

Crime Places in Context: An Illustration of the Multilevel Nature of Hot Spot Development

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Abstract

Objectives The present study provides an illustration of a statistical test of the Brantinghams' theory about the formation of hotspots and the effects that nodes, paths, and environmental backcloth have on their development.

Methods We used multilevel Poisson regression analysis to explain variation in the count of incidents at each address. Place-level proximity to nodes and paths was measured by using the Euclidian distance from each location to the closest carry-out liquor store, on-premises drinking establishment, and bus route. The broader environmental backcloth was represented by various census block-group characteristics, including density of commercial land use. A three-way place-level interaction as well as a cross-level interaction involving all four key independent variables were used to estimate the Brantinghams' concept of the overlay of nodes, paths, and backcloth.

Results The three-way interaction involving the distance to the closest on-premises liquor establishment, the distance to closest carry-out liquor facility, and the distance to the closest bus route was significantly and negatively related to place-level crime incidents. This three-way interaction had effects which varied across neighborhood contexts, with stronger negative effects on crime occurring in neighborhoods characterized by high levels of commercial density.

Conclusion This study supported the notion of a multilevel theory of crime places and has implications for more effectively addressing crime. In particular, those places with multiple nodes and paths in their proximal environments and dense commercial land within their broader environments likely need additional crime prevention measures to get the

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same benefit relative to places with multiple nodes and paths in the proximal environments yet little commercial density within their broader environment.

Keywords Hot spots · Environmental criminology · Risky places · Multilevel opportunity

Introduction

There is a long tradition in criminology that involves studying the link between crime and place. Much of that tradition has been “macro-environmental” in nature, focusing on neighborhood-level variation in criminal offending behavior (e.g., Shaw 1929; Shaw and McKay 1942; Simcha-Fagan and Schwartz 1986) and neighborhood-level variation in crime/victimization events (e.g., Bellair 1997; Bernasco and Luykx 2003; Greenberg et al. 1982; Sampson and Groves 1989; White 1990; Velez 2001). An alternative “micro-environmental” tradition studies the link between crime and place at sub-neighborhood units of analysis, including streets, blocks, land parcels, and intersections (Braga et al. 2011; Eck et al. 2005; Roncek and Maier 1991; Sherman et al. 1989; Weisburd et al. 2004, 2012).¹ Though neighborhood and sub-neighborhood influences are usually discussed theoretically and studied empirically in distinct literatures, together these traditions indicate that crime concentrates at multiple spatial levels of analysis due to unique crime potential at distinct levels (e.g., Eck et al. 2005; Taylor 1998).

In fact, there is some theoretical work which highlights *both* neighborhood and sub-neighborhood levels of analysis and the ways in which these various levels of analysis work together to produce crime at particular locations (e.g., Brantingham and Brantingham 1993a, b, 1999; Taylor and Gottfredson 1986; Wilcox et al. 2003, 2013). Brantingham and Brantingham, in particular, present an interesting conceptualization of crime at locations that is implicitly multilevel. Specifically, they argue that the nonrandom clustering of crime at certain locations is a function of the confluence of different layers of crime potential: (1) the extent to which an area is at or near major pedestrian stopping points, or *nodes* (e.g., schools, shopping malls, entertainment spots), (2) the extent to which a location is (or is near) a primary travel route to and from nodes—what they refer to as *paths* (e.g., traffic arteries), and (3) the broader and complex physical, cultural, and social features of the area in which a location is situated—referred to as the *environmental backcloth* (e.g., Brantingham and Brantingham 1993a, 1999). According to Brantingham and Brantingham (1999), the *composite* of these layers of crime potential produces a concentration of crime, or a “hotspot.” In other words, if one were to overlay a map of major nodes, a map of major traffic arteries, and a map of a crime-generating backcloth (e.g., a map of neighborhoods classified by disadvantaged economic status), hot spots would most likely occur at the locations where these layers overlap.

¹ We recognize that this dichotomy is an oversimplification. For example, some prominent scholars in the crime-and-place tradition recognize streets and blocks as “meso-level,” lying between micro-level individuals and/or specific addresses and macro-level neighborhoods, cities, counties, and so on (see, e.g., Taylor 2015). For the purposes of this paper, we define neighborhoods as census-defined collections of city blocks, and these are treated as “macro-level” units. In contrast, units smaller than these collections of blocks, including single blocks, streets, parcels, addresses, or intersections are viewed as “micro-level” places (see also Weisburd et al. 2012).

Though Brantingham and Brantingham discuss the formation of hot spots in theoretical and geographic/mapping terms, we see implications of this work for testing statistical models of crime locations. More specifically, our interpretation of their conceptual model of hot-spot formation is that it implies the statistical interplay of nodes, paths, and backcloth. Yet, we are aware of no study that has explicitly examined the intersection of all of these layers. Thus, to extend the literature on crime places, the present study provides an illustration of a statistical test of the Brantinghams' theory. In doing so, it conceptualizes the first of the two layers of crime potential that they discuss—proximity of a location to nodes and the proximity of a location to paths—as *micro-environmental* layers, both measured at the *place level of analysis*. On the other hand, “backcloth” is conceptualized as a *macro-environmental* layer and is thus measured at a broader *neighborhood level*. We estimate crime counts at specific locations (places) as a function of the intersection of: (1) micro-spatial crime potential, as measured by proximity of places to both nodes and paths, and (2) macro-spatial crime potential, as measured by neighborhood-level density of nodes. Multilevel models of crime at places are estimated using Poisson-based hierarchical regression models with 33,105 places nested within 285 census block groups in the city of Cincinnati, Ohio.

Theoretical Background: A Multilevel Conceptual Model of Crime Spots

The Brantinghams' theory of crime locations builds upon assumptions from the rational choice perspective as well as routine activity theory. As such, their starting point is the assumption that crime events happen when a person motivated or ready to offend encounters a suitable target in a situation that offers little risk relative to the reward (Cohen and Felson 1979; Cohen et al. 1980, 1981; see also Clarke 1980; Clarke and Cornish 1985). The immediate environmental setting is key in understanding where such a convergence is likely. For example, places that are nodes offer high potential for convergence between ready offenders and suitable targets. Nodes are locations—specific spots on a map—where many people congregate for the purposes of daily legitimate activity. Paths are spaces represented by the lines on a map, to and from high-activity nodes. Because paths are so vital in accessing nodes, they are also high-activity spaces that offer strong potential for the convergence of motivated offenders and suitable targets. Thus, the concepts of nodes and paths, as discussed by the Brantinghams, are helpful in understanding why some micro-spatial units—especially specific addresses or streets (both units of analysis referred to here as “places”)—experience more crime than others. Places at or near nodes and paths, including places at the edges of nodes and paths, have strong crime potential; their micro-environmental location offers ample crime opportunity (see also, Felson 1987, 1994).

However, it is not enough to consider only micro-environmental locations. Brantingham and Brantingham (1993a) state, “When looking at crime and criminal events, it is essential to see them, to the extent possible, in narrow focus. But it is also important to see them within a broader focus as well. We need to see both the tree and the forest” (p. 6). In short, it is necessary to consider the larger environment in which crime-generating nodes and paths are situated in order to have a clearer understanding of crime potential. The macro-environmental context in which nodes and paths are embedded, which the Brantinghams refer to as the environmental backcloth, is a complex and countless array of broader-area characteristics that affect more general movement patterns of motivated offenders and potential targets. For example, the density of commercial establishments within

neighborhoods affect aggregate movement patterns (i.e., the volume of traffic in a broader area) and thus the extent to which offenders and targets converge area-wide, at an aggregate level.

The importance of the “overlay” of nodes, paths, and backcloth, as presented by the Brantinghams, is similar to Felson’s (2006, pp. 116–122) discussion of crime’s ecosystem and, in particular, his notion of “thick crime habitat.” Felson describes thick crime habitat as an ecosystem in which risky places cluster with unsupervised paths, and this clustering is seen within multiple surrounding blocks. Felson implies that, while certain nodes and paths might be crime-generating themselves, the intersection of nodes and paths repeatedly within several contiguous blocks creates an environment particularly conducive to crime. Somewhat related ideas were provided by Wilcox and Eck (2011), who posited that the clustering of high-activity places at a broader environmental level is more influential in predicting crime at a location than is the characteristic of the location itself. In summarizing the literature on land uses and crime, they say “strong suggestions in the literature claim that many facilities provide crime opportunity, and it is the contextual clustering of [such] public-use facilities, especially along or near major roads that is related to area crime” (pp. 475–476).

Previous Studies of Crime Places

While the theory reviewed above certainly points to the idea that understanding crime at places necessitates contextualized, multilevel analyses including both neighborhood and sub-neighborhood units, few empirical studies of crime locations actually employ such methodology. In contrast, certain other aspects of crime patterning—such as individual victimization risk—are now routinely studied in multilevel fashion, with individual victims typically nested within neighborhood contexts (Sampson and Wooldredge 1987; Smith and Jarjoura 1989; Kennedy and Forde 1990; Miethe and McDowall 1993; Rountree et al. 1994). For example, Sampson and Wooldredge (1987) pioneered this sort of research in their analysis of the British Crime Survey. They examined variation in risk of victimization as a function of demographic characteristics, individual activity patterns, and the context of the community. Based on a series of logistic regression models, they found that individual activity patterns—such as frequently going out at night—increased the risk of burglary victimization. At the same time, however, the authors noted that burglary victimization was related to community-level variables—independent of individual activity patterns—including single person dwellings, family disruption, low social cohesion, VCR ownership, unemployment, and housing density. A good deal of subsequent research has supported Sampson and Wooldredge’s conclusions that victimization risk is affected by both individual-level and neighborhood-level opportunity structures (Kennedy and Forde 1990; Miethe and Meier 1994; Outlaw et al. 2002; Smith and Jarjoura 1989; Wilcox et al. 2007; Rountree et al. 1994; Rountree and Land 1996).

In contrast to victimization research, most empirical studies of crime events at places have *not* used a multilevel conceptual strategy and instead have relied on single-level approaches that emphasize, in particular, micro-environmental characteristics associated with crime at places—with “places” most typically operationalized as a block or street segment as opposed to a specific address or point. While such research falls short of measuring the multilevel nature of crime potential at places, the place-level findings generated from this body of research still support specific aspects of the multilevel

conceptual model of hotspots described by Brantingham and Brantingham (1999). This relevant literature includes studies of crime-generating land uses, studies related to the travel and movement patterns of both offenders and victims, and studies of social disorganization at the place level.

Crime-Generating Nodes and Movement Patterns

Previous literature suggests that non-residential locations—such as shopping centers or night clubs—generate criminal activity. For instance, Roncek and colleagues published a series of studies suggesting that street blocks with certain non-residential land uses experience higher rates of crime (Roncek and Bell 1981; Roncek and Fagianni 1985; Roncek and LoBosco 1983; Roncek and Maier 1991). Specifically, they analyzed the proximal effects of high schools and bars/liquor establishments in generating criminal opportunity for both the Cleveland and San Diego areas and found that adjacency to these facilities was linked to higher levels of crime, including murder, assault, and robbery. Such findings were presumed to result from opportunity: The users of these facilities created high traffic in the immediate environment, including a high density of adolescent or young adults (sometimes under the influence of alcohol, in the case of bars). As such, these establishments were thought to support the convergence of motivated offenders and suitable, unguarded targets.

Sherman et al.'s (1989) seminal study of calls for service in Minneapolis also supports the idea that non-residential places are nodes susceptible to becoming hot spots. Their analysis of all calls over a 1-year period showed that most places in the city experienced no crime while a few locations were responsible for a disproportionately high number of calls about crime. In fact, fully 50 % of all calls for service in Minneapolis were associated with just 3 % of the city's places. Non-residential nodes such as department stores, bars, and convenience stores were among the places with the highest numbers of calls. A good deal of work since the pathbreaking work of Roncek and colleagues and Sherman et al. has supported the idea that a variety of non-residential land uses are related to crime at micro-spatial units of analysis (Kurtz et al. 1998; LaGrange 1999; Taylor et al. 1995).

Other work has emphasized the crime-generating nature of both nodes and transportation paths. For example, recent research by Bernasco and Block (2009, 2011) used cleared robbery cases across nearly 25,000 census blocks in Chicago between 1996 and 1998 to examine why robbers choose certain areas to commit crime, including whether they rob close to home (i.e., near their “anchor points”), which areas they deem suitable or attractive, as well as what keeps them away from certain areas. Applying discrete choice analysis and negative binomial regression models, they observed that patterns of robbery location choice were related to the theoretically meaningful characteristics of target areas, to the areas where offenders live, to the joint characteristics of the two areas, and to the characteristics of offenders themselves. In particular, they noted that the presence of illegal drug and prostitution markets, as well as crime-generating nodes—such as railway systems, liquor stores, and retail businesses—made areas attractive for robbers. For instance, the presence of a liquor store on a block increased its expected robbery count by approximately 67 %, while blocks with a railway system had over four times as many robberies compared to those without (see also Clarke 1996; Felson et al. 1996; Loukaitou-Sideris 1999). Furthermore, blocks with these sorts of nodes elevated the risk of criminal activity on adjacent blocks. These effects remained valid even when characteristics of the composition of the block's residential population were taken into account.

Similarly, David Weisburd and his colleagues have studied the patterning of crime in Seattle over the course of several decades (Groff et al. 2010; Weisburd et al. 2004, 2012). This work has revealed that crime tends to cluster on street segments with non-residential nodes *and* along segments that are major paths. More specifically, their research indicated that streets segments located near public facilities (nodes) or street segments that were arterial roads or bus routes (paths) were at increased risk for being a chronic crime hot spot.² In contrast, Braga et al. (2011) found that Boston street segments and intersections along major roads experienced *fewer* street robberies than those on smaller roads, although the opposite was found in relation to commercial robbery.³

The Intersection of Nodes, Paths, and Backcloth

In addition to the studies that link criminal opportunity to various crime generators and attractors, some research has incorporated street-level measures of social disorganization in order to understand opportunity for crime events at places. Though social disorganization is measured at a micro-environmental rather than macro-environmental level in such studies, this line of inquiry is consistent with the notion that social structural aspects of the “backcloth” in which places are situated affects opportunity for crime along with the proximal nodes and paths characterizing a location.

For example, Weisburd et al.’s (2012) analysis of street segments in Seattle over a 16-year period (1989–2004) included measures of social disorganization in addition to the measures of proximity to nodes and paths already discussed above. While busy nodes and the presence of arterial roads served to increase crime on street segments, higher levels of socioeconomic status and collective efficacy at the street-level worked to decrease crime. Furthermore, crime waves and crime drops were most strongly correlated with variables at the street segment level congruent with the social disorganization perspective (e.g., physical disorder, collective efficacy), leading the authors to conclude that opportunity provided by street-level social disorganization, along with that provided by street-level proximity to nodes and paths, are both integral to fully understanding the criminology of place.

Several related studies of crime incidents during 1993 at the face-block level in a medium-sized southeastern US city incorporated both measures of crime-generating nodes and measures of social disorganization (Smith et al. 2000; Rice and Smith 2002). Furthermore, these studies integrated these two sets of measures in a manner that explicitly predicted interaction between them, thus approaching the conceptualization adopted for the present study. In particular, criminogenic nodes were posited to be more strongly related to crime on face blocks with higher levels of social disorganization. In the first of these two related studies, Smith and colleagues (2000) examined face-block-level robbery counts. Results from their regression analyses indicated that criminogenic land use attributes (e.g.,

² Curman et al. (2015) provided a partial replication of Weisburd and colleagues’ Seattle studies by examining over one million calls for service to the Vancouver Police Department (VPD) from 1991 to 2006 at the street segment level in Vancouver, British Columbia. Using group-based trajectory models (GBTM) and the k means statistic, the authors found considerable overlap between the street segment patterns in Vancouver and Seattle. For example, the authors noted that crime on Vancouver’s street blocks was highly concentrated, with 100 % of all criminal activity occurring at only 60 % of street blocks. Additionally, these crime patterns remained stable over time. Unlike Weisburd et al. (2012), however, Curman et al. (2015) did not estimate developmental trajectories of crime using opportunity-related covariates.

³ Braga et al. (2011) note that while street segments and intersections located along major roads in Boston do likely provide plentiful targets, there are also likely more passers-by with better lighting at such locations.

vacant lots) and social disorganization attributes (e.g., distance from the center of the city and single-parent households) were related to face-block robberies. Furthermore, a number of interactions between crime-generating nodes and social disorganization were found. For example, the number of motels/hotels and number of bars/restaurants/gas stations on a face block were more strongly related to robbery on face blocks with higher levels of single-parent households. Distance from the center of the city, on the other hand, attenuated the effects of numbers of bars/restaurants/gas stations, numbers of multifamily residences, and numbers of vacant or park lots (Smith et al. 2000). In fact, their models indicated that “criminogenic social disorganization attributes interact[ed] with criminogenic land use variables to produce more street robberies than would be the case if only an additive model was used to fit the data” (p. 514).

Similar results were reported by Rice and Smith (2002) in their analysis of automobile theft. For example, they found that the number of single parent households and various land uses—such as bars, gas stations, and hotels—interacted to generate circumstances favorable to automobile theft. Thus, both land uses and social disorganization variables determined street robbery and automobile theft at the face-block level. Street robberies and automobile thefts occurred in high-activity, socially disorganized places—locations that are presumably in close proximity to where offenders live, and are routinely active, and locations where targets abound.

More recently, Stucky and Ottensmann (2009) examined how proximity to nodes, paths, and micro-environmental social disorganization operate in conjunction with one another in their analysis of 1000-foot grid squares in Indianapolis. Both commercial land and high-density residential land (nodes) were positively related to violent crime, as was the total length of major roads. In contrast, non-residential land uses that produce little traffic relative to commercial areas (e.g., cemeteries, industrial land, and water) were negatively related to crime in these micro-spatial environments. Importantly, however, the effects of several nodes and paths were moderated by the level of economic disadvantage within their micro-environmental units. In particular, disadvantage enhanced the crime-generating effects of high-density residential land, thus supporting the overlay of nodes and backcloth described by the Brantinghams. However, seemingly in contrast to the predictions of crime pattern theory, Stucky and Ottensmann (2009) found that disadvantage tempered the crime-generating effects of commercial land and road length.

Most recently, Hart and Miethe’s (2014) research on robbery locations suggests that its occurrence is influenced by the “overlay” of several activity nodes and paths within their proximate (within 1000-ft) environments. They used data on location from 453 robbery locations and a matched sample of 453 non-robbery locations in Henderson, Nevada, and examined the extent to which bus stops and several types of nodes (ATMs, bars, check-cashing facilities, fast food restaurants, gas stations, shopping plazas, and smoke shops) affected robbery victimization risk. Conjunctive analyses (see also Miethe et al. 2008) were used to create robbery event profiles, “defined by the unique combination of activity nodes present or absent in the proximate environment of a street robbery” (Hart and Miethe 2014, p. 184). Results indicated that risk of robbery was strongly influenced by the unique combinations of places within the micro-environment, with most robberies clustered within a small number of micro-environmental profiles. Bus stops were more likely than any of the other types of places examined to be part of a robbery profile. That said, Hart and Miethe also found that the risk associated with bus stops depended on the presence or absence of other nodes. For example, they found that a bus stop was always part of the robbery’s proximate environment when a bar, gas station, fast food restaurant, ATM, smoke shop and shopping plaza was also present; conversely, they noted that bus

stops were part of the proximate environment only 10 % of the time when a bar was the *only* type of activity node close to the crime incident.

In summary, the Brantinghams suggest that crime hot spots form “at the confluence of high crime potentials from some multiplicity of predisposing environmental conditions and activities operating at different elemental levels” (Brantingham and Brantingham 1999, p. 11). Importantly, these scholars argue that the proximity of places to various land uses and transportation routes, as well as broader residential and activity structures of the areas in which places are embedded, work together to influence the formation of crime places, and when the overlap of these various “layers” of crime potential is substantial, a thick crime habitat can result (to borrow Felson’s term). While numerous previous empirical studies address aspects of the Brantinghams’ theory, we are aware of no study that has explicitly examined the intersection of each of the layers that they discuss. For example, the studies by Smith et al. (2000) and Rice and Smith (2002) examined interaction effects between proximity to crime-generating nodes and backcloth in the form of measures of social disorganization, but measures of crime-generating paths (e.g., traffic arteries) were omitted from their study. Stucky and Ottensmann (2009) examined interactions involving both nodes and backcloth in the form of disadvantage as well as interactions involving paths and disadvantage, but three-way interactions were not included. Hart and Miethe’s (2014) conjunctive analysis essentially got at interactions involving numerous nodes and bus stops, but they did not address backcloth. Further, all of these previous studies have been conducted at single levels of analysis. To our knowledge, there exists no multilevel

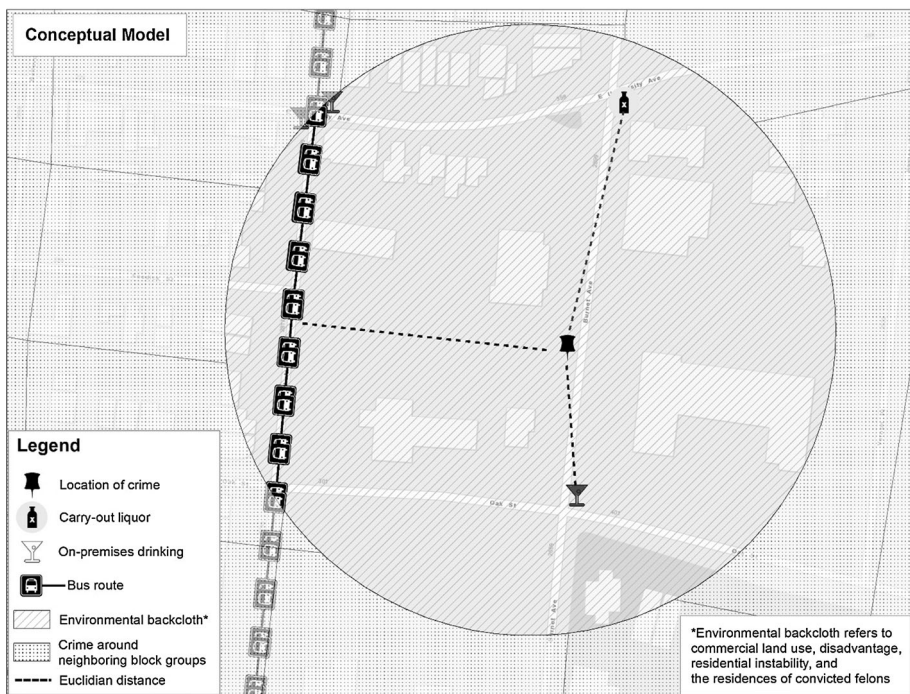


Fig. 1 A conceptualization of the multilevel interaction of nodes, paths, and backcloth affecting crime locations

examination of the synergy between crime-generating nodes and paths and the environmental backcloth in which they are situated in order to understand crime at places.

The Present Study

This study builds upon previous work that has shown how combinations of micro-environmental risk factors affect crime events and, in the process, provides a test of our interpretation of the Brantinghams' *multilevel* conceptualization of crime at places. Specifically, we nest addresses that experienced at least one crime within the study period (referred to as "crime locations") within block groups and analyze, first, the independent versus interactive roles of place-level distance to crime generating nodes (indicated here by carry-out liquor stores and on-premises drinking establishments) and place-level distance to crime-generating movement paths (indicated here by bus routes). Next, we consider how the effect of the clustering of nodes and movement paths at the micro-spatial place level might vary as a function of block-group-level commercial land concentration. It is important to note that it is not the goal of the study to estimate crime at places with an exhaustive set of measures of crime-generating nodes, paths, and backcloth characteristics. Rather, this analysis is intended to provide an empirical illustration of the complex ways in which nodes, paths, and backcloth interact toward the development of problem places. In order to keep the illustration of this complex, multilevel interplay as simple as possible, we limit our study to a few key variables (drawing from the literature reviewed above).

A conceptual model of our study is displayed in Fig. 1. In this figure, the pin represents a location experiencing at least one crime—a crime location. Such crime locations are the unit of analysis at level 1 in our study, and we aim to explain variation in crime counts at crime locations. At level 1, we are interested in the effects of the Euclidian distance from each unique crime event location to the closest crime generating nodes in terms of both carry-out liquor stores and on-premises drinking establishments, as well as crime-generating paths, as measured by bus routes. These Euclidean distances represent characteristics of crime locations in our study. The large circle encompassing the crime location and crime generator symbols represents the broader environmental backcloth in which crime places are situated.⁴ In our study, backcloth is measured primarily in terms of block-group-level density of commercial land use. However, we also control for other neighborhood characteristics that impact crime opportunity, including block-group-level disadvantage and residential instability, as well as a proxy for motivated offender concentration in the form of density of convicted felons. The dotted area around the large circle represents surrounding block groups, which are also presumed to affect total incidents of crime occurring at specific locations due to spatial proximity. In particular, through use of a spatial lag term, we consider the average crime count of neighboring block groups for each block group in our study.

Using the conceptual model just described, we tested the following three hypotheses in order to explain crime counts at specific crime locations.

Hypothesis 1 A three-way interaction involving the distance to the closest on-premises liquor establishment, the distance to the closest carry-out liquor facility, and the distance to the closest bus route should be negatively related to expected counts of events at locations (the shorter the multiplicative distance, the more a place is situated in a micro-environment of proximal or overlapping layers of crime potential). In fact, building upon work showing that

⁴ The circle in this figure does not reflect an *actual* census block and its boundaries.

it is a combination of risky nodes and paths that are more important than any one single risky facility (e.g., Hart and Miethe 2014), the multiplicative distance to all three measures of crime-generating nodes and/or paths (carry-out liquor stores, on-premises drinking establishments, and bus routes) is expected to be more important than the main effects of distance to on-premises liquor establishments, carry-out liquor facilities, and bus routes.

Hypothesis 2 The multiplicative effect of the distance to the closest carry-out liquor store, the distance to on-premises drinking establishment, and the distance to the closest bus route will vary significantly across block groups. In other words, the place-level (level-1) three-way interaction term will have a random slope.

Hypothesis 3 The multiplicative effect of the distance to the closest crime generators (the place-level 3-way interaction term) will be more negatively related to the block-group level mean counts of crime within areas with greater commercial density, controlling for other block-group-level variables. In other words, the distance to micro-environmental hubs of activity (as indicated by shorter multiplicative distances to the closest carry-out liquor store, on-premises drinking establishment, and bus route) is expected to be more strongly related to crime at locations that are situated within opportunistic broader areas.

Data and Measures

The above-stated hypotheses were tested using place- and block-group-level variables constructed using a variety of data sources. Measurement of each variable is discussed in detail below. Descriptive statistics for the study variables are shown in Table 1, and bivariate correlations for all study variables at level 1 and level 2, are reported in Appendices 1 and 2, respectively.

Dependent Variable

The dependent variable for the study is total Part I incidents at locations (street addresses) in the city of Cincinnati, Ohio, for the time period of 2010 to 2012. We restrict our analysis to those locations at which at least one incident was recorded during the study period—this was a total of 33,105 crime places. The 68,311 crime incidents that occurred between 2010 and 2012 were linked to locations; the percent match for geocoding crime incident locations was slightly higher than 97 %. Crime incidents occurring at the same locations were aggregated, creating counts for each location.⁵ The descriptive statistics reported in Table 1 indicate that crime counts ranged from 1 to 491, with the level-1 locations experiencing, on average, just over two Part I incidents.

Place-Level (Level-1) Independent Variables

The key explanatory variables at the place level are measures of distance to crime-generating nodes and paths of activity. Using ArcGIS version 10.1 and the spatial join method, Euclidian distances (in kilometers) were calculated from each crime location to the nearest carry-out liquor store, on-premises drinking establishment, and bus route.⁶

⁵ Combining co-incident locations and creating a count variable for each location was accomplished using the “collect event” tool in ArcGIS 10.1.

⁶ We inspected the possibility of collinearity among all distance measures. The maximum value for VIF was 2.9 for all place-level distance variables.

Table 1 Descriptive statistics for study variables

Level-1 variables ($N_1 = 33,105$)	Minimum	Maximum	Mean	SD
Crime count	1	491	2.060	6.196
Distance to carry-out liquor	0	3.380	0.616	0.457
Distance to on-premises drinking	0	3.400	0.522	0.488
Distance to bus routes	0	1.570	0.134	0.159
Level-2 variables ($N_2 = 285$)	Minimum	Maximum	Mean	SD
Commercial density (square root)	0	0.930	0.404	0.162
Disadvantage factor	-1.826	2.500	0	1
Instability factor	-2.212	4.037	0	1
Felon residence (square root)	1	21.840	8.351	3.706
Spatial lag	1.317	4.780	2.058	0.492

The locations of carry-out and on-premises liquor establishments come from the website of the Ohio Department of Commerce, Division of Liquor Control (<https://goo.gl/yBPJxK>). The distinction between carry-out and on-premises is based on the type of liquor license owned by the establishment. Carry-out licenses typically are held by package stores, whereas on-premises licenses are held by bars and restaurants.⁷ We separated these two alcohol-related establishments in line with previous work which has noted differences in their effects on crime (Gruenewald et al. 2006; Snowden and Pridemore 2013).

Bus routes demark the major public transportation arteries in Cincinnati, which largely follow major city roads. The shapefile that includes bus routes was downloaded from <https://www.arcgis.com>. From this site, Cincinnati public transit shapefile data (bus routes) are used for the analysis.

All three node/path distance measures were transformed using the log base 10 function due to their skewed distributions. Finally, since one of our main hypotheses (Hypothesis 1) was that the effects of these three distance measures were contingent upon one another, a three-way interaction term was created by multiplying the original distances and then logging the product term.⁸ This product term reflects our concept of *simultaneous* proximity to multiple nodes/paths. As such, it was evaluated separately from the additive effects of its components in order to determine whether simultaneous proximity to all three nodes/paths matters more than the separate proximities for influencing crime counts. Thus, for comparison purposes, we estimated one model with the three additive effects and a second model with the product term but not the additive effects (with all statistical controls included in each model). Although this differs from the traditional approach of including both additive and product terms in the same model, doing so would undermine our goal of assessing whether the proximity to these three nodes/paths should be examined simultaneously *as opposed to* separately.

⁷ We checked the possible overlap between these facilities but found none. Moreover, liquor stores associated with major grocers (such as Kroger stores) and gas stations were deleted from the main list of liquor establishments.

⁸ In all cases of variable skewness, various transformations were considered: natural log, log base ten, and square root. The transformation which yielded the closest approximation to a normal distribution was used.

All level-1 covariates were grand-mean centered in all models within the analyses.⁹ In other words, the level-1 distance measures reflect the deviation from the grand-mean distance for the entire sample. Grand-mean centering allows us to estimate the effects of level-2 variables while controlling for the compositional effects of level-1 predictors.

Neighborhood Block Group (Level-2) Independent Variables

Neighborhoods are operationalized as census-defined block groups for the purposes of this study. Our primary independent variable at the block group level was commercial density—intended to tap the extent to which crime places were situated in macro-environmental hubs of activity. To measure commercial density, we utilized land use data from the Cincinnati Area Geographic Information System’s open website: <http://cagismaps.hamilton-co.org/cagisportal>. We divided land area designated as “commercial” in each block group by the total area of the block group, thus resulting in a measure of the proportion of the commercial land use for each block group. Due to the skewed distribution of this variable, we used the square root of commercial density in the analysis presented herein.

We also controlled for block group characteristics that would likely be related to crime opportunity at locations within, drawing largely from the social disorganization theoretical tradition, while also controlling more directly for presence of motivated offenders. In particular, we measured structural disadvantage and residential instability utilizing factor analyses of data from the 2010 census and the 2007–2011 American Community Survey. First, we conducted principal component analysis (with Direct Oblimin Rotation) of items that are typically combined to create measures of structural disadvantage and residential instability: the proportion of female headed households, the proportion of residents with less than high-school education, the proportion of residents living in poverty, the proportion of residents who are unemployed, the proportion of residents who are black, the proportion of total land that is vacant, the proportion of renter households, and the proportion of residents who had moved in within the last year. Two factors emerged. First, the proportion of female headed households, the proportion of residents with less than a high-school education, the proportion of residents living in poverty, the proportion of resident who are unemployed, the proportion of resident who are black, and the proportion of total land that is vacant all loaded highly on a “disadvantage” factor ($\alpha = 0.79$). The proportion of renter households, as well as the proportion of residents who had moved in within the last year, loaded highly on a second factor, which we termed “residential instability” ($\alpha = 0.60$).¹⁰ Both factors accounted for 65 % of the overall variance.

We also control for motivated offenders in the environment using data on convicted felon residences, obtained from Hamilton County Pre-trial Services and previously used for another study. More specifically, we obtained the unique addresses of all felons convicted. If felons reported two different addresses, both addresses were included in the calculation of the number of residences of convicted felons for each block-group. Due to the skewed nature of this variable, we utilized its square root for analytic purposes.

Finally, the average block-group-level crime incidents are quite likely related to crime in neighboring block groups. In fact, using Global Moran’s I statistics, we found that the

⁹ The interaction term was centered after each term was multiplied and that product was logged.

¹⁰ This value of alpha is lower than a traditional cutoff of 0.7; however, according to Hair et al. (2007), values above 0.6 are considered acceptable, especially when analyzing reliability of scales made up of few items.

spatial distribution of crime events at the block-group level was not random ($p < .05$) (Anselin 2003). Accordingly, we included a spatial lag¹¹ at level-2 in order to control for this spatial autocorrelation.¹²

Results

Multilevel Poisson regression models (with over-dispersion) of crime counts at crime locations were estimated using HLM v7.01 (Raudenbush et al. 2000).¹³ The full maximum likelihood function option was used for this estimation. All census block groups within Cincinnati boundaries were used ($n = 285$), with each block group containing at least 8 crime locations. In total, 33,105 unique crime places were nested within the 285 block groups analyzed. An initial unconditional model was estimated in order to assess the magnitude of variation in the mean crime count across block groups. This unconditional model (not shown) revealed significant variation across level-2 units ($p < .001$), which justified the use of hierarchical modeling for our analysis.

Next, we estimated the effects of level-1 and level-2 variables in a step-wise manner. Results based on the modeling of level-1 variables only are shown in Table 2. Model 1 examines the effects of our level-1 variables that tap distances from crime places to crime-generating nodes in the form of the nearest carry-out liquor store and the nearest on-premises drinking establishment. Consistent with much previous literature on risky facilities, distances to the nearest carry-out liquor store and the nearest on-premises drinking establishment are negatively and significantly related to crime counts at crime locations. Thus, as distance increases, crime decreases. Conversely, proximity to these locations significantly increases expected crime counts.

In Model 2, the distance to the nearest bus route was added to the estimation of crime count. Recall that this measure was presumed to tap the distance to a major public transit artery—or an “activity/movement path,” using the language of environmental criminology. Results show that the distance to the nearest bus route is negatively (and significantly) related to crime counts at crime locations. Thus, as expected, as distance increases, crime counts decrease. Interestingly, the distance to nearest on-premises drinking establishment drops to non-significance, net of the distance to the nearest bus route.

Model 3 examines the product of the values of level-1 variables as opposed to their additive effects. Recall that we hypothesized that the interaction of our three measures of crime-generating nodes and paths was compatible with Brantingham and Brantingham’s (1999) theoretical argument that hot spots (or conversely, cold spots) are created due to the composite overlaying of proximity/distance to nodes and paths (see also Weisburd et al. 2012; Hart and Miethe 2014). Results from Model 3 of Table 2 indicate that the product

¹¹ In order to calculate the spatial lag variable, first, the spatial weight matrix is created for each block group’s neighbors using queen contiguity, which identifies neighboring block groups as the ones that share a border. Next, the average of crime counts of all locations within each block group is calculated. Finally, the block group average crime value is used within the spatial weight matrix to calculate the lag value for each block group. The value of the spatial lag ranges from 1.3 to 4.8.

¹² It should be noted that we also examined the possibility of collinearity among block-group-level variables using VIF values. The diagnostic did not indicate substantial collinearity among these variables (e.g., the maximum VIF was 2.5).

¹³ The negative binomial regression command (nbreg) is used in Stata to see whether the dependent variable is over-dispersed or not. The value of alpha coefficient (0.56) and its significant value indicated that our dependent variable is over-dispersed.

Table 2 Poisson hierarchical regression analysis results for place-level predictors

Fixed effect	Model 1		Model 2		Model 3	
	Coeff.	SE	Coeff.	SE	Coeff.	SE
Block group mean crime						
Base	0.717*	0.024	0.701*	0.022	0.672*	0.025
Carry-out liquor	−0.635*	0.210	−0.530*	0.197	–	–
On-premises drinking	−0.334*	0.130	−0.138	0.125	–	–
Bus routes	–	–	−0.841*	0.069	–	–
Carry-out liquor × on-premises drinking × bus routes	–	–	–	–	−0.479*	0.064
Random effect						
	Var (SD)	Chi sq.	Var (SD)	Chi sq.	Var (SD)	Chi sq.
Mean crime count	0.089 (0.30)	1233*	0.082 (0.29)	1245*	0.068 (0.26)	820*
Carry-out liquor × on-premises drinking × bus routes	–	–	–	–	0.19 (0.44)	1050*
Level-1 error	8.18 (2.86)	–	7.57 (2.75)	–	5.94 (2.44)	–

Results are based on 33,105 crime locations within 285 census block groups

* $p < .05$

term was significantly and negatively related to the expected crime counts at locations. Put differently, as the multiplicative distance to these three locations becomes smaller, the expected crime count significantly increases. Finally, results in the random-effect portion of Model 3 of Table 2 indicate that, as hypothesized, the effect of this product term varies significantly across block groups (i.e., its variance component is significant $p < .05$).

Looking further at the random effect portion of Table 2, the mean crime count variance and level-1 error decreased consistently from Model 1 to Model 3. Unfortunately, however, deviance statistics are not provided in count-based models for purposes of assessing whether there was an improved fit across different models. Thus, in an attempt to provide an alternative method for assessing the relative improvement across different models, we re-ran our same analysis within a linear model specification, using the log of the crime counts as an alternative outcome measure.¹⁴ The results revealed that the deviance statistics decreased at each subsequent model—starting with an unconditional model, moving onto a model analogous to Model 1 in Table 2, then onto a model analogous to Model 2 in Table 2, and finishing with a model analogous to Model 3 in Table 2. The decreases in deviance were statistically significant when moving from the unconditional model to Model 1, and from Model 1 to Model 2, but contrary to expectations, it was not significant when comparing Model 3 relative to Model 2 ($p < .05$). However, even though the deviance statistic did not drop significantly between models 2 and 3, note that the level-2 variance in mean crime counts decreases.

In the next step of our analysis, we build upon the final level-1 model shown in Table 2 in order to create multilevel models of crime locations. Since there was no significant

¹⁴ This method (using deviance statistics from linear models) might not reflect the exact improvement across count-based models. However, in the absence of a better test, it should provide us with a good sense of the fit of our count-based models relative to one another, especially since the results from the linear analysis were consistent with our count based analysis across all models.

difference between Model 2 and Model 3 in the first stage of the analysis (Table 2), this means the product term can be used instead of the three separate terms—it is just as strong as the three terms entered separately in the same model. Therefore, for the sake of parsimony, we used the product term at level-1 for models shown in Table 3.

In Model 1 of Table 3, we included environmental backcloth variables measured at the block group level in addition to the three-way interaction term measured at the place level (on-premises drinking establishments × carry-out liquor facilities × bus routes). Results indicate that our primary level-2 variable—block-group-level commercial density—is positively and significantly related to mean crime counts ($p < .05$). In addition, disadvantage is significantly and positively related to block-group mean crime counts ($p < .05$). Further, utilizing the same deviance-statistic methodology explained above for comparing models (based on linear models), we examined the improvement in the first model reported in Table 3 to the models reported in Table 2. The deviance statistic decreased significantly when comparing the first model in Table 3 to any of the models reported in Table 2 (with level-1 variables only). The significant changes in the deviance statistics between the models in Table 2 and Model 1 in Table 3 indicate that the level-2 predictors improved model fit beyond the level-1 predictors alone. Finally, the random-effects portion of Model 1 in Table 3 indicates that, net of the level-2 variables included here, there is still significant cross-block group variance in the average crime count as well as the effect of the level-1 interaction term.

In the second model (Model 2, Table 3), we estimated a cross-level interaction effect intended to tap the overlay of nodes, paths, and backcloth. Specifically, we examined the cross-level interaction between the level-1 multiplicative term (on-premises drinking establishments × carry-out liquor facilities × bus routes) and level-2 commercial density. The cross-level interaction was marginally significant, suggesting that the negative effect of the level-1 interaction term becomes stronger as block-group-level commercial density

Table 3 Poisson hierarchal regression analysis results with level-2 predictors and cross-level interaction

Fixed effect	Model 1		Model 2	
	Coeff.	SE	Coeff.	SE
Block group mean crime				
Base	0.594*	0.126	0.558*	0.127
Commercial density	0.438*	0.217	0.522*	0.228
Disadvantage	0.092*	0.039	0.091*	0.038
Instability	0.01	0.022	0.020	0.021
Felon residence	-0.017	0.012	-0.017	0.012
Spatial lag	0.015	0.037	0.011	0.039
Carry-out liquor × on-premises drinking × bus routes	-0.454*	0.061	-0.008	0.205
Carry-out liquor × Commercial density (cross-level interaction)	-	-	-1.076 ⁺	0.57
Random effect				
	Var (SD)	Chi sq.	Var (SD)	Chi sq.
Mean crime count	0.059 (0.24)	781*	0.060 (0.25)	784*
Carry-out liquor × on-premises drinking × bus routes	0.185 (0.43)	1064*	0.17 (0.42)	984*
Level-1 error	5.98 (2.45)	-	5.97 (2.44)	-

Results are based on 33,105 crime locations within 285 census block groups

* $p < .05$; ⁺ $p < .08$

increases ($p < .08$). These findings indicate that it is, in fact, worthwhile to model the slope of the level-1 interaction term as a function of characteristics of environmental backcloth.

Figure 2 offers a visual depiction of the cross-level interaction effect, using a map of Cincinnati block groups. Fitted level-1 interaction slopes are divided into quartiles, and block groups are shaded according to their associated level-1 interaction term slope (darker shading represents more negative slopes). Block-groups are also classified according to their level of commercial density based on quartiles. The map shows an overlap between the more negative slopes of the three-way interaction term and higher levels of commercial density (as represented by the black circles within block groups). In other words, the multiplicative distance to various nodes and paths is most inversely related to crime at locations within block-groups with high commercial density.

Discussion and Conclusion

The principal aim of this study was to provide an illustration of a statistical test of Brantingham and Brantingham's (1993a, b, 1999) initial conceptualization of crime clustering at particular locations (i.e., hotspot formation). This test involved integrating the notions of micro- and macro-environmental crime potential. More specifically, drawing from the Brantinghams', as well as subsequent work in the environmental criminology tradition (e.g., Hart and Miethe 2014; Smith et al. 2000; Stucky and Ottensmann 2009; Weisburd et al. 2012), we treated proximity of a location to on-premises liquor establishments, carry-out liquor facilities, and bus routes as place-level crime-generating nodes

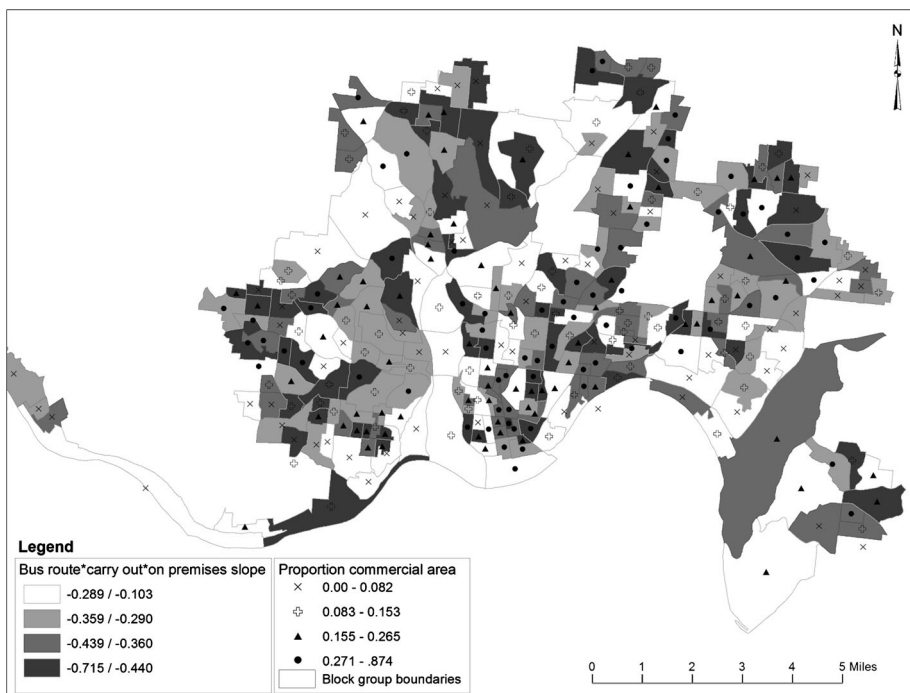


Fig. 2 Cross-level interaction between commercial density and the place-level interaction variable

and paths, and thus indicators of micro-environmental crime potential. At the same time, we treated neighborhood-level commercial density as a key element of backcloth, thus indicating macro-environmental crime potential, but also controlled for other key aspects of neighborhood opportunity and offender concentration. We posited that the multiplicative distance to all three measures of crime-generating nodes and/or paths (carry-out liquor stores, on-premises drinking establishments, and bus routes) would:

1. be negatively related to place-level crime counts, and perhaps more important for estimating crime than the main effects of distance to on-premises liquor establishments, carry-out liquor facilities, and bus routes (Hypothesis 1);
2. be variable in its effects across neighborhoods (Hypothesis 2); and
3. be more strongly (negatively) related to crime in neighborhoods with higher levels of commercial density (Hypothesis 3).

The study's findings provided at least partial support for all of the hypotheses. Hypothesis 1 was supported in that a level-1, three-way interaction involving the distance to the closest on-premises liquor establishment, the distance to closest carry-out liquor facility, and the distance to the closest bus route was negatively related to place-level crime incidents. Further, supplemental analyses suggest that a model containing this three-way interaction provided a significantly better fit than did models containing the individual main effects of the distance to closest on-premises liquor establishment and the distance to closest carry-out liquor facility (keeping in mind the previously stated potential limitations of this test). However, the model containing the three-way interaction terms was not a significant improvement over a model containing the individual main effects of the distance to closest on-premises liquor establishment, the distance to closest carry-out liquor facility, *and* the distance to the closest bus route.

Hypotheses 2 and 3 were also supported, suggesting that this three-way interaction involving the distance to the closest on-premises liquor establishment, the distance to closest carry-out liquor facility, and the distance to the closest bus route had effects which varied across neighborhood contexts, with marginally stronger negative effects on crime produced in neighborhoods with high levels of commercial density. In other words, a cross-level multiplicative term (involving the distance to the closest on-premises liquor establishment, the distance to closest carry-out liquor facility, the distance to the closest bus route, *and* neighborhood-level commercial density) proved helpful in understanding crime at specific locations.

Altogether, these results have important theoretical and practical implications. First, the findings support decades-worth of research highlighting the importance of activity nodes and paths in generating opportunities for crime. However, results presented here extend previous research by showing that the clustering of several nodes and paths in the immediate environment does not appear to necessarily generate more crime than any one node or path, *unless perhaps that micro-environmental clustering is within a broader neighborhood context that involves a high density of commercial nodes*. Such findings highlight the necessity of studying crime places not just within their micro-environmental contexts but within multiple, embedded contexts. In short, the implicitly multilevel approach to understanding crime places outlined by the Brantinghams over two decades ago was supported here through explicitly multilevel statistical modeling.

The support provided for a multilevel theory of crime places has implications for more effectively addressing crime as well. As noted in other work advocating a multilevel approach to crime opportunity, "Ignoring the possibility that effects of risk or protective factors are potentially conditional upon context can create misinformation about the extent

to which variables are risky or protective” (Wilcox et al. 2013). This misinformation might lead to an over- or under-estimation of the likely impacts of certain place-level preventive measures (e.g., place management practices, hot spots patrol, etc.). For example, if only place-level opportunity structure had been considered in this study, an implication for practice would be that distances to nodes and paths have the same impact regardless of context. Yet, this would leave some places under-protected. In particular, those places with multiple nodes and paths in their proximal environments (i.e., short multiplicative distance) and dense commercial land within their broader environments likely need additional preventive measures to get the same benefit relative to places with multiple nodes and paths in the proximal environments yet little commercial density within the broader environment.

Of course, any theoretical and policy implications of this research are tentative and stated with appropriate caution given important study limitations. First, the present study is rather exploratory in its illustration of the Brantinghams’ ideas about crime at locations. For illustration purposes, we chose to simplify the reality of crime opportunity at each of the levels of analysis explored here (the micro-environmental place level and the macro-environmental neighborhood level) and focus instead on a few key measures at each level of analysis. We felt that the level-1 three-way and cross-level interactions explored here were complex enough and that adding more variables (and increasingly complex multiplicative terms) would serve to dilute the main point we were testing—the importance of the overlay of nodes, paths, and backcloth. The variables we focused on were viewed as key examples of the concepts of nodes, paths, and backcloth, but we certainly recognize that more level-1 and level-2 measures would be necessary to more accurately reflect the complexity of crime opportunity. Relatedly, though we selected measures of opportunity that we deemed as generating a number of different crimes in order to align with our dependent variable (all Part I crime), it is important to note that opportunity structures can be crime specific (e.g., see Clarke and Cornish 1985).

Several additional concerns associated with measurement of the dependent variable are also noteworthy. Most obviously, our measure of crime is based on police-recorded data; thus, it misses crime not reported to police and is subject to recording error, imprecision, and bias. An important example of imprecision is that Cincinnati Police cannot always affix an incident to a particular address; in those cases, they use the closest address as the location of the incident. However, since our place-level measures of opportunity are distances from the crime location to nearest nodes and paths as opposed to attributes of the place per se (e.g., building type, use of security, etc.), we think this sort of imprecision should have minimal impact on the results presented.

Finally, our study utilizes a cross-sectional design and thus it cannot fully assess causal direction nor can it address the dynamic nature of crime opportunity and crime locations. That said, opportunity is presumed to be situational; thus, contemporaneous effects of the environment are more consistent with the theory than are starkly-lagged effects. Furthermore, while change in crime at the locations observed is beyond the purview of this study, seminal longitudinal research on crime locations suggest that most of the crime places studied here during the 2010–2012 period were likely stable (in terms of crime incidents) before, during, and after that observation period (e.g., Braga et al. 2011; Weisburd et al. 2004, 2012).

In closing, a very recent appraisal of theoretical work in the “ecology of crime” tradition has underscored an unnecessary and limiting divide between macro-level scholarship highlighting processes at the state, county, city, and/or neighborhood levels and micro-level scholarship focusing on processes at the street, block, and/or parcel levels

(Taylor 2015). We provide here an explicit test of principles central to a multilevel conceptualization of crime at places and, in the process, help to move toward bridging that divide.

Appendix 1: Bivariate Correlations Among Level-1 Variables

	Crime count	Carry-out	On premise	Bus stop	Interaction
Zero order correlations among place level variables					
Crime count	1				
Carry-out	-0.064**	1			
On premise	-0.049**	0.432**	1		
Bus routes	-0.073**	0.257**	0.305**	1	
Interaction	-0.076**	0.761**	0.810**	0.656**	1

** Correlation is significant at the 0.01 level (2-tailed)

Appendix 2: Bivariate Correlations Among Level-2 Variables

	Commercial	Disadvantage	Instability	Felon residence	Spatial lag
Commercial	1				
Disadvantage	0.175**	1			
Instability	0.298**	0.240**	1		
Felon residence	0.203**	0.744**	0.313**	1	
Spatial lag	0.340**	0.080	0.175**	0.106	1

** Correlation is significant at the 0.01 level (2-tailed)

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