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Situating Crime Pattern Theory Into The Explanation Of Co-Offending: Considering Area-Level Convergence Spaces

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Features of the environment including activity nodes and the level of connectivity in spaces help offenders develop awareness spaces for criminal opportunities. Based on arguments forwarded by Felson, the current study argues these environmental features also facilitate convergence spaces that promote interaction among offenders that increase the likelihood of group crime. Data include street connectivity measures from the Environmental Protection Agency and publicly available arrest information from Baltimore City (2013–16). Findings provide support for the influence of certain activity nodes and pedestrian-oriented street connectivity in explaining group crime. The discussion evaluates how crime pattern theory can be extended to understand the social nature of crime.

Key Words: co-offending, convergence settings, crime pattern theory

INTRODUCTION

Starting with Reiss' (1988) seminal piece, in which he argued co-offending deserved empirical and theoretical attention, criminology has witnessed marked gains in co-offending research over the past thirty years. Indeed, scholars have made strides in understanding the structure of co-offending networks (Sarnecki 2001; Grund and Morselli 2017), differential roles in co-offending relationships (van Mastrigt and Farrington 2011; McGloin and Nguyen, 2012), and the risks and benefits of offending with others (McCarthy *et al.* 1998; Weerman 2003; McGloin and Thomas 2016). Progress has been somewhat more uneven when it comes to understanding the predictors of co-offending, however (Conway and McCord 2002; Rowan *et al.* 2018). Most research has focused on individual-level factors that promote between-person differences in co-offending even though scholars have also stressed the potential theoretical importance of macro-level factors in shaping the emergence of co-offending events (Tremblay 1993; Felson 2003). The few scholars who have integrated neighbourhood context into co-offending inquiries demonstrated that there are insights to be gained (e.g., Schaefer 2012; Schaefer *et al.* 2014), but it remains the case that a seminal argument about the role of spatial structure in producing group crime has yet to be held to direct empirical scrutiny.

Felson (2003) proposed that offenders find and interact with accomplices–a basic precondition of co-offending–based on routine activities through the environment. As Weerman (2003) notes, there are several explanations of co-offending, with some taking a selection perspective that views group crime as a sort of artefact of other processes. van Mastrigt (2017) places Felson's view in this category, as predicting the emergence of co-offences rests less in understanding individual-level motivations and more on understanding the natural consequences of the spatial structures in which offenders are embedded. Felson (2003) contends that existing explanations of co-offending do not adequately account for co-offending's consistent regularity because scholars often invoke factors that are generally unstable (e.g., gangs, peer groups; McGloin et al. 2008; Grund and Morselli 2017). Instead, he argues that it is the relatively stable distribution of 'convergence spaces' that underlies group crime.

Convergence spaces are locations that serve as behavioural settings offering opportunities for crime at the same time they provide access to potential co-offenders (Felson 2003, 2006; see also Bichler *et al.* 2014). This represents an expansion of an offender's 'awareness' space (wherein s/he is likely to be most informed of criminal opportunities) by integrating the chance to interact with potential accomplices. Because crime (and co-offending) can be unplanned and primordial (Gottfredson and Hirschi 1990), this increases the likelihood of co-offending within these convergence spaces. In more concrete terms, crime pattern theory ties awareness spaces to specific activity nodes (e.g., bars, parks, schools) and pathways among these locations (e.g., Brantingham and Brantingham 1993; Brantingham *et al.* 2017). Whereas there is ample work underscoring the empirical validity of awareness spaces in predicting crime and a recognition of the correlation between features of the environment and personal social networks, studies have yet to address the hypothesis that they should also (uniquely) predict the distribution of group crime (e.g., Schaefer 2012; Bichler 2019).

The environmental criminology literature has provided strong evidence for the role of features of the environment in explaining crime. Yet, this perspective is largely built on theoretical traditions that assume crime is committed alone, ignoring the social nature of crime that has been linked to increasing criminogenic risk at the individual and neighbourhood-level (e.g., Bastomski *et al.* 2017). Further, efforts to understand the decision to engage in co-offending have left the process for how co-offending emerges out of focus (e.g., Felson 2003). The current study extends crime pattern theory and addresses this gap in the co-offending literature by considering whether the distribution of co-offences across census block groups in Baltimore City (Maryland) is related to measures of activity nodes and 'connected' street networks, net of the solo crime rate. Further, because the intersection of potential accomplices requires direct interaction, we differentiate the degree to which areas have pathways that are pedestrian-oriented and therefore should foster such interactions from those that are auto-oriented and should not promote these interactions. By situating other offenders into crime pattern theory, this study offers a direct commentary on Felson's (2003) view on the importance of convergence spaces for co-offending, while also joining with other work that has argued for the inclusion of co-offending in spatial inquiries (e.g., Lammers 2018).

CRIME PATTERN THEORY AND FINDING CRIMINAL ACCOMPLICES

Research has long established that crime is not equally distributed across time or space. For decades, work on differential crime rates focused on neighbourhood-level explanations (e.g., Shaw and McKay 1942; Sampson and Groves 1989), yet, research documents that crime also clusters in patterned ways across smaller units (e.g., Sherman *et al.* 1989; Bernasco and Block 2011; Weisburd *et al.* 2012). In attempting to understand more granular trends, scholars have relied on crime pattern theory (Brantingham and Brantingham 1993), which brings together concepts from rational choice and routine activity theory (see Eck and Weisburd 1995). Crime pattern theory begins from the premise that offenders, like all people, have daily routines as they navigate among home, work, school, leisure time, and other activities. These routines breed familiarity with certain areas, which inform a person's 'action' or 'awareness' space. After all, as Eck and Weisburd (1995: 6) observe, 'criminal opportunities that are not near the areas offenders routinely move through are unlikely to come to their attention'.

In concrete terms, an offender's awareness space is comprised of two key elements: nodes and pathways (Brantingham and Brantingham 1981; Frank et al. 2011; Johnson 2014). Nodes refers to the actual locations that an offender frequents, whereas pathways refer to the regular transit flow between the nodes. Just as a person has preferences for certain destinations, s/he will also have preferred routes (as opposed to a random walk) among these destinations. Places serving as primary activity nodes for many people and generally well-travelled routes produce intersecting awareness spaces, whereby individuals encounter one another and produce elevated levels of crime (Davies and Johnson 2015). Importantly, the nodes and pathways that make up an offender's awareness space should structure both planned and spontaneous crime. As Summers and Johnson (2017: 399) observe, the selection of a crime location requires familiarity to assess the risks and benefits, and unplanned crime likely occurs 'while the offender is engaged in everyday non-criminal routine activities (e.g., walking home after having gone out for a drink), in places that are typically familiar to the offender'.

Several studies offer support for the idea that crime is more likely to occur in and around popular activity nodes. Roncek and Maier (1991) found that city blocks with bars and cocktail lounges have significantly more criminal incidents. Bernasco and Block (2011) observed that census blocks with businesses such as pawnshops, gas stations, or liquor stores have more robberies. To be fair, such locations may attract crime because motivated offenders are aware of opportunities for crime at these places (Brantingham and Brantingham 1995). But, crime pattern theory also asserts that crime is generated in locations where large numbers of people intersect for reasons unrelated to crime (Brantingham and Brantingham 1995). For instance, research documents that crime is associated with the presence of schools and public transit stations (e.g., Kinney *et al.* 2008), underscoring the notion that daily routines around benign and legitimate activities are salient parts of offenders' awareness spaces.

Studies have likewise confirmed, in progressively more nuanced ways, that pathways are also related to crime patterns. In most cases, scholars consider well-travelled or accessible routes, under the assumption that these are the pathways people are likely to be familiar with (Beavon *et al.* 1994; Johnson and Bowers 2010). As Birks and Davies (2017: 903) nicely summarize, the assumption is that 'greater connectivity implies greater exposure'. Studies have demonstrated that isolated streets tend to have lower crime rates (Beavis and Nutter 1977), as do cul de sacs (Johnson and Bowers 2010), and neighbourhoods with few streets connected to major roads (White 1990). More recently, researchers adopted more finely grained measures of street networks. Birks and Davies (2017) conducted agent-based modelling analyses of residential burglary and found that despite the potential increase in guardianship on more central streets accessed by more 'eyes on the street', the increased exposure for potential victimization outweighs any guardianship effect. They also concluded that the simulated removals of connections between streets or intersections (i.e., conversion to cul-de-sacs) were associated with reductions in crime that may be driven by the dilution of offender awareness spaces.

Across various methodologies (e.g., space syntax, street/land use designations, agent-based modelling), each is challenged by the goal to measure the structure of street networks by their actual use (see review in Birks and Davies 2017). Curiously, most studies lump the concept of streets into a single category ignoring a possibly important distinction—the degree to which streets are pedestrian-oriented. Scholars primarily from urban planning tend to recognize that street connectivity is linked to increased pedestrian activities (e.g., Cozens 2008; Hillier and Sahbaz 2008); however, in most analytic work in criminology, that distinction typically is not considered. Instead, the extent to which streets have greater betweenness, activity nodes, or density is assumed to facilitate the convergence of conditions conducive to crime and at least implicitly assumes this occurs as function of the pedestrian-oriented nature of the built environment. This is notable given that the theoretical discussion about the importance of connected spaces is informed by a belief that offenders build their awareness spaces through their day-to-day routine activities, which are often associated with pedestrian movements (e.g., Summers and Johnson 2017). Arguably, it is most realistic that offenders generate awareness of criminal opportunities as a result of pedestrian-oriented streets.

There is one aspect of awareness spaces that remains significantly under-studied: co-offending. According to Felson (2003, 2006, 2009), the notion that offenders' routines systematically shape their awareness spaces should factor squarely in finding accomplices—indeed, co-offending is largely an incidental product of these same processes (van Mastrigt 2017). He argues that awareness spaces not only structure where one is likely to offend, but they also shape where one is likely to converge with other motivated offenders who may be willing to collaborate. In bringing together an offender's awareness of criminal opportunities with access to potential accomplices, the stage may be set for group crime.

Bichler (2019) further developed an integrated theory of networked opportunity to argue that both context-specific spatial and social networks of individuals explain the patterning of crime. Efforts have uncovered how crime place networks contribute to specific types of criminal behaviour (e.g., gun violence; Madensen *et al.* 2017), however existing studies still assume that offenders operate alone. Although crime pattern theory supports the notion that individuals leverage information and experience from others within their personal networks, empirical research has not yet considered how features of the environment implicate the group context (e.g., Lammers 2018; Bichler 2019). For instance, the social nature of bars or alcohol outlets may attract (and concentrate) groups of potential offenders in a way that facilitates opportunities for group offending. Transit stations, which may ordinarily traffic solo-users, could at a minimum enable interaction among potential co-offenders and also facilitate overlapping awareness spaces that could contribute to the patterning of more deliberate group offending (e.g., Kinney *et al.* 2008; Lammers 2018). These spaces may also offer the opportunity for motivated offenders to converge in time and space, setting the stage for more spontaneous group behaviour. Ultimately, research has yet to explicitly consider whether the construction of awareness spaces offers unique insight on the distribution of group crime.

Convergence spaces and co-offending

Scholars have offered varied perspectives on why offenders act with accomplices (e.g., McCarthy *et al.* 1998; Weerman 2003; McGloin and Rowan 2015). Regardless of one's reason for co-offending, however, offenders must engage in at least one necessary step prior to engaging in group crime: identify accomplices. As Felson (2003: p.156) observes, 'the field has yet to identify and define an ongoing structure that can explain how offenders find one another. Progress depends on first identifying what offenders need'. In outlining these 'needs', Felson focuses on (1) opportunities to come together in time and space in order to informally screen each other, and (2) locations that will serve as attractors for potential offenders and thereby fill accomplice pools. In short, he posits that convergence spaces can promote co-offending because they bring together motivated offenders in situations that allow for informal interactions and criminal opportunities:

> Offenders are likely to converge in certain settings, which then become central for crime. Good hangouts enable illicit cooperation. More generally, an offender convergence setting helps set the stage for criminal acts. Offenders can go there shortly before committing a crime, to find accomplices or to gain information leading directly to additional crime. …Offender convergence settings are places that set the stage for crime by assembling accomplices and getting an illicit process started. (Felson 2006: p. 9)

These locations allow group crime to flourish even if the particular people who comprised accomplice pools change over time (Felson 2006). Thus, it follows that identifying areas with popular activity nodes and connected pathways that comprise awareness spaces may not only aid in predicting the spatial distribution of crime generally, but also in predicting the emergence of co-offending specifically.

Again, these convergence locations bring together motivated offenders, which can in and of itself can lead to the situational emergence of (group) crime (Gold 1970; Felson 2003; McGloin and Thomas 2016). This notion aligns nicely with the finding that the typical co-offending relationship lasts only one event (i.e., most offenders do not re-use accomplices; McGloin *et al.* 2008; Charette and Papachristos 2017) and that offenders report joining with accomplices spontaneously (Alarid *et al.* 2009). Even if some co-offending is pre-planned, it could be argued that it should also cluster in these convergence spaces both because it brings together motivated offenders in time and space and represents common awareness space. Lammer's (2018) recent study suggests that when individuals do co-offend, they are more likely to select crime locations within these shared, as opposed to unique, awareness spaces. Thus, by virtue of being locations that facilitate the convergence of potential offenders, these spaces should also see heightened levels of group crime.

Research has yet to directly test whether areas characterized by a high degree of convergence spaces indeed generate higher levels of group crime, but there are three key studies that provide some indirect evidence to support Felson's arguments. First, using self-reported data from more than 5,000 delinquents in Southern California, Bichler *et al.* (2014) analysed the locations these youth indicated were part of their normal social routines. They identified locations that were 'magnetic', that is, places that were dominant activity nodes among the delinquents. Perhaps not surprisingly, shopping centres were key nodes for convergence. Importantly, Bichler *et al.* (2014) argued that such magnetic spaces may facilitate convergence settings that are conducive to opportunities for co-offending; however, they did not measure whether instances of co-offending occurred in these settings or whether co-offending ties were formed. Even so, we can gain additional insight into how the distribution of co-offending is impacted by the environment by integrating magnetic nodes into consideration. Second, Schaefer (2012) examined how co-offending ties produce interdependence across neighbourhoods. Specifically, he observed that co-offending ties were more likely to occur across neighbourhoods with similar social characteristics, that were spatially proximate, and within areas where offenders were sent to the same school districts. These results begin to frame how characteristics of neighbourhoods shape the likelihood of co-offending, but this study did not more broadly consider what factors build offender awareness spaces. Lastly, Schaefer *et al.* (2014) further implicate neighbourhood characteristics in explaining the likelihood of co-offending by arguing that processes known to reduce the risk of crime may actually be responsible for increasing co-offending. Specifically, Schaefer *et al.* (2014) argue that areas characterized by racial homogeneity, lower disadvantage, and greater residential stability facilitate greater trust among informal networks and ties that facilitate co-offending ties. Although Schaefer and colleagues' study underscores the context conducive to group behaviour, the current study furthers our understanding by exploring how the built environment may be related to the co-offending process.

THE CURRENT STUDY

Consistent with Felson's (2003, 2006) argument that convergent behavioural settings structure the distribution of co-offending events, we interrogate whether areas inclusive of activity nodes and streets segments with high connectivity will have higher levels of group crime, even when controlling for the distribution of solo crime. These highly connected areas contribute to the development of overlapping awareness spaces that facilitate opportunities for group crime and generate settings that enable the convergence of offenders in time and space. Incorporating a consideration of both elements that comprise convergence spaces (e.g., nodes and pathways) in the same empirical study is rare (see Summers and Johnson 2017), even though scholars argue it is ideal for models seeking to understand the spatial distribution of crime (Brantingham and Brantingham 1981). We also differentiate among types of streets in order to capture one dimension where convergence spaces and awareness spaces may diverge. In this way, whereas frequent movement through streets via a vehicle may increase one's knowledge of local criminal opportunities and therefore become part of one's awareness space, such routines are unlikely to foster the discovery of potential accomplices. Instead, those areas that have higher levels of pedestrian connectivity should facilitate the emergence of co-offences. To evaluate these hypotheses, we merge public arrest records from Baltimore City in Maryland (2013–16) with activity node data from the Baltimore City Open Data Portal, census block data from the Census Bureau, and data on street connectivity provided by the Environmental Protection Agency's Smart Location Database.

DATA AND METHODS

In order to address our questions of interest, we needed information on co-offences that could be linked with street network data. The Baltimore City Police Department (BPD) releases publicly accessible data on all adult arrests on an annual basis, including information regarding the arrest charge, arrest location, arrest date and time—which allows for the identification of co-offences—and the incident location. There are of course strengths and weaknesses to using arrest data. A major strength of the data is that it allows researchers to discern whether the arrest was the result of a solo crime or a co-offence, as discussed later (see also Papachristos *et al.* 2015). However, the use of this publicly available arrest data inherently precludes the inclusion of criminal events that did not lead to an arrest, and therefore is likely to undercount crime.

Although a good portion of co-offending research relies on official records, including key pieces that are foundational to our current understanding (e.g., Reiss and Farrington 1991; Sarnecki 2001; McGloin *et al.* 2008; Stolzenberg and D'Alessio 2008; Carrington 2009; Andresen and Felson 2010; Schaefer *et al.* 2014), it is important to question whether such data sources may inadvertently bias our understanding of co-offending. Is there a notable risk of incorrectly coding incidents as solo crimes because accomplices evaded capture? Some scholars identify a 'group hazard hypothesis', which asserts that group crime may be more likely to come to the attention of law enforcement than solo crime (Erickson 1971; Lantz 2020). Although this perspective would suggest that official records would not inherently under-count co-offending, it remains possible that not all accomplices will be detained and recorded. This would prove especially problematic in situations where researchers are interested in estimating the size of the co-offending group in some way; but, our interest is in the binary distinction between solo and group offences. For this study, because we are interested in the differential distribution of co-offending, we would be most concerned about potential bias if incidents were systematically more or less likely to be erroneously coded as a solo offence across convergence spaces. We cannot rule anything out absent direct empirical commentary, but we do not have theoretical or empirical reason to believe that this pattern is likely.

The data used in this study cover arrests from January 1, 2013 to December 31, 2016 that had complete information on the variables of interest (N = 68,393).[1] This time period was included in the analyses for two main reasons. At the time of original data collection and geocoding, arrest data from 2013 to 2016 were publicly available. We opted to use all three years of data in order to generate a large enough sample of arrest incidents with valid location information to be used to estimate co-offending incidents, as well as smooth out any particularities about a specific year or season. Second, we wanted to preserve a close temporal relationship between the main street connectivity predictors derived from 2010 Census data and our outcome. Therefore, though more recent arrest data are now available, we opted to prioritize data that were closest to 2010 rather than focus on later years.

We merged the 2013–16 geocoded arrest data with data from the Environmental Protection Agency (EPA)[2]. The EPA has a publicly available Smart Location Database that includes a wide range of contextual information about census block groups across the entire United States. This database integrates several sources of information including, Census Bureau datasets, NAVTEQ highway/streets and parks data, Protected Areas Database of the United States and data from the Center for Transit Oriented Development (Ramsey and Bell 2013). This database includes information regarding the density of pedestrian-oriented and auto-oriented streets within each census block group generated during the year 2010 (see description of each in Measures section). This information was associated with each census block group in Baltimore City, which is the smallest geographic area available in the database (as opposed to block faces or street segments). Importantly, in a city context (as opposed to suburban or rural locales), a census block is generally a small area (typically a street-bounded block) and using this unit is consistent with prior work on the relationship between co-offending and neighbourhood context, which has relied on census tracts or blocks (e.g., Schaefer 2012; Billings *et al.* 2016). Indeed, in Baltimore the census block group is relatively small: The average census block group in Baltimore has 2.4 census blocks, is .14 square miles, and has an average of 953 residents. Data on specific activity nodes (i.e., bars, schools, transit) were provided by publicly available geo-coded data from the Baltimore City Open Data Portal. Data on shopping centres were not included in the data portal, so these were geocoded using Google Map search capabilities.[3] Lastly, to account for several other contextual covariates (i.e., population, ethnic heterogeneity, population turnover, poverty) related to criminal offending at the macro-level, data from the American Community Survey conducted by the U.S. Census Bureau was used (U.S. Census Bureau 2016). Table 1 provides a summary of descriptive statistics for all of the covariates included in the analyses.

Measures

Dependent variables

Group crime. The outcome of interest in this study is the rate of group crime events in a given census block group. We used a series of systematic, conservative decision-rules to determine whether each arrest reflected a group crime event. Arrests were coded as group crime events only if: 1) Two or more arrestees shared an arrest date, arrest time, and incident location, and the arrest locations matched the incident location, or 2) Two or more arrestees shared an arrest date and time at a shared incident location, and arrest locations that differed from the shared

1 A total of 131,958 arrests were included in the dataset between 2013 and 2016, however, 54,333 arrest incidents did not include an incident location and were excluded from analyses. An additional 9,232 arrests had documented incident locations that led to failed matches in the geocoding process. For instance, many incident locations were not associated with actual addresses or failed to provide enough detail in the location to geocode the incident to a specific census block. Thus, we are unable to capture or generalize all arrests in Baltimore City during this time period.

2 This merging process occurred in 2017 at the time of collecting and geocoding the Baltimore City arrest data from 2013–16.

3 In order to identify shopping centres, Google Map search terms included 'shopping malls', 'strip mall', or 'shopping centre '.

incident location but matched among the arrestees. Arrests that we deemed to be reflective of a co-offence were collapsed into a single event and coded as 'group crime'; all other arrests were coded as a 'solo crime'.

Table 2 provides non-exhaustive examples of the decision-rules applied to the data to identify group crime events. Example A and Example B are the only two decision-rules that resulted in a group of two or more arrests being coded as a group event crime. Group crime events made up a total of 9% (N = 6,279) of all incidents between 2013 and 2016 and included of 20.8% (N = 14,222) of arrested individuals.

After coding the data in this way, we summed the number of group crime events between 2013 and 2016 within each census block group in Baltimore City. During this time period, there were a total of N = 6,249 incidents across 653 census block groups (Average Rate = 1.93 per 100 residents, SD = 11.24). Figure 1 provides a quintile intensity map of the rate of group crime incidents per 100 individuals across census block groups in Baltimore City.

Table 1 *Descriptive statistics (N = 653)*

Variables	Mean	SD	Min, Max
Group crime[4]	1.935	11.243	0, 200
Solo crime[4]	14.324	56.888	0, 1150
Number of bars	.860	2.121	0, 26
Number of schools	.291	.637	0, 5
Number of shopping outlets	.034	.189	0, 2
Number of transit stops	5.432	5.198	0, 74
Auto-network density	.642	2.97	0, 15
Pedestrian-network density	20.780	8.035	2.081, 49.220
Racial/ethnic heterogeneity	.281	.213	0, .730
Percent poverty	23.541	17.384	0, 100
Percent turnover	33.159	17.166	0, 100
Population density	21.625	14.765	.001, 136.726

Table 2 *Explanation of coding schema for dependent variable*

Conditions	Example A: Arrest group #1	Example B: Arrest group #2	Example C: Arrest group #3	Example D: Arrest group #4
Matching arrest date	True	True	True	True
Matching arrest time	True	True	False	True
Matching incident location	True	True	True	True
Matching arrest location	True	True	True	False
Incident location ≠ arrest location	False	False	True	False
Coding decision				
Coded as group crime offense	True	True	False	False
Coded as solo crime offense	False	False	True	True

4 For the purposes of descriptive statistics, group crime and solo crime have been presented as rates per 100 residents in the census block group.

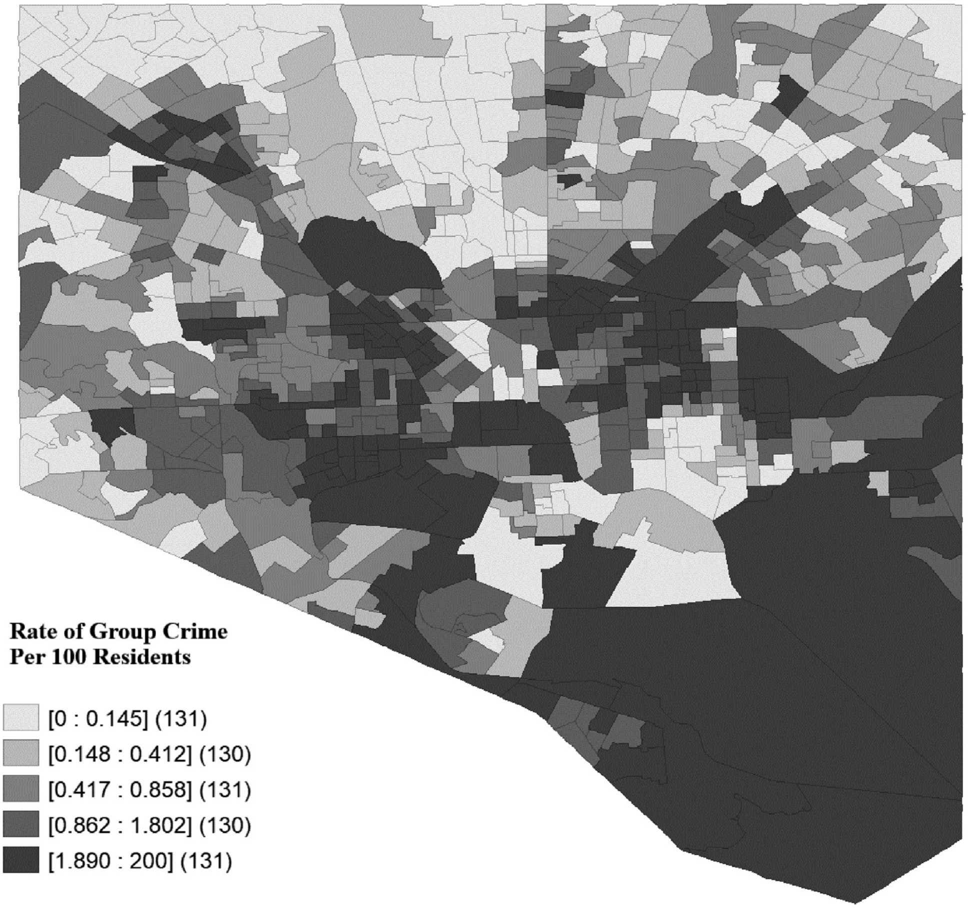

Fig. 1 Distribution of group crime rates across census block groups in Baltimore 2013–16.

Independent variables

Activity nodes. Routine activities and lifestyle theories would suggest that there are number of nodes associated with day-to-day activities that might be important crime generators (e.g., Garofalo 1987). *Bars* may attract individuals that are prone to violent or otherwise antisocial behaviour and at a greater risk of victimization (i.e., young males) (Pridemore and Grubesic 2012). To capture the influence of this important activity node, the number of alcohol outlets classified as a bar, tavern, or adult entertainment (e.g., nightclub) were geocoded for each census block group (Avg. = .86, SD = 2.12). Given the disproportionate involvement of young adults in group criminal behaviour, *schools* in a given census block group were geocoded (Avg. = .29, SD = .64) (e.g., Gottfredson *et al.* 2005; Billings *et al.* 2016). *Transit stations* are known hotspots of crime that facilitate access and the convergence of large numbers of offenders (or victims) (e.g., Block 2000; Newton 2008; Irvin-Erickson and La Vigne 2015). Bus and light-rail stations within each census block group were geocoded (Avg. = 5.43, SD = 5.20). Finally, shopping centres have been found to be hotspots for criminal activity and a convergent setting for interaction among offenders (e.g., Bichler *et al.* 2014). Shopping centres were geocoded within each census block group (Avg. = .03, SD = .19).

Auto-oriented street density. The EPA Smart Location Database utilized NAVTEQ Streets to identify streets that met a set of criteria used to calculate the total miles of auto-oriented streets. Ramsey and Bell (2013) define these criteria as:

> 1) Any controlled access highway, tollway, highway ramp, or other facility on which automobiles are allowed but pedestrians are restricted, 2) Any arterial street having a speed limit of 55 mph or higher, 3) Any arterial street having a speed limit between 41 and 54 mph where car travel is restricted to one-way traffic, 4) Any arterial street having four or more lanes of travel in a single direction, and 5) For all of the above, ferries and parking lot roads were excluded (p. 21).

Once summed, these values were divided by the total square mileage for each census block group. Across the census block groups in Baltimore City, the average auto-oriented street density was .64 miles per acre (SD = 2.97).

Pedestrian-oriented street density. A similar process was conducted to calculate the total pedestrian-oriented street density except with different criteria used to determine the type of path. Ramsey and Bell (2013) define these criteria as:

> 1) Any arterial or local street having a speed limit between 21 and 30 mph where car travel is permitted in both directions, 2) Any arterial or local street having a speed limit less than 21 mph, 3) Any local street having a speed limit between 21 and 30 mph, 4) Any pathway or trail on which automobile travel is not permitted, 5) For all of the above, pedestrians must be permitted on the link, and 6) For all of the above, controlled access highways, tollways, highway ramps, ferries, parking lot roads, tunnels, and facilities having four or more lanes of travel in a single direction are exclude (p. 22).

Once summed, the total pedestrian-oriented miles were divided by the total square mileage for each census block group. Across the census block groups in Baltimore City, the average pedestrian-oriented street density was 20.78 miles per acre (SD = 8.04).

Control variables

Social disorganization. Prior work consistently identifies social disorganization as a predictor of higher levels of crime (e.g., Bursik 1988; Sampson and Groves 1989). Areas with higher levels of ethnic heterogeneity, population turnover, and socio-economic disadvantage tend to report significantly higher rates of criminal activity. To situate the current study within a traditional macro-level framework and account for the effect of these factors on crime, the current analyses include indicators of ethnic heterogeneity, population turnover, and socio-economic disadvantage from data obtained from the American Community Survey (U.S. Census Bureau 2016). *Racial/Ethnic Heterogeneity* is defined by the Herfindahl index, which is calculated as:

$$1 - \sum_{k=1}^{N} p_{kj}^{2}$$

Where p_{kj} is the proportion of the population that is in each ethnic group k that reside in each census block group j (i.e., African American, Hispanic, White, Asian, Other). This index provides the probability that two randomly selected individuals in the census group block will belong to different ethnic groups. Values closer to 0 indicate that all individuals belong to the same ethnic group, whereas values closer to 1 indicate that all individuals belong to separate ethnic groups (Avg. = .28, SD = .21). *Population Turnover* is defined by the percentage of homeowners and renters that moved into a particular census block group between 2010 and 2014 (Avg. = 33.16, SD = 17.17). Lastly, *Poverty* is defined by the percentage of the census block group population that is living below the poverty line (Avg. = 23.54, SD = 17.38).

Population density. Each census block group has varying population totals, which might be related to differences in the amount of criminally active individuals or potential targets that reside within a particular census block group. To account for these differences, we control for population density, which is defined by dividing the total number of individuals in each census group by the total acreage of the census block group (Avg. = 21.63, SD = 14.76).

Solo crime rate. To mitigate the risk that any observed relationship between the street network density measures and group crime is simply a function of a relationship to all criminal activity, the pooled rate of solo crime within each census block group is included as a control variable. We estimated the overall solo crime rate per 100 people within a census block group by totalling the number of solo crime incidents, dividing it by the total population, and multiplying it by 100 to provide a standardized rate. On average, there were 14.32 solo crimes per 100 individuals in each census block group over the three-year period (SD = 56.89).

Analytic strategy

Prior work has demonstrated that crime rates often exhibit spatial dependence across geographic units that can contribute significant bias when modelling coefficients (e.g., Thompson and Gartner 2014; Browning *et al.* 2017). We conduct a series of spatially lagged negative binomial regression models to analyze our data because the total count of group crime incidents exhibits over-dispersion (Anselin 1988). For all models, we included the population within the census block group as an exposure measure and this estimates the outcome as a group crime rate per capita (e.g., Osgood 2000). To account for the spatial clustering of group crime rates, we estimate the following model:

$$y_j = \beta X_{jNodes} + \beta X_{jStreet\ Density} + \beta X_{jControls} + \rho W y_j + \varepsilon_j$$

where $\boldsymbol{y}$ is an N × 1 vector of observations on the group crime rate for each census block group j, $\mathbf{X}$ is an N × K matrix of independent variables including activity nodes, density, and control variables, $\boldsymbol{\beta}$ is a K × 1 vector of regression coefficients, $\mathbf{W}$ is a row-standardized first-order contiguity neighbourhood matrix using queen contiguity, in which spatially adjacent communities in all directions are considered contiguous to a particular census block group j, ρ is the spatial lag operator that was generated using GeoDa 1.14.0 (http://geoda.uiuc.edu), and $\boldsymbol{\varepsilon}$ is a vector of error terms (e.g., Browning *et al.* 2017). Models are run separately to include the activity nodes, auto-oriented pedestrian density and pedestrian-oriented density, and then follow with a combined model.

RESULTS

For ease of interpretability, all coefficients in Table 3 are presented as standardized incident rate ratios and include the population within the census block group as an exposure measure to estimate the outcome as a group crime rate.

Model 1 presents the findings for the relationship between activity nodes and group crime, accounting for all other control variables and the spatial autocorrelation of group crime. The only significant activity node that predicts the rate of group crime is the number of bars. For every additional bar in a census block group, the rate of group crime is expected to increase by about 5.2% ($p < .05$). Percent poverty in a census block group is also statically significant and

Table 3 *Negative binomial regression models predicting group crime at the census block group level (N = 653)*

Independent variables	Activity node model Model 1 IRR (SE)	Auto-oriented density model Model 2 IRR (SE)	Pedestrian-oriented density model Model 3 IRR (SE)	Auto and pedestrian density model Model 4 IRR (SE)
# of Bars	1.052*	1.052*	1.039	1.039
	(.025)	(.025)	(.025)	(.025)
# of Schools	1.066	1.064	1.075	1.075
	(.066)	(.066)	(.065)	(.066)
# of Transit stops	1.011	1.012	1.019*	1.019*
	(.009)	(.009)	(.009)	(.010)
# of Shopping outlets	1.127	1.127	1.228	1.228
	(.230)	(.230)	(.246)	(.246)
Auto-network density	---	.984		1.001
		(.019)		(.019)
Pedestrian-network density	---	--	1.028***	1.028**
			(.006)	(.007)
Racial/ethnic heterogeneity	.702	.706	.682*	.682*
	(.132)	(.133)	(.127)	(.127)
Percent poverty	1.025***	1.025***	1.025***	1.025***
	(.003)	(.003)	(.003)	(.003)
Percent turnover	1.001	1.001	1.002	1.002
	(.003)	(.003)	(.003)	(.003)
Population density	1.006	1.005	.998	.998
	(.003)	(.003)	(.004)	(.004)
Group crime spatial lag	1.039***	1.040***	1.039***	1.039***
	(.011)	(.011)	(.011)	(.011)
Solo crime rate	1.023***	1.023***	1.020***	1.020***
	(.003)	(.003)	(.003)	(.003)
Pseudo R^2	.110	.110	.114	.114
–LL	–2000.43	–2000.09	–1990.53	–1990.53

$p < .05^*$, $p < .01^{**}$, $p < .001^{***}$

positively predicts the rate of group crime (p < .001). As expected, the spatial lag for group crime is positive and statistically significant (p < .001), as is the rate of solo crime in a census block group (p < .001).

Model 2 presents the results for the relationship between auto-oriented street density, activity nodes, and group crime. Interestingly there is no statistically significant relationship between the auto-oriented street density of census block groups and the rate of group crime. For the activity nodes, the number of bars remains a significant predictor of the rate of group crime. Census block groups with higher levels of poverty report significant increases in the rate of group crime. Lastly, both the spatial lag of group crime (p < .001) and the rate of solo crime (p < .001) in a census block group are positively associated with the rate of group crime.

Model 3 presents the results for the relationship between pedestrian-oriented street density, activity nodes, and group crime. Some notable shifts in factors related to the rate of group crime occur. Among the activity nodes, bars are no longer significantly related to the rate of group crime, however, the number of transit stations emerge as statistically significant. For every additional transit station in a census block group the rate of group crime is expected to increase by 2.0% ($p < .05$). Importantly, the coefficient for pedestrian-oriented street density of census block groups in Baltimore City is statistically significant and positively related to the rate of group crime. For every one-unit increase in the pedestrian-oriented street density of census block groups in Baltimore City there is a 2.8% increase in the rate of group crime ($p < .001$). Census block groups with higher levels of poverty continue to demonstrate statistically significant increases in the rate of group ($p < .001$). In contrast, census block groups with higher levels of racial/ethnic heterogeneity report statistically significant reductions in the rate of group crime. Both the spatial lag of group crime and the rate of solo crime in a census block group are also positively associated with the rate of group crime.

Model 4 presents the model that jointly considers the role of auto-oriented street density, pedestrian-oriented street density, and activity nodes. The results are generally stable when compared to the prior model, both in terms of significance patterns and coefficient values. However, in terms of activity nodes, only the number of transit stations remains statistically significant. Pedestrian-oriented street density also remains a significant predictor of the rate of group crime. For every one-unit increase in pedestrian-oriented street density, there is a 2% increase in the rate of group crime ($p < .001$). Consistent with each of the prior models, higher percentages of poverty across census block groups are associated with higher rates of group crime. Ethnic heterogeneity also remains a statistically significant and negative predictor of the rate of group crime. The spatial group crime lag and solo crime rate are also positive and statistically significant.

Sensitivity analysis

It is possible that certain group crime types cluster at convergence spaces because these events' success may be perceived as being 'easier' with accomplices (e.g., robbery). If true, this would suggest our results are driven by instrumental decisions tied to particular crime types rather than the process supposedly under study. We, therefore, estimated supplemental models in which we removed those crimes that may be particularly likely to benefit from having co-offenders, namely robbery, theft and assault. The results from these models are consistent with the findings presented in the main text both in terms of substance and statistical significance, suggesting that this alternative explanation is unlikely to be driving our results.[5]

DISCUSSION

It is widely understood that the built environment has an important and stable influence on criminal activity (e.g., Brantingham and Brantingham 1981; Weisburd 2015). Research aimed at understanding how street connectivity and activity nodes impact offender-decision making have led to substantial investments in crime prevention through environmental design (Cozens and Love 2015). Yet, this research largely assumes that crime is committed by a *single* offender, ignoring the social nature of crime. Drawing on Felson's (2003, 2006) discussion of convergence spaces, the current study identified key activity nodes and measures of street connectivity that may be associated with the intersection of offender interactions and opportunities for group crime. Even when controlling for the rate of solo crime and the spatial correlation of

5 We thank an anonymous reviewer for raising this point.

group crime, our results suggest that certain elements of the built environment are associated with the rate of group crime in census block groups. In particular, our final model highlights the potential role of pedestrian-oriented street connectivity and transit stations within areas in the emergence of co-offending incidents.

The fact that only pedestrian-oriented (as opposed to auto-oriented) street connectivity significantly predicted rates of group crime across the census block groups provides preliminary evidence for the type of connectivity that may facilitate group behaviour. Arguably, these pathways provide the greatest opportunity for potential offenders to merge in time and space, informally assess each other, and act upon shared criminal opportunities (Felson 2003). Moreover, these sorts of pathways, and the convergence of potential offenders in areas that contain them, may actually create opportunities for more spontaneous collective behaviour (Gold 1970; Osgood *et al.* 1996). Prior work examining the decision to partake in group crime has illustrated individuals possess offending thresholds that correspond to the point at which individuals are willing to engage in crime based on the involvement of other individuals (McGloin and Rowan 2015). The accessibility and nature of these spaces may generate conditions where people have a greater likelihood of having their offending thresholds met by virtue of these interactions, leading to more instances of group crime. Further, Jacobs (2010) argues that offenders 'manufacture serendipity' by manipulating their routines to place themselves in spaces with greater odds of criminal opportunities. Immersing oneself in target-rich environments is one strategy adopted, however, Jacobs (2010) acknowledges the role of co-offenders have in catalyzing emergent criminal behaviour. Areas with highly connected spaces may facilitate this 'passive-aggressive "forag[ing]"' that shapes exposure to other offenders and promotes situations that make group crime more likely to occur (Jacobs 2010: p. 520). Clearly, this finding underscores Bichler's (2019) call to consider the interplay between spatial and social networks in order to fully understand the emergence of crime.

Our finding regarding transit stops raises some complexity and highlights the bounds of inference in this study. Transit stations are often used as an example of crime generators because they bring together large numbers of people over extended periods of time (Irvin-Erickson and La Vigne 2015). In this way, this location may reflect similar processes invoked to interpret the importance of areas with pedestrian-oriented street networks. However, there is at least one other theoretical possibility one should consider. Activity nodes may generate higher rates of co-offending not because they represent convergence spaces, but because co-offenders who already have a relationship of some sort (e.g., siblings, peers, criminal acquaintances) purposefully travel to these locations because of a criminal opportunity is known to at least one individual.[6] Even Felson (2003) allowed for the possibility that offenders may meet in a convergence space and then travel to a nearby location that reflects shared awareness space (Lammers 2018); however, this alternative assumes an instrumental, as opposed to incidental, underlying process. If this instrumental process is operating, then areas with crime attractors arguably should have notably higher co-offending rates. For example, bars may function as an attractor for individuals looking to offend, as it is a setting that has cash, potential victims, and accessibility to alcohol (e.g., Bernasco and Block 2011). Our initial models did identify a relationship between areas with bars and co-offending rates, but this association was not statistically significant in our full model; nor did areas with shopping centres, which may attract offenders interested in theft or robbery, have higher co-offending rates. Of course, transit stops may also attract, not just generate, crime, and there are multiple well-reasoned explanations of the emergence of co-offending (van Mastrigt 2017), but we believe the fact that the more common attractors are not associated

6 These results are available from the corresponding author upon request. We thank an anonymous reviewer for raising this point.

with co-offending in our final model, whereas areas with pedestrian pathways is a consistent predictor, provides some preliminary support for the idea of convergence spaces.

Although it was not a primary focus of our analysis, we also call attention to the findings on the relationship between contextual factors and group crime. First, census block groups with higher levels of poverty reported greater rates of group crime. This is consistent with findings drawn from social disorganization theory (e.g., Shaw and McKay 1942; Sampson 2012) and some prior work implicating the role of disadvantage in the co-offending process (e.g., Billings *et al.* 2016). Second, in the models accounting for pedestrian-oriented street connectivity the level of ethnic heterogeneity in a census block group negatively predicted group crime (see also Schaefer *et al.* 2014). Within more ethnically homogenous areas, perhaps accessibility and connectedness of the built environment facilitate greater interaction among individuals who may be more willing to participate in group crime due to a greater sense of trust garnered by the ethnic similarity. Still, it is important to acknowledge that the finding on poverty/disadvantage contradicts prior work examining a similar relationship (e.g., D'Alessio and Stolzenberg 2010; Schafer *et al.* 2014); however, differences in coding strategies for co-offending, geographic context, and sampling strategies may explain the divergence in the influence of this contextual factor on co-offending.

There are several limitations to the current study that warrant consideration. First, the study relies on data from a single city which limits the generalizability of these findings. The extent to which the design of Baltimore City informed the degree of pedestrian-oriented connectivity and activity nodes may be an important distinction for understanding the results. It will be important to replicate these findings across different types of locales (i.e., rural, urban, suburban) in order to understand whether connectivity and activity spaces similarly generate conditions conducive to group crime. Relatedly, the current study's unit of analysis was a census block group. Although prior co-offending research has used similar or larger geographic areas, advances within crime pattern theory have demonstrated the importance of even smaller micro-units that may more fully represent Felson (2003) description of convergence spaces (e.g., Weisburd *et al.* 2012). Next, a portion of the arrest data from the Baltimore City Open Data Portal did not include or had problematic incident location information leading to incomplete geocoding of arrests. These findings should not be generalized to all arrests, as it is difficult to know whether such missingness was at random. Besides excluding crimes not reported to the police, not all co-offenders involved in a criminal incident may be arrested. This reflects a limitation of utilizing official records to study co-offending and it may also contribute to mismeasurement of solo-offending. Because these limitations are also common to other work that uses official records (e.g., Schaefer *et al.* 2014; Charette and Papachristos 2017), future work exploring the convergence of group crime should utilize alternative data sources. As part of this expansion of data sources, we believe collecting qualitative data on the motivations and processes of co-offending is essential. Although our quantitative data is suggestive that convergence spaces facilitate co-offending, we cannot rule out other processes, nor fully understand how this mutual discovery process of accomplices unfolds, without rich narrative information from offenders. It may well be the case that some individuals do travel to these locations with enduring criminal partners, or it may that the unfolding process is one more akin to Gold's (1970) description of a 'pick up' game. In the end, understanding the mechanisms that underlie the emergence of group crime requires an array of data sources, but certainly must include interview data and perhaps observational information.

In conclusion, scholars have prioritized an individual-level focus aimed at exploring patterns, predictors, and consequences of co-offending behaviour. This work generally overlooks how people navigate the 'search' for co-offenders and come into contact with accomplices (e.g., Tremblay 1993; Weerman 2003). By situating crime pattern theory into an understanding of group behaviour, the current study reaffirms how macro-environmental factors are implicated in an important microsocial process (e.g., Short 1998). Further, the current study indicates that the role of environmental structures on crime is not seemingly straightforward. Jane Jacobs (1961) seminal eyes-on-the-street hypothesis suggests that greater connectivity and mixed-use spaces promote place-based monitoring and reductions in crime, however, connectivity may also promote interactions among (co)offenders that facilitate opportunities for group crime. It is the distinct social nature of offending that should move us to reconsider dimensions of existing criminological theory in order to better understand both how group behaviour is embedded within context and to also identify the complex influences of the built environment on crime.

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REFERENCES

Alarid, L. F., Burton Jr, V. S., & Hochstetler, A. L. (2009), 'Group and Solo Robberies: Do Accomplices Shape Criminal Form?', *Journal of Criminal Justice*, 37: 1–9.

Andresen, M. A., and Felson, M. (2010), 'The Impact of Co-Offending', *The British Journal of Criminology*, 50: 66–81.

Anselin, L. (1988). *Spatial Econometrics: Methods and Models.* Springer Science and Business Media.

Bastomski, S., Brazil, N., and Papachristos, A. V. (2017), 'Neighborhood Co-Offending Networks, Structural Embeddedness, and Violent Crime in Chicago', *Social Networks,* 51: 23–39.

Beavis, C., and Nutter, J. B. (1977). *Changing Street Layouts to Reduce Residential Burglary.* Paper presented at the American Society of Criminology, 2014.

Beavon, D. J., Brantingham, P. L., and Brantingham, P. J. (1994), 'The Influence of Street Networks on the Patterning of Property Offenses', *Crime Prevention Studies*, 2: 115–48.

Bernasco, W., and Block, R. (2011), 'Robberies in Chicago: A Block-Level Analysis of the Influence of Crime Generators, Crime Attractors, and Offender Anchor Points', *Journal of Research in Crime and Delinquency*, 48: 33–57.

Bichler, G. (2019). *Understanding Criminal Networks: A Research Guide*. University of California Press.

Bichler, G., Malm, A., and Enriquez, J. (2014), 'Magnetic Facilities: Identifying the Convergence Settings of Juvenile Delinquents', *Crime and Delinquency*, 60: 971–98.

Billings, S. B., Deming, D. J., and Ross, S. L. (2016), 'Partners in Crime: Schools, Neighborhoods and the Formation of Criminal Networks', (NBER Working Paper No. 21962). Retrieved from National Bureau of Economic Research: https://www.nber.org/papers/w21962.pdf (accessed January 18, 2020).

Birks, D., and Davies, T. (2017), 'Street Network Structure and Crime Risk: An Agent-Based Investigation of the Encounter and Enclosure Hypotheses', *Criminology*, 55: 900–37.

Block, R. (2000), 'Gang Activity and Overall Levels of Crime: A New Mapping Tool For Defining Areas of Gang Activity Using Police Records', *Journal of Quantitative Criminology,* 16: 369–83.

Brantingham, P. J., and Brantingham, P. L. (Eds.). (1981). *Environmental Criminology.* Sage Publications.

Brantingham, P. L., and Brantingham, P. J. (1993), 'Nodes, Paths and Edges: Considerations On The Complexity of Crime and The Physical Environment', *Journal of Environmental Psychology*, 13: 3–28.

Brantingham, P., and Brantingham, P. (1995), 'Criminality of Place', *European Journal on Criminal Policy and Research*, 3: 5–26.

Brantingham, P. J., Brantingham, P. L., and Andresen, M. A. (2017). The Geometry of Crime and Crime Pattern Theory. In Wortley, R. and Townsley, M. (Eds.) *Environmental Criminology and Crime Analysis*, 98–115. Routledge.

Browning, C. R., Calder, C. A., Boettner, B., and Smith, A. (2017), 'Ecological Networks and Urban Crime: The Structure of Shared Routine Activity Locations and Neighborhood-Level Informal Control Capacity', *Criminology*, 55: 754–78.

Bursik Jr, R. J. (1988), 'Social Disorganization and Theories of Crime and Delinquency: Problems and Prospects', *Criminology*, 26: 519–52.

Carrington, P. J. (2009), 'Co-offending and the Development of the Delinquent Career', *Criminology*, 47: 1295–329.

Charette, Y., and Papachristos, A. V. (2017), 'The Network Dynamics of Co-Offending Careers', *Social Networks*, 51: 3–13.

Conway, K. P., and McCord, J. (2002), 'A Longitudinal Examination of the Relation Between Co-Offending with Violent Accomplices and Violent Crime', *Aggressive Behavior: Official Journal of the International Society for Research on Aggression*, 28: 97–108.

Cozens, P. M. (2008), 'New Urbanism, Crime and The Suburbs: A Review of the Evidence', *Urban Policy and Research*, 26: 429–44.

Cozens, P., and Love, T. (2015), 'A Review and Current Status of Crime Prevention Through Environmental Design (CPTED)', *Journal of Planning Literature*, 30: 393–412.

D'Alessio, S. J., and Stolzenberg, L. (2010), 'Do Cities Influence Co-Offending?', *Journal of Criminal Justice*, 38: 711–9.

Davies, T., and Johnson, S. D. (2015), 'Examining the Relationship Between Road Structure and Burglary Risk via Quantitative Network Analysis', *Journal of Quantitative Criminology,* 31: 481–507.

Eck, J. E., and Weisburd, D. (Eds.). (1995). *Crime and Place* (Vol. 4). Criminal Justice Press.

Erickson, M. L. (1971), 'The Group Context of Delinquent Behavior', *Social Problems,* 19: 114–29.

Felson, M. (2003), 'The Process of Co-Offending', *Crime Prevention Studies,* 16: 149–68.

Felson, M. (2006). *Crime and Nature.* Sage Publications.

Felson, M. (2009), 'The Natural History of Extended Co-Offending', *Trends in Organized Crime,* 12: 159–65.

Frank, R., Dabbaghian, V., Reid, A., Singh, S., Cinnamon, J., and Brantingham, P. (2011), 'Power of Criminal Attractors: Modeling the Pull of Activity Nodes', *Journal of Artificial Societies and Social Simulation*, 14: 6.

Garofalo, J. (1987). Reassessing the Lifestyle Model of Criminal Victimization. In Gottfredson, M., Hirschi, T., and Hindelang, M.J. (Eds.), *Positive Criminology*, 23–42. Sage Publications.

Gold, M. (1970). *Delinquent Behavior in an American City.* Brooks/Cole.

Gottfredson, G. D., Gottfredson, D. C., Payne, A. A., and Gottfredson, N. C. (2005), 'School Climate Predictors of School Disorder: Results from a National Study of Delinquency Prevention in Schools', *Journal of Research in Crime and Delinquency*, 42: 412–44.

Gottfredson, M. R., and Hirschi, T. (1990), *A General Theory of Crime*. Stanford University Press.

Grund, T., and Morselli, C. (2017), 'Overlapping Crime: Stability and Specialization of Co-Offending Relationships', *Social Networks,* 51: 14–22.

Hillier, B., and Sahbaz, O. (2008). An Evidence Based Approach to Crime and Urban Design. In Cooper, R., Boyko, C., Evans, G., Adams, M. (Eds.), *Urban Sustainability for the 24 Hour City.* Routledge.

Irvin-Erickson, Y., and La Vigne, N. (2015), 'A Spatio-Temporal Analysis of Crime at Washington, DC Metro Rail: Stations' Crime-Generating and Crime-Attracting Characteristics as Transportation Nodes and Places', *Crime Science*, 4: 1–13.

Jacobs, J. (1961). *The Death and Life of Great American Cities.* Random House.

Jacobs, B. A. (2010), 'Serendipity in Robbery Target Selection', *The British Journal of Criminology*, 50: 514–29.

Johnson, S. D. (2014), 'How Do Offenders Choose Where to Offend? Perspectives from Animal Foraging', *Legal and Criminology Psychology*, 19: 193–210.

Johnson, S. D., and Bowers, K. J. (2010), 'Permeability and Burglary Risk: Are Cul-De-Sacs Safer?', *Journal of Quantitative Criminology*, 26: 89–111.

Kinney, J. B., Brantingham, P. L., Wuschke, K., Kirk, M. G., and Brantingham, P. J. (2008), 'Crime Attractors, Generators and Detractors: Land Use and Urban Crime Opportunities', *Built Environment,* 34: 62–74.

Lammers, M. (2018), 'Co-offenders' Crime Location Choice: Do Co-Offending Groups Commit Crimes in Their Shared Awareness Space?', *The British Journal of Criminology*, 58: 1193–211.

Lantz, B. (2020), 'Co-Offending and Arrest: An examination Of The "Group Hazard" Hypothesis', *Crime & Delinquency*, 66(4), 572–600.

Madensen, T. D., Herold, M., Hammer, M. G., and Christenson, B. R. (2017), 'Place-based Investigations to Disrupt Crime Place Networks', *The Police Chief*, 14–5.

McCarthy, B., Hagan, J., and Cohen, L. E. (1998), 'Uncertainty, Cooperation, and Crime: Understanding the Decision to Co-Offend', *Social Forces,* 77: 155–84.

McGloin, J. M., and Nguyen, H. (2012), 'It Was My Idea: Considering the Instigation of Co-Offending', *Criminology*, 50: 463–94.

McGloin, J. M., and Rowan, Z. R. (2015), 'A Threshold Model of Collective Crime', *Criminology*, 53: 484–512.

McGloin, J. M., Sullivan, C. J., Piquero, A. R., and Bacon, S. (2008), 'Investigating the Stability Of Co-Offending and Co-Offenders Among a Sample of Youthful Offenders', *Criminology*, 46: 155–88.

McGloin, J. M., and Thomas, K. J. (2016), 'Incentives for Collective Deviance: Group Size and Changes in Perceived Risk, Cost, and Reward', *Criminology,* 54: 459–86.

Newton, A. (2008), 'A Study of Bus Route Crime Risk in Urban Areas: The Changing Environs of a Bus Journey', *Built Environment*, 34: 88–103.

Osgood, D. W. (2000), 'Poisson-based Regression Analysis of Aggregate Crime Rates', *Journal of Quantitative Criminology*, 16: 21–43.

Osgood, D. W., Wilson, J. K., O'Malley, P. M., Bachman, J. G., & Johnston, L. D. (1996), 'Routine Activities and Individual Deviant Behavior', *American sociological review*, 61: 635–55.

Papachristos, A. V., Wildeman, C., and Roberto, E. (2015), 'Tragic, But Not Random: The Social Contagion of Nonfatal Gunshot Injuries', *Social Science and Medicine*, 125: 139–50.

Pridemore, W. A., and Grubesic, T. H. (2012), 'A Spatial Analysis of The Moderating Effects Of Land Use on the Association Between Alcohol Outlet Density and Violence in Urban Areas', *Drug and Alcohol Review*, 31: 385–93.

Ramsey, K., and Bell, A. (2013). *Smart Location Database User Guide.* Environmental Protection Agency.

Reiss Jr, A. J. (1988), 'Co-offending and Criminal Careers', *Crime and Justice*, 10: 117–70.

Reiss Jr, A. J., and Farrington, D. P. (1991), 'Advancing Knowledge About Co-Offending:Results From a Prospective Longitudinal Survey of London Males', *Journal of Criminal Law and Criminology*, 82: 360–95.

Roncek, D. W., and Maier, P. A. (1991), 'Bars, Blocks, and Crimes Revisited: Linking the Theory of Routine Activities to the Empiricism of "Hot Spots"', *Criminology*, 29: 725–53.

Rowan, Z. R., McGloin, J. M., and Nguyen, H. (2018), 'Capitalizing on Criminal Accomplices: Considering the Relationship Between Co-Offending and Illegal Earnings', *Justice Quarterly*, 35: 280–308.

Sampson, R.J. (2012) *Great American City: Chicago and the Enduring Neighborhood Effect.* University of Chicago Press.

Sampson, R. J., and Groves, W. B. (1989), 'Community Structure and Crime: Testing Social-Disorganization Theory', *American Journal of Sociology*, 94: 774–802.

Sarnecki, J. (2001). *Delinquent Networks: Youth Co-Offending in Stockholm.* Cambridge University Press.

Schaefer, D. R. (2012), 'Youth Co-Offending Networks: An Investigation of Social and SpatialEffects', *Social Networks*, 34: 141–9.

Schaefer, D. R., Rodriguez, N., and Decker, S. H. (2014), 'The Role of Neighborhood Context in Youth Co-Offending', *Criminology*, 52: 117–39.

Shaw, C. R., and McKay, H. D. (1942). *Juvenile Delinquency and Urban Areas.* University of Chicago Press.

Sherman, L. W., Gartin, P. R., and Buerger, M. E. (1989), 'Hot Spots of Predatory Crime: Routine Activities and the Criminology of Place', *Criminology*, 27: 27–56.

Short Jr, J. F. (1998), 'The Level of Explanation Problem Revisited—The American Society of Criminology 1997 Presidential Address', *Criminology*, 36: 3–36.

Stolzenberg, L., & D'Alessio, S. J. (2008), 'Co-offending and the Age-Crime Curve', *Journal of Research in Crime and Delinquency*, 45: 65–86.

Summers, L., and Johnson, S. D. (2017), 'Does the Configuration of The Street Network Influence Where Outdoor Serious Violence Takes Place? Using Space Syntax to Test Crime Pattern Theory', *Journal of Quantitative Criminology*, 33: 397–420.

Thompson, S. K., and Gartner, R. (2014), 'The Spatial Distribution and Social Context of Homicide in Toronto's Neighborhoods', *Journal of Research in Crime and Delinquency*, 51: 88–118.

Tremblay, P. (1993). Searching for Suitable Co-offenders. In Clarke, R.V.G. and Felson, M. (Eds.), *Routine Activity and Rational Choice*, 17–36. Transaction Publishers.

United States Census Bureau. (2016). 2011–2015 American community survey 5-year estimates. Retrieved from https://data.census.gov/cedsci/ (accessed January 18, 2020).

van Mastrigt, S. B. (2017). Co-offending and Co-offender Selection. In Bernasco, W., Van Gelder, J.-L. and Elffers, H. (Eds.), *The Oxford Handbook of Offender Decision Making*, 338–60. Oxford Handbooks

van Mastrigt, S. B., and Farrington, D. P. (2011), 'Prevalence and Characteristics of Co-Offending Recruiters', *Justice Quarterly*, 28: 325–59.

Weerman, F. M. (2003), 'Co-offending as Social Exchange. Explaining Characteristics of Co-Offending', *British Journal of Criminology*, 43: 398–416.

Weisburd, D. (2015), 'The Law of Crime Concentration and the Criminology of Place', *Criminology*, 53: 133–57.

Weisburd, D., Groff, E. R., and Yang, S. M. (2012). *The Criminology of Place: Street Segments and Our Understanding of the Crime Problem.* Oxford University Press.

White, G. (1990), 'Neighborhood Permeability and Burglary Rates', *Justice Quarterly*, 7: 57–67.