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ORIGINAL PAPER

Is it Important to Examine Crime Trends at a Local "Micro" Level?: A Longitudinal Analysis of Street to Street Variability in Crime Trajectories

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Abstract Over the last 40 years, the question of how crime varies across places has gotten greater attention. At the same time, as data and computing power have increased, the definition of a 'place' has shifted farther down the geographic cone of resolution. This has led many researchers to consider places as small as single addresses, group of addresses, face blocks or street blocks. Both cross-sectional and longitudinal studies of the spatial distribution of crime have consistently found crime is strongly concentrated at a small group of 'micro' places. Recent longitudinal studies have also revealed crime concentration across micro places is relatively stable over time. A major question that has not been answered in prior research is the degree of block to block variability at this local 'micro' level for all crime. To answer this question, we examine both temporal and spatial variation in crime across street blocks in the city of Seattle Washington. This is accomplished by applying trajectory analysis to establish groups of places that follow similar crime trajectories over 16 years. Then, using quantitative spatial statistics, we establish whether streets having the same temporal trajectory are collocated spatially or whether there is street to street variation in the temporal patterns of crime. In a surprising number of cases we find that individual street segments have trajectories which are unrelated to their immediately adjacent streets. This finding of heterogeneity suggests it may be particularly important to examine crime trends at very local geographic levels. At a policy level, our research reinforces the importance of initiatives like 'hot spots policing' which address specific streets within relatively small areas.

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> [V]ariation in crime within communities is probably greater than variations across communities. The very meaning of the concept of a bad neighborhood is an open empirical question: whether the risk of crime is randomly or evenly distributed throughout the neighborhood, or so concentrated in some parts of the neighborhood that other parts are relatively safe (Sherman et al. 1989, p. 29).

Scholars have long been interested in how crime varies over space and the topic has received increasing attention over the last 40 years.[1] Seminal studies examining crime across larger geographic units such as states (Guerry 1833; Loftin and Hill 1974; Quetelet 1831[1984]), cities (Baumer et al. 1998), and even neighborhoods (Boggs 1965; Bursik and Grasmick 1993; Bursik and Webb 1982; Byrne and Sampson 1986; Chilton 1964; Kornhouser 1978; Reiss and Tonry 1986; Schuerman and Kobrin 1986; Skogan 1986; Stark 1987) establish the foundation for the continuing interest. More recent studies point to the potential theoretical and practical benefits of focusing research on micro crime places (Eck and Weisburd 1995; Sherman 1995; Sherman and Weisburd 1995; Taylor 1997; Weisburd 2002). Cross-sectional micro level studies suggest that significant clustering of crime at place exists, regardless of the specific micro unit of analysis defined (Brantingham and Brantingham 1999; Crow and Bull 1975; Groff and LaVigne 2001; Pierce et al. 1986; Potchak et al. 2002; Roncek 2000; Sherman et al. 1989; Weisburd and Green 1994; Weisburd et al. 1992). Longitudinal work examining the developmental trajectories at micro levels (Weisburd et al. 2004a, 2009b) has consistently identified tremendous crime concentration at specific places. These micro level findings provide evidence of significant intra-neighborhood variance in crime that is lost when neighborhoods are examined as homogenous units.

A major question that has not been answered in prior research concerns the geography (i.e., the form and the degree) of street to street variability of temporal crime trends at micro levels of analysis.[2] The initial study identifying developmental crime trends across micro places (Weisburd et al. 2004a, b) did not use full geographic tools. To more precisely answer this question, we examine both temporal and spatial variation in crime across street segments in the city of Seattle Washington.

In this paper we explore the spatial distribution developmental trajectories. We begin by using 16 years of crime incident data (1989–2004) to produce developmental trajectories of crime in Seattle, WA (Weisburd et al. 2009a). We then use spatial statistics to examine the geography of street segments in each group. Rigorous geographic analysis enables us to more exactly describe the spatial relationships among temporal crime patterns and to examine the open question of whether it is important to examine crime trends at a ‘micro’ level. We address the following research questions: (1) What is the distribution of temporal crime trajectories across Seattle? (2) What is the spatial pattern of street segments within the same temporal crime trajectory (i.e., clustered, dispersed or random)? and (3) Are street segments of certain trajectories found near one another or are they spatially independent?

[1] Due to space constraints only selected references are mentioned here. More complete overviews of the history of place-based criminology can be found in the introductory chapters of Eck and Weisburd (1995) and Weisburd et al. (2008).

[2] For an exception see Groff et al. 2008. They use the same methodology but explore the patterns of crimes committed by juveniles.

Finally, we discuss the implications of our findings both to the theoretical development of a 'geography of crime concentration' and to policy and practice.

Geography and the Criminology of Place

In the 1970s a group of scholars began to develop theories that focus on why crime happens where it does. The 'opportunity' theories they developed have been instrumental in guiding the investigation of place and crime. Routine activity theory (Cohen and Felson 1979) and crime pattern theory (Brantingham and Brantingham 1991 [1981], 1993) both emphasize the context of crime events and importance of human activity in understanding crime patterns. As a group, opportunity theories hold that crimes occur when the normal everyday activities of offenders and victims intersect with no guardian present. Thus, routine activities are the key dynamic element because they directly affect the convergence of the other elements necessary for a crime to occur. Opportunity theories focus on how the built and social environments shape human activity and thus provide the foundation for understanding why crime happens where it does. After all, it is the interactions between humans and their environment which serve as the source of explanation of observed spatial patterns (Aitken et al. 1989; Gold 1980; Golledge and Timmermans 1990; Timmermans and Golledge 1990; Walmsley and Lewis 1993). As software improved and data became more widely available, the work of these theorists inspired many empirical studies of micro places (Weisburd and McEwen 1997).

Just as Wolfgang et al.'s (1972, p. 89) identification of the 'chronic six percenters' (i.e., 6% of study participants were responsible for over 50% of the offenses committed) galvanized research into individual level criminality, Sherman et al.'s (1989) finding that 3% of the addresses in Minneapolis produced 50% of the calls for service sparked renewed interest in micro level crime patterns and how they develop over time. There is now a significant body of literature demonstrating the existence of clustering of crime at place regardless of the specific micro unit of analysis defined (Brantingham and Brantingham 1999; Crow and Bull 1975; Groff and LaVigne 2001; Pierce et al. 1986; Roncek 2000; Sherman et al. 1989; Smith et al. 2000; Weisburd and Braga 2002; Weisburd et al. 2004a; Weisburd and Green 1994). Taylor and Gottfredson (1986) took the examination of micro places one step further by making the connection between the physical and social environments of micro level places and their crime levels. This body of work suggests the salience of Sherman et al.'s call for the development of a "criminology of *places*" (emphasis in original, Sherman et al. 1989, p. 30).

Building a place-based criminology necessitates pursuing a deeper understanding of the developmental aspects of crime at micro level places (Weisburd et al. 2004a, 2009a). Weisburd et al. (2004a, b) used group-based trajectory analysis (Nagin 1999, 2005; Nagin and Land 1993) to classify crime on street segments from 1989 to 2002 in Seattle, Washington. They identified 18 trajectory groups that reflect distinct longitudinal crime patterns. Echoing Wolfgang et al. (1972) and Sherman et al. (1989) they found approximately 4–5% of the street segments in each year account for 50% of all crime. At the other end of the spectrum, each year between 47 and 52% of street segments had no crime at all. In a related study of crimes committed by juveniles, Weisburd et al. (2009b) applied trajectory analysis and once again found both concentration and stability in the patterns.

The results of Weisburd and colleagues in Seattle are consistent with other micro level longitudinal examinations which focused on a subset of places. In Baltimore, Maryland, Taylor and National Consortium On Violence Research (1999) reported a high degree of stability in both crime and fear of crime across ninety street blocks using data collected in 1981 and 1994 (see also Robinson et al. 2003; Taylor 2001). Spelman's examination of high schools, public housing communities, subway stations, and parks in Boston over 3 years found about 10% of locations account for 50% of the calls for service to the places he examines. Importantly, those 'worst' places remain fairly stable over the 3 years of his study.

While these longitudinal micro level studies examine the temporal distribution of crime across places, they leave the question of the geographic distribution of those trajectories largely unexplored. Weisburd et al. (2004a, b) took a first step in this direction. They examined the distribution of trajectories via kernel density maps. The maps showed stable trajectories tended to be found in all areas of the city but were concentrated in areas with less residential density and higher income. Additionally, the maps revealed overlap in the downtown area between areas with the highest concentrations of increasing trajectories and those with decreasing trajectories; leading them to speculate that some of the same processes may underlie both. In a later study of crimes for which a juvenile was arrested, Weisburd et al. (2009b) used point maps of the locations of the streets in the highest rate trajectories to show they were found all over Seattle. They once again discovered evidence of strong street to street variability in that subset of crimes (Groff et al. 2008). Together these studies suggest the importance of more fully describing the variation in crime across micro places.

Toward a Geography of Crime Concentration

The previously outlined developments provide ample evidence for the existence of geographic concentration and spatio-temporal stability. What remains is the need for a more in-depth examination of the *structure* of geographic concentration across micro places; specifically addressing the degree of block to block variability. Sherman et al. (1989, p. 28) made the case for studying the geography of crime concentration by arguing that the study of the "variation across space is one of the basic tools of science." They noted that crime concentration itself does not necessarily mean clustering. What if the high crime places are randomly distributed across space? The theoretical and policy implications of such a finding would be very different from a finding of clustering.

Sherman et al. (1989) tested for clustering in the distribution of calls for service by comparing the observed distribution to the expected distribution under a Poisson model and uncovered significant clustering. Other researchers have used spatial statistics to show how concentration in the distribution of crime incidents exists in 'hot spots of crime' (Spring and Block 1988). Since then, the identification of geographic 'hot spots' of crime has been the topic of many studies.[3] More recent work has expanded to include the temporal structure of hotspot areas (Grubesic and Mack 2008; Johnson et al. 2008). These authors call for more work to identify hot spots by the temporal trajectory of their crime; "upwards, downwards and time-stable" (Johnson et al. 2008, p. 43).[4]

Other researchers have described the structure of concentration by measuring the distance between hot places. As part of the design of a patrol experiment, Sherman and Weisburd (1995) identified 420 clusters of hot spot addresses with 20 or more calls for

[3] The literature around hot spots is immense. Two recent overviews provide the insight into the state of the art (Chainey et al. 2008; Eck et al.2005). See Weisburd et al. (1992) for a theoretical introduction.

[4] Weisburd et al. (2004a, b) came at this from the opposite direction. They first identified temporal trends in crime and then used kernel density maps to find hotspots of temporal trajectory patterns.

service related to Part I offenses that were within one-half a block of one another. Other work identified the mean distance between clusters of robbery hot spots in Minneapolis as only 888 feet, which is approximately two blocks in most urban areas (Linnell 1988). The same study revealed 90% of robbery hotspots in Minneapolis were on just seven arterial roads. These studies provide ample evidence about the structure of crime concentration; namely that concentration takes the form of hot spots (i.e., clusters) and tends to be found near one another and in places with high amounts of human activity. They also begin to describe the structure of the clustering.

Another open question about crime concentration pertains to whether areas such as hot spots and neighborhoods are uniformly hot. Early evidence suggests these areas may be heterogeneous rather than uniform. In other words, 'bad neighborhoods' may contain 'good streets' and 'good neighborhoods' may be home to 'bad streets'. Roughly 60 years ago, Henry McKay noted the lack of offenders on some blocks within high crime neighborhoods (Albert J. Reiss, Jr., personal communication as cited in Sherman and Weisburd 1995). More recently, Weisburd and Mazerolle (2000) found activity in drug hot spots to be more related to the hot spots themselves, than the levels of crime and disorder in the surrounding neighborhood. Taylor and Gottfredson (1986) uncovered street block level variation in crime and found it to be related to the social and physical environment. Urban planners have long pointed to street to street variation in characteristics of the physical environment and their relationship to crime (Jacobs 1961). Crime prevention through environmental design (Jeffery 1971) and 'defensible space' (Newman 1972) explained why such variation may be related to the physical environment (For an opposing view see Merry 1981). Hillier (1999) made a compelling case for focusing on the built environment directly and measuring its affect on crime and other social variables of interest. By quantifying both the accessibility and the type street pattern he demonstrated that traditional street patterns (i.e., grid) are safer (Hillier 2004). More recent studies uncovered evidence of extensive street to street variation in both the characteristics of the physical environment and measures of criminal activity such as burglary (Groff and LaVigne 2001) and auto thefts (Potchak et al. 2002). As a whole, these studies point toward the existence of bad places in good neighborhoods as well as good places in bad neighborhoods. Our research takes the next step and provides a direct, quantitative examination of that question.

Achieving a More Complete Description of Crime Variation Across Places

The concentration and stability of micro crime places suggest they are an important unit of study for understanding crime at place. But those characteristics do not put to rest a key concern in assessing the importance of such small geographic units in the crime equation. If the focus on micro places adds to our study of crime, then it should represent a type of 'reductionism'; the understanding of small parts will lead to an explanation of the whole which is not provided by higher units of analysis. While prior studies have shown that crime is concentrated at micro units of analysis, they have not examined whether this variability is distinct from what would be observed had they focused on higher geographic units such as communities or neighborhoods. For example, do macro level studies simply mask concentrations of crime that are found in high crime communities? More specifically, is there street to street variability in crime trends at micro places, or do examinations of micro crime places simply divide up larger area trends?

The answers to these questions have implications for both theory and crime prevention policy. If geographically proximal street segments have the same or similar temporal crime patterns, it would suggest there is no need for micro-level examination of places. It would also provide support for neighborhood-level crime prevention initiatives rather than micro level ones. If, however, street segments of the same trajectory are spread throughout the city and/or street segments spatially adjacent to one another vary in their temporal crime pattern, then further examination of micro level patterns is supported. In this case, more narrowly focused efforts on individual street segments may provide more crime prevention impact. Our focus in this study is on providing more comprehensive evidence of the variation in crime across micro level places.

Analytic Strategy

The incorporation of spatial methods into criminological research has increased rapidly since the 1990s (Messner and Anselin 2004). Researchers have taken seriously the error introduced by failing to account for spatial effects when analyzing inherently spatial data and have responded by incorporating a range of spatial data analysis techniques.[5] This research continues that trend by using spatial statistics to describe geographic patterns of crime trajectories across street segments.

Study Area

Our study focuses on Seattle Washington. Seattle was a logical choice because the city had an extended and unbroken series of electronic crime incident data. Seattle is located on the west coast of the United States. It is bounded on the west by the Puget Sound and on the east by Lake Washington. This unusual geography has significant ramifications for human activity patterns. The western border of the city is permeable only to water traffic (via a ferry system). Automobile and bus traffic can enter Seattle from the east using one of two bridges. It is only on the two shortest borders (on the north and the south) that typical levels of porosity in boundaries are found. The lack of permeable boundaries has the benefit of reducing concerns about spatial edge effects. Once inside Seattle, there are additional natural barriers in the form of waterways. The southern section of the city is split northwest to southeast by the Duwamish Waterway (three bridges cross it). The northern section of the city is split from the central by a waterway consisting of Salmon Bay, Lake Union, Portage Bay, and Union Bay. Seattle is a mature city. There was no additional development of residential or commercial areas requiring changes to the street network between 1989 and 2004. There were two changes to the built environment of note over the study period; a major baseball stadium was opened in 1999 (Safeco Field) and a new cultural center opened in the Seattle Center downtown in 2003.

Unit of Analysis

We use the street segment, both sides of a street between two intersections, as our unit of analysis ($n = 24{,}023$).[6] The average length of a street segment in Seattle is 387 feet. The

[5] The volume of research explicitly examining spatial dependence or spatial error in models is far too large to detail here (as examples see Baller et al. 2001; Chakravorty and Pelfrey 2000; Cohen and Tita 1999; Cork 1999; Jefferis 2004; Morenoff and Sampson 1997; Roman 2002).

[6] This unit of analysis is slightly different from the 'hundred block' measure used in the original Seattle study. See the final report for more information on the 'hundred block' definition (Weisburd et al. 2004b). More detailed information on the creation of geographically defined street segment is available (see Weisburd et al. 2009a).

majority of the streets (roughly 64%) are between 200 and 600 feet. Using our definition, very few streets (less than 2%) ended up longer than 1,000 feet. In addition to the theoretical and technical reasons discussed earlier, we have several other substantive reasons and a technical one for using street segments as our unit of analysis including: (1) routine activity theory is essentially a micro-level theory and thus informs patterns observed at the micro level (Eck 1995; Sherman et al. 1989); (2) using micro places such as individual addresses, intersections and street segments minimizes the aggregation in the analysis and consequently, the risk of ecological fallacy (Brantingham et al. 1976); (3) when considering policing strategies as they relate to place, a key factor is how much of the variation in crime involves factors the police are able to address (Taylor 1998) and whether the policy implications from such will be immediately actionable. On the technical end, street segments reduce spatial heterogeneity among the units of observation that has been shown to exist when larger areal units are used (e.g., block groups and census tracts) (Smith et al. 2000).

Data

We use computerized records of crime incident reports to represent crime for the period from 1989 to 2004. Incident reports are generated by police officers or detectives after an initial response to a request for police service. In this sense, they represent only those events which were both reported to the police and deemed to be worthy of a crime report by the responding officer and thus provide a measure of vetted crime. We include all crime events for which a report was taken except those which occur at an intersection.[7] In addition, we exclude records that lack a specific address, occur on the University of Washington campus or at a police precinct or police headquarters, and those written for crimes that occur outside city limits. We geocode the remaining records and are left with 1,697,212 incident reports over the time period.[8]

Dependent Variable

We apply group-based trajectory analysis (Nagin and Land 1993; Nagin 1999, 2005) to cluster street segments into groups with distinct developmental trends over the time period studied (see "Appendix 1" for technical details). Our approach follows closely the methodology of an earlier study using 14 years of data and hundred blocks (Weisburd et al. 2004a, b). In our study we use 16 years of data and redefined the unit of analysis. Despite the use of two additional years and a redefinition of the unit of analysis, the trajectory results are roughly similar to the earlier study (Weisburd et al. 2004a). Twenty-two

[7] There are two main reasons for excluding intersection crime. First, since events at intersections could be considered 'part of' any one of the participating street segments, there is no satisfactory method for assigning them to one or another. However, it is also the case that incident reports at intersections differed dramatically from those at street segments. Traffic-related incidents accounted for only 3.77% of reports at street segments, but for 45.3% of reports at intersections.

[8] All geocoding was done in ArcGIS 9.1 using a geocoding locator service with an alias file of common place names to improve our hit rate. The geocoding locater used the following parameters: spelling sensitivity = 80, minimum candidate score = 30, minimum match score = 85, side offset = 0, end offset 3%, and Match if candidates tie = no. Manual geocoding was done on unmatched records in ArcGIS 9.1 and then in ArcView 3.x using the 'MatchAddressToPoint' tool (which allowed the operator to click on the map to indicate where an address was located) to improve the overall match rate. Research has suggested hit rates above 85% are reliable (Ratcliffe 2004). Our final geocoding percentage for crime incidents was 97.3%.

distinct groups are predicted by the model (as opposed to 18 groups in the original study). To simplify our description and focus our discussion more directly on patterns in the level and direction of temporal changes in crime at place across time, we divide the initial trajectories into eight patterns based on a visual inspection of the level of crime over the time period and the overall direction of change (Table 1; Fig. 1a). These eight patterns capture eight distinct types of temporal crime patterns and thus become our dependent variable in the spatial analysis.

The first general pattern represents the street segments in our study that can be seen as relatively *crime free* during this period (Fig. 1a). They experienced an average of less than two crimes per year over the entire time period. One trajectory started the period with three crimes and declined to less than two and the other started low and increased to three crimes per year. They account for about half of the street segments in Seattle. Approximately 30% of the street segments are associated with what we have called the *low stable* pattern (Fig. 1b). As with the relatively crime free segments, these places evidence low and essentially stable crime trends (between 3 and 12 crimes per year) and they reinforce the simple descriptive finding that most places in the city have little or no crime. Two other trajectory classifications represent places with much more serious crime problems, though they also evidence strong stability in trends over time. What we term the *moderate stable* pattern, includes about 1.2% of the street segments (Fig. 1e). These street segments average around 20 crime incidents throughout the study period and are basically stable over the study period. Street segments in what we term the *chronic high* pattern can be defined as the most serious crime hot spots in the city (Fig. 1h). The average number of crimes per segment is consistently more than 80 crime incidents per year. The difference in level of crime is what made this trajectory group earn its own pattern. Only 1% of the street segments ($n = 247$) are found in this pattern.

The trajectory patterns we have described so far all represent stable crime trends. The four remaining trajectory patterns include only about one in five street segments in the city. But nonetheless, they help recognize that crime trends at very micro levels of geography are more complex than overall city trends would suggest. Two of the trajectory patterns evidence decreasing crime trends during this period. We use the level of crime and the trend to group these trajectories into the following patterns. The *low decreasing* pattern accounts for almost 10% of the street segments in the city and ranges from 8 to 18 crime incidents on average (Fig. 1c). Importantly, by the end of the study period crime had declined to less than half of the crime averages evidenced at the outset. Similarly the street

Table 1 Number of street segments per temporal trajectory grouping

Group	Number	Percentage
1 Crime free	11,898	49.5
2 Low stable	7,688	32.0
3 Low decreasing	2,202	9.2
4 Low increasing	903	3.8
5 Moderate stable	292	1.2
6 High decreasing	572	2.4
7 High increasing	221	.9
8 Chronic high	247	1.0
Total	24,023	10.0

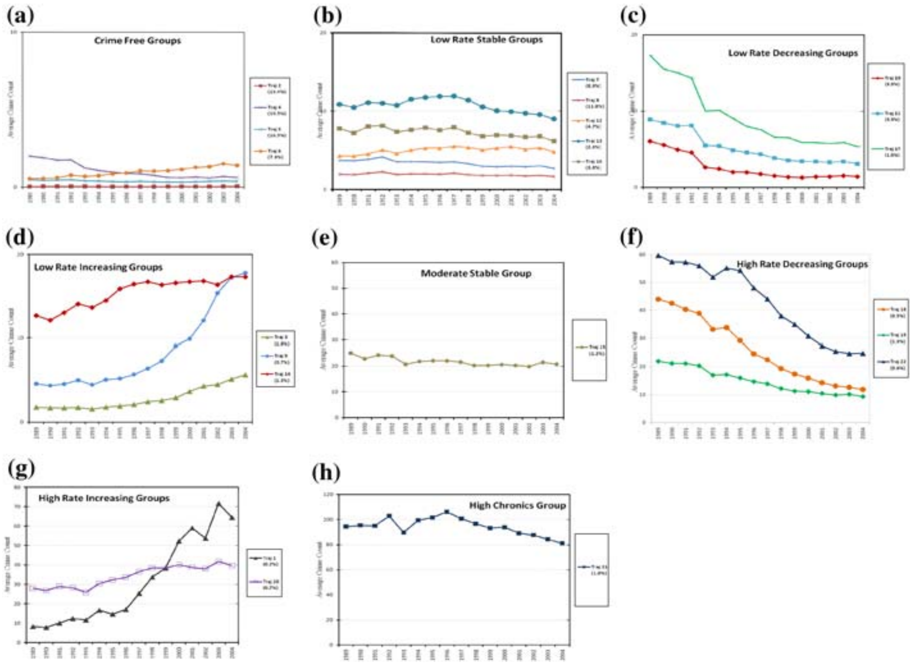

Fig. 1 Temporal crime trajectories

segments in the crime pattern we term *high decreasing* evidence strong crime declines (Fig. 1f). Here the base levels of crime in 1989 are much higher ranging between 20 and 60 crime incidents on an average street segment. Only about 2.4% of the street segments in our study are *high decreasing*.

The last pattern of trajectories is particularly interesting in light of the overall crime decline in Seattle. We term these trajectories *low increasing* (Fig. 1d). About 4% of the street segments fall in crime trajectories with a *low increasing* pattern. The *high increasing* pattern shows a similar trend but at a higher level (Fig. 1g). Roughly 1% of the street segments fall in these groups.

Identifying Spatial Relationships in Group Distributions

Previous studies identifying spatial relationships among trajectory group members have used a sequential approach, conducting a spatial analysis of the output of the developmental statistic (Griffiths and Chavez 2004; Kubrin and Herting 2003; Weisburd et al. 2004a). We also follow a sequential approach but instead of descriptive analysis we systematically apply a series of point pattern statistical techniques are used to analyze the spatial patterns of street segments.[9] We use the Ripley's *K*-function and a bivariate-*K* function to examine the second order effects (i.e., local relationships) related to spatial dependence (Bailey and Gatrell 1995; Fotheringham et al. 2000). Together the two

[9] In order to apply point pattern statistics to street segments we use the midpoint of each line/street to represent the street segment.

techniques provide a more nuanced picture of local variation than would be possible with either alone. Unfortunately no single software package exists which combines the required spatial statistics with a powerful cartographic display engine, so data analysis and display were done using a variety of software packages including R, SPlancs, CrimeStat©, GeoDa© and ArcGIS© 9.3.

Ripley's *K* describes the proximity of street segments in the same trajectory to one another. For each street segment, it counts the number of street segments of the same trajectory that fall within a specified distance band and then repeats for subsequent distance bands. In this way it characterizes spatial dependence among locations of street segments with the same trajectory at a wide range of scales. In order to make more formal statements about the point patterns, we compare the summary statistics calculated from the observed distribution of street segments with those calculated from a model distribution (i.e., complete spatial randomness (CSR)). When used in this way the *K*-function is able to identify whether the observed pattern is significantly different than what would be expected from a random distribution (Bailey and Gatrell 1995). Ripley's *K* is calculated and then compared to a reference line that represents CSR: if $\mathrm{K}(h) > \pi d^2$ then clustering is present (Bailey and Gatrell 1995, 90–95; Kaluzney et al. 1998, 162–163).

A bivariate- *K* (also called a cross *K*) function is used to test for independence between movement patterns. The bivariate- *K* answers whether the pattern of street segments belonging to one trajectory is related to the pattern of street segments in another trajectory (Bailey and Gatrell 1995; Rowlingson and Diggle 1993). As described by Rowlingson and Diggle (1993) and applied here, the bivariate- *K* function expresses the expected number of street segments of a particular trajectory (e.g., *high decreasing*) within a distance of an arbitrary point of a second type of street segment (e.g., *high increasing*), divided by the overall density of *high increasing* street segments. As with Ripley's *K,* simulation is used to test whether two patterns are independent.[10] The output is a graph representing three possible relationships: independence, attraction, and repulsion for the tested distance range (400 foot bins from 0 to 2,800 feet). If the two patterns are independent of one another; they are most likely the result of different processes (Bailey and Gatrell 1995). A finding of spatial interaction between them can take two forms, attraction or repulsion. Since street segments are stationary, attraction in this context refers to a tendency for street segments of one trajectory to be found in closer proximity to street segments of another trajectory than would be expected under independence (i.e., their patterns are similar). Repulsion refers to a tendency for street segments of one particular trajectory to be found at longer distances from another.

[10] This is accomplished by using a series of random toroidal shifts on one set of points and comparing the cross *K*-function of the shifted points with another fixed set (Rowlingson and Diggle 1993). A toroidal shift provides a simulation of potential outcomes under the assumption of independence by repeatedly and randomly shifting the set of locations for one type of street segment and calculating the cross *K*-function for that iteration. The outcomes are used to create test statistics in the form of an upper and lower envelope. One thousand iterations are used for each simulation. In order to better explore micro level relationships, the bivariate - *K* analysis examines the distribution of the trajectory pairs at distances up to 2,800 feet (using 400 foot bins which approximate one street block). This strategy also allows us to more closely inspect the relationship of the bivariate k statistic to the upper bound of the simulation envelope. The null hypothesis of the bivariate- *K* test is independence (i.e., the spatial pattern of one trajectory group is unrelated to the pattern of the other group being compared).

Findings

We begin with a simple visualization of the distribution of all the temporal trajectories across Seattle. Seattle is divided into three sections: northern (Fig. 2), middle (Fig. 3) and southern (Fig. 4). Lower crime street segments are represented by thinner lines and the higher crime street segments by thicker lines. For example, *crime free* groups are the thinnest and lightest grey lines. *Low stable* street segments are darker but still very thin. Street segments which are *low increasing* are symbolized using thin dark lines and those that are *high increasing* are thicker and darker in color.

At first glance the impression is one of large areas in which streets are the same color and thickness broken up by linear patterns. Closer inspection reveals the variety in the pattern. While there are large areas consisting of predominantly *crime free* and *low stable* groups (not surprising given their overwhelming numbers, 12,033 and 7,696 street segments, respectively), street segments from higher rate trajectory groups are interspersed within those areas. Street segments that are thicker (designating a high rate group) are most often arterial roads (i.e., roads which have higher speed limits and collect traffic from residential streets). A closer examination of the pattern of temporal trajectories reveals differences by section of Seattle.

In the northern part of the city (Fig. 2), we see most places are *crime free* or in another low crime trajectory. However, there are thicker/darker lines interspersed throughout. There is a definite linear arrangement to the patterns related to connected streets with similar temporal patterns. The area with the most concentrated heterogeneity is a

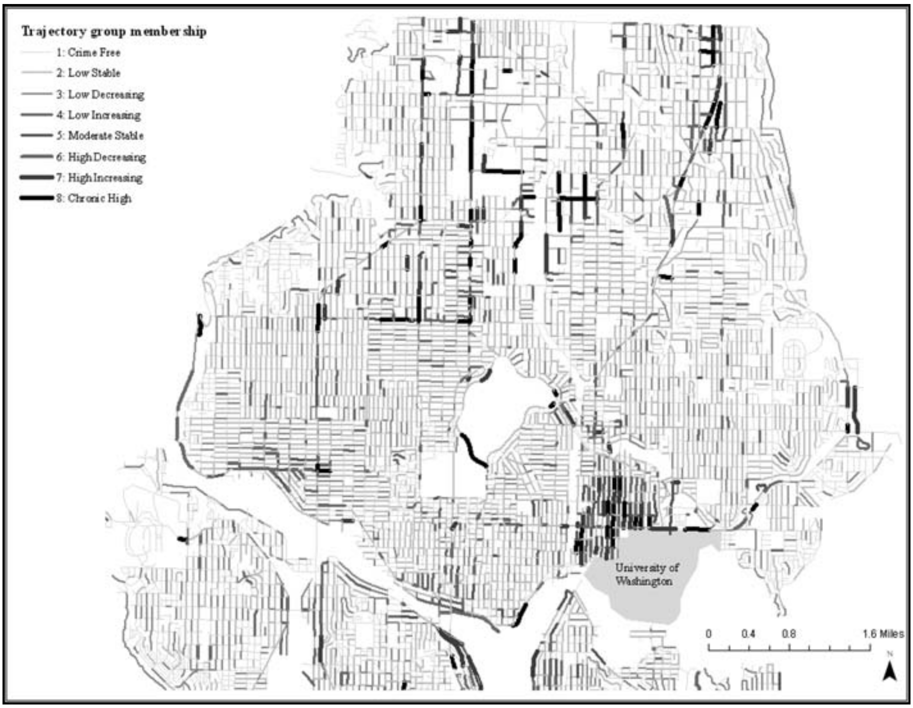

Fig. 2 Spatial distribution of temporal trajectories (northern Seattle)

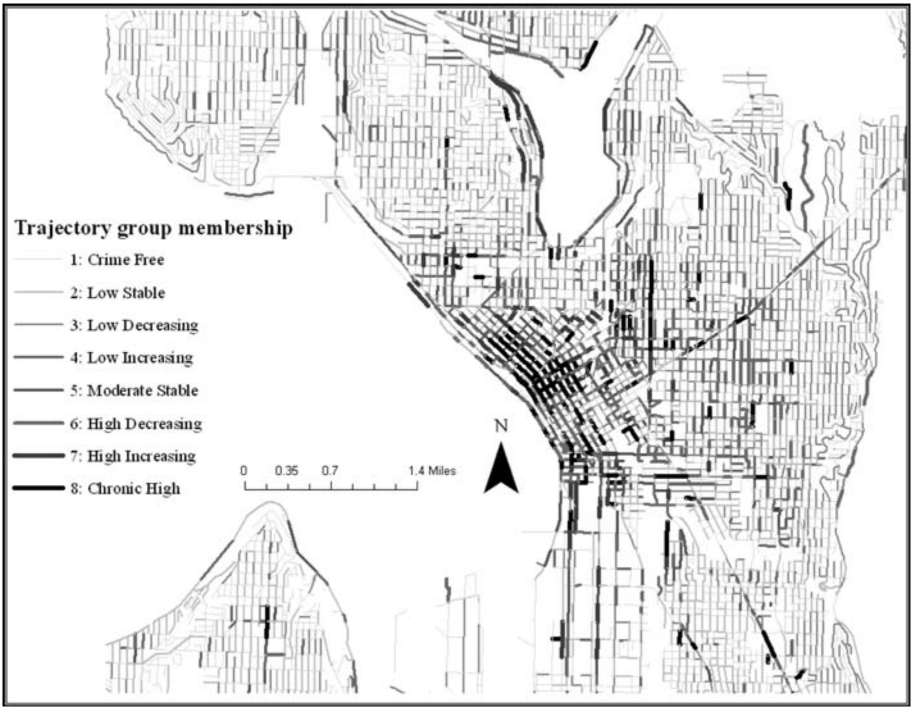

Fig. 3 Spatial distribution of temporal trajectories (central)

commercial area near the University of Washington campus (solid gray area). In this one small area (approximately 50 street segments) we see tremendous street segment by street segment variation in high rate temporal trajectory groups; all high rate trajectory groups are represented there. There is also a sharp transition at the commercial area's edge into predominantly *crime free* and *low stable* trajectory pattern street segments.

Turning to the middle section of the city we immediately notice the influence of the downtown area of Seattle on the western portion (Fig. 3). It is here we observe the greatest magnitude of variation of the temporal trajectories from street to street and the greatest concentration of streets with high crime.[11] A high degree of variability is also present in the older residential sections east of downtown. Finally, in the southwestern and southeastern sections of the city a slightly different pattern emerges (Fig. 4). Once again large areas of predominantly low crime and *crime free* street segments are interspersed with the other trajectory types. However, the southern section seems to have the greatest number of linear patterns of high rate street segments often following arterial roads.

While these maps do not provide quantitative substantiation for the significance of the spatial associations revealed, they do offer a strong indication of heterogeneity as well as homogeneity in crime patterns at the street segment level. Thus, it is not the case that we can understand the action of crime by simply extrapolating from large area trends. Something seems to be going on at the micro level that needs explanation.

[11] Readers should note slight scale changes among maps 1, 2 and 3. These were necessary to provide maximum enlargement of the three sections of Seattle.

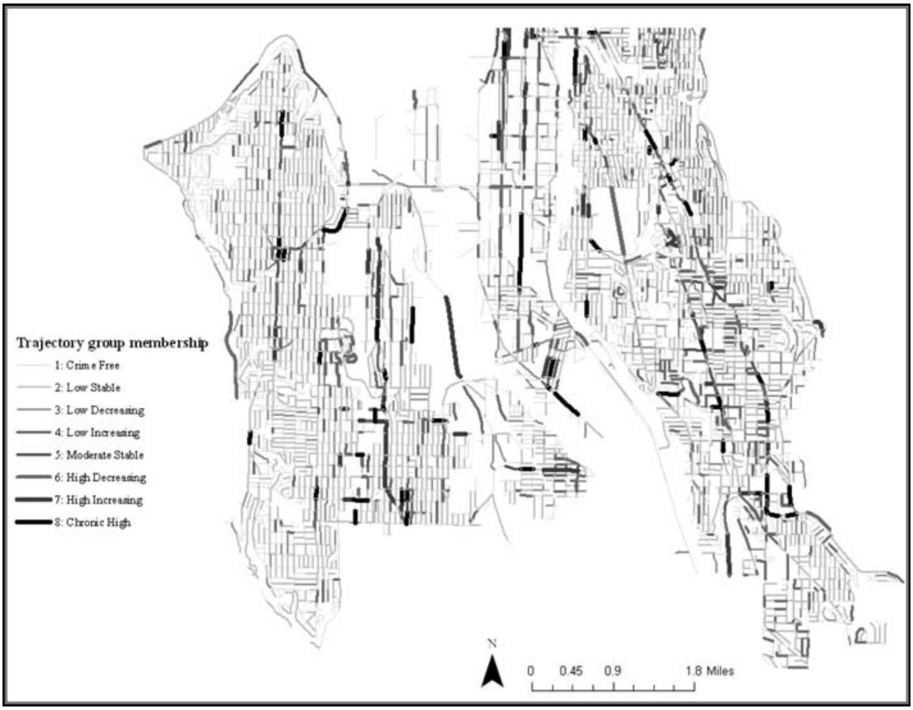

Fig. 4 Spatial distribution of temporal trajectories (southern Seattle)

Next, we use Ripley's *K* to examine whether street segments of the same temporal trajectory are clustered in space.[12] The statistic reported from Ripley's *K* in CrimeStat (Levine 2005) is the *L* value. This is a rescaled Ripley's *K* where CSR is represented by a horizontal zero line. Figure 5 shows the *L*(*t*) line for each of the trajectories; the higher the line, the greater the degree of clustering among the places which are members of the trajectory group. The *X*-axis provides information as to the scales at which the clustering occurs. Since we are interested in comparing neighborhood level clustering with street segment level clustering only distances up to about one-half mile (2,640 feet) are discussed.

In general, we find the degree of clustering increases with the rate of crime exhibited by the temporal trajectory (Fig. 5). More specifically, *chronic high* street segments have the greatest degree of local clustering. There is essentially no difference in the lines for the other three higher trajectory groups until between 1.5 and 2 blocks (.12 and .15 miles) where they begin to diverge. At this point, *high increasing* street segments are most likely to be near other one another followed by *high decreasing* and *moderate stable* groups. At the other end of the spectrum, among low rate street segments, it is the low increasing street segments which are most likely to be found near one another followed by the *low*

[12] Ripley's *K* also reveals whether the observed clustering is greater or less than would be expected under an assumption of Complete Spatial Randomness (CSR). CSR is of limited use when examining human-related distributions such as crime because the opportunity for a crime to occur is constrained to accessible areas adjacent to streets. By calculating the Ripley's *K* for the street network, we can provide a more realistic metric with which to compare patterns in the trajectory group member ship of street segments (see 'Street segments' line in Fig. 4).

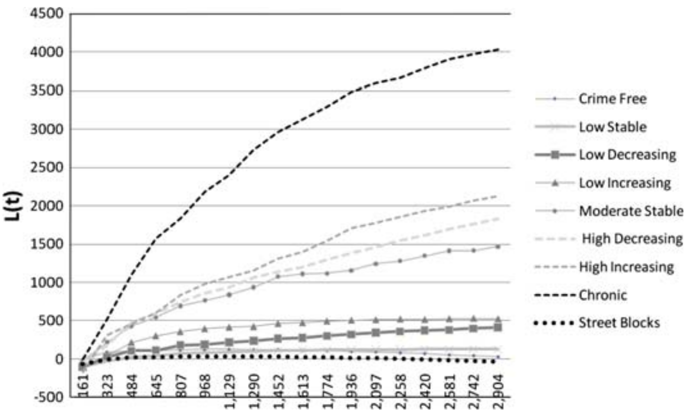

Fig. 5 Ripley's *K* of all trajectories

decreasing street segments. The *crime free* and *low stable* street segments are the least clustered which reflects their ubiquitousness. All are more clustered than the reference line representing the level of intrinsic clustering in the street network. In sum, street segments of the same temporal trajectory group to be generally more clustered at distances of less than a half-mile than would be expected as compared to either the intrinsic clustering in the street network or under CSR. Only the degree of clustering varies by the temporal pattern of crime. Street segments exhibiting high crime trajectory patterns show the strongest clustering.

While Ripley's K provides important information about the degree and scale of clustering of street segments within the same temporal trajectory, we must use a variation on Ripley's *K*, the bivariate- *K* statistic, to answer our question about whether there are specific temporal trajectory pairs that tend to be physically proximal (e.g., *low increasing* streets near *high increasing* streets). We conduct a series of pairwise comparisons to evaluate the patterns of each group as compared to those of every other group (i.e., group 1 to group 2, group 1 to group 3 etc.). The results indicate whether the patterns of two groups tend to systematically 'hang together' (attraction) or be found in different places (repulsion) or whether their locations are independent of one another.[13]

We find no evidence for repulsion; a pair of temporal trajectory patterns which are consistently far from one another (Fig. 6). We did find evidence for independence (i.e., members of two trajectory patterns which are neither consistently near to nor far from one another) and for spatial interaction in the form of attraction. To simplify our discussion, we discuss independence first and then attraction. The patterns of streets in the following trajectory pairs are not related (independent) at some distances up to about a half-mile:

- *Crime free* as compared to *moderate stable* (at distances less than or equal to about 1,200 feet), *high decreasing*, *high increasing*, and *chronic high*.
- *Low stable* as compared to *chronic high* (at distances less than or equal to about 800 feet).
- *Low decreasing* as compared to *high increasing* (at distances less than or equal to about 1,200 feet) and *chronic high* (at distances less than or equal to 400 feet).

[13] These analyses produced 28 graphs. Space constraints do not allow the inclusion of the graphs in the paper; however, they are available from the authors.

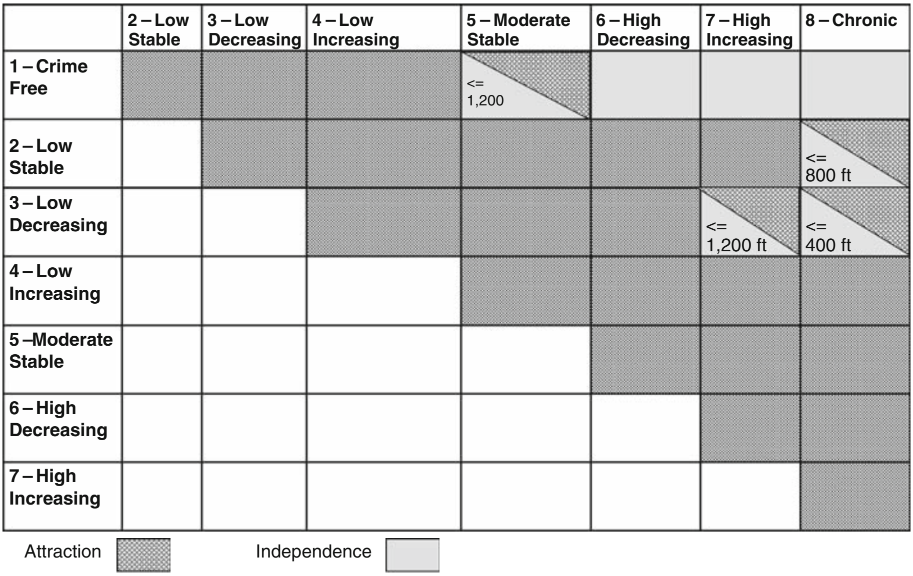

Fig. 6 Graphical representation of pairwise comparisons

- *Moderate stable* as compared to *crime free* (at distances less than or equal to about 1,200 feet).
- *High decreasing* as compared to *crime free*.
- *High increasing* as compared to *crime free* and *low decreasing* (at distances less than or equal to about 1,200 feet).
- *Chronic high* as compared to *crime free*, *low stable* (at distances less than or equal to about 800 feet), and *low decreasing* (at distances less than or equal to about 400 feet).

These results indicate the process which is producing *crime free* trajectory patterns is different from the one producing the high crime trajectory patterns but not independent from the process or processes producing low rate crime patterns. *Crime free* street segments are the most independent overall; they are unrelated to the patterns three of the other crime trajectories at all distances and to one other (*moderate stable*) up to about 1,200 feet. *Low stable* street segments are independent from *chronic* street segments at distances two blocks and under (about 800 feet) before showing evidence of attraction at larger distances. *Low decreasing* street segments are independent from both *high increasing* and *chronic high* at short distances (1,200 feet and 400 feet, respectively). These results make intuitive sense since low crime places are typically very different from very high crime places. Overall, the degree of independence between *crime free, low stable*, and *low decreasing* as compared to high crime temporal patterns suggests the existence of distinct processes underlying the level of crime observed across places.

The predominant type of spatial interaction in these pairwise relationships at micro distances is attraction. The members of the following trajectory pattern pairs exhibit attraction at most distances up to one-half mile (i.e., they tend to 'hang together'):

- *Crime free* with *low stable*, *low decreasing*, *low increasing*, and *moderate stable* (at distances greater than 1,200 feet).

- *Low stable* with *low decreasing*, *low increasing*, *moderate stable*, *high decreasing*, and *high increasing* and *chronic high* (after 800 feet).
- *Low decreasing* with *low increasing*, *moderate stable*, *high decreasing*, and *high increasing* (after 1,200 feet), and *chronic high* (after 400 feet).
- *Low increasing* with *moderate stable*, *high decreasing*, and *high increasing*.
- *Moderate stable* with *crime free* (after 1,200 feet), *low stable*, *low decreasing*, *low increasing*, *high decreasing*, *high increasing*, and *chronic high*.
- *High decreasing* with *low stable*, *low decreasing*, *low increasing*, *moderate stable*, *high increasing*, and *chronic high*.
- *High increasing* with *low stable*, *low decreasing* (after 1,200 feet), *low increasing*, *moderate stable, high decreasing*, and *chronic high*.
- *Chronic high* with *low stable* (after 800 feet), *low decreasing* (after 400 feet), *low increasing, moderate stable*, *high decreasing*, and *high increasing*.

The finding of attraction indicates common processes may be underlying these pairs of temporal crime patterns. Turning first to the low rate groups, we find spatial attraction between street segments with *crime free*, *low stable*, *low decreasing*, and *low increasing* trajectory patterns at all distances (Fig. 6). The attraction between *moderate stable* and *crime free* street segments is only present at distances of greater than 1,200 feet. Thus moderate stable street segments tend to be within a half mile of crime free street segments but not within approximately three blocks of them.

Low stable trajectory patterns are attracted to all other trajectory patterns except *chronic high* (but only at distances of greater than 800 feet). Here again, we uncover a pattern of independence related to adjacent streets and those within two blocks but general attraction at distances up to one-half mile. One explanation for this finding is that the processes underlying the realization of *low stable* places are similar to those underlying the places with both higher and lower crime trajectories. However, there may be place-specific differences that occur at nearby streets which cause their temporal crime patterns to change. Alternatively, it could indicate the role low stable places play as 'jumping off points' for changes in crime rates. At the same time, the finding confirms the significant geographic dispersion of *crime free* and *low stable* places. They are found all across Seattle, not just in 'good' areas.

The spatial distribution of low rate street segments that are experiencing decreasing or increasing temporal crime patterns is especially interesting. *Low decreasing* street segments tend to be found near higher rate crime trajectory members such as *moderate stable* and *high decreasing* at all distances. However, similar to the finding just discussed for *low stable* street segments, they are only attracted to *high increasing* (at distances greater than 1,200 feet) and *chronic high* (at distances of greater than 400 feet) at distances greater than one block. On the other hand, *low increasing* street segments are also near *moderate stable*, *high decreasing*, *high increasing*, and *chronic high*. It may be the processes sustaining or increasing crime on streets nearby are also influencing the *low increasing* street segments.

We find much more heterogeneity among temporal trajectory groups representing high rate crime places. The pattern of *chronic high* street segments is related to *moderate stable*, *high decreasing*, and *high increasing* places at all distances. *High increasing* street segments tend to be found near *low increasing*, *moderate stable*, *high decreasing*, and *chronic high* at all distances. However, *high increasing* street segments are independent of *low decreasing* streets up to 1,200 feet. This spatial separation hints at the existence of significant differences between the processes underlying *low decreasing* and *high increasing* street segments. Streets which are part of *high decreasing* temporal patterns tend to found near street segments of both low and high rate trajectory patterns (i.e., *low stable*, *low* *increasing*, *high increasing*, and *chronic high*) at most distances. Thus, in general, streets with higher crime or changing temporal trajectories tend to be more frequently associated with other streets which are also higher crime or undergoing a change in crime rates.

In sum, our descriptive and statistical analysis reveals temporal crime trajectory pattern membership often varies from street segment to street segment. This is apparent in both the descriptive maps and in our finding of widespread spatial attraction among different temporal trajectory groups. Overall, these results are consistent with the spatial pattern we saw on the descriptive maps showing proximal places can have very divergent temporal crime trajectories. While certain areas of the city consist of predominantly *crime free* and *low stable* trajectory patterns, other areas are characterized by extreme spatial heterogeneity with street to street variation in both the level and pattern of temporal crime pattern membership. A set of any four nearby streets might include one *crime free*, one *moderate stable*, one *high decreasing* and one *chronic* street segment.

The outcomes of the pairwise comparisons are consistent with earlier analyses. In general, high rate groups tend to attract other high rate groups. This may be a reflection of the built environment. Place characteristics such as land use patterns, disorder, housing quality etc. tend to be shared among nearby street segments. Thus it is not surprising that high level and low level streets might generally attract. Our results clearly indicate independence between the pattern of crime free streets and all high rate street segments (although moderate stable is only up to three blocks away). Thus the processes which create crime free streets are most likely very different from those which result in streets with significant amounts of crime.

The finding of attraction between *low stable* and *low decreasing* and the high rate groups is more puzzling. It may be the geographic patterns of street segments in *low stable* and *low decreasing* temporal patterns are a reflection of their proximity to high crime places. *Low stable* street segments are found near both low and high crime street segments and thus are influenced by processes operating to produce both low crime and high crime places. Similarly, *low decreasing* street segments may be ones which have experienced changes in their characteristics which run counter to the general high crime environment in which they are situated and have resulted in a decreasing crime trajectory pattern. Together these results demonstrate the micro level of analysis is capturing important variability in trends; variability that would be masked at a more macro level.

At the same time, we do find two phenomena that demand we explain and understand clustering at different scales. First, we find that there is a dependence of street segments within the same temporal crime trajectories at distances up to one-half mile. Second, we find evidence for significant attraction between specific types of temporal crime trajectories. This is especially true with low or no crime segments, where we observe large areas in which these trajectories prevail. However, it is also true of chronic segments and other high crime segments for example in the city center.

Discussion

But what do these findings mean to our understanding of the spatial pattern of temporal crime trajectories and of the structure of crime concentration at places more generally? What does the existence of varying degrees of heterogeneity in street to street temporal crime trajectories indicate? How do we interpret our finding that street segments within a single trajectory group are more likely to be found near one another? What can we learn from the knowing certain pairs of temporal crime patterns tend to be found in the same general areas? Since these observations are not mutually exclusive, how do we reconcile places where more than one of the above relationships exist? Absent data on the nature of places we can of course only speculate on what might be driving the observed patterns.

One interpretation is that there are simply two sets of influences operating on crime in the city. One set of influences may reflect the existence of ecological labels. Ecological labels provide a shared perception of places that is generally homogeneous across larger areas of a city (Brantingham and Brantingham 1991 [1981]). Assuming perceptions influence actions, shared perceptions can lead to shared actions which in turn serve to reinforce the existing crime situations. While these perceptions apply to an area they are 'played out' at the micro level of street segments. This cycle may explain the existence of generally high crime rate areas as well as generally low crime rate areas and thus our finding that streets with similar trajectories are generally clustered.

A second interpretation focuses on micro level influences of opportunity factors on crime and the importance of local trends. Theories such as routine activity theory (Cohen and Felson 1979; Felson 1986, 2002) and crime pattern theory (Brantingham and Brantingham 1984, 1991 [1981], 1993) focus on the spatio-temporal characteristics of crime events in an attempt to explain why some places have more crime than others (Eck 1995). The urban backcloth provides a local baseline susceptibility to crime through a shared set of crime-related characteristics (Brantingham and Brantingham 1991 [1981]; Jacobs 1961). In this way, place characteristics also play a significant role in shaping the differential distribution of potential targets and motivated offenders across space and time.

At the micro level, opportunity theories would predict variation in micro level crime if there was significant variation in characteristics of places that facilitate the convergence of the elements necessary for a crime to occur. However, variation in crime across larger areas and even neighborhoods could also be consistent with the perspective. If there is no significant variation in characteristics which affect the frequency of convergence, then we would expect relatively homogenous and stable crime patterns over time. In this way, opportunity theories can explain both heterogeneity and homogeneity in the geographic pattern of temporal crime rates.

In the same vein, our finding of street to street variability in temporal crime trajectories may simply be a reflection of the street to street variability in the urban environment. Activity generators such as employment centers and retail stores attract both residents and non-residents, law abiding and those open to criminal opportunity, to specific places and in doing so produce local variation above and beyond the baseline for a place (Brantingham and Brantingham 1995; Felson 1987; Kinney et al. 2009). Additionally, the influence of activity generators/attractors is not confined to the street segment on which they are located. As individuals travel to and from the activity/crime generator they become familiar with the places along their route. Their awareness of opportunities is highest along their route and at the places they visit; it declines with distance from each.

In this way, micro level patterns can also explain the pair-wise clustering of street segments with different temporal crime patterns. While there is much street to street variability in the urban backcloth, there is also general continuity. The general continuity explains why low rate temporal crime trajectories tend to be found near other low rate street segments. At the same time, the character of streets is influenced by the mixture of land uses present and by unique characteristics of places that may influence the amount of crime experienced.

Together these assumptions lead us to believe that crime attractors/generators have a differential impact. Levels of traffic along blocks provide an indicator of the number of people for whom that block is part of their activity space. The more activity spaces of which a block is a part, the greater the potential that an offender and a target will converge without a capable guardian present and thus supply the necessary elements for a crime to occur (Cohen and Felson 1979). These mechanisms are at work regardless of neighborhood level influences. As we saw in our results, what varies by neighborhood is the degree to which increased opportunity translates into increased crime (e.g., is the change from *crime free* to *low stable* or from *moderate stable* to *chronic high*). The exact form of the change may also be a function of variability in the temporal crime patterns of nearby places.

Given the above, our work would propose the importance of recognizing commonalities among micro level places that stem from consistency in the built environment. However, while our data suggest the importance of recognizing crime trends at micro places, they do not necessarily reinforce the importance of community level influences. This is especially the case in our finding of clustering of similar trajectories in certain areas. For example, the clustering of *chronic* segments near one another may reflect important similarities in social and built environment characteristics. In this context it would be the street segment characteristics that are important to understanding the concentration in crime at place.

Other researchers have advocated for starting small (Brantingham and Brantingham 2008; Groff et al. 2008; Oberwittler and Wikstrom 2008; Rengert and Lockwood 2008; van Wilselm 2008). Even if some of the variability present at micro levels does work its way up to more macro levels, we will still have wanted to know that. Otherwise, we will be unable to separate observed macro level patterns which are being driven by variability at micro levels from those that are not.

We think it also important to recognize that there may not be a simple dichotomy between social disorganization and opportunity theories as they have often been linked to units of geographic analysis. Since both social disorganization and opportunity variables are related to the urban backcloth, it may be too simplistic a model to attribute area trends to social disorganization factors and local trends to opportunity factors. The story of crime at place may be more complex.

At a policy level, our research reinforces the importance of initiatives like 'hot spots policing which address specific streets within relatively small areas (Braga 2001; Sherman and Weisburd 1995; Weisburd and Green 1995). If police become better at recognizing the 'good streets' in the bad areas, they can take a more holistic approach to addressing crime problems. For example, they can more precisely target community building and law enforcement operations to maximize efficiency and effectiveness. More broadly, they can work with other city agencies to change the physical and social environment of problem places (Johnson et al. 2008). Alterations to the built environment which improve surveillability, control access, and increase the capacity for territoriality among legitimate users can reduce crime (Lab 2007).

Before concluding we want to note some specific limitations of our work and make suggestions for future study. While our findings break new ground in describing the spatio-temporal relationships among street blocks, there are two limitations to our micro-level examination of spatio-temporal crime patterns. Although our study examined a longer time period than has been available to other scholars at the micro level of analysis, it remains only a snapshot in the development of places. Accordingly, our analysis might have underestimated some dynamic elements while overestimating others. Another limitation involves the low numbers of incidents at street segments. This feature of street segment level research necessitated we use total crime events rather than exploring specific types of crime as is recommended in place-based research (Clarke 1983; Clarke and Felson 1993). Future research may want to follow Braga et al. (2009) and isolate high crime street segments for more in-depth study.

This paper establishes the importance of looking at the micro level. Of course, our data only allow us to identify the importance of temporal crime patterns. To advance the field future work should collect street segment level characteristics which would allow the identification of characteristics which are associated with particular temporal crime patterns. Only by conducting research that uses street blocks as the unit of analysis and by thoroughly describing their characteristics will we be able to shed additional light on these questions. Future work should utilize prospective data collection to take advantage of the more robust information systems available today. In addition, prospective data collection allows for the inclusion of systemic social observation (SSO) (Sampson and Raudenbush 1999) and ethnographic components that are crucial to 'adding flesh to the bones' of quantitative research. Neither of which are possible with retrospective studies.

Conclusions

While there is a growing body of evidence regarding the value of examining micro level places, the predominant paradigms of place and crime focus on large area trends. Firmly grounded in the ecological tradition, no one doubts the importance or salience of these investigations to understanding crime and delinquency. However, the work herein reinforces the idea that we need to focus on small area trends as well.

Our systematic examination of the spatial patterns within temporal crime trajectory groups allows us to enrich our understanding of the structure of concentration in crime patterns at micro level places. In doing so our study reveals the significant geographic variability in temporal trends from street segment to street segment which suggests something is going on at the micro level that requires explanation. Since our study lacks any information on the characteristics of places we are unable to explain why these patterns are occurring or to conjecture about the underlying processes at work. We leave those explorations to future work.

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Appendix 1: Technical Note of the Production of Developmental Trajectories for Street Segments

The trajectory modeling reported here was developed for a larger study of crime and place in Seattle, WA (Weisburd et al. 2009a). The group-based trajectory model, first described by Nagin and Land (1993) and further elaborated in Nagin (1999, 2005), is specifically designed to identify clusters of individuals with similar developmental trajectories, and it has been utilized extensively to study patterns of change in offending and aggression as people age (see Nagin 1999). As such, we believe it is particularly well suited to our goal of exploring the patterns of change in the Seattle data.

Formally, the model specifies that the population is comprised of a finite number of groups of individuals who follow distinctive developmental trajectories. Each such group is allowed to have its own offending trajectory (a map of offending rates throughout the time period) described by a distinct set of parameters that are permitted to vary freely across groups. This type of model has three key outputs: the parameters describing the trajectory for each group, the estimated proportion of the population belonging to each group, and the posterior probability of belonging to a given group for each individual in the sample. The posterior probability, which is the probability of group membership after the model is estimated, can be used to assign individuals to a group based on their highest probability.[14]

This approach is less efficient than linear growth models but allows for qualitatively different patterns of behavior over time. There is broad agreement that delinquency and crime are cases where this group-based trajectory approach might be justified, in large part because not everyone participates in crime, and people appear to start and stop at very different ages (Nagin 1999, 2005; Raudenbush 2001). Given that we have no strong expectation about the basic pattern of change, the group-based trajectory approach appears to be an excellent choice for identifying major patterns of change in our data set.[15]

There are two software packages available that can estimate group-based trajectories: Mplus, a proprietary software package, and Proc Traj, a special procedure for use in SAS, made available at no cost by the National Consortium on Violence Research (for a detailed discussion of Proc Traj, see Jones et al. 2001).[16] In using Proc Traj, we had three choices when estimating trajectories of count data: parametric form (Poisson vs. normal vs. logit), functional form of the trajectory over time (linear vs. quadratic vs. cubic), and number of groups.

The Poisson distribution is a standard distribution used to estimate the frequency distribution of offending that we would expect given a certain unobserved offending rate (Lehoczky 1986; Maltz 1996; Osgood 2000).[17] We found that the quadratic was uniformly a better fit than the linear model, and that the cubic model did not improve the fit over the quadratic in the case of a small number of groups. In choosing the number of groups we relied upon the Bayesian Information Criteria (BIC) because conventional

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[14] The group-based trajectory is often identified with typological theories of offending such as Moffitt (1993) because of its use of groups (see Nagin et al. 1995). But it is important to keep in mind that group assignments are made with error. In all likelihood, the groups only approximate a continuous distribution. The lack of homogeneity in the groups is the explicit trade off for the relaxation of the parametric assumptions about the random effects in the linear models (Bushway et al. 2003). For a different perspective on this issue, see Eggleston et al. (2004).

[15] Those interested in a more detailed description of the group-based trajectory approach should see Nagin (1999) or (2005).

[16] The procedure, with documentation, is available at www.ncovr.heinz.cmu.edu.

[17] Proc Traj also provides the option of estimating a Zero Inflated Poisson (ZIP) model. The ZIP model builds on a Poisson by accommodating more non-offenders in any given period than predicted by the standard Poisson distribution. The zero-inflation parameter can be allowed to vary over time, but cannot be estimated separately for each group. It is sometimes called an intermittency parameter, since it allows places to have "temporary" spells of no offenses without recording a change in their overall rate of offending. In this context, the ZIP model's differentiation between short-term and long-term change is problematic. The Poisson model, on the other hand, tracks movement in the rate of offending in one parameter, allowing all relatively long-term changes to be reflected in one place. We believe this trait of the Poisson model makes it the better model for modeling trends, especially over relatively short panels, even though the ZIP model provides a better fit according to the BIC criteria used for model selection. For a similar argument see Bushway et al. (2003).

likelihood ratio tests are not appropriate for defining whether the addition of a group improves the explanatory power of the model (D'Unger et al. 1998). BIC $= \log(L) - .5 \times \log(n) \times (k)$; where "$L$" is the value of the model's maximized likelihood estimates, "n" is the sample size, and "k" is the number of parameters estimated in a given model. Because more sophisticated models almost always improve the fit of a given analysis, the BIC encourages a parsimonious solution by penalizing models that increase the number of trajectories unless they substantially improve fit. In addition to the BIC, trajectory analysis requires that researchers also consider posterior probabilities of trajectory assignments, odds of correct classification, estimated group probabilities, and whether meaningful groups are revealed (for a more detailed discussion, see Nagin 2005).

These models are highly complex, and researchers run the risk of arriving at a local maximum, or peak in the likelihood function, which represents a sub-optimal solution. The stability of the answer when providing multiple sets of starting values should be considered in any model choice. In the final analysis, the utility of the groups is determined by their ability to identify distinct trajectories, the number of units in each group, and their relative homogeneity (Nagin 2005).

We began our modeling exercise by fitting the data to three trajectories. We then fit the data to four trajectories and compared this fit with the three-group solution. When the four-group model proved better than the three-group, we then estimated the five-group model and compared it to the four-group solution. We continued adding groups, each time finding an improved BIC, until we arrived at 24 groups. Models for 23 and 24 groups were not stable and could not be replicated consistently. After reviewing the Bayesian Information Criteria and the patterns observed in each solution, it was determined that a 22 group model was the most optimal model for the crime data. We therefore chose the 22 group model.

The validity of the model was also confirmed by conducting the posterior probability analysis. The majorities of the within-group posterior probabilities in the model are above .90, and the lowest posterior probability is .77. The lowest value of the odds of correction classification (OCC) is 26.58. Nagin (2005) suggests that when average posterior probability is higher than .7 and OCC values are higher than 5, the group assignment represents a high level of accuracy. Judging by these standards, the 22-group model performs satisfactorily in classifying the various crime patterns into separate trajectories.

References

Aitken SC, Cutter SL, Foote KE, Sell JL (1989) Environmental perception and behavioral geography. In: Wilmott Gaile (ed) Geography in America. Columbus, Merrill, pp 218–238

Bailey TC, Gatrell AC (1995) Interactive spatial data analysis. Longman Group Limited, Essex

Baller RD, Anselin L, Messner Steven F, Deane G, Hawkins DF (2001) Structural covariates of US county homicide rates: incorporating spatial effects. Criminology 39:561–590

Baumer EP, Lauritsen JL, Rosenfeld R, Wright R (1998) The influence of crack cocaine on robbery, burglary, and homicide rates: a cross-city, longitudinal analysis. J Res Crime Delinq 35:316–340

Boggs S (1965) Urban crime patterns. Am Sociol Rev 30:899–908

Braga AA (2001) The effects of hot spots policing on crime. Ann Am Acad Pol Soc Sci 578:104–125

Braga AA, Papachristos AV, Hureau D (2009) The concentration and stability of gun violence at micro places in Boston, 1980–2008. J Quant Criminol. doi:10.1007/s10940-009-9082-x

Brantingham PJ, Brantingham PL (1984) Patterns in crime. Macmillan, New York

Brantingham PJ, Brantingham PL (1991) Environmental criminology. Waveland Press, Inc., Prospect Heights (1981)

Brantingham PL, Brantingham PJ (1993) Environment, routine, and situation: toward a pattern theory of crime. In: Clarke RV, Felson M (eds) Routine activity and rational choice, vol 5. Transaction Publishers, New Brunswick, pp 259–294
Brantingham PL, Brantingham PJ (1995) Criminality of place: crime generators and crime attractors. Eur J Crim Pol Res 3:5–26
Brantingham PL, Brantingham PJ (1999) Theoretical model of crime hot spot generation. Stud Crime Crime Prev 8:7–26
Brantingham PL, Brantingham PJ (2008) Crime analysis at multiple scales of aggregation: a topological approach. In: Weisburd D, Bernasco W, Bruinsma G (eds) Putting crime in its place: units of analysis in spatial crime research. Springer, New York, pp 87–108
Brantingham PJ, Dyreson DA, Brantingham PL (1976) Crime seen through a cone of resolution. Am Behav Sci 20:261–273
Bursik RJJ, Grasmick HG (1993) Neighborhoods and crime: the dimensions of effective community control. Lexington Books, New York
Bursik RJJ, Webb J (1982) Community change and patterns of delinquency. Am J Soc 88:24–42
Bushway SD, Thornberry TP, Krohn MD (2003) Desistance as a developmental process: a comparison of static and dynamic approaches. J Quant Criminol 19:129–153
Byrne JM, Sampson RJ (eds) (1986) Social ecology of crime. Springer, New York
Chainey S, Tompson L, Uhlig S (2008) The utility of hotspot mapping for predicting spatial patterns of crime. Secur J 21:4–28
Chakravorty S, Pelfrey WVJ (2000) Exploratory data analysis of crime patterns: preliminary findings from the Bronx. In: Goldsmith V, McGuire P, Mollenkopf G,JH, Ross TA (eds) Analyzing crime patterns: frontiers of practice. Sage Publications, Thousand Oaks, pp 65–76
Chilton RJ (1964) Continuity in delinquency area research: a comparison of studies for Baltimore, Detroit, and Indianapolis. Am Sociology Rev 29:71–83
Clarke RV (1983) Situational crime prevention: its theoretical basis and practical scope. In: Tonry M, Morris N (eds) Crime and justice: an annual review of research, vol 14. University of Chicago Press, Chicago, pp 225–256
Clarke RV, Felson M (1993) Introduction: criminology, routine activity, and rational choice. In: Clarke RV, Felson M (eds) Routine activity and rational choice, vol 5. Transaction Publishers, New Brunswick, pp 1–14
Cohen LE, Felson M (1979) Social change and crime rate trends: a routine activity approach. Am Sociol Rev 44:588–608
Cohen J, Tita G (1999) Diffusion in homicide: exploring a general method for detecting spatial diffusion processes. J Quant Criminol 15:451–493
Cork D (1999) Examining space-time interaction in city-level homicide data: crack markets and the diffusion of guns among youth. J Quant Criminol 15:379–406
Crow W, Bull J (1975) Robbery deterrence: an applied behavioral science demonstration—final report. Western Behavioral Science Institute, La Jolla
D'Unger AV, Land KC, McCall PL, Nagin DS (1998) How many latent classes of delinquent/criminal careers? Results form mixed poisson regression analysis. Am J Sociol 103:1593–1630
Eck JE (1995) Examining routine activity theory: a review of two books. JQ 12:783–797
Eck JE, Weisburd D (1995) Crime places in crime theory. In: Eck JE, Weisburd D (eds) Crime and place. Willow Tree Press, Monsey, NY, pp 1–33
Eck JE, Chainey S, Cameron JG, Leitner M, Wilson RE (2005) Mapping crime: understanding hotspots. National Institute of Justice, Washington, DC
Eggleston EP, Laub JH, Sampson RJ (2004) Methodological sensitivities to latent class analysis of longterm criminal trajectories. J Quant Criminol 20:1–26
Felson M (1986) Predicting crime potential at any point on the city map. In: Figlio RM, Hakim S, Rengert GF (eds) Metropolitan crime patterns. Criminal Justice Press, Monsey, pp 127–136
Felson M (1987) Routine activities and crime prevention in the developing metropolis. Criminology 25:911–931
Felson M (2002) Crime in everyday life, 3rd edn. Sage, Thousand Oaks
Fotheringham AS, Brundson C, Charlton M (2000) Quantitative geography. Sage Publications, London
Gold JR (1980) An introduction to behavioural geography. Oxford University Press, New York
Golledge RG, Timmermans H (1990) Applications of behavioural research on spatial problems I: cognition. Prog Hum Geogr 14:57–99
Griffiths E, Chavez JM (2004) Communities, street guns, and homicide trajectories in Chicago, 1980–1995: merging methods for examining homicide trends across space and time. Criminology 42:941–978

Groff ER, LaVigne NG (2001) Mapping an opportunity surface of residential burglary. J Res Crime Delinq 38:257–278
Groff ER, Weisburd D, Morris N (2008) Where the action is at places: examining spatio-temporal patterns of juvenile crime at places using trajectory analysis and GIS. In: Weisburd D, Bernasco W, Bruinsma G (eds) Putting crime in its place: units of analysis in spatial crime research. Springer, Berlin
Grubesic TH, Mack EA (2008) Spatio-temporal interaction of urban crime. J Quant Criminol 24:285–306
Guerry A-M (1833) Essai sur la Statisticque morale de la France. Crochard, Paris
Hillier B (1999) The common language of space: a way of looking at the social, economic and environmental functioning of cities on a common basis. Retrieved February 17, 2004, from http://www.spacesyntax.org/publications/commonlang.html
Hillier B (2004) Can streets be made safe? Urban Des Int 9:31–45
Jacobs J (1961) The death and life of great American cities. Vintage Books, New York
Jefferis E (2004) Criminal places: a micro-level study of residential theft . Unpublished Dissertation, University of Cincinnati, Cincinnati
Jeffery CR (1971) Crime prevention through environmental design. Sage Publications, Beverly Hills
Johnson SD, Lab SP, Bowers KJ (2008) Stable and fluid hotspots of crime: differentiation and identification. Built Environ 34:32–45
Jones BL, Nagin DS, Roeder K (2001) A SAS procedure based on mixture models for estimating developmental trajectories. Sociol Methods Res 29:374–393
Kaluzney SP, Vega SC, Cardoso TP, Shelly AA (1998) S+SpatialStats: users manual for Windows and UNIX. Insightful, Seattle, WA
Kinney JB, Brantingham PL, Wuschke K, Kirk MG, Brantingham PJ (2009) Crime attractors, generators and detractors: land use and urban crime opportunities. Built Environ 34:62–74
Kornhouser R (1978) Social sources of delinquency: an appraisal of analytic models. University of Chicago, Chicago
Kubrin CE, Herting JR (2003) Neighborhood correlates of homicide trends: an analysis using growth-curve modeling. Sociol Quart 44:329–350
Lab SP (2007) Crime prevention: approaches, practices, evaluations. Anderson Publishing, Cincinnati
Lehoczky J (1986) Random parameter stochastic process models of criminal careers. In: Blumstein A, Cohen J, Roth JA, Visher CA (eds) Criminal careers and career criminals. National Academy of Sciences Press, Washington, DC
Levine N (2005) CrimeStat: a spatial statistics program for the analysis of crime incident locations, vol 3.0. Ned Levine & Associates, Houston, TX and National Institute of Justice, Washington, DC
Linnell D (1988) The geographic distribution of hot spots of robbery, rape, and auto theft in Minneapolis . Unpublished MA, University of Maryland, College Park
Loftin C, Hill RH (1974) Regional subculture and homicide: an examination of the Gastil-Hackney thesis. Am Sociol Rev 39:714–724
Maltz MD (1996) From Poisson to the present: applying operations research to problems of crime and justice. J Quant Criminol 12(1):3–61
Merry SE (1981) Defensible space undefended: social factors in crime control through environmental design. Urban Aff Q 16:397–422
Messner SF, Anselin L (2004) Spatial analysis of homicide with areal data. In: Goodchild MF, Janelle DG (eds) Spatially integrated social science. Oxford University Press, New York, pp 127–144
Moffitt TE (1993) Adolescence-limited and life-course persistent antisocial behavior: a developmental taxonomy. Psychol Rev 100:674–701
Morenoff JD, Sampson RJ (1997) Violent crime and the spatial dynamics of neighborhood transition: Chicago, 1970–1990. Soc Forces 76:31–64
Nagin DS (1999) Analyzing developmental trajectories: a semiparametric group-based approach. Psychol Methods 4:139–157
Nagin DS (2005) Group-based modeling of development over the life course. Harvard University Press, Cambridge
Nagin DS, Land KC (1993) Age, criminal careers, and population heterogeneity: specification and estimation of a nonparametric, mixed poisson model. Criminology 31:327–362
Nagin DS, Farrington DP, Moffitt TE (1995) Life-course trajectories of different types of offenders. Criminology 33:111–139
Newman O (1972) Defensible space: crime prevention through environmental design. Macmillan, New York
Oberwittler D, Wikstrom P-O (2008) Why small is better: advancing the study of the role of behavioral context in crime causation. In: Weisburd D, Bernasco W, Bruinsma G (eds) Putting crime in its place: units of analysis in spatial crime research, vol 35–60. Springer, New York

Osgood DW (2000) Poisson-based regression analysis of aggregate crime rates. J Quant Criminol 16(1): 21–43
Pierce G, Spaar S, Briggs LR (1986) The character of police work: strategic and tactical implications. Center for Applied Social Research, Northeastern University, Boston
Potchak MC, McGloin JM, Zgoba KM (2002) A spatial analysis of criminal effort: auto theft in Newark, New Jersey. Crim Just Pol Rev 13:257–285
Quetelet AJ (1831[1984]) Research on the propensity for crime at different ages (trans: Test Sylvester SF). Anderson Publishing Co, Cincinnati
Ratcliffe JH (2004) Geocoding crime and a first estimate of a minimum acceptable hit rate. Int J Geogr Inf Syst 18:61–72
Raudenbush SW (2001) Comparing personal trajectories and drawing causal inferences from longitudinal data. Annu Rev Psychol 52:501–525
Reiss A J Jr, Tonry M (1986) Preface. In: Reiss A J Jr, Tonry M (eds) Communities and crime. University of Chicago Press, Chicago, pp 1–34
Rengert G, Lockwood B (2008) Geographical units of analysis and the analysis of crime. In: Weisburd D, Bernasco W, Bruinsma G (eds) Putting crime in its place: units of analysis in spatial crime research, vol 109–122. Springer, New York
Robinson JB, Lawton BA, Taylor RB, Perkins DD (2003) Multilevel longitudinal impacts of incivilities: fear of crime, expected safety, and block satisfaction. J Quant Criminol 19:237–274
Roman CG (2002) Schools as generators of crime: routine activities and the sociology of place . Unpublished Dissertation, American University, Washington DC
Roncek DW (2000) Schools and crime. In: Goldsmith V, McGuire P, Mollenkopf G,JH, Ross TA (eds) Analyzing crime patterns: frontiers of practice. Sage Publications, Thousand Oaks, pp 153–165
Rowlingson BS, Diggle PJ (1993) Splancs: spatial point pattern analysis code in S-plus. Comput Geosci 19:627–655
Sampson RJ, Raudenbush SW (1999) Systematic social observation of public spaces: a new look at disorder in urban neighborhood *s*. Am J Soc 105:603–651
Schuerman L, Kobrin S (1986) Community careers in crime. In: Reiss AJJ, Tonry M (eds) Communities and crime. University of Chicago, Chicago, pp 67–100
Sherman LW (1995) Hot spots of crime and criminal careers of places. In: Eck J, Weisburd DL (eds) Crime and place, vol 4. Willow Tree Press, Monsey
Sherman LW, Weisburd D (1995) General deterrent effects of police patrol in crime ‘hot spots’: a randomized, controlled trial. JQ 12:625–648
Sherman LW, Gartin P, Buerger ME (1989) Hot spots of predatory crime: routine activities and the criminology of place. Criminology 27:27–55
Skogan WG (1986) Fear of crime and neighborood change. In: Reiss AJJ, Tonry M (eds) Communities and crime. University of Chicago Press, Chicago, pp 203–230
Smith WR, Frazee SG, Davison EL (2000) Furthering the integration of routine activity and social disorganization theories: small units of analysis and the study of street robbery as a diffusion process. Criminology 38:489–523
Spring JV, Block CR (1988) Finding crime hot spots: experiments in the identification of high crime areas. Paper presented at the Midwest Sociological Society
Stark R (1987) Deviant places: a theory of the ecology of crime. Criminology 25:893–909
Taylor RB (1997) Social order and disorder of street blocks and neighborhoods: ecology, microecology, and the systemic model of social disorganization. J Res Crime Delinq 34:113–155
Taylor RB (1998) Crime and small-scale places: what we know, what we can prevent, and what else we need to know. In: Taylor RB, Bazemore G, Boland B, Clear TR, Corbett RPJ, Feinblatt J, Berman G, Sviridoff M, Stone C (eds) Crime and place: plenary papers of the 1997 conference on criminal justice research and evaluation, National Institute of Justice, Washington, DC, pp 1–22
Taylor RB (2001) Breaking away from broken Windows: baltimore neighborhoods and the nationwide fight against crime, grime, fear and decline. Westview Press, Boulder
Taylor RB, Gottfredson SD (1986) Enivronmental design, crime, and prevention: an examination of community dynamics. In: Reiss A J Jr, Tonry M (eds) Communities and crime. University of Chicago Press, Chicago, pp 387–416
Taylor RB, National Consortium on Violence Research (1999) A longitudinal look at the incivilities thesis: does disorder bring later crime and decline? Paper presented at the Eastern Sociological Association, Boston, MA
Timmermans H, Golledge RG (1990) Applications of behavioural research on spatial problems II: preference and choice. Prog Hum Geogr 14:311–354

van Wilselm J (2008) Urban streets as micro contexts to commit violence. In: Weisburd D, Bernasco W, Bruinsma G (eds) Putting crime in its place: units of analysis in spatial crime research. Springer, Berlin, pp 199–216

Walmsley DJ, Lewis GJ (1993) People and environment: behavioral approaches in human geography. Longman Scientific & Technical, Essex

Weisburd D (2002) From criminals to criminal contexts: reorienting crime prevention. In: Waring E, Weisburd D (eds) Crime & social organization, vol 10. Transactions Publishers, New Brunswick, pp 197–216

Weisburd D, Braga AA (2002) Hot spots policing. In: Kury H, Fuchs O (eds) Crime prevention: new approaches. Mainz, Germany, Weisner Ring

Weisburd D, Green L (1994) Defining the drug market: the case of the Jersey City DMA system. In: MacKenzie DL, Uchida CD (eds) Drugs and crime: evaluating public policy initiatives. Sage, Newbury Park

Weisburd D, Green L (1995) Policing drug hot spots: the Jersey City drug market analysis experiment. JQ 12:711–735

Weisburd D, Mazerolle L (2000) Drug hot spots and crime. Police Quart 3:331–349

Weisburd D, McEwen T (1997) Introduction: crime mapping and crime prevention. In: Weisburd DL, McEwen T (eds) Crime mapping and crime prevention: crime prevention studies, vol 8. Criminal Justice Press, Monsey, pp 1–26

Weisburd D, Maher L, Sherman LW (1992) Contrasting crime general and crime specific theory: the case of hot spots of crime. In: Adler F, Laufer WS (eds) Advances in criminological theory, vol 4. Transaction Press, New Brunswick, NJ, pp 45–70

Weisburd D, Bushway S, Lum C, Yang S-M (2004a) Trajectories of crime at places: a longitudinal study of street segments in the city of Seattle. Criminology 42:283–321

Weisburd D, Lum C, Yang S-M (2004b) The criminal careers of places: a longitudinal study. US Department of Justice, National Institute of Justice, Washington, DC

Weisburd D, Bruinsma G, Bernasco W (2008) Units of analysis in geographic criminology: historical development, critical issues and open questions. In: Weisburd D, Bernasco W, Bruinsma G (eds) Putting crime in its place: units of analysis in spatial crime research. Springer, New York, pp 3–31

Weisburd D, Groff E, Yang S-M (2009a) Explaining developmental crime trajectories at places: a study of "crime waves" and "crime drops" at micro units of geography. National Institute of Justice, Washington DC (in progress)

Weisburd D, Morris N, Groff ER (2009b) Hot spots of juvenile crime: a longitudinal study of street segments in Seattle, Washington. J Quant Criminol 24:443–467

Weisburd D, Groff E, Yang S-M (under review) Understanding developmental crime trajectories at places: social disorganization and opportunity perspectives at micro units of geography. National Institute of Justice, Washington, DC

Wolfgang ME, Figlio RM, Sellin T (1972) Delinquency in a birth cohort. The University of Chicago Press, Chicago