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Home Nodes, Criminogenic Places, and Parolee Failure: Testing an Environmental Model of Offender Risk

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Abstract

This article examines whether potentially criminogenic places (including bars, liquor stores, restaurants, public transport hubs, drug markets, and more), located within a 1,240-feet radius of parolees' residences (the home "node"), predict their rearrest or revocation. Taking these features into account, in addition to individual traits and behaviors, might pave the way for more accurate risk assessment that could help make supervision sensitive to place-based risks. However, multivariate survival analysis of 1,632 parolees released to Newark during July 2007 to June 2009 found little evidence that these factors increased the risk of failure. Successful operationalization of environmental risk will probably need to incorporate more detailed measures of parolees' routine activities, including the settings and paths they frequent beyond their home environment.

Keywords

parole, crime pattern theory, node, risk assessment

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Introduction

In recent decades, actuarial offender risk assessment has played an increasingly important role in community corrections policy (Jones, Johnson, Latessa, & Travis, 1999; Pew Center on the States, 2007; Solomon et al., 2008). Assessments enumerate offender traits and past behavior to predict recidivism or other forms of misconduct (Clear, Wasson, & Rowland, 1988; Gottfredson & Moriarty, 2006). In turn, assessments of risk can guide decisions about release from prison, supervision levels, and appropriate types of programming or intervention (Andrews, Bonta, & Wormith, 2006; Bonta, 1996; Taxman, Shepardson, & Byrne, 2004).

This article assesses the predictive value of spatial factors, alongside individual attributes, in assessing the risk of failure among adult parolees. In particular, it takes the novel step of examining the effects of criminogenic places, as highlighted by environmental criminology (P. J. Brantingham & Brantingham, 1981; P. L. Brantingham, & Brantingham, 1995; Cohen & Felson, 1979; Cullen, 2011; Wortley & Mazerolle, 2008). Although the emergence of the latter has had clear and significant impacts on criminological thinking and crime policies over the last three or four decades (Clarke, 2009; Clarke & Eck, 2005; Cozens, 2008; Cullen, 2011), its impact on community corrections has, so far, been quite limited.

Risk Assessment and Community Corrections Supervision

Contemporary risk assessment tools use actuarial principles that emerged many decades ago when research identified correlations between characteristics of offenders and their subsequent behavior (Burgess, 1928; Glueck & Glueck, 1950; Miller & Lin, 2007). Characteristics are scored and combined to form an empirically validated scale that is indicative of "risk"—such as the risk of rearrest or reconviction, the risk of absconding while on bail, or the risk of violating conditions of parole or probation (Clear et al., 1988; Gottfredson & Moriarty, 2006). Replacing traditional "first generation" risk assessment, relying solely on practitioners' clinical judgment, "second generation" assessments score static, unchangeable, offender characteristics (such as age, criminal history etc.) to predict behavior, while more recent "third" and "fourth" generation" risk assessments also include dynamic risk factors that are prone to change and may be susceptible to supervision and programming (such as substance use, peer groups, employment etc.).

In this way, contemporary risk assessment directly supports mainstream supervision practices. It facilitates a *rehabilitation* approach by providing a basis for supervision plans and programming decisions that target offenders needs (Andrews & Robinson, 1984; Bonta & Andrews, 2007). It also supports a *surveillance and control* approach, involving the monitoring of conditions, rule enforcement, and threats of incarceration (Clear & Latessa, 1993; Klockars, 1972; Skeem & Manchak, 2008; Taxman, 2008; Taxman et al., 2004), where this is targeted according to an offender's risk level. These approaches, respectively, have theoretical roots in positivism, which locates the causes of crime in biological, psychological, or social characteristics of offenders (Glueck & Glueck, 1950; Hooton, 1939; Lombroso, 1876; Sutherland, 1939) and classical criminology that emphasizes certain, swift, and proportionate punishment to deter would-be offenders (Beccaria, 1995; Becker, 1968; Von Hirsch, Bottoms, Burney, & Wickstrom, 1999).

Contemporary supervision practice, however, owes far less to the theoretical principles of environmental criminology. The latter shifts attention away from the underlying propensities of people to commit crime to the distribution and accessibility of crime opportunities (Clarke & Eck, 2005; Eck, 1995). It sees these opportunities as rooted in the daily activities of actors, their intersection with one another, and their interactions with the social and physical structures around them. This produces patterns of crime that are distributed unevenly through space and time (P. J. Brantingham & Brantingham, 1981; Cohen & Felson, 1979).

The relevance of environmental criminology to community corrections may, however, be changing. In a vision of "environmental corrections," Cullen, Eck, and Lowenkamp (2002) advocate a model that addresses how supervised offenders are "*tempted by and come into contact with opportunities for crime*" (p. 31). Recommending offender assessment that uses activity calendars and geographical mapping of offender activities, they argue for a problem-solving approach in which corrections officers, family, friends. and community members, as well as community stakeholders such as bar tenders, store owners, or police officers, work together to reduce crime opportunities faced by supervised offenders. This could include strategies to steer offenders away from specific places or people, while developing alternative programs of prosocial activities. Dickey and Klingele (2004) offer some similar suggestions for parolees, advocating a release planning model that assesses the interaction of parolees with their environment and supervision strategies that make use of stakeholders who manage or oversee the contexts where risks arise.

Some recent trends in community corrections policy and practice are consistent with a more environmental model. Notably, in the case of sex offenders, the last couple of decades has seen a proliferation of laws and ordnances to restrict their residency (and in some cases, employment and activities) to settings away from places where children congregate, such as schools, day care centers, and parks (Chajewski & Mercado, 2009; Mulford, Wilson, & Parmley, 2009; Zgoba, 2011). In the language of environmental criminology, these measures seek directly to limit offenders' exposure to crime opportunities. More generally, trends toward direct community engagement, local partnership, and geographical specialization in caseloads by community corrections agencies provide a potential platform for approaches that take account of environmental criminological principles (Clear, 2005; diZerega & Verdone, 2011; Re-Entry Policy Council, 2005; Reinventing Probation Council, 2000; Solomon et al., 2008; Taxman, 2008).

Notwithstanding these developments, principles of environmental criminology have yet to be incorporated into the design of risk assessment tools. This is despite the fact that the ideas of Cullen et al. (2002) and Dickey and Klingele (2004) rely on forms of environmental risk assessment. It certainly seems plausible that the incorporation of environmental factors could enhance the predictive accuracy of existing risk assessment approaches, and help to shape effective supervision strategies.

Understanding Environmental Risk

Empirical studies of community corrections have started to draw links between spatial factors and offender adjustment on supervision. These studies have drawn primarily on neighborhood-based theories. Social disorganization theory (Shaw & McKay, 1931), which connects crime with deprived neighborhoods characterized by instability and weak institutions, provides a foundation for the neighborhood tradition. More recently, "broken windows" theory has emphasized the connections between physical and social disorder, community withdrawal, and crime (Kelling & Coles, 1998; Wilson & Kelling, 1982), while scholarship on "collective efficacy" suggests the willingness of community members to intervene for the common good is negatively associated with (violent) crime (Sampson, Raudenbush, & Earls, 1997). Research shows that parolee failure is variously predicted by measures associated with these theories, including disadvantage, residential stability, inequality, and social disorder (Hipp, Petersilia, & Turner, 2010; Kubrin & Stewart, 2006; Morenoff, 2011).

Despite the growing interest in spatial influences on supervised offenders, a consideration of localized criminogenic *places* within neighborhoods—as highlighted by environmental criminology—is largely absent from studies. These places might include "crime generators"—such as public transport stations, shopping malls, entertainment locations, schools or parks—to which large numbers of people are attracted for reasons unrelated to crime, but nonetheless provide opportunities for people to commit crime (Bernasco & Block, 2011; P. L. Brantingham & Brantingham, 1995; P. J. Brantingham & Brantingham, 2008; Clarke & Eck, 2005). They could also include “crime attractors” that directly attract motivated offenders because they have a concentration of targets that are inadequately protected, for example, around drug markets, prostitution areas, or bars (P. L. Brantingham & Brantingham, 1995; P. J. Brantingham & Brantingham, 2008; Clarke & Eck, 2005). According to crime pattern theory, these crime-prone locations emerge from a dynamic environmental “backcloth” formed through the interplay of roads, land use, and economic structures (P. J. Brantingham & Brantingham, 1981, 2008; P. L. Brantingham & Brantingham, 1993).

The distribution of criminogenic places tends to be quite different, and more fine-grained, than the distribution of broader community-level causes of crime (Block & Block, 1995; Eck, Chainey, Cameron, Leitner, & Wilson, 2005). For example, ethnographic research by St. Jean (2007) in a deprived Chicago neighborhood found that even among blocks lacking collective efficacy and with high levels of social disorder, crime was far from universal. While some blocks were relatively crime-free, others included “pockets of crime.” In the latter case, local features such as businesses, neighborhood markets, check-cashing centers, or bars, drew offenders and victims or drug-buyers together. These crime generators and attractors helped account for localized crime hotspots that can be found routinely, for example, on particular corners, street segments, or city blocks (Clarke & Eck, 2005; Eck et al., 2005; Harries, 1999; Sherman, Gartin, & Buerger, 1989; Weisburd & Eck, 1995).

A Model of Environmental Risk Assessment

Operationalizing the risk associated with criminogenic places for individual offenders seems challenging, given the complex interactions between offenders, space, and crime opportunities. Crime pattern theory (P. J. Brantingham & Brantingham, 1981, 2008) describes how the “activity space” of an offender is defined by key nodes in their daily activity: home, work, school, sites of shopping and entertainment areas, and so on, along with the paths between nodes where potential offenders travel. Daily routines of potential offenders within these activity spaces, and their “search” activities at the borders of these spaces, have important structuring properties for the likely crime locations chosen by an offender. Offending will tend to occur in locations where these activity spaces intersect with opportunities, and where there are cues to those opportunities that offenders can read.

In line with crime pattern theory, a comprehensive environmental risk assessment would ideally draw information about the specific locations frequented by offenders, and the paths trodden between them, and compare these with environmental crime risks in and around these locations. However, while a range of land-use data is today available, information on daily routines of offenders is not. Notwithstanding the use of location-based monitoring technologies for a subset of supervised offenders (Cornish, 2010), in most cases, community corrections agencies will tend to collect geographical information on offender residences, and perhaps on jobs and service programs, but usually not too much else. This places significant limits on our ability to operationalize the full range of environmental risks to which supervised offenders will be ordinarily exposed.

Focusing on the Home "Node"

A more pragmatic, but still compelling, approach to environmental risk assessment is to focus on risks around the supervised offender's home—approximating their home "node" (P. J. Brantingham & Brantingham, 1981, 2008). This is the approach developed in this article. It not only makes use of readily available residential data but also represents a practical approach that is likely meaningful for community corrections practitioners. Parole officials already often evaluate intended home addresses (upon release) that are provided by parole eligible inmates in pre-parole plans. Residential addresses, particularly those of sex offenders, may be assessed according to their proximity to criminogenic places such as known gang territories or open-air drug markets, as well as schools, playgrounds, or other restricted areas (Harries, 2002).

This approach is also promising in light of some aspects of the literature. Research suggests that crimes are spatially biased toward offenders' homes, following a distance decay function that reflects a "least effort" principle (Rossmo, 2000; Rossmo & Rombouts, 2008; Zipf, 1949). Some studies even suggest offending may be common within short distances, such as a block away from offenders' homes (e.g., Bernasco & Block, 2011; P. J. Brantingham & Brantingham, 1981; Bullock, 1955). According to the logic of crime pattern theory (P. J. Brantingham & Brantingham, 1981, 2008; Rossmo, 2000; Rossmo & Rombouts, 2008), we might expect journeys to crime to be shorter when there are more local opportunities that can be exploited. Notwithstanding, the literature is ambiguous. There is some evidence of buffer zones of reduced offending probability around offenders' homes, owing to heightened perceived risks of detection (P. J. Brantingham & Brantingham, 1981; Rengert, 1996; Rossmo, 2000), though this apparently is not consistent across studies and crime types (Rengert, Piquero, & Jones, 1999). More generally, the average distances travelled by offenders to commit crimes tend to fall within ranges running up to a couple of miles (see Bichler, Christie-Merrall, & Sechrest, 2011, for a summary), taking them a substantial distance beyond the immediate home environment. These dynamics would tend to limit the influence of place-based risks within the home node.

Specifying Environmental Risk Factors

Finally, an environmental risk model must identify places that represent risk factors for failure. To be clear, we are concerned with places that can draw potential offenders and victims or targets together (P. L. Brantingham & Brantingham, 1995), which could include parolees among them, to produce concentrations of crime, and perhaps also elevated rates of parolee offending. One approach might be to identify stable crime hotspots indicative of underlying criminogenic places. However, a simpler strategy, used in this article, is to examine the specific types of places that theory and research indicate are criminogenic. Recent scholarship suggests the latter may have greater predictive validity, at least with respect to specific crime types (Caplan, Kennedy, & Miller, 2011). It is likely also a more practical approach, consistent with routine risk assessment, relying on readily available information on local infrastructure, in place of more labor-intensive, up-to-date, crime analysis products.

Among a range of criminogenic settings highlighted by the literature, and which might draw parolees toward opportunities to offend, are bars, clubs, or liquor stores (Briscoe & Donnelly, 2001; Roman, Reid, Bhati, & Tereshchenko, 2008; Roncek & Maier, 1991; Scott & Dedel, 2006; Sherman, 1995; Stevenson, Lind, & Weatherburn, 1999), restaurants and retail establishments (Bernasco & Block, 2011; P. L. Brantingham & Brantingham, 1995; Spelman, 1995), transport nodes (Newton, 2004; Yu, 2009), schools (LaGrange, 1999; Roman, 2003; Roncek & Lobosco, 1983), parks (Groff & McCord, 2012), public or other crime-prone housing (Dunworth & Saiger, 1994; Griffiths & Tita, 2009; Millie, 2008; U.S. Department of Housing and Urban Development, 1999), drug-dealing locations (Bernasco & Block, 2011; Scott & Dedel, 2006; U.S. Department of Justice, National Gang Intelligence Center, 2009), and gang hang-outs or "activity spaces" (Tita, Cohen, & Engberg, 2005). These examples inform the operationalization of environmental risk presented in this article.

Research Hypothesis

The current research tests the pragmatic model of environmental risk assessment, described above, and embodied in the following hypothesis:

Hypothesis: Environmental risk factors (bars and clubs, liquor stores, take-out restaurants, sit-down restaurants, retail stores, bus stops, light rail stops, schools, parks, "crime-prone" housing, drug-dealing hotspots, and known gang residences) located within a parolee's "home node" (defined within a radius of 1,240-feet from a parolee's residence), predict their failure on supervision, after controlling for individual and neighborhood-level risk factors.

The hypothesis is tested on parolees in Newark, New Jersey. The city is the largest, the most densely populated, and one of the most ethnically diverse in New Jersey. It has a population estimated at 278,154 in 2009 with more than half Black and about a third Latino (U.S. Census Bureau, 2011b). It also represents one of the most disadvantaged communities within the state: Based on 2005-2009 data, 24.3% of residents live below the poverty line (compared with 8.8% across the state; U.S. Census Bureau, 2011b). The Newark population is also notable for its high level of criminal justice involvement, serving as New Jersey's largest sender and receiver of prison and jail inmates.

Method

Data. The analysis focuses on a cohort of New Jersey prisoners who returned to the community from prison under parole supervision between July 2007 and June 2009 and who, according to New Jersey State Parole Board data, spent some time living in Newark while on parole in the subsequent period up to 30 April 2010. In total, this cohort numbered 2,880 individual parolees. However, the study narrowed its focus to a group of 1,632 (56.7% of the total cohort). This group excluded about a third of cases that fell within a distance shorter than 1,240 feet of the edge of the study, for which environmental risks could not be properly calculated. It also excludes cases with missing data on key analytic variables, which would have dropped out in listwise modeling. The most common reason for missing data was cases without an Level of Service Inventory–Revised (LSI-R) risk score, totaling about one in six of the full cohort. In doing this, we recognize the possibility that this might produce biases in our model coefficients if the dropped cases were atypical, though we have no reason to believe these biases would be large.

Information on parolees' characteristics, release dates, residential episodes, addresses, criminal histories, patterns of rearrest, and returns to custody following revocations were obtained from state criminal justice databases maintained by or accessible to the New Jersey State Parole Board. These sources provide comprehensive information on events that occurred within the state of New Jersey, with the limitation that arrests or convictions outside of New Jersey would not be included. From these data, residential address information was geocoded to street centerlines in Newark, with a 98% match rate. Achieving a perfect match rate is rare, but ours was well above the minimum reliable geocoding hit rate of 85% recommended by Ratcliffe (2004).

Most information on criminogenic places was derived from Infogroup, a leading commercial provider of business and residential information for reference, research, and marketing purposes. It compiles data from multiple sources, including Yellow and White Page directories, county-level public sources, real-estate data, press releases, news feeds, postal processing, and beyond (Infogroup, 2010). In using commercially available data on land use, we follow the example of other scholars of high-quality criminological research (e.g., Bernasco & Block, 2011). We chose a vendor with sophisticated data control procedures enhancing our confidence in data quality.[1] Additional data on criminogenic places was obtained from Newark Police Department, drawing on crime data and practitioner input.

Finally, tract-level census data were obtained from the 2000 U.S. census to develop neighborhood measures related to social disorganization, also used in the analysis.

Analysis Strategy. The assessment of environmental risk factors relied on multivariate Cox proportional hazards survival models of parolee failure (Cox, 1972). These use a semiparametric technique that makes no assumptions about the shape of an underlying survival distribution, except that it is the same for all participants. The method usefully accommodates multiple episodes per participant.

Specifically, models analyze 2009 episodes nested within 1,632 parolees. Although key demographic and criminal history variables (race, gender, prior convictions, etc.) are constant across episodes, other variables—geographical and environmental variables and age—vary between them. Models additionally incorporate controls for social disorganization constructs, measured at the census tract level. These geographical units are taken to approximate neighborhoods, the key focus of social disorganization theory (Shaw & McKay, 1931). Although tracts are imperfect proxies for defined neighborhoods (Sampson et al., 1997; Weisburd, Bruinsma, & Bernasco, 2009), they are a convenient administrative unit for which census data are available, and are used as the basis for all prior studies examining neighborhood influences on parolee failure (Hipp et al., 2010; Kubrin & Stewart, 2006; Morenoff, 2011).

Robust standard errors adjusted for tract-level clustering were incorporated into models to address the fact that episodes were clustered within neighborhoods (as well as parolees), an adjustment in line with prior studies of parolees (Hipp et al., 2010; Morenoff, 2011). All modeling was carried out using Stata 12.0. The software adjusts for gaps during the follow-up period because of time spent living in excluded or unrecorded locations, making adjustments to the active pool of parolees at risk at particular time points (Cleves, Gould, & Gutierez, 2002).

Dependent Variables. Parolee failure was measured in two different ways. One counted only a new arrest as a failure. This approximates a criminal act, the focus of our theoretical interest. However, because parole revocations censor survival times in a way which is unlikely to be independent of rearrest—and could therefore bias coefficients (Clark, Bradburn, Love, & Altman, 2003)—we also modeled a failure measure combining arrests and revocations for technical violations. The latter arises for a variety of reasons and may include positive urine tests, failing to report to a parole officer, not attending treatment or employment, or violations of conditions such as avoiding association with particular offenders. While they do not directly resemble crimes, combining revocations with arrests allows the estimation of statistically unbiased models. Modeling both outcomes together provides a range for more confident inferences.

Measuring Environmental Risk in the Parolee's Home Node. As noted, home nodes were operationalized as buffer zones of 1,240 feet around each individual parolee address. In specifying this size, we sought to define an area in which parolees are likely to move as part of their home-centered activities (e.g., "hanging out" on the street, socializing with neighbors, buying milk from a local store) and any related "search" activities for nearby crime opportunities. We reasoned that home-centered activities probably took place within a couple of blocks or so of parolees' residences. Research also suggests that crime-prone behavior settings typically comprise just one or two street blocks (e.g., Felson, 1995; Taylor, 1997; Taylor & Harrell, 1996), suggesting that criminogenic features within a couple of blocks of a parolee's address would tend to place these addresses directly within such settings. In practice, a block's distance is not consistent across Newark, with many blocks more rectangular than square. We used a liberal operationalization of our home node concept by specifying two longer block-face distances as the basis for calculations. This produced the 1,240-feet radius chosen, equivalent to 2.5 times the mean block length for the city.

A set of 12 environmental risk variables were then selected and assessed for their presence within each parolee's home node, for each of their addresses. Variables correspond to the discussion of crime-prone places, above. Nine were extracted from the Infogroup commercial data set: bars and clubs, liquor stores, take-out restaurants, sit-down restaurants, retail stores, bus stops, light rail stops, schools, and parks. Three additional variables were developed using intelligence from Newark Police Department. “Crime-prone” housing described complexes characterized by gun violence and drug activity. They had been identified by the police department crime analyst based on surveys and discussions with the captain of the police department’s operations bureau and the four precinct commanders. Drug-dealing hotspots were also identified by the police department crime analyst, using a methodology that highlighted high scoring locations on an index made up of drug arrests and violent crime (weighted according to seriousness and recentness of occurrence), edited to eliminate some less important sites based on the input of precinct commanders. Finally, known gang residences were represented by point data derived by the police department from locations of identified gang members. All but three measures counted the number of each risk factor located within the home node. In the case of bus stops, the measure counted some individual bus shelters multiple times, where there were multiple bus routes using them (presumably therefore with more passengers using them). However, crime-prone housing, drug market areas, and parks were polygon features, so their presence was operationalized as the percentage of each parolee’s 1,240-feet address buffer zone that overlapped with the polygon feature.

An important consideration is the extent to which these 12 variables are measuring genuinely distinct phenomena, rather than being indicators of essentially the same underlying patterns of land use. Reassuringly, Pearson correlation coefficients between them were generally small: about a third was negative, and three quarters were less than 0.2. The highest correlation coefficient (0.71) was between sit-down restaurants, and bars and clubs. However, there was no evidence of problematic multicollinearity among variables, with variance inflation factors (VIFs) all below 3 for environmental variables, even when analyzed alongside other neighborhood and individual variables (described below).

Individual-Level Control Variables. A set of personal characteristics were measured to reflect the conventional individual risks associated with parolee failure. These included a composite risk score for offenders derived from the LSI-R, a comprehensive and widely used third-generation risk assessment tool. Unfortunately, individual items were not recorded electronically, and so we could not separately include them as independent variables. However, the composite score has strong predictive validity (Andrews & Bonta, 2006) and builds off 54 items that assess 10 criminogenic domains: criminal history, education/employment, financial, familial relationships, accommodations, leisure and recreation, companions, alcohol and drug use, emotional health and attitudes, and orientations (Andrews & Bonta, 1995). As a supplement to this global risk score, we also included individual items expected to correlate with recidivism risk: gender, age (and age-squared), race/ethnicity, prior convictions (Gendreau, Little, & Goggin, 1996), and current offense.

Tract-Level Control Variables. Tract-level variables were calculated to control for neighborhood effects, specifically those corresponding to social disorganization theory (Shaw & McKay, 1931). We directly followed the example of Hipp et al. (2010) by calculating three construct measures, based on the 2000 census data (U.S. Census Bureau 2011a). *Concentrated disadvantage* was a principal component score incorporating percent of residents below the poverty line, percent unemployed, percentage of single-parent households, median income, and median home value. Residential stability was also a principal component score based on measures of: median length of residence, percent of households that moved into their units in the last 5 years, and percentage of units that are currently vacant. Racial/ethnic heterogeneity was calculated using the Herfindahl index (Gibbs & Martin, 1962) based on five racial groupings (White, African American, Latino, Asian, and other races).[2]

Descriptive Statistics

In total, the sample involved 2,009 known residential episodes within the study site, spread across 1,632 parolees. This ignores parolees' spells outside of the study site or with a "missing" address. In a follow-up period that averaged 260.7 days to failure or censor, parolees spent 80.4% of their time, on average, at known study site addresses, with 57.0% recording exactly 100% of their postrelease time there. Parolees overall had an average of 1.2 episodes in the study area, with 81.6% counting just a single episode—with numbers ranging from 1 to 4.

Table 1 provides descriptive characteristics of the parolees upon release. The cohort was primarily male and Black, and aged about 35, on average. Parolees tended to be seasoned offenders, on average having more nearly 6 convictions and close to 11 prior arrests. They included a large proportion of drug offenders, with more than half convicted of these offenses in their first listed charge. Three in 10 experienced some kind of failure during the follow-up period, counting parole revocations. The most common failure type was for "other" arrests, followed by drugs arrests, technical revocations, and violent, property- and weapons-related arrests. Using the cutoff scores recommended by the tool developers (Andrews & Bonta, 1995; Lowenkamp & Bechtel, 2007), a little more than half of parolees are at moderate risk, and a

Table 1. Characteristics of Parolees (n = 1,632).

	M or %	*SD*
Female	8.9%	—
White	4.4%	
Black	84.2%	—
Latino	11.2%	—
Other	0.3%	—
Age at release	35.2	9.4
LSIR: low risk (0-13)	3.2%	—
Low/moderate (14-23)	34.3%	—
Moderate (24-33)	55.6%	—
High/moderate (34-40)	6.5%	—
High (41-54)	0.3%	—
Violent offense	13.8%	—
Drug	52.8%	—
Property	19.1%	—
Weapons	4.4%	—
Other	10.0%	—
Prior convictions	6.0	4.3
Prior arrests	10.8	7.5
Failure (including revocation)	28.2%	
Violence arrest	3.8%	—
Drugs arrest	8.8%	—
Property arrest	3.2%	—
Weapons arrest	2.6%	—
Other arrest	10.5%	—
Technical parole revocation	8.3%	—

Note: LSIR = Level of Service Inventory–Revised.

further third are at low/moderate risk. Relatively few parolees fall into the other, higher or lower risk, categories.

Table 2 describes residential episode level measures based on tract variables and the environmental risk measures. The risk factors show wide differences in their concentrations within the home nodes. Bus stops appear particularly common, with an average of about 28 per node (partly reflecting the fact that individual bus shelters could be counted multiple times, where they served multiple bus routes), while light rail stations are very infrequent at just 0.24 per node.

Table 2. Measures for Residential Episodes (n = 2,009).

	M	*SD*
Tract-level variables		
Racial/ethnic heterogeneity	0.33	0.18
Concentrated disadvantage	0.54	0.71
Residential stability	0.04	0.94
Environmental risk factors		
Bars/clubs	2.41	2.61
Liquor stores	1.26	1.10
Take-out restaurants	2.93	2.90
Sit-down restaurants	2.88	4.31
Retail stores	0.51	0.94
Bus stops	27.50	28.94
Light rail stations	0.24	0.79
Schools	2.23	1.62
Park area[a]	4.65	8.38
Crime-prone housing[a]	5.56	7.19
Drug markets[a]	3.97	5.66
Gang residence	18.70	13.40

[a]These three risk factors measured the percentage of the 1,240 buffer overlapping with the risk factor polygon. Other measures counted numbers of each risk factor in the buffer.

Survival Models

Tables 3 and 4 present the model results for each of the two failure measures: arrest, and arrest or technical revocation, respectively. In building the models, in addition to using variables described in Table 1, we incorporated an age-squared term, alongside age, to account for its potentially quadratic effects (this was calculated by squaring the age variable after centering, to avoid problems of collinearity). Meanwhile, we excluded the prior arrests variable, which had some collinearity with the prior convictions variable (VIFs for prior convictions and arrests were 4.3 and 4.0, respectively) and also contributed to problems satisfying proportional hazards assumptions. The models used time to failure or censoring variables measured in days. We considered making model adjustments to address potential spatial dependency processes, for example, by using tract-level spatial lag variables (Kubrin & Stewart, 2006). However, Moran's I calculated for census tracts, based on their aggregated 100-day failure rates, provided no evidence of spatial autocorrelation, so we decided against modeling any spatial process.[3]

Table 3. Cox Proportional Hazards Survival Models for Arrest Only (2,009 Episodes, 1,632 Parolees, 73 Census Tracts).

	Model A			Model B			Model C			Model D		
Factors	HR	95% CI	*p*	HR	95% CI	*p*	HR	95% CI	*p*	HR	95% CI	*p*
Personal												
Age	0.935	(0.920-0.950)	.000**	0.934	(0.919-0.949)	.000**	0.933	(0.918-0.948)	.000**	0.933	(0.918-0.948)	.000**
Age squared	1.002	(1.001-1.003)	.002**	1.002	(1.001-1.003)	.003**	1.002	(1.001-1.003)	.003**	1.002	(1.001-1.003)	.002**
Female	0.563	(0.333-0.954)	.033*	0.560	(0.331-0.947)	.031*	0.555	(0.320-0.963)	.036*	0.782	(0.312-1.964)	.601
Hispanic	0.635	(0.319-1.263)	.195	0.623	(0.307-1.263)	.190	0.643	(0.296-1.398)	.265	0.653	(0.300-1.417)	.281
Black	1.433	(0.777-2.646)	.250	1.490	(0.791-2.809)	.217	1.565	(0.783-3.127)	.205	1.568	(0.783-3.141)	.204
Property offense	0.767	(0.515-1.143)	.192	0.764	(0.514-1.137)	.185	0.775	(0.508-1.184)	.239	0.802	(0.517-1.242)	.322
Drugs offense	1.027	(0.665-1.587)	.904	1.019	(0.664-1.564)	.930	1.022	(0.653-1.600)	.924	1.065	(0.673-1.684)	.789
Weapons offense	0.602	(0.345-1.052)	.075	0.598	(0.344-1.038)	.068	0.589	(0.332-1.048)	.072	0.620	(0.341-1.131)	.119
Other	0.910	(0.558-1.484)	.705	0.899	(0.548-1.477)	.675	0.940	(0.574-1.538)	.804	0.977	(0.590-1.618)	.928
LSI-R	1.040	(1.020-1.061)	.000**	1.040	(1.019-1.061)	.000**	1.039	(1.018-1.061)	.000**	1.040	(1.019-1.061)	.000**
Prior convictions	1.077	(1.050-1.105)	.000**	1.077	(1.050-1.105)	.000**	1.075	(1.048-1.104)	.000**	1.074	(1.046-1.102)	.000**
Neighborhood												
Racial/ethnic heterogeneity				1.359	(0.702-2.631)	.362	1.745	(0.813-3.745)	.153	1.736	(0.792-3.807)	.168
Concentrated disadvantage				0.997	(0.846-1.176)	.976	1.121	(0.937-1.341)	.211	1.122	(0.937-1.344)	.210
Residential stability				0.983	(0.862-1.122)	.804	0.911	(0.813-1.021)	.110	0.911	(0.813-1.022)	.113

(continued)

Table 3. (continued)

	Model A			Model B			Model C			Model D		
Factors	HR	95% CI	*p*	HR	95% CI	*p*	HR	95% CI	*p*	HR	95% CI	*p*
Environmental												
Bars/clubs							0.968	(0.896-1.047)	.420	0.968	(0.894-1.049)	.429
Liquor stores							0.923	(0.832-1.024)	.131	0.928	(0.835-1.032)	.168
Takeout restaurants							1.001	(0.924-1.084)	.979	0.999	(0.922-1.082)	.973
Sit-down restaurants							0.998	(0.951-1.048)	.940	0.998	(0.950-1.049)	.943
Retail stores							1.013	(0.814-1.259)	.909	1.010	(0.812-1.255)	.929
Bus stops							0.996	(0.990-1.003)	.237	0.996	(0.990-1.003)	.282
Light rail stations							0.974	(0.774-1.226)	.822	0.976	(0.774-1.229)	.834
Schools							1.005	(0.932-1.084)	.892	1.005	(0.932-1.083)	.906
Park area							0.998	(0.985-1.011)	.754	0.982	(0.964-1.001)	.061
Crime-prone housing							0.975	(0.956-0.994)	.009**	0.974	(0.955-0.993)	.007**
Drug markets							1.016	(0.980-1.053)	.401	1.015	(0.980-1.052)	.402
Gang residences							1.000	(0.991-1.010)	.925	1.000	(0.990-1.010)	.984
Time dependent interactions												
Female x Time (years)										0.612	(0.183-2.049)	.426
Park area x Time (years)										1.020	(1.005-1.035)	.007**
Log pseudo-likelihood		−1,961.44			−1,960.93			−1,955.95			−1,953.51	

Notes: HR=hazard ratio; CI=confidence interval; LSI-R = Level of Service Inventory Revised. Robust cluster standard errors are used to adjust for clustering within census tracts. The reference category for race/ethnic variables is white/other. The reference category for offense variables is violent offense.
* p<0.05, ** p<0.01.

Table 4. Cox Proportional Hazards Survival Models for Arrest and Revocation (2,009 episodes, 1,632 parolees, 73 census tracts).

	Model E			Model F			Model G		
Factors	HR	95% CI	*p*	HR	95% CI	*p*	HR	95% CI	*p*
Personal									
Age	0.962	(0.952-0.972)	.000**	0.961	(0.950-0.972)	.000**	0.960	(0.949-0.972)	.000**
Age squared	1.001	(1.000-1.002)	.007**	1.001	(1.000-1.002)	.007**	1.001	(1.000-1.002)	.005**
Female	0.688	(0.485-0.975)	.036*	0.684	(0.484-0.967)	.032*	0.695	(0.489-0.988)	.043*
Hispanic	0.927	(0.532-1.613)	.787	0.902	(0.513-1.586)	.720	0.890	(0.478-1.655)	.712
Black	1.336	(0.780-2.289)	.291	1.404	(0.801-2.463)	.236	1.419	(0.784-2.567)	.247
Property offense	0.783	(0.577-1.061)	.114	0.780	(0.576-1.056)	.108	0.799	(0.583-1.095)	.163
Drug offense	1.151	(0.824-1.606)	.410	1.140	(0.818-1.587)	.439	1.159	(0.824-1.630)	.397
Weapon offense	0.681	(0.433-1.072)	.090	0.676	(0.431-1.061)	.089	0.677	(0.424-1.081)	.102
Other	0.935	(0.598-1.464)	.770	0.922	(0.584-1.455)	.726	0.972	(0.615-1.538)	.905
LSI-R	1.049	(1.032-1.067)	.000**	1.049	(1.031-1.067)	.000**	1.048	(1.029-1.066)	.000**
Prior convictions	1.052	(1.032-1.073)	.000**	1.052	(1.031-1.073)	.000**	1.051	(1.030-1.073)	.000**
Neighborhood									
Racial/ethnic heterogeneity				1.454	(0.812-2.603)	.208	2.381	(1.259-4.504)	.008**
Concentrated disadvantage				0.994	(0.872-1.132)	.922	1.037	(0.911-1.181)	.579
Residential stability				0.974	(0.874-1.086)	.634	0.930	(0.849-1.019)	.120

(continued)

Table 4. (continued)

	Model E			Model F			Model G		
Factors	HR	95% CI	*p*	HR	95% CI	*p*	HR	95% CI	*p*
Environmental									
Bars/clubs							0.951	(0.893-1.012)	.420
Liquor stores							0.953	(0.869-1.045)	.131
Takeout restaurants							0.976	(0.920-1.037)	.979
Sit-down restaurants							0.996	(0.954-1.040)	.940
Retail stores							1.046	(0.903-1.212)	.909
Bus stops							0.999	(0.994-1.005)	.237
Light rail stations							0.922	(0.758-1.121)	.822
Schools							1.054	(0.985-1.127)	.892
Park area							0.995	(0.983-1.007)	.754
Crime-prone housing							0.984	(0.968-1.001)	.009**
Drug markets							1.014	(0.985-1.043)	.401
Gang residences							1.002	(0.994-1.010)	.925
Log pseudolikelihood		–2,843.64			–2,842.46			–2,835.00	

Notes: HR=hazard ratio; CI=confidence interval; LSI-R = Level of Service Inventory Revised. Robust cluster standard errors are used to adjust for clustering within census tracts. The reference category for race/ethnic variables is white/other. The reference category for offense variables is violent offense.
* $p<0.05$, ** $p<0.01$.

Each table presents a series of models, reflecting the sequential introduction of variable groups. For each dependent variable, the base models (A and D) use only personal characteristics as predictors, whereas the subsequent models introduce neighborhood-level variables (B and E), and then environmental risk variables (C and G). In Table 3, the additional model (D) included time-dependent interaction terms, for gender and park variables, to address violations of the proportional hazards assumptions in Model C identified by the Schoenfeld residual test (Cleves et al., 2002). These terms are calculated by multiplying the main effect variable (centered to avoid problems of multicollinearity) with time (measured in years to aid interpretability) after dividing the data set into sub-episodes, formed by splitting each episode into sub-episodes for each and every failure within the data set (Cleves et al., 2002).

The tables present results as hazard ratios, which are exponents of model coefficients. These are more interpretable and indicate the difference in likelihood of failure, at any given time point, associated with a unit increase in an independent variable. For example, the hazard ratio for female in Model G, Table 4, is 0.695 which indicates that females have a hazard ratio—or likelihood of failure—that is, 69.5% that of males, at any given point in time. Unit increases in environmental risk variables reflect either each additional case of a particular environmental feature in the home node (most environmental risk variables) or a 1% increase in the overlap of the home node with risk feature polygons (park areas, crime-prone housing, drug markets).

Results show somewhat consistent patterns across the two dependent variables. Personal characteristics are, as expected, predictive across all models. Specifically age, age-squared, gender, LSI-R risk score and conviction history are significant for dependent variables and models with and without neighborhood and environmental geographical variables, though gender is no longer significant in Model D, after including a time-dependent interaction term for gender alongside the main effect. Neighborhood variables are, surprisingly, not predictive of arrests alone, while racial/ethnic heterogeneity is predictive of arrest and failure together ($p < .01$; Model G).

Most important, however, are the minimal effects for the theoretically central environmental risk variables. Most of these variables are not associated with the dependent variables while, for the couple that are, relationships do not line up neatly with our hypothesis. In the arrest-only analysis (Table 3), Models C and D indicate that crime-prone housing has a significant *negative* relationship with outcomes, at odds with the positive relationship hypothesized. After introducing the time-dependent interactions in Model D, a more complex pattern emerges. Although they have a negative main effect ($p < .1$), a significant ($p < .01$) positive time-dependent effect suggests parks may have a positive effect after the passing of time. Combining model coefficients for main effect and interaction terms (Bellera et al., 2010) gives a combined hazard ratio of 0.982 at time zero, 1.002 at 1 year, and 1.022 at 2 years, showing that an initially negative relationship between parks and arrests gives way to positive one after a year or two.[4] In the final arrest and revocation model (G), only crime-prone housing is has any statistically significant effect ($p <$ .1), and the relationship is, once again, negative.

The consistent negative effect of crime-prone housing on both failure measures in final models may reflect a reluctance of police or parole officers to conduct enforcement efforts in these settings, a finding supported by conversations with local criminal justice officials. The time-varying relationships of parks is a little harder to explain, but may reflect the varying adjustment of the parolee in the community during different residential episodes. However, models provide little clear evidence of any consistently positive environmental effects that we would expect based on environmental criminological theory.[5]

Conclusion

This article began by contemplating whether offender risk assessment in community corrections could be improved by incorporating measures of criminogenic places. This recognizes that, in their daily lives, offenders are exposed to a variety of such places and that this exposure may increase their risk of offending. A full assessment of environmental risks is a significant challenge, given the varied locations that offenders pass through or spend time. The pragmatic approach, taken here, has assessed the predictive value of criminogenic places around the parolee's home address. In the language of crime pattern theory, we have assessed environmental risks within the parolee's home node (P. J. Brantingham & Brantingham, 1981, 2008).

To carry out the analysis, we measured the concentration of a varied set of possible crime generators and attractors within 1,240 feet of parolee's address—approximating two or more blocks from their residence. These criminogenic features included bars and clubs, liquor stores, take-out restaurants, sit-down restaurants, retail stores, bus stops, light rail stations, schools, park area, crime-prone housing, drug markets, and gang residences. The measures were included in a set of survival models constructed to estimate the hazard rates for failure, post-release. The latter was measured as arrest, and as arrest or revocation for a technical violation. Models included an extensive list of control variables, including individually measured risk factors, as well as tract-level measures of social disorganization.

Our results were quite striking. Contrary to our working hypothesis, the likelihood of a parolee being arrested or having their parole revoked for a technical violation showed very few relationships with the presence of criminogenic places in the home node. Furthermore, where relationships did exist, they were either in the opposite direction to that hypothesized, or had a time-dependent influence that was not consistent across a residential episode.

Before drawing firm conclusions, we should consider any threats to the validity of findings. First, it is possible that our measures of environmental features were imprecise. However, this is unlikely, given their source in high quality up-to-date commercial data and triangulated operational police data. Threats could also arise from inaccuracy in parolee addresses. However, this also seems unlikely: relevant data fields were, by and large, well populated within the data, and the high geocoding match rate between parolee address data and Newark street centerline files suggests these fields are carefully maintained. A different possibility is that the addresses provided by parolees do not describe the places where they actually spend time. Perhaps they stay for long stretches in the homes of friends or partners, rather than at their official addresses. However, this speaks less of error, and more of a substantive issue that would explain results that a parolee's address may play a minor role among locations where parolees spend time.

This leads us, then, to reject the study's hypothesis: None of a variety of environmental risk factors convincingly predicts parolee failure in the cohort.

Discussion

We offer a number of reflections on the reasons for our largely null findings and go on to consider their implications for research and policy. First, we note the possibility that the features we counted as environmental crime risks do not consistently act as such. This might happen, for example, if guardianship and place management at these sites is strong (Clarke & Eck, 2005; Cohen & Felson, 1979; Felson, 1995). In fact, recent research provides support for this idea by showing that crime incidence is very unevenly distributed across similar types of potentially criminogenic locations (e.g., Eck, Clark, & Guerette, 2007). Even under these circumstances, though, we would still expect some of the environmental features to be criminogenic, and we might also therefore expect their influence to contribute to at least modest detectable average effects on parolee failure.

Another possibility is that the places we have theorized as criminogenic also trigger mechanisms that inhibit criminality among parolees, masking positive effects on failure. For example, proximity to transportation may be a means to access employment or services, while restaurants and bars may be sources of local employment. However, this logic seems only to apply to some of the environmental risk variables analyzed: It is harder to imagine that gang residences, drug markets, crime-prone housing, or even schools or parks, have inhibitory effects on parolee failure.

We might also imagine that environmental risk factors are specific in their effects, either because they tend to promote particular types of failure or that they are relevant only to a subgroup of parolees. For example, they may be more or less relevant to offenders according to their general propensity toward crime, lifestyles, or crime preferences. They may also vary according to the characteristics of the communities in which they live, perhaps because of differences in patterns of social disorganization. The current analysis' focus on a general cross-section of parolees, communities, and failure measures may obscure some more specific and local variations in effects. Future research that differentiates parolees by community type, individual characteristics, and failure circumstances, could explore the varied ways in which environmental risks affect failure according to particular circumstances.

Finally, as already discussed, the home location is just one of a number of settings in which offenders spend time. Other settings include the places they may work, study, shop, or socialize and so on (P. J. Brantingham & Brantingham, 1981, 2008). Importantly, these locations also contribute to the overall pattern of an offender's environmental risk exposure. The fact that offenders tend, on average, to travel up to a couple of miles to commit crimes is consistent with these observations (Bichler et al., 2011). As such, environmental risks in the home node may simply be a small part of a much broader range of environmental risk exposure, which was not studied here.

In contemplating the policy implications of our findings, we should be cautious: This is just a single study and would benefit from replication, as well as further research of the kind discussed above. Nonetheless, the findings here are largely consistent with emerging evidence on sex offenders, showing that residency restrictions (that limit residential proximity to schools, child care centers, parks and so on) do not reduce sex offense recidivism (and may actually make recidivism in general worse; Duwe, Donnay, & Tewksbury, 2008; Kang, 2012). On their face, findings speak against a heavy emphasis on where offenders live and local criminogenic characteristics, in place of a more holistic approach that involves assessing and responding to environmental risks in the range of places that offenders spend time. These may be linked to friends' residences, service programs, employment or recreational activity, as well as home, and the journeys between them.

Overall, despite our null findings, we are not pessimistic about the prospects for forms of environmental risk assessment to aid the release and supervision of parolees or other offenders in the community. The theoretical basis for an environmental approach seems strong (Cohen & Felson, 1979; Cullen et al., 2002; P. J. Brantingham & Brantingham, 1981, 2008), and it may just be a matter of time before a more developed environmental risk assessment model can be tested. As we have suggested in the course of this article, such a model ideally should be undergirded by data collection on the places offenders spend time and their travel routes between them, and perhaps also the kinds of activities they engage in within those places. For some groups of offenders, place-based monitoring may provide opportunities from existing data sources. For others, protocols could be expanded to measure the routine travel patterns and activities of offenders while in the community, as part of their routine risk and needs assessments, as has been implemented in at least one setting already (Bichler et al., 2011). Pilot data collection in this format would provide the basis for testing more sophisticated environmental models, and could ultimately provide a template for doing this kind of assessment should it prove to be valuable. We look forward to seeing these developments in the future, and watching how environmental criminology helps shape theory and practice in community corrections.

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Notes

1. In compiling data, Infogroup examines each record by hand for accuracy and completeness. They also call the phone numbers of the businesses to confirm the record and collect additional information on businesses (Infogroup, 2010). In a separate study, Piza, Caplan, and Kennedy (2011) conducted checks on Newark lists of corner stores and take out eateries from Infogroup, by driving around and checking them for himself. They found them to be correct.
2. The Herfindahl index is calculated with the equation: $EH_K = \sum_1^{j=1} G_j^{\,2}$ where J is the number of ethnic racial groups, G is the proportion of the population accounted for by each ethnic group.
3. For arrest-only failure, Moran's I = −0.116 (p = .123), while for arrest or revocation, Moran's I= −0.077 (p = .340). In calculating Moran's I, we used a 100-day

cutoff to calculate aggregated failure rates for each census tract. This provided a sufficient follow-up time to allow for divergent outcomes to become manifest, while maximizing uncensored cases upon which estimates could be reliably calculated. Only tracts within Newark were used to calculate Moran's I, meaning that parolees closer to the edge of the study area did not use adjacent non-Newark tracts in the calculation. However, the edges of the city mostly coincide with sharp geographical changes (water on one side, and affluent suburbs on the other) suggesting that spatial influence of these nonincluded tracts will tend to be less important. Moran's I calculations also excluded tracts where there were less than five parolee episodes upon which to base a tract aggregate failure measure. Finally, multivariate models were calculated that incorporated spatial lags of aggregate tract measures as a further check on spatial dependency (this required the data set to be trimmed by 20 parolee episodes that fell in that had adjacent tracts dominated by missing values). These models provided no further evidence of spatial effects.

4. Drawing on Bellera et al. (2010), we estimated the hazard ratio at time t, in the context of a time-varying effect, as follows (where β is the fixed effect coefficient, γ is the coefficient for the time-varying term):

$$HR(t) = \exp[\beta + \gamma t]$$

When $t = 0$ (at the beginning of each episode), each unit increase in the parks variable is associated only with the main effect hazard ratio for parks already reported in Model D (0.982). At 1 year ($t = 1$), we add together the main and time-varying effect coefficients (−0.018 and 0.020; or equivalently multiply together the hazard ratios for the two terms). The exponent of added coefficients is a hazard ratio of 1.002. At 2 years, we calculate a hazard ratio by adding the main effect coefficient to twice the time-dependent effect coefficient, and calculating the exponent. This gives a hazard ratio of 1.022.

5. Some alternative model specifications were constructed to see if they would produce different results for environmental variables. These included models assessing only one environmental risk variable at a time. They also included models in which environmental risk variables were specified as binary instead of continuous variables. These alternative specifications produce results in line with the models presented.

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