between the dependent variable of new charges and year of release ($r = -.081$, $p<.01$), race/ethnicity ($r = -.069$, $p<.01$), and age at release ($r = -.142$, $p<.01$). This indicates that individuals who were released in 2014, were White, and older were less likely to receive a new charge. Further, several significant positive correlations were presented between new charges and gender ($r = .053$, $p<.01$), LSI-R:SV ($r = .157$, $p<.01$), prior charges ($r = .185$, $p<.01$), prior jail incarcerations ($r = .168$, $p<.01$), and prior prison incarcerations ($r = .061$, $p<.01$). This indicates that males and individuals with a more extensive risk score and prior criminal record were more likely to receive a new charge.

Several significant relationships were also presented when examining correlations between the dependent variable of new convictions and the independent variables. A significant negative correlation was found between new convictions and year of release ($r = -.054$, $p<.01$), race/ethnicity ($r = -.061$ $p<.01$), age at release ($r = -.147$, $p<.01$), and current offense type ($r = -.026$, $p<.05$). This indicates that individuals who were released in 2014, were White, older, and received a violent offense were less likely to receive a new conviction. Additionally, significant positive correlations were shown between new convictions and gender ($r = .052$, $p<.01$), LSI-R:SV ($r = .148$, $p<.01$), prior charges ($r = .165$, $p<.01$), prior jail incarcerations ($r = .160$, $p<.01$), and prior prison incarcerations ($r = .050$, $p<.01$). This indicates that males and individuals with a more extensive risk score and prior criminal record were more likely to receive a new conviction.

For the dependent variable of new incarceration terms, several independent variables indicated significant correlations. A significant negative correlation was found between new incarceration terms and year of release ($r = -.115$, $p<.01$), race/ethnicity ($r = -.087$ $p<.01$), age at release (r = -.142, p<.01), and current offense type (r = -.041, p<.01). This indicates that individuals who were released in 2014, were White, older, and received a violent offense were less likely to receive a new incarceration term. Further, significant positive correlations were found between new incarceration terms and gender (r = .069, p<.01), LSI-R:SV (r = .167, p<.01), prior charges (r = .193, p<.01), prior jail incarcerations (r = .189, p<.01), and prior prison incarcerations (r = .083, p<.01). This indicates that males and individuals with a more extensive risk score and prior criminal record were more likely to receive a new conviction.

Binary Logistic Regression Results for New Charges

The results of the logistic regression models that estimated the influence of individual-level variables on new charges are presented in Table 6. Findings indicated that gender, race, ethnicity, age at release, and LSI-R:SV were significantly associated with the likelihood of receiving a new charge within three years of being released from jail. More specifically, males were significantly more likely than females to recidivate, indicating 1.352 higher odds of receiving a new charge. Race/ethnicity was also a significant predictor, with White and Hispanic individuals being about 25-26% less likely to receive a subsequent charge compared to Black individuals. Further, as the age of an offender increased their likelihood of receiving a new charge significantly decreased. Risk score was positively correlated with recidivism, with higher risk individuals being roughly 1.2 times more likely to receive a subsequent charge.

Several legal variables were also found to be significantly related to the likelihood of recidivism. Those with an increased number of prior charges had significantly higher odds of receiving a subsequent charge within three years. Prior incarcerations (jail or prison) were not significantly related to new charges for the current sample. For current offense type, individuals who were initially convicted of a violent, drug, public order, or traffic-related offense were significantly less likely to receive a new charge compared to those who were initially convicted of a property offense. Further, time served was determined to have a negative correlation, where increased time served was associated with decreased odds of receiving a subsequent charge.

Table 6: Binary Logistic Regression Results for New Charges

	B	S.E.	Wald	Sig.	Exp(B)	Lower C.I	Upper C.I.
Gender	.301	.081	13.714	.000	1.352	1.152	1.585
Race/Ethnicity							
White, non-Hispanic	-.293	.075	15.128	.000	.746	.644	.865
Hispanic/Latino	-.307	.104	8.657	.003	.736	.600	.903
Other	-.478	.324	2.179	.140	.620	.329	1.170
Age at release	-.033	.003	162.119	.000	.968	.963	.973
LSI-R:SV total score	.187	.018	105.800	.000	1.205	1.163	1.249
Prior criminal record							
Prior charges	.134	.024	32.516	.000	1.144	1.092	1.198
Prior jail incarcerations	.057	.041	1.959	.162	1.059	.977	1.147
Prior prison incarcerations	-.108	.071	2.322	.128	.898	.782	1.031
Current offense type							
Violent	-.488	.099	24.320	.000	.614	.505	.745
Drug	-.387	.095	16.727	.000	.679	.564	.817
Public order	-.387	.078	24.469	.000	.679	.583	.792
OWI-related	-.052	.106	.244	.621	.949	.771	1.168
Traffic-related	-.361	.100	13.110	.000	.697	.573	.847
Other	-.214	.139	2.363	.124	.807	.614	1.061
Time served	-.001	.000	17.972	.000	.999	.998	.999
Year of release	.046	.064	.518	.471	1.047	.924	1.187

Note: Black, non-Hispanic and property offenses were used as the reference categories.
Note: The analysis was also analyzed using violent offense as the reference category. The only counterparts to reach significance was property (b=.488***) and OWI-related (b=.436***) offenses. Additionally, public order offense was employed as the reference category, finding a statistical significance with property (b=.387***) and OWI-related (b=.001***) offenses.

Table 7 presents the findings of the race, ethnicity, and gender interactions for new charges. All independent variables were included in the models, but only race, ethnicity, and gender coefficients are presented. Hispanic females (n=34), other-race males (n=38), and other-race females (n=13) were not included in the analysis due to small sample sizes. As illustrated in the table, Black males had significantly higher odds of receiving a new charge than all other counterparts. In fact, White males, Hispanic males, and Black females were roughly 24-29% less likely than Black males to recidivate. Additionally, White females were 46.9% less likely than Black males to receive a new charge. There were no significant racial differences found between White and Black females.

Table 7: Binary Logistic Regression Results for New Charges Using Race/Ethnicity × Gender Interaction Terms[a] (N=6,397)

Race/Ethnicity x Gender	B	S.E.	Wald	Sig.	Exp(B)	Lower C.I.	Upper C.I.
Black male (*reference*)							
White male	-.275	.082	11.167	.001	.759	.646	.892
Hispanic male	-.335	.108	9.601	.002	.715	.578	.884
White female	-.633	.156	16.361	.000	.531	.391	.722
Black female	-.314	.096	10.771	.001	.731	.606	.881

Note: Regression analyses were analyzed for White males (n=875), Black males (n=4,241), Hispanic males (n=461), White females (n=220), and Black females (n=600).
Note: Regression analyses could not be analyzed for Hispanic females, Other-race males, and other-race females because the sample sizes were too small.
[a]For all interaction tables, significant relationships are only shown once. For example, Black male is treated as the reference variable first. Significant relationships presented in that model are not presented in the table again when the models were reanalyzed with a different reference variable.

Table 8 presents the findings when race, ethnicity, gender, and age interactions were examined for recidivism. Only the significant coefficients are presented in the table for brevity[20]. When young White males were used as the reference category, middle-aged Hispanic males, middle-aged White females, middle-aged Black females, older White males, and older Black males were all significantly less likely to receive a new charge. Young Black males though were significantly more likely to recidivate and had 1.757 higher odds compared to young White males. When young Black males were used as the reference category, they had significantly higher odds than all other groups of receiving a subsequent charge. Young Hispanic males were

[20] Younger Hispanic females, younger other-race males, younger other-race females, middle-age Hispanic females, middle-age other-race males, middle-age other-race females, older Black females, older White females, older Hispanic males, older Hispanic females, older other-race males, and older other-race females because the sample sizes were too small.

found to have significantly higher odds of recidivism compared to middle-aged White females, middle-aged Black females, older White males, and older Black males. Young White females had greater odds of recidivism than middle-aged White females, older White males, and older Black males, but were significantly less likely to receive a new charge when compared to young Black females. Additionally, young Black females, when used as the reference category, had significantly higher odds of recidivism compared to middle-aged Hispanic males, middle-aged White females, middle-aged Black females, older White males, and older Black males. Both middle-aged White males and middle-aged Black males [when used as the reference categories] were significantly more likely to receive a new charge than young Black females, middle-aged White females, older White males, and older Black males. Middle-aged Black males were also more likely to recidivate than middle-aged Black females. Finally, middle-aged Hispanic males, middle-aged White females, middle-aged Black females, and older Black males were all significantly more likely to recidivate when compared to older White males; and middle-aged Hispanic males had significantly higher odds of also recidivating compared to older Black males. Overall, it appears that being young resulted in a higher likelihood of recidivism, with younger Black males having the highest odds of receiving a subsequent charge.

Table 8: Binary Logistic Regression Results for New Charges Using Race/Ethnicity × Gender × Age[a] Interaction Terms[b] (N=6,065)

Race x Gender x Age	B	S.E.	Wald	Sig.	Exp(B)	Lower C.I.	Upper C.I.
Young White male (*reference*)							
Young Black male	.563	.091	37.969	.000	1.757	1.468	2.101
Middle-aged Hispanic male	-.341	.172	3.923	.048	.711	.508	.996
Middle-aged White female	-.602	.251	5.735	.017	.548	.335	.896
Middle-aged Black female	-.400	.169	5.610	.018	.670	.482	.933
Older White male	-.762	.224	11.622	.001	.467	.301	.723
Older Black male	-.433	.135	10.303	.001	.649	.498	.845
Young Black male (*reference*)							
Young Hispanic male	-.355	.157	5.093	.024	.701	.515	.954
Young White female	-.734	.229	10.302	.001	.480	.307	.752
Middle-aged White male	-.589	.116	26.002	.000	.555	.442	.696
Middle-aged Black male	-.530	.071	56.128	.000	.589	.513	.676
Middle-aged Hispanic male	-.790	.159	24.578	.000	.454	.332	.620
Middle-aged White female	-1.055	.243	18.891	.000	.348	.216	.560
Middle-aged Black female	-.858	.155	30.582	.000	.424	.313	.575
Older White male	-1.205	.215	31.560	.000	.300	.197	.456
Older Black male	-.890	.117	26.551	.000	.411	.326	.517
Young Hispanic male (*reference*)							
Middle-aged White female	-.599	.254	5.567	.018	.549	.334	.904
Middle-aged Black female	-.397	.173	5.289	.021	.673	.480	.943
Older White male	-.768	.226	11.278	.001	.468	.300	.729
Older Black male	-.430	.139	9.541	.002	.651	.495	.855
Young White female (*reference*)							
Young Black female	.354	.153	5.336	.021	1.424	1.055	1.923
Middle-aged White female	-.506	.257	3.892	.049	.603	.364	.997
Older White male	-.668	.230	8.461	.004	.513	.327	.804
Older Black male	-.338	.145	5.459	.019	.713	.537	.947
Young Black female (*reference*)							
Young Black male	.483	.091	28.400	.000	1.622	1.358	1.937
Middle-aged Hispanic male	-.417	.172	5.851	.016	.659	.470	.924
Middle-aged White female	-.680	.251	7.329	.007	.506	.309	.829
Middle-aged Black female	-.480	.168	8.132	.004	.619	.445	.861
Older White male	-.836	.224	13.890	.000	.434	.279	.673
Older Black male	-.511	.135	14.382	.000	.600	.461	.781
Middle-aged White male (*reference*)							
Young Black female	.353	.143	6.130	.013	1.423	1.076	1.882
Middle-aged White female	-.506	.250	4.098	.043	.603	.370	.984
Older White male	-.665	.221	9.058	.003	.514	.333	.793
Older Black male	-.337	.132	6.507	.011	.714	.551	.925

Middle-aged Black male (*reference*)							
Young Black female	.321	.131	6.015	.014	1.379	1.067	1.782
Middle-aged White female	-.539	.244	4.870	.027	.583	.362	.942
Middle-aged Black female	-.336	.158	4.550	.033	.714	.524	.973
Older White male	-.700	.216	10.523	.001	.497	.326	.758
Older Black male	-.369	.120	9.411	.002	.691	.546	.875
Middle-aged Hispanic male (*reference*)							
Older White male	-.612	.226	7.352	.007	.542	.349	.844
Older Black male	-.285	.139	4.189	.041	.752	.573	.988
Middle-aged White female (*reference*)							
Older White male	-.612	.230	7.109	.008	.542	.346	.850
Middle-aged Black female (*reference*)							
Older White male	-.591	.226	6.854	.009	.554	.356	.862
Older Black male (*reference*)							
Older White male	-.521	.222	5.508	.019	.594	.384	.918

[a]Categories for age were defined as: young (29 years and younger), middle-aged (30-49 years), and older (50 years and older).
Note: Regression analyses were analyzed for young White males (n=300), young Black males (n=2,285), young Hispanic males (n=193), young White females (n=95), young Black females (n=310), middle-aged White males (n=411), middle-aged Black males (n=1,380), middle-aged Hispanic males (n=216), middle-aged White females (n=92), middle-aged Black females (n=224), older White males (n=135), and older Black males (n=424).
Note: Regression analyses could not be analyzed for young Hispanic females, young other-race males, young other-race females, middle-aged Hispanic females, middle-aged other-race males, middle-aged other-race females, older Black females, older White females, older Hispanic males, older Hispanic females, older other-race males, and older other-race females because the sample sizes were too small.
[b]For all interaction tables, significant relationships are only shown once. For example, younger White male is treated as the reference variable first. Significant relationships presented in that model are not presented in the table again when the models were reanalyzed with a different reference variable.

Binary Logistic Regression Results for New Convictions

Table 9 presents the results of the binary logistic regression models that estimated the influence of individual characteristics on new convictions. Similar to new charges, it was revealed that gender, race, ethnicity, age at release, and LSI-R:SV were significantly related to the receiving a new conviction within three-years post-release. In fact, males had 1.371 higher odds of recidivism than females. Both White and Hispanic individuals were significantly less likely (18.1% and 27.6% respectively) to receive a subsequent conviction compared to Black individuals. Further, age at release was negatively correlated, where increased age was associated with decreased odds of receiving a new conviction. Risk score indicated a significant and positive correlation, where a one-unit increase on the LSI-R:SV total score was associated with roughly 1.2 increased odds of recidivism. In addition to these extra-legal variables, the year of release was found to be significantly associated with the likelihood of receiving a new conviction. Individuals who were released from the HOC in 2014 were significantly more likely to receive a subsequent conviction compared to those who were released in 2013.

Several legal variables were also found to be significant, including prior criminal record, current offense type, and time served. More specifically, individuals with a higher number of prior charges and prior jail incarcerations were significantly more likely to receive a new conviction within three-years post-release. Those with a current property offense had significantly higher odds of recidivating compared to those with a current drug (31.8% less likely), public order 33.3% less likely), traffic-related (34.6% less likely), or violent (37.7% less likely) offense. Further, a significant and negative correlation was revealed for time served, signifying that increased time served was associated with decreased odds of receiving a new conviction.

Table 9: Binary Logistic Regression Results for New Convictions

	B	S.E.	Wald	Sig.	Exp(B)	Lower C.I	Upper C.I.
Gender	.315	.083	14.267	.000	1.371	1.164	1.614
Race/Ethnicity							
White, non-Hispanic	-.199	.076	6.805	.009	.819	.705	.952
Hispanic/Latino	-.323	.107	9.054	.003	.724	.587	.893
Other	-.271	.323	.706	.401	.762	.405	1.436
Age at release	-.035	.003	171.104	.000	.966	.961	.971
LSI-R:SV total score	.174	.018	90.095	.000	1.191	1.148	1.234
Prior criminal record							
Prior charges	.101	.023	19.625	.000	1.106	1.058	1.156
Prior jail incarcerations	.103	.040	6.581	.010	1.108	1.025	1.199
Prior prison incarcerations	-.084	.070	1.413	.235	.920	.801	1.056
Current offense type							
Violent	-.473	.100	22.246	.000	.623	.512	.758
Drug	-.383	.095	16.110	.000	.682	.566	.822
Public order	-.404	.079	26.318	.000	.667	.572	.779
OWI-related	-.108	.108	1.001	.317	.898	.727	1.109
Traffic-related	-.425	.101	17.660	.000	.654	.536	.797
Other	-.209	.141	2.202	.138	.812	.616	1.069
Time served	-.001	.000	11.770	.001	.999	.998	1.000
Year of release	.142	.065	4.791	.029	1.153	1.015	1.310

Note: Black, non-Hispanic and property offenses were used as the reference categories.
Note: The analysis was also analyzed using violent offense as the reference category. The only counterparts to reach significance was property (b=.473***) and OWI-related (b=.365**) offenses. Additionally, public order offense was employed as the reference category, finding a statistical significance with property (b=.404***) and OWI-related (b=.296**) offenses.

Table 10 presents the findings of the race, ethnicity, and gender interactions for subsequent convictions. For all reference categories that were analyzed, it was determined that Black males were significantly more likely than their counterparts to receive a subsequent conviction within three-years post-release. White males were 16.6% less likely, Hispanic males were 28.6% less likely, White females were 42.3% less likely, and Black females were 27.2% less likely than Black males to recidivate. White females were also significantly less likely to receive a subsequent conviction than White males, indicating 29.9% fewer odds. A racial difference was not found between White and Black females.

Table 10: Binary Logistic Regression Results for New Convictions Using Race/Ethnicity × Gender Interaction Terms[a] (N=6,397)

Race/Ethnicity x Gender	B	S.E.	Wald	Sig.	Exp(B)	Lower C.I.	Upper C.I.
Black male (*reference*)							
White male	-.182	.083	4.755	.029	.834	.708	.982
Hispanic male	-.337	.111	9.165	.002	.714	.574	.888
White female	-.550	.160	11.828	.001	.577	.421	.789
Black female	-.317	.098	10.455	.001	.728	.601	.882
White male (*reference*)							
White female	-.355	.171	4.303	.038	.701	.502	.981

Note: Regression analyses were analyzed for White males (n=875), Black males (n=4,241), Hispanic males (n=461), White females (n=220), and Black females (n=600).
Note: Regression analyses could not be analyzed for Hispanic females, Other-race males, and other-race females because the sample sizes were too small.
[a]For all interaction tables, significant relationships are only shown once. For example, Black male is treated as the reference variable first. Significant relationships presented in that model are not presented in the table again when the models were reanalyzed with a different reference variable.

Table 11 presents the findings when race, ethnicity, gender, and age interactions were examined for new convictions. Overall, it appears that young males were significantly more likely to receive a new conviction, with young Black males presenting the highest odds. Young Black males were roughly two times more likely to receive a new conviction compared to all other groups used in the current sample. When examining young females, both White and Black females were significantly more likely to receive a new conviction compared to older White and Black males. Young Black females, however, were also found to have higher odds of receiving a subsequent conviction than middle-aged Hispanic males, middle-aged White females, and middle-aged Black females.

For the current sample, older individuals presented the lowest odds of receiving a new conviction post-release from local corrections in Milwaukee County. Older White males were significantly less likely to receive a new conviction compared all other younger and middle-aged categories. Older Black males also had lower odds of receiving a new conviction compared to all other younger and middle-aged categories, with the exception of middle-aged Black females. For this exception, there was no significant difference found between middle-aged Black females and older Black males on the likelihood to receive a subsequent conviction. Older Black males, however, were found to be significantly more likely to receive a new conviction when compared directly to older White males.

Table 11: Binary Logistic Regression Results for New Convictions Using Race/Ethnicity × Gender × Age[a] Interaction Terms[b] (N=6,065)

Race x Gender x Age	B	S.E.	Wald	Sig.	Exp(B)	Lower C.I.	Upper C.I.
Young White male (*reference*)							
Young Black male	.555	.093	36.004	.000	1.743	1.454	2.089
Middle-aged Hispanic male	-.362	.177	4.157	.041	.697	.492	.986
Middle-aged White female	-.537	.257	4.381	.036	.584	.353	.966
Middle-aged Black female	-.383	.173	4.905	.027	.682	.486	.957
Older White male	-.847	.237	12.746	.000	.429	.269	.682
Older Black male	-.474	.139	11.628	.001	.623	.474	.817
Young Black male (*reference*)							
Young Hispanic male	-.352	.160	4.855	.028	.703	.514	.962
Young White female	-.740	.236	9.869	.002	.477	.301	.757
Middle-aged White male	-.492	.116	17.898	.043	.611	.487	.768
Middle-aged Black male	-.602	.072	69.429	.000	.548	.476	.631
Middle-aged Hispanic male	-.799	.164	23.611	.000	.450	.326	.621
Middle-aged White female	-.978	.248	15.590	.000	.376	.231	.611
Middle-aged Black female	-.829	.159	27.166	.000	.436	.319	.596
Older White male	-1.278	.228	31.332	.000	.279	.178	.436
Older Black male	-.919	.121	57.408	.000	.399	.314	.506
Young Hispanic male (*reference*)							
Middle-aged Black female	-.348	.177	2.296	.050	.706	.499	.999
Older White male	-.812	.203	11.453	.001	.444	.277	.710
Older Black male	-.439	.144	9.323	.002	.645	.486	.855
Young White female (*reference*)							
Young Black female	.329	.157	4.412	.036	1.389	1.022	1.888
Older White male	-.714	.243	8.596	.003	.490	.304	.789
Older Black male	-.340	.149	5.184	.023	.712	.531	.954

Young Black female (*reference*)							
Young Black male	.528	.092	32.692	.000	1.695	1.415	2.032
Middle-aged Hispanic male	-.386	.178	4.721	.030	.680	.480	.963
Middle-aged White female	-.564	.257	4.821	.028	.569	.344	.941
Middle-aged Black female	-.411	.173	5.665	.017	.663	.472	.930
Older White male	-.869	.238	13.341	.000	.419	.263	.668
Older Black male	-.500	.139	12.924	.000	.139	.462	.797
Middle-aged White male (*reference*)							
Older White male	-.773	.235	10.829	.001	.462	.291	.732
Older Black male	-.399	.136	8.566	.003	.671	.514	.877
Middle-aged Black male (*reference*)							
Young White male	.266	.132	4.040	.044	1.305	1.007	1.692
Young Black female	.332	.134	6.158	.013	1.393	1.072	1.810
Older White male	-.710	.230	9.578	.002	.491	.313	.771
Older Black male	-.337	.125	7.268	.007	.714	.559	.912
Middle-aged Hispanic male (*reference*)							
Older White male	-.661	.240	7.615	.006	.516	.323	.826
Older Black male	-.290	.144	4.065	.044	.748	.564	.992
Middle-aged White female (*reference*)							
Older White male	-.672	.244	7.624	.006	.510	.317	.823
Older Black male	-.300	.150	4.001	.045	.741	.552	.994
Middle-aged Black female (*reference*)							
Older White male	-.653	.240	7.418	.006	.521	.325	.833
Older Black male (*reference*)							
Older White male	-.564	.236	5.711	.017	.569	.358	.904

[a]Categories for age were defined as: young (29 years and younger), middle-aged (30-49 years),and older (50 years and older).

Note: Regression analyses were analyzed for young White males (n=300), young Black males (n=2,285), young Hispanic males (n=193), young White females (n=95), young Black females (n=310), middle-aged White males (n=411), middle-aged Black males (n=1,380), middle-aged Hispanic males (n=216), middle-aged White females (n=92), middle-aged Black females (n=224), older White males (n=135), and older Black males (n=424).

Note: Regression analyses could not be analyzed for young Hispanic females, young other-race males, young other-race females, middle-aged Hispanic females, middle-aged other-race males, middle-aged other-race females, older Black females, older White females, older Hispanic males, older Hispanic females, older other-race males, and older other-race females because the sample sizes were too small.

[b]For all interaction tables, significant relationships are only shown once. For example, younger White male is treated as the reference variable first. Significant relationships presented in that model are not presented in the table again when the models were reanalyzed with a different reference variable.

Binary Logistic Regression Results for New Incarceration terms

The results of the logistic regression models that estimated the influence of individual-level variables on new incarceration terms are presented in Table 12. Findings indicated that being male, Black, younger, and having a lower risk score were all significantly associated with increased odds of receiving a new incarceration term within three-years. In fact, males were roughly 1.5 times more likely to receive an incarceration term than females. Additionally, White individuals were 27.8% less likely than Black individuals to receive a new incarceration term; and Hispanic individuals were 36% less likely than Black individuals to receive a new incarceration term. Similar to other outcome measures in this study, age at release was negatively correlated with recidivism, where increased age was associated with decreased odds of receiving a subsequent incarceration term. Further, individuals with a higher LSI-R:SV total score were significantly more likely to recidivate. In fact, a one unit increase in an individual's risk score was associated with 1.221 times higher odds of receiving a new incarceration term. The year of release was also associated with the current dependent measure, yet this was in the opposite direction found for new convictions. Individuals who were released in 2014 were less likely to receive a new incarceration term than those who were released in 2013. It appears that individuals who were released from the HOC in 2014 were more likely to receive a conviction, but less likely to be incarcerated for that conviction.

When legal variables were examined, it was revealed that increased prior charges and prior jail incarcerations were associated with increased odds of receiving a new incarceration term. Further, individuals with a current property offense were significantly more likely to receive a new incarceration term compared to those with a current violent, drug, public order, and traffic-related offense. Additionally, OWI-related offenses became significant in this model.

Individuals who initially received an OWI-related offense were about 40% less likely to receive a new incarceration term than those with a property offense. Time served was no longer found to be significant in the likelihood of receiving a new incarceration term.

Table 12: Binary Logistic Regression Results for New Incarceration Terms

	B	S.E.	Wald	Sig.	Exp(B)	Lower C.I	Upper C.I.
Gender	.450	.092	23.762	.000	1.568	1.309	1.879
Race/Ethnicity							
White, non-Hispanic	-.326	.083	15.233	.000	.722	.613	.850
Hispanic/Latino	-.446	.119	14.018	.000	.640	.507	.808
Other	-.434	.378	1.316	.251	.648	.309	1.360
Age at release	-.034	.003	135.787	.000	.967	.962	.973
LSI-R:SV total score	.200	.020	104.677	.000	1.221	1.176	1.269
Prior criminal record							
Prior charges	.069	.023	9.158	.002	1.071	1.024	1.120
Prior jail incarcerations	.129	.040	10.290	.001	1.138	1.052	1.232
Prior prison incarcerations	-.007	.071	.010	.920	.993	.864	1.141
Current offense type							
Violent	-.419	.106	15.694	.000	.658	.534	.809
Drug	-.327	.099	10.898	.001	.721	.594	.876
Public order	-.370	.082	20.186	.000	.691	.588	.812
OWI-related	-.513	.123	17.417	.000	.599	.470	.762
Traffic-related	-.374	.106	12.346	.000	.688	.559	.848
Other	-.155	.147	1.114	.291	.856	.642	1.142
Time served	-.001	.000	3.782	.052	.999	.999	1.000
Year of release	-.206	.070	8.727	.003	.814	.710	.933

Note: Black, non-Hispanic and property offenses were used as the reference categories.
Note: The analysis was also analyzed using violent offense as the reference category. The only counterpart to reach significance was property (b=.419***) offense. Additionally, public order offense was employed as the reference category, finding a statistical significance with property (b=.370***) offenses.

Table 13 displays the findings of the race, ethnicity, and gender interactions for new incarceration terms. Like previous models, Black males were significantly more likely to receive a new incarceration term within three years compared to their counterparts. White males were 27.1% less likely to recidivate than Black males; and Hispanic males and Black females were about 35-36% less likely than Black males to recidivate. White females were found to be 53.1% less likely than Black males and 34% less likely than White males to receive a new incarceration term There were no racial differences found between White and Black females.

Table 13: Binary Logistic Regression Results for New Incarceration Term Using Race/Ethnicity × Gender Interaction Terms[a] (N=6,397)

Race/Ethnicity x Gender	B	S.E.	Wald	Sig.	Exp(B)	Lower C.I.	Upper C.I.
Black male (*reference*)							
White male	-.315	.091	12.089	.001	.729	.611	.871
Hispanic male	-.436	.123	12.600	.000	.647	.508	.823
White female	-.758	.183	17.199	.000	.469	.328	.671
Black female	-.454	.107	17.916	.000	.635	.515	.784
White male (*reference*)							
White female	-.415	.195	4.521	.033	.660	.451	.968

Note: Regression analyses were analyzed for White males (n=875), Black males (n=4,241), Hispanic males (n=461), White females (n=220), and Black females (n=600).
Note: Regression analyses could not be analyzed for Hispanic females, Other-race males, and other-race females because the sample sizes were too small.
[a]For all interaction tables, significant relationships are only shown once. For example, Black male is treated as the reference variable first. Significant relationships presented in that model are not presented in the table again when the models were reanalyzed with a different reference variable.

Table 14 presents the findings when race, ethnicity, gender, and age interactions were examined for new incarceration terms. When young White males were used as the reference category, middle-aged Hispanic males, middle-aged White females, older White males, and older Black males had significantly decreased odds of receiving a new incarceration term. Young Black males, like in previous models, had significantly increased odds of receiving an incarceration term than all other categories in the current analysis. Young Hispanic males, young Black females, and middle-aged Black males [when each was used as the reference category] were all significantly more likely to recidivate when compared to middle-aged Hispanic males, middle-aged White females, older White males, and older Black males. Young White females were significantly more likely to receive a new incarceration term compared only to older White males; and middle-aged White males had increased odds of recidivism compared only to older White males. Lastly, results indicated that middle-aged Hispanic males, middle-aged White females, middle-aged Black females, and older Black males were significantly more likely to receive a subsequent incarceration term than older White males.

Table 14: Binary Logistic Regression Results for New Incarceration Terms Using Race/Ethnicity × Gender × Age[a] Interaction Terms[b] (N=6,065)

Race x Gender x Age	B	S.E.	Wald	Sig.	Exp(B)	Lower C.I.	Upper C.I.
Young White male (*reference*)							
Young Black male	.616	.099	38.897	.000	1.851	1.526	2.247
Middle-aged Hispanic male	-.512	.205	6.235	.013	.599	.401	.896
Middle-aged White female	-.674	.297	5.152	.023	.510	.285	.912
Older White male	-.763	.267	8.163	.004	.466	.276	.787
Older Black male	-.372	.151	6.106	.013	.689	.513	.926
Young Black male (*reference*)							
Young Hispanic male	-.336	.170	3.909	.048	.714	.512	.997
Young White female	-1.025	.274	13.989	.000	.359	.210	.614
Middle-aged White male	-.702	.129	29.543	.000	.496	.385	.638
Middle-aged Black male	-.580	.076	58.242	.000	.560	.482	.650
Middle-aged Hispanic male	-1.008	.191	27.735	.000	.365	.251	.531
Middle-aged White female	-1.173	.288	16.616	.000	.309	.176	.544
Middle-aged Black female	-.831	.172	23.359	.000	.435	.311	.610
Older White male	-1.253	.257	23.695	.000	.286	.173	.473
Older Black male	-.875	.131	44.801	.000	.417	.323	.539
Young Hispanic male (*reference*)							
Middle-aged Hispanic male	-.499	.209	5.724	.017	.607	.403	.914
Middle-aged White female	-.660	.300	4.844	.028	.517	.287	.930
Older White male	-.750	.270	7.708	.005	.472	.278	.802
Older Black male	-.359	.156	5.292	.021	.699	.515	.948
Young White female (*reference*)							
Older White male	-.588	.274	4.593	.032	.555	.324	.951
Young Black female (*reference*)							
Young Black male	.664	.100	44.280	.000	1.942	1.597	2.361
Middle-aged Hispanic male	-.464	.206	5.070	.024	.629	.420	.942
Middle-aged White female	-.626	.297	4.431	.035	.535	.299	.958
Older White male	-.714	.268	7.086	.008	.490	.290	.828
Older Black male	-.324	.151	4.582	.032	.723	.537	.973

Middle-aged White male (*reference*)							
Older White male	-.609	.265	5.264	.022	.544	.324	.915
Middle-aged Black male (*reference*)							
Middle-aged Hispanic male	-.434	.194	5.009	.025	.648	.443	.947
Middle-aged White female	-.595	.290	4.226	.040	.551	.313	.973
Older White male	-.085	.259	6.993	.008	.504	.303	.838
Older Black male	-.294	.135	4.727	.030	.746	.572	.971
Middle-aged Hispanic male (*reference*)							
Older White male	-.533	.271	3.866	.049	.587	.345	.998
Middle-aged White female (*reference*)							
Older White male	-.566	.275	4.243	.039	.568	.332	.973
Middle-aged Black female (*reference*)							
Older White male	-.584	.270	4.674	.031	.558	.329	.947
Older Black male (*reference*)							
Older White male	-.527	.266	3.928	.047	.590	.350	.994

[a]Categories for age were defined as: young (29 years and younger), middle-aged (30-49 years), and older (50 years and older).
Note: Regression analyses were analyzed for young White males (n=300), young Black males (n=2,285), young Hispanic males (n=193), young White females (n=95), young Black females (n=310), middle-aged White males (n=411), middle-aged Black males (n=1,380), middle-aged Hispanic males (n=216), middle-aged White females (n=92), middle-aged Black females (n=224), older White males (n=135), and older Black males (n=424).
Note: Regression analyses could not be analyzed for young Hispanic females, young other-race males, young other-race females, middle-aged Hispanic females, middle-aged other-race males, middle-aged other-race females, older Black females, older White females, older Hispanic males, older Hispanic females, older other-race males, and older other-race females because the sample sizes were too small.
[b]For all interaction tables, significant relationships are only shown once. For example, younger White male is treated as the reference variable first. Significant relationships presented in that model are not presented in the table again when the models were reanalyzed with a different reference variable.

CHAPTER 5

DISCUSSION AND CONCLUSIONS

The challenges of reentry from local jails, in many ways, mirror that of reentry from prisons. While there is an abundance of research on prison reentry, the literature on jail recidivism remains scant. Research that is available has revealed that certain individual and neighborhood characteristics have a significant impact on recidivism for jail ex-inmates. The research thus far on jail reentry offers some insight into the correlates that influence recidivism patterns, yet several gaps in the literature remained that needed to be addressed. The limited research available on jail recidivism has produced mixed results, possibly due to the various choices of independent and outcome measures. Further, there is a lack of research that examines both individual- and neighborhood-level influences of jail recidivism while using theory to explore the role of jails. Therefore, the current study sought to examine the influence of both individual and neighborhood characteristics on the likelihood for individuals to receive a subsequent charge, conviction, or incarceration term once released from a local jail in Milwaukee, WI.

The following sections will discuss the effect that both individual- and neighborhood-level influences had on the likelihood of recidivism. Policy implications will also be discussed, as well as suggestions for future research. Finally, a summary of the research and conclusions will be provided.

Individual-level Influences

Individual characteristics were analyzed to assess the influence on the likelihood to receive a subsequent charge, conviction, or incarceration term within three-years post-release. Overall, the results conform to a robust body of existing research which demonstrates that individual characteristics are strong and consistent predictors of recidivism. Examinations revealed that being younger, male, and Black, non-Hispanic resulted in a significant increase on all three dependent variables. These findings present support for Hypothesis one, as well as much of prior literature that has examined the influence of gender, race, ethnicity, and age (Caudy, et al., 2018; Freudenberg, et al., 2005; Fritsche, 2019; Olson, 2011; Verheek, 2015; Weller, 2012; Yamatani, 2008). These demographic characteristics have also been presented as some of the strongest static risk factors to influence the likelihood of recidivism, as offered by the RNR model (Singh & Frazel, 2010; Stahler, et al., 2013).

Interaction effects were also analyzed in the current study to examine whether the combination of gender, race, ethnicity, and age were influential in the likelihood of recidivism. When gender, race, and ethnicity were analyzed, findings revealed that Black males were significantly more likely than their counterparts to receive a new charge, conviction, or incarceration term. There was no racial difference found between Black and White females. Once age was included in the analysis, results determined that young males had increased odds of recidivism, with young Black males presenting the highest odds on all three dependent variables. Young Black males were roughly 1.5-2 times more likely than their counterparts to receive a new charge, conviction, or incarceration term. When racial differences were examined between young females it appeared that young Black females had higher odds of recidivating than White females. Older White and Black males were shown to have some of the lowest odds of recidivating compared to their counterparts. Overall, hypothesis seven was partially supported.

Both the risk level of an individual and their prior criminal record were also found to be significantly associated with the likelihood of recidivism in the current sample, presenting support for Hypothesis two. Based on the LSI-R:SV, it was determined that having a higher risk score was associated with an increased likelihood of receiving a new charge, conviction, or incarceration term. The RNR model postulates several dynamic and static risk factors that are indicative of recidivism patterns (Andrews & Bonta, 1994). Likewise, prior research has often concluded that risk level produces one of the highest values for predicting recidivism (Caudy, et al., 2018; Gendreau, et al., 1996; Lyman, 2017; Lyman & LoBuglio, 2006). This study presented similar findings and provides further support towards the RNR model. Additionally, prior criminal record is supported under the RNR model for predicting the likelihood of recidivism. Results of the current study revealed that having more prior charges was significantly associated with an increased likelihood of receiving a subsequent charge, conviction, or incarceration term. It was also found that an increased number of prior jail incarcerations was associated with increased odds of receiving a new conviction or incarceration term. Prior prison incarcerations were not found to significantly influence recidivism in the current study. Overall, this provides support for Hypothesis two and much of prior literature that concludes a positive association between prior criminal record and recidivism (Fritsche, 2019; Gendreau, et al., 1996; Rempel, et al., 2018; Singh & Frazel, 2010; Stahler, et al., 2013).

In addition to prior criminal history, the current type of offense for an individual was examined to determine the impact on jail reentry. Prior literature has often indicated that violent offenses are associated with the lowest rates of recidivism, while those with a property, public order, or drug-related offense tend to have higher odds of recidivism (Fritsche, 2019; Lyman & LoBuglio, 2006; Sawyer & Wagner, 2017; Singh & Frazel, 2010; Stahler, et al., 2013). The present analysis did follow that of prior research and found support for Hypothesis three. Results revealed that individuals with a current property offense were significantly more likely to recidivate on all three outcome measures compared to those with a drug, public order, traffic-related, and violent offense. Property offenses were also found to have increased odds of receiving a new incarceration term when compared to a current OWI-related offense. It appears, for this sample, that no significant differences exist between property and OWI-related offenses in the odds of new charges or convictions, but for incarceration, those with an OWI-related offense are less likely to be confined.

Lastly, Hypothesis four pertaining to individual-level influences proposed a non-directional hypothesis for time served. Empirical research on time served has presented inconsistent findings, with some studies finding a positive association with recidivism and others finding a negative association or no significant association (Bahr, et al., 2010; Huebner, et al., 2010; Jung, et al., 2010; Tartar & Jones, 2016). The current study determined that time served was negatively associated with the likelihood of receiving a new charge and a new conviction within three years. As time served in jail increased, the likelihood of recidivism on these two outcome measures significantly decreased. There was no significant difference found among new incarceration terms. It appears that longer time served in jail provides a protective factor for individuals once they are released.

Neighborhood Context

Reentry research has often suggested the inclusion of neighborhood context to provide a holistic understanding of the recidivism process (Clear, 2007; La Vigne & Thomson, 2003; Wright, Pratt, Lowenkamp, & Latessa, 2012). Social disorganization theory offers several neighborhood-level variables that are likely a function of criminal activity. Poverty, residential mobility, and racial/ethnic heterogeneity are some of the characteristics found to be associated with crime (Pratt & Cullen, 2005; Shaw & McKay, 1969). The use of theory and the inclusion of neighborhood context has largely been lacking in the research on jail reentry. Studies that have used social disorganization theory as a theoretical underpinning for jail reentry have produced mixed results (Fritsche, 2019; Verheek, 2015). The current study sought to add to the literature by examining the influence of neighborhood-level variables on the likelihood of recidivism from a local jail in Milwaukee, WI. Contrary to expectations, this study found no relationship between neighborhood context and recidivism, lacking support for Hypotheses five and six. Multilevel modeling was initially employed to examine the relationship between individual and neighborhood characteristics on the likelihood of recidivism for jail ex-inmates. However, the variance component for the random slope on all three outcome measures were not significant. This indicated that there was not sufficient variation in recidivism across census block groups. Thus, the results determined that recidivism for the current sample was largely a matter of individual risk.

The current study analyzed neighborhood-level variables based on the first home address reported by offenders upon their initial release from jail. It is possible, though, that individuals may have moved over the course of the three-year follow-up period (Bensel, Gibbs, & Lytle, 2015; Petersilia, 2003). This could have provided an inaccurate representation of the location at which an individual frequently resides, leading to insignificant findings. It should also be mentioned that the present research measured characteristics of an individual's *home* neighborhood, rather than the neighborhood for which they were *arrested*. A study conducted by Warner and colleagues (2016) found that almost half of all arrests in New York City occurred outside of the individual's residential neighborhood. It is possible this could have had an effect on the results produced in the current study.

Summary of Findings

Overall, the results indicate that recidivism was largely a matter of individual risk for the current sample. Gender, race, ethnicity, and age were significantly associated with the likelihood of receiving a new charge, conviction, and incarceration term. Younger Black males presented the greatest disadvantage in the likelihood of recidivism. This finding has been consistent with prior studies in other locations that have examined these static risk factors (Caudy, et al., 2018; Freudenberg, et al., 2005; Fritsche, 2019; Jung, et al., 2010; Olson, 2011; Verheek, 2015; Weller, 2012; Yamatani, 2008). Additionally, prior criminal history, current offense type, risk score, and time served were all found to be significantly associated with the likelihood of recidivism for jail ex-inmates. This suggests further evidence and support for the RNR model and its' conclusions that various individual-level risk factors are influential in predicting recidivism (Andrews & Bonta, 1990, 2006; Christensen, Jannetta, & Willison, 2012; Fritsche, 2019; James, 2018; Weller, 2012).

Furthermore, the results of this study did not find support for the relationship between neighborhood context and recidivism from local corrections in Milwaukee, WI. While is it often suggested that individual characteristics are largely influenced by the social forces within one's immediate environment (Kubrin & Weitzer, 2003), this study determined that individual-level factors were exclusively predictive of recidivism. These findings show a contradiction with social disorganization theory that neighborhood characteristics are influential in the existence of criminal activity. Considering the inconsistent and overall lack of prior research on neighborhood context and jail reentry, the results of the current analysis only present a further need for investigations to better understand the potential relationship between neighborhood characteristics and jail recidivism.

Limitations

A limitation of the current study concerns the generalizability of the findings beyond the research setting. This study was limited to one urban city in the state of Wisconsin. Analyses were conducted on a sample of individuals who served a sentence at the House of Corrections (HOC) in Milwaukee County. Additionally, this study only examined individuals who were released from the HOC in either 2013 or 2014. Applying these findings to other areas, as well as to other time periods, may be problematic given that the nature of their communities and neighborhoods may differ.

Next, there were several individual-level variables that were not analyzed in the current study. The present research was able to examine individual characteristics of gender, race, ethnicity, age, prior criminal history, current offense type, risk score, and time served. While these represent important indicators of recidivism, there was a lack of investigation on the influence of dynamic risk factors. As offered by the RNR model, substance abuse, mental health, employment, housing, education, and correctional programming among others have also been found to be important indicators of recidivism (Andrews & Bonta, 1994; Fritsche, 2019; Gendreau, et al., 1996; Rempel et al., 2018; Singh & Frazel, 2018; Stahler, et al., 2013). It is possible these variables provide an important understanding to the literature related to the correlates of jail recidivism.

Another limitation encountered during this dissertation was the lack of variation in recidivism rates across census block groups. This lack of variation limited the use of multilevel modeling techniques, as well as limited the overall findings of the study. In a preliminary set of analyses, Bernoulli unconditional models indicated a lack of significance on all three dependent variables. Throughout prior literature, there has been a lack of empirical investigations on the relationship between neighborhood context and jail reentry. Research that is available presents mixed results, with one study finding support for neighborhood context (Verheek, 2015) and another study revealing a lack of support for neighborhood context and jail reentry (Fristche, 2019). While this study offered further research on the correlates of neighborhood and jail recidivism, it revealed that neighborhood context was not a significant influence for the current sample.

Finally, the current study examined recidivism through official court records. Self-report measures of recidivism were not available for this study. As such, this dissertation was not able to gauge on incidents of recidivism where an individual committed a new offense but was not formally caught. Additionally, multiple indicators of recidivism were analyzed in this dissertation, including new charges, convictions, and incarceration terms. The use of multiple measures was advantageous compared to prior research, yet it does not offer the entire spectrum of recidivism patterns. Data was not available in the current study to analyze the likelihood of subsequent arrests. Further, data could not be separated to examine the differences between individuals who were incarcerated for a new criminal offense or a technical violation.

Future Research

The findings and limitations of the current study offer opportunities for further empirical investigations. While individual-level factors were found to significantly influence recidivism from local corrections, neighborhood context was not found to be significant. Prior research examining neighborhood characteristics on jail reentry have produced mixed results, with one study finding support for social disorganization theory (Verheek, 2015) and another study finding non-significance among neighborhood characteristics (Fritsche, 2019). The results of the current study, along with an overall lack of prior research on neighborhood context and jail reentry, presents a need for further investigations. Additional research could provide a better understanding on the potential relationship between neighborhood characteristics and jail recidivism.

The current study found empirical support that various individual-level characteristics are influential on recidivism following release from jail. The present research was able to examine variables such as gender, race, ethnicity, age, criminal record, risk score, and time served. These characteristics represent some of the strongest predictors of recidivism that are offered by the RNR model (Andrews & Bonta, 1994; Fritsche, 2019; Gendreau, et al., 1996; Rempel et al., 2018; Singh & Frazel, 2018; Stahler, et al., 2013). Yet, the current study was unable to gain information related to dynamic risk factors that have also been found in prior research to influence the likelihood of recidivism. Future research on jail recidivism should strive to include additional factors such as substance abuse, mental health, employment, housing, education, and correctional programming among others.

In addition to the opportunities offered above, there is still a dire need for research, overall, on jail reentry. Jails can present unique challenges for empirical investigations however this should not discourage researchers. Further exploring jail reentry, while also addressing some of the gaps in the literature, can allow for a more comprehensive understanding of who recidivates following release from jail, which factors drive that recidivism, and what policy implications can be offered to better prevent future criminal activity within local communities (Janetta, 2009).

Policy Implications

Jail inmates represent a majority of the overall incarcerated population, with an estimated 12 million individuals cycling in and out of U.S. jails each year (Beck, 2006; Lyman & LoBuglio, 2006; Sawyer & Wagner, 2019; Solomon, Osborne, LoBuglio, Mellow, & Mukamal, 2008; Subramanian, Delaney, Roberts, Fishman, & McGarry, 2015). In any given month, jails have contact with as many offenders as prisons do in a year (Beck, 2006), making it imperative that scholars and policymakers understand the driving forces behind recidivism for those individuals who are released from local corrections. The Risk-Needs-Responsivity (RNR) model has offered various individual-level risk factors that have been shown to significantly influence an individual's odds of recidivism (Andrews & Bonta, 1994). The current study supports that argument and has found that recidivism, for the current sample, is largely an indicator of individual-level risk. As such, policymakers should continue to focus on these criminogenic risk factors to better serve the needs of these individuals and to reduce the likelihood of recidivism. These risk factors should be identified early-on and used to better address *all* principles of the RNR model: risk, needs, and responsivity.

Among the individual-level factors in the current analysis, gender, race, ethnicity, and age were found to be largely influential in receiving a subsequent charge, conviction, or incarceration term. Wisconsin, in particular, is at the forefront of racial disparity for Black male incarceration rates, representing an overall rate that is 12 times the rate for White males (Levine, 2019). The present research examined a sample of individuals who were serving a sentence at the House of the Corrections in Milwaukee County and were released in 2013 and 2014. The results indicated that Black males were significantly more likely to recidivate on all three dependent variables compared to their counterparts. Further, younger Black males presented the highest odds of recidivism, receiving roughly two times higher odds of recidivism than all other groups used in the analysis. These results do not attempt to explain *behaviors*, but they do suggest significant disparities found within the criminal justice system (policing, courts, etc.).

While neighborhood context was not found to hold a relationship with recidivism in the current sample, it should not be discontinued as a potentially important indicator. It is possible that limitations of the current study influenced results related to neighborhood context. It is also possible that neighborhood context could be influential on other local populations or across other time periods. Research and policy should still continue to consider neighborhood context when evaluating jail recidivism. As stated by Kubrin and Weitzer (2003), individual characteristics can be influenced by the social forces within one's immediate environment. Thus, the inclusion of neighborhood context in reentry research remains important to gain a holistic understanding of the recidivism process (Clear, 2007; La Vigne & Thomson, 2003; Wright, Pratt, Lowenkamp, & Latessa, 2012).

Summary and Conclusions

The purpose of the current study was to examine how various individual and neighborhood characteristics may influence the likelihood for individuals to recidivate following release from jail. Prior literature on jail reentry offers some insight into the correlates that influence recidivism patterns, yet several gaps in the research remain that needed to be addressed. Therefore, the present research sought to provide additional insight on jail reentry using multiple indicators of recidivism, while also examining the influence of individual and neighborhood context through the perspectives of the RNR model and social disorganization theory. This study was able to use local data to assess the characteristics of a correctional population and provide a critical step in identifying who recidivated, which factors drove that recidivism, and ultimately how resources could be allocated to better prevent criminal activity.

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APPENDIX A

Descriptive Statistics for City of Milwaukee vs. Milwaukee County[21] Individuals (N=7,334[22])

	City of Milwaukee (N=6,424)	Milwaukee County (N=910)
Individual-level Independent		
Gender		
Male	86.6%	79.9%
Female	13.4%	20.1%
Race/Ethnicity		
White, non-Hispanic	16.9%	78.9%
Black, non-Hispanic	74.7%	11.8%
Hispanic/Latino	7.6%	7.9%
Other	0.8%	1.4%
Age at release (years)	31.9(11.3)	35.2(11.6)
LSI-R:SV total score	3.6(1.6)	3.7(1.6)
Prior criminal record		
Prior charges	1.4(2.4)	1.2(2.2)
Prior jail incarcerations	0.6(1.3)	0.6(1.1)
Prior prison incarcerations	0.1(0.4)	0.1(0.4)
Current offense type		
Violent	11.9%	9.1%
Property	19.8%	18.4%
Drug	12.8%	11.2%
Public order	28.7%	16.2%
OWI-related	11.3%	35.6%
Traffic-related	11.3%	6.0%
Other	4.3%	3.5%
Time served (days)	86.1(94.7)	91.1(88.8)
Year of Release		
2013	58.8%	61.5%
2014	41.2%	38.5%
Neighborhood-level Independent		
Concentrated disadvantage	0.3(0.1)	0.2(0.1)
Concentrated affluence (ICE)	-0.4(0.5)	0.4(0.5)

[21] Milwaukee County refers to those individuals who live within Milwaukee County, but are outside of the City of Milwaukee limits.

[22] The total sample size refers to those addresses that were successfully matched (98%) using the Milwaukee County address locator in ArcGIS.

Concentrated immigration	0.1(0.2)	0.1(0.1)
Racial/ethnic heterogeneity (HHI)	0.3(0.2)	0.2(0.2)
Population density (sq. mi.)	10,961.5(6,945.0)	5,633.3(3,759.9)
Residential stability	0.6(0.1)	0.7(0.1)
Dependent variables		
New Eligible Charge	41.7%	37.7%
New Eligible Conviction	37.4%	33.5%
New Eligible Incarceration	30.3%	23.2%

APPENDIX B

Dichotomous measures comparing City of Milwaukee vs. Milwaukee County

	City of Milwaukee	Milwaukee County	Chi-Square
Gender			
Male	5,564(86.6%)	727(79.9%)	29.530***
Female	860(13.4%)	183(20.1%)	
Race/Ethnicity			
White, non-Hispanic	1,085(16.9%)	718(78.9%)	1,653.219***
Black, non-Hispanic	4,798(74.7%)	107(11.8%)	1,425.1***
Hispanic/Latino	491(7.6%)	72(7.9%)	0.081
Other	50(0.8%)	13(1.4%)	3.957*
Current offense type			
Violent	766(11.9%)	83(9.1%)	6.119*
Property	1,271(19.8%)	167(18.4%)	1.039
Drug	821(12.8%)	102(11.2%)	1.789
Public order	1,841(28.7%)	147(16.2%)	63.076***
OWI-related	723(11.3%)	324(35.6%)	386.176***
Traffic-related	723(11.3%)	55(6.0%)	22.823***
Other	279(4.3%)	32(3.5%)	1.341
Year of Release			
2013	3,776(58.8%)	560(61.5%)	2.510
2014	2,648(41.2%)	350(38.5%)	
New charge			
None	3,746(58.3%)	567(62.3%)	5.252*
One or more	2,678(41.7%)	343(37.7%)	
New conviction			
None	4,024(62.6%)	605(66.5%)	5.058*
One or more	2,400(37.4%)	305(33.5%)	
New incarceration term			
None	4,480(69.7%)	699(76.8%)	19.227***
One or more	1,944(30.3%)	211(23.2%)	

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

APPENDIX C

Continuous measures comparing City of Milwaukee vs. Milwaukee County

	City of Milwaukee *mean (SD)*	Milwaukee County *mean (SD)*	T-test
Age at release (years)	31.9(11.3)	35.2(11.6)	8.130***
LSI-R:SV total score	3.6(1.6)	3.7(1.6)	1.710
Prior criminal record			
Prior charges	1.4(2.4)	1.2(2.2)	2.370*
Prior jail incarcerations	0.6(1.3)	0.6(1.1)	0.951
Prior prison incarcerations	0.1(0.4)	0.1(0.4)	3.652***
Time served (days)	86.1(94.7)	91.1(88.8)	1.503
Concentrated disadvantage	0.3(0.1)	0.2(0.1)	41.831***
Concentrated affluence (ICE)	-0.4(0.5)	0.4(0.5)	45.979***
Concentrated immigration	0.1(0.2)	0.1(0.1)	6.411***
Racial/ethnic heterogeneity (HHI)	0.3(0.2)	0.2(0.2)	16.421***
Population density	10,961.5(6,945.0)	5,633.3(3,759.9)	22.677***
Residential stability	0.6(0.1)	0.7(0.1)	26.762***

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

APPENDIX D

Bivariate Correlation Matrix

Variable	(1)	(2)	(3)	(4)	(5)	(6)
(1) Year of Release	1					
(2) Gender	.014	1				
(3) Race	-.010	-.019	1			
(4) Age at release	.001	.001	.089**	1		
(5) LSI-R:SV	-.035**	.057**	-.039**	.039**	1	
(6) Prior charges	-.489**	.067**	-.024*	.037**	.184**	1
(7) Prior jail incarcerations	-.413**	.044**	-.016	.049**	.200**	.838**
(8) Prior prison incarcerations	-.273**	.060**	-.047**	-.041**	.111**	.352**
(9) Current offense	.024*	.089**	.061**	.050**	-.077**	-.021
(10) Time served	.064**	.099**	.017	.005	.067**	-.002
(11) New charge	-.081**	.053**	-.069**	-.142**	.157**	.185**
(12) New conviction	-.054**	.052**	-.061**	-.147**	.148**	.165**
(13) New incarceration	-.115**	.069**	-.087**	-.142**	.167**	.193**

(contd.)

Variable	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) Year of Release							
(2) Gender							
(3) Race							
(4) Age at release							
(5) LSI-R:SV							
(6) Prior charges							
(7) Prior jail incarcerations	1						
(8) Prior prison incarcerations	.170**	1					
(9) Current offense	-.055**	.019	1				
(10) Time served	.023	.046**	-.140**	1			
(11) New charge	.168**	.061**	-.017	-.039**	1		
(12) New conviction	.160**	.050**	-.026*	-.026*	.913**	1	
(13) New incarceration	.189**	.083**	-.041**	-.008	.780**	.854**	1

**Correlation is significant at the .01 level*
***Correlation is significant at the .05 level*

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- CRM JST 662: Methods of Social Welfare Research

Fall 2017
- CRM JST 662: Methods of Social Welfare Research

Fall 2016 (*Teaching Assistant*)
- CRM JST 756: Proseminar: Analysis of Criminal Justice Research – (Graduate course)

[23] Legal name-change from Pfeiffer to Sheeran throughout curriculum vitae.

Spring 2016

- CRM JST 305: Crime and Criminal Justice Policy – online course

Fall 2015

- CRM JST 275: Criminal Court Process – online course

BOOKS

Freiburger, T.L. & **Sheeran, A.M. (2019).** *Cognella series on career development in criminology and criminal justice: Teaching research methods* (1st ed.). San Diego, CA: Cognella Academic Publishing.

MANUSCRIPTS

Sheeran, A.M., Hilinski-Rosick, C., Richie, M., Freiburger, T.L. (2018). Correlates of elderly inmate misconduct: A comparison of younger, middle-age, and elderly inmates. *Corrections: Policy, Practice and Research.* DOI: 10.1080/23774657.2018.1549965.

Freiburger, T.L., & **Sheeran, A.M.** (2018). Evaluation of Safe Streets Treatment Option to reduce recidivism among repeat drunk driving offenders. *Criminal Justice Policy Review, 1-17.*

Freiburger, T.L., & **Sheeran, A.M.** (2017). The joint effects of race, ethnicity, gender, and age on the incarceration and sentence length decision. *Race and Justice,* 1-20.

REPORTS

Freiburger, T.L., & **Sheeran, A.M.** (2020). *Enhanced Mental Health Diversion and Deferral Program Outcome Evaluation Results.* Presented to the Milwaukee County Circuit Court, Milwaukee County, Wisconsin.

Sheeran, A.M., & Freiburger, T.L. (2019). *Evaluation of the Milwaukee County Adult Drug Treatment Court Final Report 2018.* Presented to the Milwaukee County Adult Drug Treatment Court team, Milwaukee County, Wisconsin.

Sheeran, A.M., Freiburger, T.L., & LeBel, T.P. (2018). *Evaluation of the Milwaukee County Adult Drug Treatment Court Final Report 2016-2017.* Presented to the Milwaukee County Adult Drug Treatment Court team, Milwaukee County, Wisconsin.

Sheeran, A.M., & Freiburger, T.L. (2018). *Office of African American Affairs (OAAA) Project Aspire – Measures of Recidivism Report.* Presented to the Office of African American Affairs, Milwaukee County, Wisconsin.

Pfeiffer, A.M. & Freiburger, T.L. (2017). *Outagamie County Recidivism Rates.* Presented to Outagamie County, Wisconsin.

Freiburger, T.L. & **Pfeiffer, A.M.** (2017). *Assessment of the "Safe Streets Treatment Options Program" (SSTOP).* Presented to Outagamie County, Wisconsin.

Freiburger, T.L. & **Pfeiffer, A.M.** (2015). *S.T.O.P. St. Louis Evaluation 2015-2016: Final Report.* Presented to the St. Louis Police Foundation.

Freiburger, T.L. & **Pfeiffer, A.M.** (2015). *S.T.O.P. Racine 2015-2016: Final Report.* Presented to the Racine Police Department and the Mt. Pleasant Police Department.

Freiburger, T.L. & **Pfeiffer, A.M.** (2015). *Assessment of the "Makin' It Work" Program: Years Three and Four.* Presented to the Eastern District of Wisconsin United States Probation Office.

COMMUNITY PRESENTATONS

Freiburger, T.L., & **Sheeran, A.M**. "Equity, inclusion, and diversity: The importance of data and what it says." Presented at the Wisconsin Association of Treatment Court Professionals (WATCP) Coordinators Conference in October 2019.

Freiburger, T.L., & **Sheeran, A.M.** "Outcome evaluation of Safe Streets Treatment Options Program (SSTOP)." Presented at the County Executive Board Meeting, Outagamie County, WI in October 2017.

PRESENTATIONS AT ACADEMIC MEETINGS

Sheeran, A.M., Richie, M., Hilinski-Rosick, C., & Freiburger, T.L. "Inmate misconduct: A test of the importation and deprivation theories." Accepted for presentation at the annual meeting of the American Society of Criminology in November 2018.

Sheeran, A.M. & Freiburger, T.L. "The joint effects of race, ethnicity, gender, and age on the likelihood of reoffending." Accepted for presentation at the annual meeting of the Midwestern Criminal Justice Association in September 2018.

Pfeiffer, A.M., & Freiburger, T.L. "A qualitative examination of the veteran's treatment initiative in Milwaukee County." Accepted for presentation at the annual meeting of the Academy of Criminal Justice Sciences in February 2018.

Freiburger, T.L., & **Pfeiffer, A.M**. "A quasi-experimental evaluation of the safe streets treatment options program (SSTOP) in Outagamie County, WI." Accepted for presentation at the annual meeting of the Midwestern Criminal Justice Association in September 2017.

Freiburger, T.L., & **Pfeiffer, A.M.** "Improving juveniles' attitudes toward the police: Results from an experimental design in two cities." Accepted for presentation at the annual meeting of the Academy of Criminal Justice Sciences in March 2017.

Pfeiffer, A.M., Richie, M., Freiburger, T.L., & Hilinski-Rosick, C. "Factors contributing to prison misconduct among elderly inmates." Accepted for presentation at the annual meeting of the Academy of Criminal Justice Sciences in March 2017.

Freiburger, T.L., & **Pfeiffer, A.M.** "Improving juveniles' perceptions of the police". Accepted for poster session at the annual meeting of the American Society of Criminology in November 2016.

Pfeiffer, A.M., & Freiburger, T.L. "The impact of race and gender on the likelihood of incarceration". Accepted for presentation at the annual meeting of the Academy of Criminal Justice Sciences in March 2016.

Pfeiffer, A.M. "Community members' perceptions of the police using Educate to Empower: Police and Citizens Together". Accepted for presentation at the annual meeting of the Midwestern Criminal Justice Association in September 2015.

ACADEMIC AND UNIVERSITY AWARDS

Graduate Student Excellence Fellowship Award

- University of Wisconsin – Milwaukee (2019-2020 academic year)

Adjunct Faculty Teaching Award

- Helen Bader School of Social Welfare, UWM (2019)

Dean's Random Acts of Kindness Award

- Helen Bader School of Social Welfare, UWM (2016, 2018, 2019)

Distinguished Graduate Student Fellowship Award

- University of Wisconsin – Milwaukee (2017-2018 academic year)

Graduate Student Award in Criminal Justice

- Helen Bader School of Social Welfare, UWM (2016)

Dean's Fellowship

- Helen Bader School of Social Welfare, UWM (2015-2016 academic year)

MEMBERSHIP IN DEPARTMENT, SCHOOL, UNIVERSITY COMMITTEES

University of Wisconsin – Milwaukee, Graduate Scholastic Appeals Committee (2019 – present)

Helen Bader School of Social Welfare, PhD Programs Committee (2018 – 2019)

Helen Bader School of Social Welfare, PhD Admissions Committee (2017 – 2019)

Student Grievance and Grade Appeal Committee (2015 – 2017)

MANUSCRIPT REVIEWS

Corrections: Policy, Practice, and Research – since 2018

PRIOR RESEARCH AND PROGRAM EXPERIENCE

Associate Researcher
May 2019 – present
Milwaukee, WI

- Project: Milwaukee County Adult Drug Treatment Court: Treatment Service Expansion Project
    - Project funded by SAMSHA [#1H79TI081922-01]
- Responsibilities: Attend weekly staffing meetings and court proceedings; observe interactions between drug court team members and participants; conduct focus groups and in-depth interviews with MCADTC participants, as well as members of the treatment court team; transcribe, organize, and analyze qualitative data; assist in creating and implementing an exit survey for MCADTC participants gauging mental and physical health, education, employment, housing, and AODA needs; analyze outcome data from exit surveys; analyze additional data to examine treatment court effectiveness; develop evaluation reports on MCADTC participants and client outcomes.

Associate Researcher
May 2019 – January 2020
Milwaukee, WI

- Project: Evaluation of the Enhanced Mental Health Diversion and Deferral Program
- Responsibilities: Conduct in-depth interviews with program participants; administer exit surveys for graduating participants; analyze outcome data from exit surveys and qualitative interviews; analyze quantitative data (program completion & recidivism) using propensity score matching to compare treatment group and comparison group (standard DPA); develop evaluation report on effectiveness of the program.

Research Assistant
September 2016 – September 2017; May 2018 – September 2019[24]
Milwaukee, WI

- Project: Treatment Service Enhancement Evaluation of the Milwaukee County Adult Drug Treatment Court (MCADTC) and the Veteran's Treatment Initiative (VTI)
    - Project funded by SAMSHA [# MIL111928]
- Responsibilities: Attend weekly staffing meetings and court proceedings; observe interactions between drug court and veterans court team members and participants; conduct focus groups and in-depth interviews with MCADTC and VTI participants, as well as members of the treatment court team; transcribe, organize, and analyze qualitative data; assist in creating and implementing an exit survey for MCADTC participants gauging mental and physical health, education, employment, housing, and AODA needs; analyze outcome data from exit surveys; analyze additional data to examine treatment court effectiveness; develop evaluation reports on MCADTC participants and client outcomes.

Research Assistant
May 2018 – August 2018
Milwaukee, WI

- Project: Eviction Defense Project Evaluation
    - Project funded by the Legal Action of Wisconsin
- Responsibilities: Attended legal aid sessions; administered and collected satisfaction surveys from clients; managed and organized survey data for reports and follow-up surveys.

Research Assistant
June 2017 – July 2018
Office of African American Affairs, Milwaukee, WI

- Project: Office of African American Affairs Project ASPIRE – Measures of Recidivism
- Responsibilities: Merged and cleaned numerous large-scale databases containing jail booking information and post-release criminal case information; developed "unique identifiers" for defendants to accurately link information between data sets; determined eligibility for recidivism based on various outcome measures and recidivism windows; calculated and analyzed recidivism rates for the county of Milwaukee; conducted statistical analyses to examine the relationship between various individual and legal factors and the likelihood of recidivism; developed and maintained positive working relationships with government agencies; prepared an evaluation report for the Office of African American Affairs.

Research Assistant
June 2016 – August 2017
Milwaukee, WI and Outagamie County, WI

- Project #1: Outcome Evaluation of the Safe Streets Treatment Options Program (SSTOP)
- Responsibilities: Collected recidivism data for treatment and comparison group participants; determined eligibility for recidivism based on several outcome measures; conducted outcome analyses of program data; developed and maintained positive

[24] Leave of absence as "research assistant" was taken during the 2017-2018 academic year due to receiving the Distinguished Graduate Student Fellowship Award. Involvement in the research project and collaboration efforts remained during this time though.

working relationships with government and community agencies; co-created an evaluation report for Outagamie County on the effectiveness of implementing SSTOP; presented evaluation findings at a county board meeting in Appleton, WI.

- Project #2: Assessment of Recidivism Rates for Outagamie County, WI
- Responsibilities: Collected recidivism data for a sample of individuals in Outagamie County, WI who were convicted of either a criminal traffic, misdemeanor, or felony offense; determined eligibility for recidivism based on various outcome measures and recidivism windows; calculated and analyzed recidivism rates for Outagamie County; conducted statistical analyses to examine the relationship between various individual and legal factors and the likelihood of recidivism; developed and maintained positive working relationships with government and community agencies; prepared an evaluation report for Outagamie County.

Research Assistant
August 2015 – September 2016
Milwaukee, WI and St. Louis, MO

- Project: Process and outcome evaluation of the Students Talking it Over with Police (S.T.O.P.) program – Implemented in Racine, WI and St. Louis, MO
- Responsibilities: Administered pre- and post-test surveys to three schools in Racine, WI; observed and coded 27 program sessions for Racine (in-person) and St. Louis (video-recorded); traveled to and conducted focus groups with student participants in St. Louis, MO regarding program effectiveness; assessed officers' program implementation and officer-student interactions; entered and maintained program related data; supervised additional coding and data entry by several university student program assistants; co-created evaluation reports for both the Racine and St. Louis Police Departments on the implementation and delivery of S.T.O.P.

Field Placement Program - Project Assistant
August 2014 – May 2015
University of Wisconsin – Milwaukee, Milwaukee, WI

- Responsibilities: Coordinated student field placements with various agencies in the Milwaukee area; graded final papers and evaluation reports.

Graduate Assistant
August 2014 – May 2015
University of Wisconsin – Milwaukee, Milwaukee, WI

- Responsibilities: Graded assignments and quizzes for CRM JST 295: Crime and Criminal Justice Policy; Coded, entered, and maintained program related data for a study related to federal probation and parole; coded, entered, and maintained program related data for a study involving women in jail.

Graduate Intern
September 2014 – December 2014
The Office of Community Outreach and Education
Milwaukee Police Department, Milwaukee, WI

- Responsibilities: Administered pre- and post-test surveys for the S.T.O.P. program; entered and maintained data for an educational program (Educate to Empower) implemented by the Milwaukee Police Department; developed and maintained positive working relationships with government and community agencies; assisted in developing a pilot session for an anti-bullying program created by the Milwaukee Police Department; contributed to the Auto-Theft Deterrence Initiative (assisted in organizing the initiative, created an evaluation survey used to assess program effectiveness, collected participant survey data and vehicle/driver information, and conducted basic analyses for the Milwaukee Police Department and the Chief of Police).

Research Assistant
January 2014 – August 2014
Milwaukee, WI

- Project: Process and Outcome Evaluation of the Students Talking it Over with Police (S.T.O.P.) program – Implemented in Milwaukee, WI.
- Responsibilities: Administered pre- and post-test surveys to students in various public and private schools throughout Milwaukee; observed and coded 14 program sessions; assessed officers' program implementation and officer-student interactions; coded, entered and maintained program related data for 765 student participants.

PROFESSIONAL AFFILIATIONS

Midwestern Criminal Justice Association – member since 2017

Academy of Criminal Justice Sciences – member since 2016

The American Society of Criminology – member since 2016

TRAININGS AND WORKSHOPS

Achieving Cultural Competency and Addressing Behavioral Health Disparities – 2018 (hosted by SAMSHA)

ICPSR workshop on Multilevel Modeling with HLM and SPSS – 2019 (Amherst, MA)