Recidivism and Community Context: Integrating the Environmental Backcloth

Authors
Grant Drawve, Ph.D.
University of Arkansas
Assistant Professor
Associate Director of Crime and Security Data Analytics Lab (CASDAL)
Email: drawve@uark.edu

Susan McNeeley, Ph.D.
Minnesota Department of Corrections
Senior Research Analyst
Email: susan.mcneeley@state.mn.us
Phone: 651-361-7615

This information will be made available in alternative format upon request.
Printed on recycled paper with at least 10 percent post-consumer waste.
RESEARCH SUMMARY

Typically, when place is considered to influence individual-level recidivism, the primary focus is community-level disadvantage through a social disorganization framework. Extant studies have been pivotal in the development of spatial recidivism research; however, there are limited approaches integrating elements from the larger environmental backcloth. Building from social disorganization and the three theoretical pillars of environmental criminology (RC, RAT, CPT), the current study sought to expand on what measures are considered at the tract-level to reflect a wider body of spatial criminological research. The current study employed a multilevel model to analyze a statewide sample of people on parole released from Minnesota state prisons to private residences in 2009, accounting for individual and tract-level covariates. Neighborhood-level presence of prosocial places (churches, employment services, and civil and social organizations) was negatively related to recidivism, but this relationship was weaker in disadvantaged neighborhoods. The discussion is nested with the broader ecological and environmental corrections literature on better accounting for and measuring “where” characteristics for recidivism to use jointly with the known “who” characteristics.
INTRODUCTION

Most incarcerated people will return to the community; even with a 14 percent reduction of people on community supervision from 2008 to 2018, there were still about 4.4 million people on either probation or parole (BJS, 2020). At the same time, a nine-year follow-up of people released from prisons across 30 states in 2005 found 83% were rearrested (Alper et al., 2018). A majority of those rearrests (68%) occurred within the first three years of release; 44% occurred within the first year. With such high likelihood of people released on parole being rearrested, recidivism-based research needs to extend beyond its often person-centric focus and account for the larger environment of where people are returning to upon release. The issue that surmounts is in our understanding of whether and how place matters for people on parole when returning to their communities.

Typically, if recidivism takes a spatial approach, social disorganization is used as a framework, mostly pointing to Kubrin and Stewart’s (2006) work to the reconsideration of community (Clark, 2016; Grunwald et al., 2010; Huebner & Pleggenkuhle, 2015; Kubrin & Stewart, 2006; Kubrin et al., 2007; Mears et al., 2008; McNeeley, 2018a, 2018b; Onifade et al., 2011; Tillyer & Vose, 2011; Wright et al., 2014). This is further reiterated when Clear (2009) explains people who were incarcerated are likely to return to disadvantaged neighborhoods. With that, a general focal point is on a community-level disadvantage measure, often constructed from Census of American Community Survey estimates, to understand the potential influence of concentrated disadvantage on individual-level recidivism. Problematic though, commonly-tested social disorganization measures are only one aspect of the larger environmental backcloth.

Brantingham and Brantingham (1993) introduce a concept known as the environmental backcloth that speaks to how people move through and within spaces. Specifically, “The backcloth
matters. All of our activities (including criminal activities) play out across a backcloth composed of social, economic, political, and physical dimensions” (Brantingham, Brantingham, & Andresen, 2017, p 100). Absent from much of the community approaches to recidivism are aspects of the backcloth related to local institutions and criminogenic establishments, each argued to influence crime occurrence in their own capacity (e.g., Drawve et al., 2019; Hipp et al., 2010; Miller et al., 2016; Wallace, 2015; Wallace & Papachristos, 2014). That is, local institutions are argued to have a protective effect by increasing social controls in the community while criminogenic establishments, often referred to as crime generators and attractors (see Brantingham & Brantingham, 1995), are argued to increase crime in and around their locations. Recidivism research needs to further integrate multiple elements of the environmental backcloth to identify if, and how, place matters in relation to individual-level recidivism.

The current study seeks to bridge this gap in literature by focusing on multiple elements of the environmental backcloth. Specifically, we use the concept of the backcloth to bridge concepts and approaches often seen in social disorganization and environmental criminology. We view these theoretical foundations as complementary to one another rather than competing, and use them as an integrated theory here. Social disorganization and environmental criminology are inherently intertwined theoretical perspectives that scholars should test together to better understand the role of community in human behavior. To do so, we examine the backcloth of Minnesota communities to further our understanding of individual-level recidivism through a multi-level approach. Supplementing the statewide study, we explore whether prior community crime influences the likelihood of recidivism in the state’s largest city, Minneapolis.

**REVIEW OF LITERATURE**

The focus of the current study is to expand on much of the foundational work related to
how and whether community or place matter in relation to individual-level recidivism. Traditionally, recidivism research typically takes an individual approach given the individual process in the re-offending or non-guideline following behaviors. That is, a decision is made to re-offend or not follow guidelines in some nature. This has led to strong evidence that individual-level factors such as prior criminal history, sex, race, and age (see Gendreau et al., 1996; Piquero et al., 2015; Wang et al., 2010) significantly influence recidivism. This line of inquiry has been instrumental in understanding recidivism; however, much of the recidivism literature is void of community measures (i.e., block group or tract). This is important given Harding et al.’s (2013) findings that 41% of people on parole reside within a half-mile of their pre-prison neighborhoods, or more generally return to neighborhoods with similar characteristics as their pre-incarceration homes. In short, many people are returning to places where they acted on criminal opportunities previously. Because of this, we focus our review of literature on theories related to community and place as well as prior neighborhood-level approaches to understanding recidivism.

**Environmental Backcloth**

We opt to discuss the larger theoretical context of our study in relation to the environmental backcloth. Brantingham and Brantingham (1993) discuss in detail the interconnectedness of the uncountable characteristics of the backcloth that influence individual behavior though an environmental psychology perspective. Because of this, it is necessary to integrate criminological theoretical approaches and concepts to account for these various characteristics. Most commonly applied to the study of recidivism from a neighborhood perspective are social characteristics of communities often tied to social disorganization theory. This is likely because of Kubrin and Stewart’s (2006) reinvigoration of potential neighborhood effects stemming from Gottfredson and Taylor’s (1988) work outlining the potential person-environment interactions from a neighborhood
perspective. We argue aspects of the environmental criminology subfield could offer additional insights into the likelihood of recidivism based on the presence of criminal opportunities. We do not view these theoretical approaches as competing but rather as intrinsically tied together.

Social Backdrop of Communities

Extant literature has long supported the connection between community social characteristics and crime (e.g., Bursik & Grasmick, 1999; Hipp, 2007; Krivo & Peterson, 1996; Sampson, 2012). Work emanating from Shaw and McKay’s (1942) social disorganization theory has led to measures of concentrated disadvantage remaining one of the strongest and most stable predictors of crime occurrence (see Pratt & Cullen, 2005 meta-analysis). Broadly speaking, social disorganization argues crime, and delinquency, results from communities’ inability to maintain and regulate normative behaviors (i.e., lack of neighborhood social control; Kornhauser, 1978). Most often associated with social disorganization theory are the three structural characteristics of communities: poverty, residential instability, and ethnic heterogeneity. Communities characterized with high amounts of residential instability and ethnic heterogeneity is often the result of poverty level (i.e., economic deprivation; Bursik, 1988, p. 520). These characteristics stem from Shaw & McKay’s groupings that were used to differentiate different areas: Physical Status; Economic Status; and Population Composition (Shaw & McKay, 1969). In the inner zones of an urban city (zones I and II) - which characterized by higher rates of delinquency, decreases in population, more families on relief, less expensive rentals, less home ownerships, and greater population diversity - there are often competing value systems which could lead to more enticing cultural transmission of delinquent behaviors to achieve status (Shaw & McKay, 1969).1

While the structural characteristics of communities garner much of the social

---

1 For a greater discussion on strain, see Merton (1938).
disorganization research focus, land-use, and in particular mixed-land-use, has become increasingly important to account for when examining communities and crime and/or social control (Browning, Byron, Calder, Krivo, Kwan, Lee, & Peterson, 2010; Lockwood, 2007; Sampson & Raudenbush, 1999; Snowden & Pridemore, 2013; Stucky & Ottensmann, 2009; Wilcox, Quisenberry, Cabrera, & Jones, 2004; Wo, 2019). With an increase in mixed-land-use, primarily away from residential use, a greater volume of outsiders travel to those communities for non-residential purposes (e.g., commercial/retail, recreational, and transportation), making it difficult to distinguish between insiders (residents) and outsiders. As argued by Peterson et al. (2000), residents of disadvantaged communities already suffer from the inability to work together which also leads to a “... lack of power to demand that local government and private agencies develop institutions to meet community needs and to fight the development of establishments, such as bars, that foster deviant behavior” (p 33). Important to note here, Hipp (2007, p 670) states that neighborhood crime rates are “consequences” of how community members interact with one another.

The rapid population turnover in communities consistently disrupts the socialization process, and as Bursik (1988) further discusses, could lead to the inability of community members to work together to solve shared problems. Bursik and Grasmick (1993) expand on this premise by describing how neighborhood structures are affected by both informal and formal networks (i.e., systemic model of social disorganization). That is, informal social control within communities is, in part, reliant on localized networks of organizations, institutions, and residents (see Sampson, 2012). As pointed out by Kubrin and Weitzer (2003, p 376), many early social disorganization studies “assumed” this relationship, leaving it untested. It was not until Sampson and Groves’ (1989) examination of how local friendship networks, organizational participation,
and unsupervised peer groups intervene between the common structural measures and crime and delinquency. Explained by Sampson (2012), when there is greater social cohesion and shared expectations between of residents within communities, the collective efficacy – or the ability of residents to take overt actions to control behaviors within community - of the community is capable of mediating the relationship between social structural measures and neighborhood crime (see Sampson, Raudenbush, and Earls, 1997). Taylor (1996, p 42) provides further insight on this point, “... some neighborhoods have residents who go their own way, do not know their neighbors or local improvement association, and view their neighborhood not as home, but just a place to live.” This becomes problematic in the formation of social control within communities when needed to exercise control over fellow community insiders or outsiders (Bursik, 1988; Bursik & Grasmick, 1993). The lack of informal social control over behaviors (see Shaw & McKay, 1969) is often linked to the social ties that allow for effective social control within communities (Sampson & Lauritsen, 1994).

Key to developing social ties and community social control is that the institutional base often operates through local organizations and businesses within communities (Bursik & Grasmick, 1993; Peterson, Krivo, & Harris, 2000; Sampson & Groves, 1989; Sharkey, Torrats-Espinosa, & Takyar, 2017; Triplett, Gainey, & Sun, 2003; Wilson, 1987; Wo, 2016). In short, it is argued that local organizations and businesses mediate the influence of the structural characteristics on community crime. These institutions allow for insiders to congregate, develop social ties, and build social cohesion. For instance, in Sharkey et al.’s (2017) study, as the number of local nonprofits increase within communities, there are long-term decreases in the crime rates. Similar relationships have been found for other institutions such as recreation centers (Peterson et al., 2000), civic organizations (Lee, 2008; Putnam, 2000), coffee shops and cafes (as third places;
Wo, 2016), and religious organizations (Beyerlein & Hipp, 2005). This is not to say all institutions are the same (see Wo, 2016); as Slocum et al. (2013) tests in detail, the link between organizations and crime could be conditioned based on the racial composition of a neighborhood (Slocum, Rengifo, Choi, & Herrmann, 2013).

At the other end of the spectrum, there are local institutions that could amplify crime in a neighborhood, as seen with the presence of bars and alcohol outlets (Peterson et al., 2000; Wo, 2016). Additionally, Slocum et al. (2013) found that schools were associated with an increase in property crime. When there are stores located on streets, Kurtz et al. (1998) argues these blocks, both residents and businesses, may need to work harder to organize to reduce crime than primarily residential blocks (Kurtz, Koons, & Taylor, 1998). This is important to distinguish since not all institutions are protective in nature; some could have aggravating-criminogenic effects, leading to an increase in criminal opportunities. With this, the environmental criminology literature provides a basis for how criminal opportunities vary across space.

**Physical Infrastructure & Environmental Criminology**

Highlighted within the environmental backcloth is the physical infrastructure that, like the social element, is dynamic and changes over time (Brantingham & Brantingham, 1993). In relation to the physical infrastructure, Brantingham and Brantingham (1993, p 367) state, “Someone who wants to commit some specific crime will search for a place that he (or she) interprets as ‘ideal’ for that crime, a place that fits a target template, a mental image of the right place and the right victim for the crime.” This underlying spatial association of target selection and criminal opportunity is often explained through the three pillars of environmental criminology: rational choice theory (Cornish & Clarke, 1986), routine activities theory (Cohen & Felson, 1979), and crime pattern theory (Brantingham & Brantingham, 1981, 1993). These three theories are often
grouped together as a theoretical foundation when examining spatial-temporal characteristics of crime.

Rational choice theory (Cornish & Clarke, 1986) argues that when presented with a criminal opportunity, the potential offender weighs the potential risk and efforts involved against the potential rewards. This is often nested within target selection research (e.g., Beauregard, Rossmo, & Proulx, 2007; Marchment, Bouhana, & Gill, 2020; Townsley, Birks, Ruiter, Bernasco, & White, 2016). Targets, and more broadly, criminal opportunities, present themselves over the course of individuals’ routine daily activities. Cohen and Felson (1979) argue criminal opportunities exist because of the convergence of a motivated offender and a likely-suitable target in time and space in the absence of capable guardianship. This framework is often linked to spatial patterns, usually described as hotspots (see Eck, Chainey, Cameron, Leitner, & Wilson, 2005; Sherman, 1995) and/or temporal trends (see Andresen & Malleson, 2015; de Melo, Pereira, Andresen, & Matias, 2018; Haberman, Sorg, & Ratcliffe, 2017). With crime patterned around routine activities, potential offenders encounter criminal opportunities within many places they are familiar with rather than having to search for opportunities in lesser-known places.

Brantingham and Brantingham (1984, 1993) expand on this argument of crime opportunities through crime pattern theory. Building from the premises of routine activities theory, crime pattern theory asserts individuals develop an awareness space of places they visit routinely. The awareness space is influenced by their activity spaces (where they spend a considerable amount of time), pathways to and from different activity spaces (whether by street network, transit, or by foot), and edges (social or physical boundaries around these spaces and pathways). Offenders, and the non-offending, develop an awareness space, leading to overlapping awareness spaces across individuals. It is within this awareness space where criminal opportunities are
exploited and aggregate patterns become detectable. That is, for instance, if multiple offenders are familiar with a local shopping mall and identify a specific shopping mall as ripe for criminal opportunities, their individual criminal actions create an aggregate identifiable crime pattern.

In this example, the local shopping mall would be described as a crime attractor since it is a well-known place for criminal opportunities that attracts offenders to it for criminal purposes. Brantingham and Brantingham (1995) further argue how the known aspect of criminal opportunities could lead to strongly motivated offenders traveling further to a specific location since the crime opportunity is already known. On the other hand, there are also crime generators that attract large volumes of people for non-criminal purposes but, based on the mix of potential offenders at these places, criminal opportunities are then exploited. The point here is not to delve into differences of generators or attractors (for a discussion, see Brantingham & Brantingham, 1995) but to indicate that these establishments influence crime in and around their locations. This is strongly supported by extant literature focusing on a variety of different crime generators and attractors such as bars (Madensen & Eck, 2008; Ratcliffe, 2012), liquor stores (Bernasco & Block, 2011; Block & Block, 1995), pawnshops (Kubrin & Hipp, 2016), restaurants (Askey et al., 2018), hotels/motels (LeBeau, 2011), stadiums (Kurland, Johnson, & Tilley, 2014), and by many studies that include multiple types (e.g., Steenbeek, Volker, Flap, & van Oort, 2012; Tillyer, Wilcox, & Walter, 2020).

Environmental criminology offers theoretical insights into the variation in criminal opportunities across space and time. Stated by Brantingham and Brantingham (1995, p 5), “The ways in which we assemble these large building blocks of routine activity into the urban backcloth can have enormous impact on our fear levels and on the quantities, types and timing of the crimes we suffer.” The location of businesses and organizations are not random in space and is often
related to the operating cost, potential profit, and service(s) offered. Because of this, certain communities become more attractive than others for certain businesses and organizations.

Interconnectedness of the Social & Physical Characteristics of the Backcloth

There is an inherent interconnectedness between the physical infrastructure and the social backdrop of communities. This is not to say previous research has not bridged across the theoretical foundations (e.g., see Hewitt, Beauregard, Andresen, & Brantingham, 2018; Smith, Frazee, & Daison, 2006), but we argue this should occur more frequently. For instance, Peterson et al. (2000) argue insiders of disadvantaged communities often lack the ability to come together to fight against more deviant-behavior-related establishments being located within their communities, while simultaneously lacking the economic and social resources to attract stable institutions and organizations. Said differently, communities that are more disadvantaged and lack social cohesion are more likely to have criminogenic establishments (crime generators/attractors) since the insiders are less likely to band together to prevent the opening. Additionally, as criminogenic establishments open within these communities, this brings more outsiders to the neighborhood, limiting insiders’ social control while increasing the outsiders’ awareness space and potential for criminal opportunities. On the other hand, insiders who are motivated offenders but lacking suitable criminal opportunities could benefit from the presence of establishments. This also provides insiders of these communities' criminal opportunities with the influx of potential suitable targets (outsiders) who are not as familiar with the community as the insiders.² To this point, Brantingham and Brantingham (1995) discuss how crime attractors, especially commercial areas, are located near poor areas, making targets more accessible to insiders. To this endeavor, the current study uses characteristics of the environmental backcloth described above to approach a

² For a greater discussion on outsiders and insiders, see Brantingham and Brantingham (1993).
topic with limited spatial applications, recidivism.

**Spatial Approaches to Recidivism**

Since Kubrin and Stewart (2006) compelled researchers and practitioners to think beyond individual factors, there has been continual interest in understanding if the larger neighborhood environment that people on parole/probation return to influences recidivism (e.g., Breetzke & Polaschek, 2018; Chamberlain, 2018; Craw & ten Bensel, 2020; Han, 2020; Houser, McCord, & Nicholson, 2018; Konkel, 2019, 2020; Liu, 2020; Lockwood, Harris, & Grunwald, 2019). Kubrin and Stewart (2006) originally found that people who were released from prison and returned to more disadvantaged neighborhoods had higher recidivism rates. Since then, much of the attention has been focused on the social-structural characteristics of neighborhoods given their robust findings when predicting neighborhood crime rates; however, as Jacobs and Skeen (2020) eloquently state, residential location matters for recidivism, but not equally across people, indicating that context matters (see also McNeeley, 2018a, 2018b).

There have been two recent meta-analyses, by Jacobs, Ashcraft, Sewall, Wallace, and Folb (Unpublished) and Jacobs, Ashcraft, Sewall, Folb, and Mair (2020), focused on neighborhood characteristics and recidivism or re-offending. Overall, concentrated disadvantage was not a significant measure once adjusting for individual-level measures; however, the effects were found to vary by age and type of recidivism. That is, concentrated disadvantaged had a lower effect on recidivism operationalized as conviction or incarceration than revocation or rearrest. Also, in Jacobs et al.’s (2020) meta-analysis of juvenile recidivism and ecological factors, of the 36 tests (from 18 studies) including a structural measure related to concentrated disadvantage, 19 resulted in a significant effect, while 17 were non-significant. Few studies in the meta-analysis included additional social-structural measures outside of concentrated disadvantage.
Extending from the social-structural examination of neighborhoods and recidivism, spatial recidivism research has examined the potential impact of local institutions and organizations on recidivism (Hipp, Petersilia, & Turner, 2010; Konkel, 2019, 2020; Wallace, 2015). The argument is that people are likely to return to disadvantaged neighborhoods lacking collective efficacy and social networks capable of instilling normative behaviors. Local institutions and organizations aim to fill this void by bringing insiders and other establishments within the community together to work together to solve local problems – developing social control. Wallace (2015) explored how the presence or loss of local organizations (food and shelter emergency assistance, employment, and education) impacted recidivism, finding the loss of two or more educational organizations resulted in an increase in recidivism of that neighborhood. Interesting here, Wallace (2015) found the current level of organizations did not affect neighborhood recidivism.

Konkel (2020) furthered this perspective by examining the potential of churches for reducing recidivism in Philadelphia; finding community-oriented (Mainline Protestant, Catholic) churches had no effect on recidivism while congregation-oriented (Evangelical Protestant) churches increased the odds of reincarceration. Still within Philadelphia, Konkel (2019) found general service providers within neighborhoods increased reincarnation, but reincarceration was lower when disadvantaged neighborhoods contained Pennsylvania Department of Corrections-referred service providers. Hipp et al. (2010) also found the presence of social service providers to reduce the likelihood of recidivism, and in particular, for African Americans on parole. While limited, there are promising findings that local institutions and organizations could provide a protective effect, forming a level of social control, on reducing recidivism.

At the same time local institutions are expected to reduce recidivism, there are criminogenic establishments expected to increase recidivism by creating criminal opportunities.
Although Hipp et al. (2010) argue this from a social disorder framework, and find support for an increase in bar/liquor store capacity and increased recidivism, environmental criminology also provides a foundation. While the influence of the physical infrastructure on crime is well-studied, there are limited applications applying this field of study to recidivism (Drawve et al., 2019; Houser et al., 2018; Miller et al., 2016).\(^3\) Drawve et al. (2019) sought to quantify the potential risk associated with crime generators and attractors through risk terrain modeling, creating a risk of crime measure around each person on parole. People on parole were more likely to have a profile of high risk of crime around their residence. Miller and colleagues (2016) constructed a buffer count of 12 different crime generators/attractors around each person on parole (1,200ft). They opted to do this to try and measure home nodes of the people on parole. No evidence was found that the count of crime generators and attractors within home nodes affected failure while on supervision. That being said, Houser et al. (2018) found the likelihood of reincarceration did increase when the number of bars and liquor outlets within walking distance of a person on parole’s home increased. The effect of crime generators and attractors on recidivism is understudied given our understanding of the criminal opportunities their presence creates.

Extending from this argument, few studies of recidivism have accounted for prior levels of neighborhood crime (e.g., Breetzke et al., 2019; Lockwood et al., 2019; Miller et al., 2016). This is troublesome since a more basic argument is that people on parole or probation are returning to crime-prone areas (e.g., Clear, 2009; Harding et al., 2013), increasing their encounters with already-known criminal opportunities. An interesting approach by Lockwood et al. (2019) provides a framework for how crime could be considered in context-specific studies. In their study on juvenile drug recidivism, they found that as the number of juvenile and adult drug seller density

\(^3\) Hipp et al. (2010) used a bar and liquor store capacity measure at the tract level, but used it as a measure of social disorder, beyond the normal structural characteristics measured through social disorganization theory.
increases within neighborhoods, the likelihood of a juvenile re-offending through drug sales also increases. On the other hand, Breetzke et al. (2019) found no significant association between four different crime categories and short-term recidivism of high-risk males in New Zealand once controlling for individual- and neighborhood-level measures. Similar to local institutions and criminogenic establishments, neighborhood levels of crime do not garner enough attention considering that people are going to be returning to neighborhoods with different levels of criminal opportunities. Known crime levels is a straightforward way of measuring a neighborhood’s criminal opportunity.

**Current Study**

The current study aims to bridge these often-siloed approaches used to understand individual-level recidivism through the environmental backcloth. First, we account for common individual characteristics such as risk level – measured with the Level of Service Inventory-Revised (LSI-R) and the MnSTARR 2.0 – and race. Building upwards from individuals to neighborhoods (measured as census tracts), we examine the potential role of social disorganization through a disadvantage measure supplemented with an Index of Concentrated Extremes (ICE). While research on recidivism is mixed, given the broader community literature, we expect people returning to more disadvantaged neighborhoods to be more likely to recidivate and those returning to more affluent neighborhoods to be less likely to recidivate. From here, we developed measures for the number of prosocial-local institutions across Minnesota neighborhoods as well as the number of criminogenic establishments known to function as crime generators and attractors. Given the underlying premise of each type of establishment, we expect prosocial establishments to have a protective effect (lowering recidivism) and criminogenic establishments to have an aggravating effect (increasing recidivism). To further explore potential contributors to
neighborhood-level effects, we conduct a supplemental analysis on Minneapolis. Address-level crime data were obtained for Minneapolis allowing for the level of violence per Minneapolis neighborhood to be included in the model.

To more fully account for how the elements of the environmental backcloth may combine to influence risk of recidivism, we explore whether there are interactions between the presence of prosocial or criminogenic establishments and the community’s level of disadvantage or affluence. The literature suggests several ways that social disorganization could moderate the impact of the built environment. On the one hand, the criminogenic effects of community disadvantage and crime generators/attractors may accumulate to further increase risk of recidivism. In other words, criminogenic businesses may increase recidivism more greatly in disadvantaged communities. Similarly, disadvantage may weaken the protective effect of prosocial businesses. On the other hand, prior research suggests the negative influence of social disorganization may be mitigated by the presence of prosocial organizations (Konkel, 2019; Wallace, 2015). Therefore, we might actually expect prosocial organizations to have stronger effects when they are located within more disadvantaged areas.

**RESEARCH METHODS**

**Data and Sample**

This study analyzes a sample of people released from Minnesota state prisons to supervised release in Minnesota in calendar year 2009. Some were released multiple times in 2009; only their first release was included in the dataset. Each person’s first address was collected from the Minnesota Department of Corrections’ (MnDOC) Correctional Operations Management System.

---

4 125 offenders were removed because they did not have a listed address or only listed their supervision agent’s office address. While some of those with no address data may have been homeless, it is also possible that this information was accidentally omitted or was stored elsewhere. Unfortunately, data on homelessness are not stored centrally in COMS; therefore, it was not possible to examine homelessness as part of this study.
(COMS), and the census tract in which they would reside after release was identified. Although examining multiple addresses would be ideal, later addresses could not be used for this study because they are not tracked centrally by MnDOC. Still, it is useful to examine the first place where one lives after release, since it can serve as a “launch pad” that puts them on the path toward success or failure (Fontaine & Biess, 2012).

Because prior research indicates that neighborhood characteristics may not affect recidivism among those who move into non-residential housing such as homeless shelters, halfway houses, or treatment facilities (McNeeley, 2018), we examined a subsample of those who moved into residential addresses. In addition, we removed cases with missing data on the individual risk score variables, as these are important controls. After removing cases living in non-residential housing and those without risk scores, the sample included 1,903 people within 831 neighborhoods. The number of people per neighborhood ranged from 1 to 192, with an average of 4.61. Scholars have argued that, while there is less statistical power in analyses with small samples within the Level 2 units, multilevel analyses can still be accurately performed under these circumstances (e.g., Bell et al., 2014; Clarke & Wheaton, 2007; Scherbaum & Ferreter, 2009).

The majority of the sample was male (91%). Over half (59%) were non-Hispanic white, 25% were African American, 11% were American Indian, 4% were Hispanic, and 1% were Asian. Approximately 20% were incarcerated for person offenses, while 18% were property offenders, 28% were drug offenders, 8% were sex offenders, 12% were DWI offenders, and 14% were incarcerated for other offenses.

**Dependent Variables**

Recidivism was measured using two binary variables indicating whether releasees had been 1) rearrested for a new offense or 2) returned to prison for a revocation of supervised release (either
a violation of technical conditions or low-level criminal activity that constitutes a violation of the conditions of supervised release but would not result in a new prison sentence). Data on rearrest were obtained from the Minnesota Bureau of Criminal Apprehension (BCA), and data on revocation were obtained from COMS. Because official measures of recidivism (i.e., those that only measure behavior known to the criminal justice system) are used, the dependent variables likely underestimate the true rates of recidivism. Descriptive statistics for all variables used in the analysis are presented in Table 1.

Table 1. Descriptive Statistics

<table>
<thead>
<tr>
<th></th>
<th>Statewide Sample</th>
<th></th>
<th>Minneapolis Sample</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
<td>Range</td>
<td>Mean</td>
</tr>
<tr>
<td>Recidivism</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rearrest</td>
<td>34%</td>
<td>---</td>
<td>0-1</td>
<td>44%</td>
</tr>
<tr>
<td>Revocation</td>
<td>26%</td>
<td>---</td>
<td>0-1</td>
<td>25%</td>
</tr>
<tr>
<td>MnSTARR 2.0 risk level</td>
<td>2.03</td>
<td>1.14</td>
<td>1-4</td>
<td>2.29</td>
</tr>
<tr>
<td>LSI-R risk level</td>
<td>2.68</td>
<td>1.11</td>
<td>1-5</td>
<td>2.52</td>
</tr>
<tr>
<td>Race</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>59%</td>
<td>---</td>
<td>0-1</td>
<td>21%</td>
</tr>
<tr>
<td>Asian</td>
<td>1%</td>
<td>---</td>
<td>0-1</td>
<td>1%</td>
</tr>
<tr>
<td>Black</td>
<td>25%</td>
<td>---</td>
<td>0-1</td>
<td>70%</td>
</tr>
<tr>
<td>Hispanic</td>
<td>4%</td>
<td>---</td>
<td>0-1</td>
<td>2%</td>
</tr>
<tr>
<td>Native American</td>
<td>11%</td>
<td>---</td>
<td>0-1</td>
<td>7%</td>
</tr>
<tr>
<td>Neighborhood Characteristics</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Criminogenic places</td>
<td>16.89</td>
<td>19.48</td>
<td>0-259</td>
<td>15.10</td>
</tr>
<tr>
<td>Prosocial places</td>
<td>7.66</td>
<td>5.76</td>
<td>0-53</td>
<td>8.16</td>
</tr>
<tr>
<td>Concentrated disadvantage</td>
<td>-0.43</td>
<td>0.84</td>
<td>-1.29-3.88</td>
<td>0.47</td>
</tr>
<tr>
<td>ICE</td>
<td>0.22</td>
<td>0.23</td>
<td>-0.80-0.83</td>
<td>0.03</td>
</tr>
<tr>
<td>Aggravated assault rate</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>2.67</td>
</tr>
</tbody>
</table>

Statewide: Releasees (N=1,903), Census tracts (N=831).
Minneapolis: Releasees (N=296), Census tracts (N=82)

Because parolees are likely to change residence within the first few years of release from prison (Steiner et al., 2015), the follow-up period in which recidivism was measured was one year. Although a longer follow-up period would be ideal, studies show that a large percentage of people who recidivate do so within the first year after release from prison (Durose et al., 2014; Langan &
Levin, 2002). About a third (34%) of our sample was rearrested and 26% was returned to prison for a technical violation revocation during the follow-up period.

**Neighborhood-Level Independent Variables**

First, data from ReferenceUSA/InfoGroup were used to identify the types of business located within neighborhoods. This dataset has been used in a number of criminological studies (e.g. Drawve et al., 2019; Hipp et al., 2019; Miller et al., 2016; Tillyer & Walter, 2019). InfoGroup data contains NAICS and SIC business descriptions by year across the United States. The historical business records dataset also contains geographical identifiers: address, city, state, latitude, and longitude. We created two variables reflecting the number of businesses within census tracts. First, criminogenic places (Cronbach’s $\alpha = 0.755$) included bars, banks, coffee shops, department stores, grocery stores, laundromats, parking facilities, retail stores, liquor stores, convenience stores, pawn shops, lottery retailers, tobacco retailers, check-cashing businesses, hotels and motels, and restaurants. Second, prosocial places (eigenvalue = 1.416, factor loadings between 0.632 and 0.785, Cronbach’s $\alpha = 0.336$) included churches, employment services, and civil and social organizations.

Second, Minneapolis crime data from calendar year 2008 were obtained from a prior National Institute of Alcohol Abuse and Alcoholism grant awardee (R01AA016309-02). The original crime data were collected from the Minneapolis Police Department (MPD; see Toomey et al., 2012). We geocoded the data using the Google Sheets Geocoder (see Dougherty & Ilyankou, 2020 – handsondataviz.org), which provides latitude and longitude for the address-level data. We examined aggravated assault rates per 1,000 residents as a measure of neighborhood violence. In supplemental analyses available upon request, we also examined the raw number of aggravated assaults; the results were similar to those presented below.
Next, based on prior research (Kubrin & Stewart, 2006; Clark, 2016), we included two census-tract level measures of the social environment using the U.S. Census Bureau’s 2010 American Communities Survey. Concentrated disadvantage was a factor score comprised of the following seven variables (Cronbach’s α = .834): proportion of households living under the poverty line, proportion of households with children younger than 18 years old headed by single females, proportion of the population that is Black, proportion of households that are rented, proportion receiving public assistance, proportion of households receiving food stamps, and proportion unemployed. These variables loaded together on a single factor (eigenvalue = 4.723) with factor loadings above .710.

Neighborhood affluence was examined using the ICE measure, computed with the following formula (Massey, 2001): \[(number of affluent families) – (number of poor families)] / total number of families. Affluent families are defined as having household incomes above $75,000 per year. Poor families are defined as having household incomes below the poverty line based on the U.S. Census. ICE ranges from -1 (all families are poor) to +1 (all families are affluent), with a score of 0 indicating that there are equal numbers of poor and affluent families. Higher scores on the ICE measure represent greater concentrations of affluence.

**Individual-Level Independent Variables**

To account for individual criminal propensity, scores from two risk assessments are used. First is the LSI-R, which is a validated risk assessment instrument that measures prior criminal history, education and employment, family relationships, antisocial and prosocial companions,

---

5 We examine LSI-R because MnDOC used this assessment in 2009. However, because the LSI-R performs worse on U.S. populations than Canadian populations (Giguère & Lussier, 2016; Olver, Stockdale, & Wormith, 2014), we also include the MnSTARR 2.0 due to its stronger performance among Minnesota prisoners (Duwe, 2014). The correlation between LSI-R and MnSTARR scores was weak to moderate, but statistically significant (r = 0.371, p < .01). Collinearity checks showed that including both in the same model was not an issue (MnSTARR: tolerance = 0.857, VIF = 1.167; LSI-R: tolerance = 0.828, VIF = 1.207).
leisure and recreation activities, substance use, emotional issues, and antisocial attitudes (see Andrews & Bonta, 1995). The variable used here captures the most recent LSI-R score before their release from prison. Scores on the LSI-R can range from 0 to 54, and higher scores correspond with higher risk for recidivism. In this study, the LSI-R is collapsed into five risk levels (ranging from low risk to high risk) using the cutoffs recommended by Multi-Health Systems (MHS). The average LSI-R risk level in this sample was 2.91.

Second, the Minnesota Screening Tool Assessing Recidivism Risk (MnSTARR) was validated using a sample of Minnesota prisoners (Duwe, 2014). Although the MnSTARR 2.0 was not implemented until 2016 (see Duwe & Rocque, 2017), scores were available for use in this study because the test sample was made up of people released in 2009-2010. The MnSTARR 2.0 calculates separate risk scales for males and females. The scores are computed using 48 variables that measure prior criminal history, institutional behavior, participation in effective programming, and post-release supervision type. Scores are then classified into one of four risk levels: low risk contains the bottom 40% of scores, medium risk contains the next 20%, high risk contains the next 20%, and very high risk contains the top 20% of scores. The average MnSTARR risk level in this sample was 2.01.

In addition, we control for race/ethnicity. In the statewide analyses, race/ethnicity was measured as a series of dichotomous variables indicating whether the person was White (reference group), Asian or Pacific Islander, Black, Hispanic, or Native American. When examining the subset released to Minneapolis neighborhoods, there were few Asians, Hispanics, or Native Americans (n = 3, 5, and 21, respectively); therefore, these groups were combined to create an “other race” category. Lastly, other characteristics that are commonly used as control variables in recidivism studies (such as age and gender) are accounted for in the two risk variables, so they are
not added separately into the models.

**Data Analysis**

Because the data are structured as parolees within neighborhoods, which can lead to incorrect results in traditional regression models due to inflated standard errors, the statewide analyses used multilevel Bernoulli modeling with a logit link function, which allows the models to meet the linearity assumption of regression. Multilevel modeling produces more accurate coefficients and standard errors than traditional regression, and allows for simultaneous examination of individual and neighborhood characteristics (Raudenbush & Bryk, 2002). A series of unconditional models, or models with no predictors at either level (not presented here), was estimated to determine whether multilevel analyses were appropriate for the data. The results showed that there was significant variation in rearrest (variance component = 0.179, p < .01) and revocation (variance component = 0.248, p < .001) across census tracts. Therefore, it is appropriate to proceed with multilevel analyses.⁶

In the analyses, the individual-level predictors were grand mean centered to allow for an examination of contextual effects (see Raudenbush & Bryk, 2002). Level 2 variables were not centered, except when examining interactions between variables. The slopes of individual-level predictors were fixed. We examined criminogenic places and prosocial-local institutions in separate models in order to estimate their unique effects on recidivism as well as to increase statistical power by reducing the number of neighborhood-level variables in the model.⁷ Because ICE and concentrated disadvantage were highly correlated (r = -0.897, p < .001), these variables

---

⁶ We conducted ANCOVA models that included only individual-level predictors (available upon request). The Level 2 variance components for rearrest and revocation were not significant in these models, suggesting that compositional differences may explain the variation in recidivism that exists across neighborhoods. Future research should explore whether certain groups of releasees (e.g., certain demographic groups) are more likely to move into disadvantaged or otherwise criminogenic neighborhoods after release.

⁷ When both criminogenic places and prosocial places were added to the same model (results available upon request), neither variable was significantly related to rearrest or revocation.
were examined in separate models. Collinearity was not an issue for the other variables in the model; the lowest tolerance value was 0.648 (highest VIF = 1.544).

RESULTS

Statewide Analyses

The results of the logistic regression models predicting statewide recidivism are presented in Table 2. Those living in census tracts with prosocial businesses were less likely to be rearrested; the odds of rearrest decreased by 1-2% for each additional prosocial business in the neighborhood. However, the presence of criminogenic establishments was not significantly related to rearrest. Consistent with previous studies, concentrated disadvantage was marginally related to higher odds of rearrest. With each one-unit increase in the concentrated disadvantage index, the odds of rearrest increased by 8-10%; however, this result was not statistically significant. At the individual level, risk levels as measured by MnSTARR 2.0 and LSI-R were related to rearrest; the odds of rearrest increased by 9-10% for each increase in LSI-R risk category and by 78-79% for each increase in MnSTARR risk level. Additionally, compared to Whites, Blacks were 77-86% more likely to be rearrested, while Native Americans were 63-66% more likely to be rearrested.

On the other hand, none of the neighborhood-level variables were related to revocation. At the individual level, both risk scores were related to revocation; the odds of revocation increased by 13% for each increase in MnSTARR risk level and by 21% for each increase in LSI-R risk category. Compared to Whites, Blacks were 41-46% more likely to experience revocation, while Native Americans were 90-92% more likely to experience revocation.

Next, we examined whether the relationship between criminogenic or prosocial-local institutions and recidivism varied by neighborhood disadvantage or affluence (as measured by ICE). These interaction effects are displayed in Table 3. To ease presentation of the results from
the eight models in which interaction terms were estimated, we do not report the Level 1 and Level 2 fixed effects, as no substantive changes in such effects existed from those reported in Tables 2 and 3. There were no significant interactions in the models predicting revocation. However, when examining rearrest, there was a significant positive interaction between prosocial local institutions and concentrated disadvantage. This interaction effect is illustrated in Figure 1, which shows the relationship between prosocial places and rearrest when concentrated disadvantage is one standard deviation above the mean and when it is one standard deviation below the mean. As shown in the figure, the negative relationship between the presence of prosocial institutions and rearrest was weaker in neighborhoods with high concentrated disadvantage. In other words, prosocial places have a more pronounced protective effect among people living in less-disadvantaged neighborhoods.
### Table 2. Hierarchical Logistic Regression Models Predicting Recidivism Among Releasees Statewide

<table>
<thead>
<tr>
<th></th>
<th>Rearrest</th>
<th></th>
<th></th>
<th></th>
<th>Revocation</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1</td>
<td>Model 2</td>
<td>Model 3</td>
<td>Model 4</td>
<td>Model 1</td>
<td>Model 2</td>
<td>Model 3</td>
<td>Model 4</td>
</tr>
<tr>
<td>Constant</td>
<td>0.50 (0.07)***</td>
<td>0.54 (0.09)***</td>
<td>0.51 (0.08)***</td>
<td>0.57 (0.10)***</td>
<td>0.33 (0.07)***</td>
<td>0.34 (0.09)***</td>
<td>0.33 (0.08)***</td>
<td>0.34 (0.10)***</td>
</tr>
<tr>
<td>MnSTARR 2.0 risk level</td>
<td>1.78 (0.05)***</td>
<td>1.78 (0.05)***</td>
<td>1.79 (0.05)***</td>
<td>1.79 (0.05)***</td>
<td>1.13 (0.05)*</td>
<td>1.13 (0.05)*</td>
<td>1.13 (0.05)*</td>
<td>1.13 (0.05)*</td>
</tr>
<tr>
<td>LSI-R category</td>
<td>1.09 (0.05)†</td>
<td>1.10 (0.05)*</td>
<td>1.09 (0.05)†</td>
<td>1.10 (0.05)†</td>
<td>1.21 (0.05)***</td>
<td>1.21 (0.05)***</td>
<td>1.21 (0.05)***</td>
<td>1.21 (0.05)***</td>
</tr>
<tr>
<td>Race</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asian</td>
<td>1.04 (0.48)</td>
<td>0.07 (0.48)</td>
<td>1.07 (0.49)</td>
<td>1.03 (0.48)</td>
<td>1.68 (0.39)</td>
<td>1.67 (0.39)</td>
<td>1.72 (0.38)</td>
<td>1.70 (0.39)</td>
</tr>
<tr>
<td>Black</td>
<td>1.77 (0.14)***</td>
<td>1.74 (0.15)***</td>
<td>1.86 (0.13)***</td>
<td>1.84 (0.13)***</td>
<td>1.41 (0.14)*</td>
<td>1.41 (0.14)*</td>
<td>1.46 (0.13)**</td>
<td>1.45 (0.13)**</td>
</tr>
<tr>
<td>Hispanic</td>
<td>1.13 (0.30)</td>
<td>1.13 (0.30)</td>
<td>1.13 (0.30)</td>
<td>1.13 (0.30)</td>
<td>1.21 (0.29)</td>
<td>1.21 (0.29)</td>
<td>1.22 (0.29)</td>
<td>1.22 (0.29)</td>
</tr>
<tr>
<td>Native American</td>
<td>1.63 (0.16)**</td>
<td>1.66 (0.17)**</td>
<td>1.63 (0.17)**</td>
<td>1.65 (0.17)**</td>
<td>1.91 (0.16)***</td>
<td>1.90 (0.16)***</td>
<td>1.92 (0.16)***</td>
<td>1.91 (0.16)***</td>
</tr>
<tr>
<td>Neighborhood Characteristics</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Concentrated disadvantage</td>
<td>1.08 (0.05)</td>
<td>1.10 (0.05)†</td>
<td>---</td>
<td>---</td>
<td>1.04 (0.06)</td>
<td>1.04 (0.06)</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>ICE</td>
<td>---</td>
<td>---</td>
<td>0.81 (0.23)</td>
<td>0.72 (0.24)</td>
<td>---</td>
<td>---</td>
<td>0.93 (0.23)</td>
<td>0.93 (0.24)</td>
</tr>
<tr>
<td>Criminogenic places</td>
<td>-1.00 (0.002)</td>
<td>---</td>
<td>1.00 (0.002)</td>
<td>---</td>
<td>1.00 (0.002)</td>
<td>---</td>
<td>1.00 (0.002)</td>
<td>---</td>
</tr>
<tr>
<td>Prosocial places</td>
<td>---</td>
<td>0.99 (0.01)*</td>
<td>---</td>
<td>0.98 (0.01)*</td>
<td>---</td>
<td>1.00 (0.01)</td>
<td>---</td>
<td>1.00 (0.01)</td>
</tr>
<tr>
<td>Random effects</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Variance component</td>
<td>0.006</td>
<td>0.005</td>
<td>0.006</td>
<td>0.005</td>
<td>0.125</td>
<td>0.130</td>
<td>0.124</td>
<td>0.128</td>
</tr>
<tr>
<td>SD</td>
<td>0.078</td>
<td>0.070</td>
<td>0.075</td>
<td>0.067</td>
<td>0.354</td>
<td>0.361</td>
<td>0.352</td>
<td>0.357</td>
</tr>
<tr>
<td>χ²</td>
<td>820.656</td>
<td>816.547</td>
<td>819.581</td>
<td>815.461</td>
<td>823.732</td>
<td>822.422</td>
<td>822.814</td>
<td>821.887</td>
</tr>
</tbody>
</table>

Odds ratios are presented with standard errors in parentheses. Results are based on 1,903 offenders within 831 census tracts. ***p < .001, **p < .01, *p < .05, †p < .10
Table 3. Interaction Effects Among Releasees Statewide

<table>
<thead>
<tr>
<th>Interaction</th>
<th>Rearrest</th>
<th>Revocation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Criminogenic places * Concentrated disadvantage</td>
<td>-0.001 (0.003)</td>
<td>0.004 (0.003)</td>
</tr>
<tr>
<td>Criminogenic places * ICE</td>
<td>0.01 (0.01)</td>
<td>-0.02 (0.01)</td>
</tr>
<tr>
<td>Prosocial places * Concentrated disadvantage</td>
<td>0.02 (0.01)*</td>
<td>0.01 (0.01)</td>
</tr>
<tr>
<td>Prosocial places * ICE</td>
<td>-0.05 (0.04)</td>
<td>-0.05 (0.03)</td>
</tr>
</tbody>
</table>

Coefficients are presented with standard errors in parentheses.
Results are based on 1,903 offenders within 831 census tracts.

***p < .001, **p < .01, *p < .05, †p < .10

--- Insert Figure 1 about here ---

Figure 1. The Effects of Prosocial Places on Rearrest, by Neighborhood Disadvantage
Supplemental statewide analyses. Supplemental analyses were conducted using the total statewide sample (N = 3,585), regardless of the type of housing they moved into (see Appendix A). The results of those analyses showed that, unlike the results for those living in residential housing, neither criminogenic places nor prosocial institutions were related to rearrest or revocation. However, when examining interactions, we found the same positive interaction between prosocial-local institutions and concentrated disadvantage that was reported above. In addition, a second interaction – between criminogenic places and ICE – approached significance. There was a positive relationship between criminogenic places and rearrest in more affluent neighborhoods, but a slight negative relationship between criminogenic establishments and rearrest in less affluent neighborhoods. See Appendices B and C for illustrations of these interaction effects.

Minneapolis Analyses Examining Local Crime Rates

Next, we conduct analyses using only a subset released to residential housing in Minneapolis in order to examine whether moving into violent areas influences recidivism. Because of the small sample size (231 persons within 76 census tracts), we conducted logistic regression...
analyses with robust standard errors (specifically, the Huber-White sandwich, see Rogers, 1993; Wooldridge, 2002) to account for the clustering of individuals within neighborhoods. The results are presented in Table 4. The rate of aggravated assaults in the census tract did not influence either rearrest or supervised release revocation. Similarly, the other neighborhood-level variables were also unrelated to these types of recidivism. These null results may be due to the small sample size or the inability to conduct hierarchical models. At the individual level, those with higher MnSTARR risk levels and Black offenders were more likely to be rearrested, while those with higher LSI-R risk levels were more likely to return to prison due to supervised release revocation.

Next, we examined whether the rate of aggravated assaults interacted with other neighborhood characteristics to influence recidivism. The results of these tests are presented in Table 5. First, we estimated interaction effects between aggravated assault rates and the physical infrastructure, controlling for neighborhood disadvantage; no significant interactions were found. Second, we estimated interaction effects between aggravated assault rates and the social environment, controlling for criminogenic establishments. No significant interactions were found between aggravated assault rates and neighborhood disadvantage or ICE.
### Table 4. Logistic Regression Models Predicting Recidivism Among Releasees in Minneapolis Census Tracts

<table>
<thead>
<tr>
<th></th>
<th>Rearrest</th>
<th>Revocation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1</td>
<td>Model 2</td>
</tr>
<tr>
<td>Constant</td>
<td>0.15 (0.51)**</td>
<td>0.14 (0.52)**</td>
</tr>
<tr>
<td>MnSTARR 2.0 risk level</td>
<td>1.80 (0.13)**</td>
<td>1.80 (0.13)**</td>
</tr>
<tr>
<td>LSI-R category</td>
<td>0.92 (0.15)</td>
<td>0.93 (0.15)</td>
</tr>
<tr>
<td>Black</td>
<td>2.36 (0.32)**</td>
<td>2.38 (0.32)**</td>
</tr>
<tr>
<td>Other Race</td>
<td>1.80 (0.57)</td>
<td>1.76 (0.56)</td>
</tr>
<tr>
<td>Concentrated disadvantage</td>
<td>1.12 (0.11)</td>
<td>1.16 (0.12)</td>
</tr>
<tr>
<td>ICE</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Criminogenic places</td>
<td>0.99 (0.01)</td>
<td>---</td>
</tr>
<tr>
<td>Prosocial places</td>
<td>---</td>
<td>0.99 (0.02)</td>
</tr>
<tr>
<td>Aggravated assault rate</td>
<td>0.95 (0.05)</td>
<td>0.94 (0.05)</td>
</tr>
<tr>
<td>$\chi^2$</td>
<td>43.10***</td>
<td>38.94***</td>
</tr>
<tr>
<td>Pseudo $R^2$</td>
<td>0.100</td>
<td>0.099</td>
</tr>
</tbody>
</table>

Coefficients are presented with standard errors in parentheses. Results are based on 231 offenders within 76 census tracts. **p < .01, *p < .05, †p < .10

### Table 5. Interactions Effects Among Releasees in Minneapolis Census Tracts

<table>
<thead>
<tr>
<th></th>
<th>Rearrest</th>
<th>Revocation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Aggravated assault rate * Criminogenic places</td>
<td>-0.0031 (0.004)</td>
<td>-0.0002 (0.002)</td>
</tr>
<tr>
<td>Aggravated assault rate * Prosocial places</td>
<td>-0.0038 (0.008)</td>
<td>-0.0168 (0.013)</td>
</tr>
<tr>
<td>Aggravated assault rate * Neighborhood disadvantage</td>
<td>0.0280 (0.032)</td>
<td>-0.0409 (0.0454)</td>
</tr>
<tr>
<td>Aggravated assault rate * ICE</td>
<td>-0.1848 (0.243)</td>
<td>0.1511 (0.347)</td>
</tr>
</tbody>
</table>

Coefficients are presented with standard errors in parentheses. Results are based on 1,903 offenders within 831 census tracts. **p < .01, *p < .05, †p < .10
DISCUSSION

The current study sought to understand the potential role of neighborhood-level prosocial-local institutions and criminogenic establishments on recidivism. This goes beyond the traditional approach of social disorganization by using a broader environmental backcloth approach. The only significant neighborhood-level finding was the relationship between the number of prosocial-local institutions and rearrest (this did not hold for revocation). As the number of prosocial institutions increased within neighborhoods, the likelihood of a person on parole being rearrested decreased. This differs from Wallace (2015), who found current levels of organizations did not influence neighborhood recidivism; rather, it was the change in the number of organizations that mattered. Our cross-sectional results indicate that the current level of prosocial institutions does matter. Through further analysis, we found the effect of prosocial establishments was more pronounced in less-disadvantaged neighborhoods. This could suggest the structural nature of the most disadvantaged neighborhoods matters more than the presence of prosocial institutions. Additionally, prosocial institutions may have difficulty operating as planned in more disadvantaged areas, reducing their protective effect. Organizations offering services to people on parole should consider whether aspects of the neighborhood environment have any positive or negative impact on the quality of their services and tailor their approaches accordingly.

Interestingly, Thomas and Drawve (2018) found criminogenic establishments were not a significant predictor of neighborhood crime in the most disadvantaged neighborhoods, while the measure was significant in less-disadvantaged neighborhoods. This is partially in line with the results of our supplemental analyses that examined all releasees regardless of their housing type upon release. However, in line with Miller et al. (2016), the presence of criminogenic establishments was not significantly related to recidivism. Our findings could partially be a result
of how criminogenic establishments were treated. We treated establishments as homogeneous when broader environmental criminological research has established differences between facilities of the same type. Eck and colleagues (2007) demonstrate a subset within a facility type (20%) usually accounts for a majority of crime problems (80%). For example, while bars are known to be risky, crime-prone places, not all bars are risky. Accounting for this 80-20 principle can greatly increase crime prediction accuracy (Steinman et al., 2020). Similar approaches should be extended into recidivism research to be in line with an environmental corrections lens (Cullen, Eck, & Lowenkamp, 2002; Schafer, Cullen, & Eck, 2015), merging environmental criminological approaches with corrections. This could better reflect a measure of criminal opportunities at the neighborhood level.

Additionally, in line with Breetzke et al. (2019), our measure of neighborhood violent crime was not significant. Given the sparse literature controlling for neighborhood crime when examining recidivism, this was exploratory in nature. It would be worthwhile to examine additional or alternative crime measures (such as less severe violence) that speak to more common crime occurrence within neighborhoods. For instance, Miller et al. (2016) created proximity measures for people on parole to property, drug, and violent crime hot spots. There were no significant effects for any distances to violent crime hot spots while, depending on the distance, being near property and drug crime hot spots was significantly related to recidivism. Also, we examined neighborhoods, measured through census tracts, when a growing body of criminological literature focuses on smaller geographic units such as street segments to pick up more spatial variability in crime levels (i.e., Law of Crime Concentration; see Weisburd, 2015).

Finally, we found concentrated disadvantage and ICE to be non-significant across models. The null relationship between recidivism and concentrated disadvantage is counter to prior
research (e.g., Kubrin & Stewart, 2006; Clark, 2016; McNeeley, 2018a, 2018b) and is likely due to the use of additional control variables (i.e., the inclusion of criminogenic and prosocial places). Because of the small sample, it is possible that the analyses lacked power to detect all neighborhood effects. Given that neighborhood disadvantage is one of the most robust predictors for crime (Pratt & Cullen, 2005), future research should continue to examine the built environment along with social disorganization when examining recidivism among large samples.

Given our findings, the presence of prosocial establishments/organizations have the potential to assist in lowering recidivism. Hipp et al. (2010) found close proximity to social service providers decreased the likelihood of recidivating for Black people on parole. In the current study, we found the within-neighborhood count of prosocial establishments (churches, recreation centers, and non-profits) lowered the likelihood of rearrest, and that this relationship was stronger in more affluent communities. When people on parole are returning to communities, attention needs to be drawn to the presence of and access to prosocial- local institutions and social service organizations. Additionally, as with the heterogeneity of criminogenic facilities, Hipp et al. (2010) argue that not all service providers are alike. These potential differences are key to understanding the context of how prosocial places can affect recidivism at the neighborhood level.

As with all research, this study has limitations that must be acknowledged. First, because of the small sample size, it is possible that the analysis may not have detected all neighborhood effects. Future research on this topic should analyze larger samples to avoid this problem. Second, first addresses were used to determine neighborhood context; subsequent addresses were unavailable. Because people released from prison often move at least once during their first year in the community (La Vigne & Parthasarathy, 2005; Steiner et al., 2015; but see Visher & Courtney, 2007), the neighborhood-level variables may not capture the ecological context of areas
in which some people lived when they recidivated.

Despite the limitations, the current study contributes to our understanding of neighborhood influences on recidivism. We found that increases in the presence of neighborhood-level prosocial-local institutions lowered the likelihood of rearrest. Although limited support was found for neighborhood measures, the null results offer a number of advantageous research avenues. People under correctional supervision return to communities with varying levels of social structure, social support, and criminal opportunities. Our study focused on a statewide approach and then moved to focus on one city. Given the growth in data collection within localized contexts, we argue that the study of potential neighborhood effects should start within a city and only then move to examine larger study sites. This could assist in localized knowledge of access to services (such as public transportation) that create and allow movement across geographic units, local crime problems (which can be identified using police data), and social service allocation in a geographical context.

REFERENCES


Harding, D.J., Morenoff, J.D., and Herbert, C.W. 2013. Home is hard to find: Neighborhoods,


5–28.


### Appendix A. Effects of Criminogenic and Prosocial Places on Rearrest and Revocation Among All Released Offenders

<table>
<thead>
<tr>
<th></th>
<th>Rearrest</th>
<th></th>
<th>Revocation</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Controlling for CD</td>
<td>Controlling for ICE</td>
<td>Controlling for CD</td>
<td>Controlling for ICE</td>
</tr>
<tr>
<td><strong>Main Effects</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Criminogenic places</td>
<td>0.001 (0.001)</td>
<td>0.001 (0.001)</td>
<td>-0.002 (0.001)</td>
<td>-0.002 (0.001)</td>
</tr>
<tr>
<td>Prosocial places</td>
<td>-0.003 (0.004)</td>
<td>-0.002 (0.001)</td>
<td>0.004 (0.01)</td>
<td>0.004 (0.01)</td>
</tr>
<tr>
<td><strong>Interactions Between Neighborhood Variables</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Risky places * Concentrated disadvantage</td>
<td>0.001 (0.002)</td>
<td>---</td>
<td>-0.001 (0.002)</td>
<td>---</td>
</tr>
<tr>
<td>Risky places * ICE</td>
<td>---</td>
<td>0.02 (0.01)†</td>
<td>---</td>
<td>-0.01 (0.01)</td>
</tr>
<tr>
<td>Prosocial places * Concentrated disadvantage</td>
<td>0.01 (0.004)**</td>
<td>---</td>
<td>-0.002 (0.004)</td>
<td>---</td>
</tr>
<tr>
<td>Prosocial places * ICE</td>
<td>---</td>
<td>-0.02 (0.02)</td>
<td>---</td>
<td>-0.001 (0.03)</td>
</tr>
</tbody>
</table>

Results are based on 3,585 offenders within 861 census tracts. Unstandardized coefficients are presented with standard errors in parentheses.

**p < .01, *p < .05, †p < .10**
Appendix B. The Effects of Prosocial Businesses on Rearrest, by Neighborhood Disadvantage, Among All Released Offenders

Appendix C. The Effects of Risky Businesses on Rearrest, by ICE, Among All Released Offenders