TRAJECTORIES OF CRIME AT PLACES: A LONGITUDINAL STUDY OF STREET SEGMENTS IN THE CITY OF SEATTLE*

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KEYWORDS: crime places, hot spots, crime drop, trajectory analysis, routine activities, spatial analysis

Studies of crime at micro places have generally relied on cross-sectional data and reported the distributions of crime statistics over short periods of time. In this paper we use official crime data to examine the distribution of crime at street segments in Seattle, Washington, over a 14-year period. We go beyond prior research in two ways. First, we view crime trends at places over a much longer period than other studies that have examined micro places. Second, we use

* This research was supported by National Institute of Justice grant #2001-IJ-CX-0022 to the University of Maryland. Points of view in this paper are those of the authors and do not necessarily represent the U.S. Department of Justice. We want to express our gratitude for the cooperation of the Seattle Police Department, and especially to Chief Gil Kerlikowske for his interest and support of our work. We would also like to thank Lt. Ronald Rasmussen for his assistance in identifying and transferring data for the project, and Anthony Braga, John Eck, Elizabeth Kroff, Daniel Nagin and Lorraine Mazerolle for their thoughtful comments and advice in revising our paper. We owe a special debt to Daniel Nagin for his guidance in applying the trajectory approach to micro crime places.
group-based trajectory analysis to uncover distinctive developmental trends in our data. Our findings support the view that micro places generally have stable concentrations of crime events over time. However, we also find that a relatively small proportion of places belong to groups with steeply rising or declining crime trajectories and that these places are primarily responsible for overall city trends in crime. These findings are particularly important given the more general decline in crime rates observed in Seattle and many other American cities in the 1990s. Our study suggests that the crime drop can be understood not as a general process that occurred across the city landscape but one that was generated in a relatively small group of micro places with strong declining crime trajectories over time.

Traditionally, research and theory in criminology have focused on individuals and communities (Nettler, 1978; Sherman, 1995), with communities examined primarily at larger geographic units such as states (Loftin and Hill, 1974), cities (Baumer et al., 1998) and neighborhoods (Bursik and Grasmick, 1993; Sampson, 1985). Recently, however, criminologists have begun to explore other units of analysis that may contribute to our understanding of the crime equation. An important catalyst for this work came from theoretical perspectives that emphasized the context of crime and the opportunities presented to potential offenders (Weisburd, 2002). In a groundbreaking article on routine activities and crime, for example, Cohen and Felson (1979) suggest the importance of recognizing that the availability of suitable crime targets and the presence or absence of capable guardians influence crime events. Researchers at the British Home Office in a series of studies examining “situational crime prevention” also challenged the traditional focus on offenders and communities (Clarke and Cornish, 1983). These studies showed that crime situations and opportunities play significant roles in the development of crime (Clarke, 1983).

One implication of these emerging perspectives is that micro crime places are an important focus of inquiry (Eck and Weisburd, 1995; Sampson and Groves, 1989; Taylor, 1997). While concern with the relationship between crime and place goes back to the founding generations of modern criminology (Guerry, 1833; Quetelet, 1842), the “micro” approach to places suggested by recent theories has just begun to be examined by criminologists.1 Places in this “micro” context are specific locations within the larger social environments of communities and

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1. It should be noted that a few early criminologists did examine the “micro” idea of place as discussed here (see Shaw et al., 1929). However, interest in micro places was not sustained and did not lead to significant theoretical or empirical inquiry.
neighborhoods (Eck and Weisburd, 1995). They are sometimes defined as buildings or addresses (see Green, 1996; Sherman et al., 1989), sometimes as block faces or street segments (see Sherman and Weisburd, 1995; Taylor, 1997), and sometimes as clusters of addresses, block faces or street segments (see Block et al., 1995; Weisburd and Green, 1995). Research in this area began with attempts to identify the relationship between specific aspects of urban design (Jeffrey, 1971) or urban architecture (Newman, 1972) and crime, but broadened to take into account a much larger set of characteristics of physical space and criminal opportunity (see Brantingham and Brantingham, 1975, 1981; Duffala, 1976; Hunter, 1988; LeBeau, 1987; Mayhew et al., 1976; Rengert, 1980, 1981).

Recent studies point to the potential theoretical and practical benefits of focusing research on micro crime places (Eck and Weisburd, 1995; Sherman, 1995; Taylor, 1997; Weisburd, 2002). A number of studies, for example, suggest that significant clustering of crime at place exists, regardless of the specific unit of analysis defined (see Brantingham and Brantingham, 1999; Crow and Bull, 1975; Pierce et al., 1986; Roncek, 2000; Sherman et al., 1989; Weisburd and Green, 1994; Weisburd et al., 1992). Lawrence Sherman (1995) argues that such clustering of crime at places is even greater than the concentration of crime among individuals. Using data from Minneapolis, Minnesota and comparing these to the concentration of offending in the Philadelphia Cohort Study (see Wolfgang et al., 1972), he notes that future crime is “six times more predictable by the address of the occurrence than by the identity of the offender” (1995:36-37). Sherman asks, “why aren’t we doing more about it? Why aren’t we thinking more about wheredunit, rather than just whodunit?”

The concentration of crime at place suggests significant crime prevention potential for such strategies as hot spots patrol (Sherman and Weisburd, 1995; Weisburd and Braga, 2003) which focus crime prevention resources at specific locations with large numbers of crimes. However, concentration itself does not provide a solid empirical basis for either refocusing crime prevention resources or calling for significant theorizing about why crime is concentrated at places. For example, if “hot spots of crime” shift rapidly from place to place it makes little sense to focus crime control resources at such locations, because they would naturally become free of crime without any criminal justice intervention (Spelman, 1995). Similarly, if crime concentrations can move rapidly across the city landscape, it may not make much sense to focus our understanding of crime on the characteristics of places. Sociologists, for example, have long recognized that the “opportunity for a criminal act” influences the occurrence of crime (Sutherland, 1947:5). However, if such opportunity is widespread with little geographic stability, a focus on
criminal motivation would likely be a more productive concern of criminological inquiry.

While the geographic concentration of crime at place has been well documented in recent years, the stability of crime at hot spots over time has received little research attention. Studies of crime at micro places have generally relied on cross-sectional data and reported the distributions of crime statistics over short periods of time, usually just over a year or two (see Chakravorty and Pelfrey, 2000; Eck et al., 2000; Sherman and Rogan, 1995; Weisburd and Green, 1994). Even studies concerned with the possible stability or instability of the distribution of crime events at micro places have used only a few years of crime data or compared discrete periods separated by long gaps (see Spelman, 1995; Taylor, 1999).

In this paper we use official crime data to examine the distribution of crime at street segments in Seattle, Washington, over a 14-year time period. Our study allows us to go beyond prior research in this area in two ways. First, we are able to view crime trends over a much longer period than other studies that have examined micro crime places. Second, we utilize a group-based statistical technique drawn from developmental criminology that is tailor-made to uncover distinctive developmental trends in the outcome of interest (Nagin, 1999, in press; Nagin and Land, 1993). This technique has the added desirable characteristic of being easy to present in tables and graphs, not an insignificant feature given that our dataset has almost 30,000 units of analysis each with recorded crime for 14 years. While this approach, termed “trajectory analysis,” has not been used to examine micro places in earlier studies, we think it particularly appropriate for gaining a fuller understanding of the development of crime at places over time.

We begin our paper with a discussion of what is known about the nature of the distribution of crime at place over time. We then turn to a description of our data and methods and basic findings. The findings support the view that micro places generally have stable concentrations of crime incidents over time. However, we also find that a relatively small proportion of the total number of places belong to groups that have steeply rising or declining crime trajectories, and that these places are primarily responsible for overall city trends in crime. These findings are particularly important given the more general decline in crime rates observed in most American cities in the 1990s (Blumstein and Wallman, 2000; Hoover, 2000; Travis and Waul, 2002). Our study suggests that the crime drop can be understood not as a general process across the city landscape but one generated in a relatively small group of micro places

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2. For a paper that is applying the trajectory approach to places at a higher geographic level of analysis, see Griffiths and Chavez, 2004.
with strong declining crime trajectories over time. In our discussion and conclusions, we discuss the implications of our findings for future study of crime at place and crime control policies that focus on crime hot spots.

**DISTRIBUTION OF CRIME AT PLACE OVER TIME**

Recent study of crime places has focused primarily on the question of the concentration of crime at micro places often defined as "hot spots." The first use of the term in the case of crime places was brought by Sherman et al. (1989), though the basic idea that crime events were clustered in specific places had been documented in earlier studies (see Abeyie and Harries, 1980; Crow and Bull, 1975; Pierce et al., 1986) and suggested by work in environmental criminology (Brantingham and Brantingham, 1975, 1981). Sherman et al. (1989) found that only 3 percent of the addresses in Minneapolis produced 50 percent of all calls to the police. Their proposal that crime was concentrated in hot spots in urban areas has now been confirmed in a series of studies conducted in different cities using different definitions of hot spot areas (see Brantingham and Brantingham, 1999; Eck et al., 2000; Roncek, 2000; Spelman, 1995; Weisburd and Green, 1994, 2000; Weisburd et al., 1992). For example, Weisburd and Green (2000) found that approximately 20 percent of all disorder crimes and 14 percent of crimes against persons were concentrated in 56 drug crime hot spots in Jersey City, New Jersey, that comprised only 4.4 percent of street segments and intersections in the city. Similarly, Eck et al. (2000) found that the most active 10 percent of places (in terms of crime) in the Bronx and Baltimore accounted for approximately 32 percent of a combination of robberies, assaults, burglaries, grand larcenies and auto thefts.

While scholars have provided a strong empirical basis for the assumption that crime is strongly clustered at crime hot spots, they have so far directed little attention to the question of the distribution of crime at micro places over time. We could identify only two published studies that specifically examined this issue longitudinally. One study conducted by Spelman (1995), looks at specific places such as high schools, public housing projects, subway stations and parks in Boston, using 3 years of official crime information. Dividing his data set into 28-day periods, Spelman used a pooled time series cross-sectional design to examine the sources of variability over time and across the types of sites examined. His findings again replicate the more general assumption of a concentration of crime at specific hot spots, with the "worst 10 percent of locations and times accounting for about 50 percent of all calls for service" (Spelman, 1995:129). But he also finds evidence of a very high degree of stability of crime over time at the places he examines. Long-run differences among locations were responsible for the largest
source of variation in each of the analyses Spelman conducted, leading him to conclude that it "makes sense for the people who live and work in high-risk locations, and the police officers and other government officials who serve them, to spend the time they need to identify, analyze and solve their recurring problems" (1995:131).

Taylor (1999) also reports evidence of a high degree of stability of crime at place over time, examining crime and fear of crime at ninety street blocks in Baltimore, Maryland using a panel design with data collected in 1981 and 1994 (see also Robinson et al., 2003; Taylor, 2001). Data included not only official crime statistics, but also measures of citizen perceptions of crime and observations of physical conditions at the sites. Although Taylor and his colleagues observed significant deterioration in physical conditions at the blocks studied, they found that neither fear of crime nor crime showed significant or consistent differences across the two time periods.

The finding of stability of crime at micro places over time is mirrored in early research on the nature of longitudinal patterns of crime within communities. For example, Shaw and McKay (1942) found that patterns of delinquency in the city of Chicago remained relatively stable over time despite continuous population changes. They argued that the process of invasion and succession of individuals moving into and out of communities contributed to social disorganization, and that subcultures of delinquency were passed on from those leaving to those coming in through institutionalized mechanisms. In particular, the zones of transition were characterized not only by consistently high levels of delinquency but also by many other social ills, such as high infant morbidity, vacant housing and increased opportunities for illegitimate activities.

Calvin Schmid (1960) also identified evidence of stability of crime in communities over time when analyzing geographic patterns in Seattle using a panel approach. Using census tract boundaries and comparing relatively short time frames (from 1939 to 1941 and from 1949 to 1951) Schmid found that when comparing the frequency of homicide, rape, robbery and burglary in these two sets of years, zones that were high in crime remained high and zones that were lower in frequency also remained low. Crime concentrations in Schmid's research were most likely located at the center of the city within the "business district." Schmid also studied the city of Minneapolis from 1933 to 1936 and found similar evidence that areas of the city that had higher concentrations of crime in 1933 also evidenced high concentrations of crime across the four year period.

The assumption of a stability of crime over time in communities was challenged by Bursik and Webb in the 1980s (Bursik, 1986; Bursik and Webb, 1982; Heitgerd and Bursik, 1987). When re-analyzing Shaw and McKay's dataset as well as more recent data from the 1970s on
delinquency in Chicago, they found that Shaw and McKay's argument of the stability of crime in communities with high levels of invasion, succession and population changes may have been a historical artifact, relevant only prior to 1950. Their data suggest that after 1950 there was evidence that large-scale demographic changes corresponded with changes in delinquency rates. They argue that dramatic changes in population can increase social disorganization in communities and that corresponding increases in delinquency rates will only begin to settle when communities reestablish themselves.

Bursik and his colleagues' work was to spark further thinking about how crime develops in communities that we think particularly relevant to understanding the development of crime at micro places over time. In particular, some scholars began to discuss the possibility of communities having "criminal careers." Schuerman and Kobrin (1986), for example, suggested the application of a developmental model to explain neighborhood crime characteristics over time. Although their research focused on the non-recursive relationship between physical deterioration and crime, it emphasized the move away from thinking about longitudinal crime patterns as stable towards explaining changing crime frequencies over geography (see also McDonald, 1987 who discusses the effect of gentrification on crime rates).

The idea that the developmental concept of criminal careers might also apply to micro crime places has recently been raised by Sherman (1995) and Weisburd (1997). They argue that a fuller understanding of crime places must examine the dynamics of change over time and look to innovations in developmental models of individual criminal careers for insights into the criminal careers of places. As we have described above, research on the distribution of crime at place over time has been restricted both by the data available and the statistical tools used. Below, we examine crime data over a much longer time series than available to other researchers to explore the nature of longitudinal crime trends in Seattle, Washington. We also employ a dynamic statistical model that permits identification of varying trajectories of criminal careers of places.

DATA AND UNIT OF ANALYSIS

The specific focus of our study is micro crime places, defined as street segments, over a 14-year period in Seattle, Washington. We chose that city after a careful screening of available crime data on American cities with populations of over 200,000. We found the Seattle Police Department to be among a small group of police agencies with a relatively long history of official data on crime trends collected in computerized format. Seattle was also chosen because it included a diverse population, significant levels of
crime during the study period, and was guided by a police administrator fully committed to aiding a basic research program on crime places.

Seattle spans approximately 84 square miles. According to the 2000 U.S. census, it is the 22nd most populous city (563,374) in the United States and its population has remained relatively constant from 1970 to 2000. Although Seattle's population is primarily Caucasian (70.1 percent), it has a substantial ethnic mix of African Americans (8.4 percent), Asians (13.1 percent), Hispanics (5.3 percent) and American Indians (1.0 percent). The number of crimes per 100,000 people in Seattle was 8,004 in 2002, 1.4 times the average for cities with populations between 100,000 and 1,000,000 (Federal Bureau of Investigation, 2002). Compared with cities in a narrower population range (±100,000 of Seattle's population), Seattle's crime rate was slightly higher than the average (7,640) and ranked eighth in sixteen jurisdictions in this category.

We used computerized records of written reports often referred to as "incident reports" to examine crime trends. Incident reports are generated in the Seattle Police Department by police officers or detectives after an initial response to a request for police service. In this sense, incident reports are more inclusive than arrest reports but less inclusive than calls for service. We chose not to use calls for service primarily because such data are kept by Seattle for only 4 years. Also, in a separate analysis on these data, Lum (2003) found that calls for service and crime reports often generate very similar distributions of crime across place. We did not use arrest reports because we thought they would screen too much crime from our field of observation.

The geographic unit of interest for this study is the street segment (sometimes referred to as a street block or face block) defined as the two block faces on both sides of a street between two intersections. We chose the street segment for a number of reasons. Scholars have long recognized its relevance in organizing life in the city (Appleyard, 1981; Jacobs, 1961; Smith et al., 2000; Taylor, 1997). Taylor, for example, argues that the visual closeness of block residents, interrelated role obligations, acceptance of certain common norms and behavior, common regularly recurring rhythms of activity, the physical boundaries of the street, and the historical evolution of the street segment make the street block or street segment a particularly useful unit for analysis of place (see also Hunter and Baumer, 1982; Taylor et al., 1984).

The choice of street segments over smaller units such as addresses (see Sherman et al., 1989) also minimizes the error likely to develop from miscoding of addresses in official data (see Klinger and Bridges, 1997; Weisburd and Green, 1994). We recognize however, that crime events may be linked across street segments. For example, a drug market may operate across a series of blocks (Weisburd and Green, 1995; Worden et
al., 1994), and a large housing project and problems associated with it may transverse street segments in multiple directions (see Skogan and Annan, 1994). Nonetheless, we thought the street segment a useful compromise because it allows a unit large enough to avoid unnecessary crime coding errors, but small enough to avoid aggregation that might hide specific trends.

We decided at the outset to exclude those incidents that occurred at an intersection or could not be linked to a specific street segment. Of the 2,028,917 crime records initially obtained from the city from 1989 to 2002, 19 percent were linked to an intersection. Our decision to exclude these events was primarily technical. Intersections could not be assigned to any specific street segment because they were generally part of four different ones. However, it is also the case that incident reports at intersections differed dramatically from those at street segments. Traffic-related incidents accounted for only 4.5 percent of reports at street segments, but for 44 percent of reports at intersections. Places without specific geographic identifiers (for example, “University of Washington” or “Hay Street Market”) that could not be linked to a specific street segment were also excluded. Such geographically undefined places accounted for 2 percent of the incident reports in our data base. After excluding intersections, generally defined places, and records without locations, we were left with 1,544,604 incident reports across the 14-year period requiring conversion into a Seattle street segment.

Linking incident reports with street segments was a two-step process: ensuring that the location recorded was legitimate and recognizable, and then converting it to its corresponding street segment. We identified 29,849 street segments from the street map of Seattle. To convert event locations into a corresponding segment, we used both a geographic

3. Normally, a street segment in Seattle is delimited in multiples of 100. For example, addresses from 100 to 199 Main Street would most likely occur on one street segment, between two intersections or other divisions. However, there are cases in Seattle where segments could potentially extend from 100 to 299, without an intersection break. To ascertain which of Seattle segments were within the scope of a “hundred block” and which extended further would have required physically examining each street in Seattle, a task beyond the scope of this research. Even the computerized map used (from the City of Seattle’s Information Technology Division) did not provide any clues regarding the extent of this problem. The database supporting the shapefile (computerized map) of Seattle’s streets simply gave the street name and the beginning and ending house numbers for each street on the odd and even sides. To overcome this issue, the database supporting the Seattle street map was used to develop “hundred blocks” for each city street in Seattle. For example, if the base map listed a street as spanning house numbers 1 through 399, we created four segments from this range: 1-99, 100-199, 200-299, and 300-399.
information system (ARCGIS 8.2) as well as data manipulation software (Visual Foxpro). Geographic information systems (GIS) are designed to find the positions on the earth's surface of addresses in a database (a process known as "geocoding"), which can then be mathematically analyzed or electronically mapped. In our study we used ARCGIS both to verify whether addresses were legitimate and to help correct or "clean" addresses (interactively with Foxpro) that could not initially be matched to a computerized street map in Seattle.

Approximately 2.5 percent of the 1,544,604 records could not be matched to a legitimate address. We exclude these and two other types of records: those whose location was given as a police precinct or police headquarters and those written for crimes that occurred outside city limits. The use of a police precinct's address as a location of a crime is common, according to the Seattle police department, when no other address can be ascertained by the reporting officer. This left 1,490,725 crime records that were then converted into their corresponding street segments so that crime frequencies for each of the 29,849 segments for each year could be calculated.

DESCRIBING THE OVERALL DISTRIBUTION

Table 1 provides the overall distribution of incident reports in our 14 observation years. The most common was property crime (49.3 percent) followed by disorder, drug and prostitution offenses (17 percent) and violent person-to-person crime (11.4 percent). Another 16.6 percent of the incident reports were defined in various related categories such as weapon offenses, violations, warrants, domestic disputes, missing persons, juvenile-related offenses, threats and alarms. The remaining events were coded as traffic-related or unknown.

4. ARCGIS 8.2 is a product of Environmental Systems Research Institute.
5. Visual FOXPRO is a product of the Microsoft Corporation.
6. It should be noted that street segments could have been added or removed from the Seattle street map over the 14-year period. While the City of Seattle could only provide us with their most recent up-to-date street map as of the year 2001, we recognize that this issue could be a small source of error.
7. We were not able to distinguish for "traffic" and "unknown" cases whether incidents were crime related because the incident report database does not include details of the events recorded. According to the Seattle Police Department, traffic incident reports were most likely not traffic citations, but rather hit and run crimes, drunk driving and accidents involving injuries. In cases where events were clearly not crime related, such as reports of assistance or administrative activities of police, we excluded them.
Before we turn to our analysis of the dynamic patterns of crime at place over time, we wanted to examine our data in the context of the more general assumption of the concentration of crime at place. Of the 29,849 existing streets segments in Seattle, 23,135 had at least one incident over the 14-year period, leaving 6,714 segments with none. The mean number of incidents per segment was approximately 3.6 (sd = 11.8). Crime trends in Seattle overall followed the national pattern (see Blumstein and Wallman, 2000), with a decline in incident reports at least since 1992 (see Figure 1). Between 1989 and 2002, Seattle street segments experienced a 24-percent decline in the number of incidents recorded.

Table 1. Overall Distribution of Incident Reports

<table>
<thead>
<tr>
<th>Type of Incident Report</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Property Crimes (all theft, burglary, property destruction)</td>
<td>49.3%</td>
</tr>
<tr>
<td>Disorder, Drugs, Prostitution</td>
<td>17.0%</td>
</tr>
<tr>
<td>Person Crimes (homicide, all assault, rape, robbery, kidnapping)</td>
<td>11.4%</td>
</tr>
<tr>
<td>Other Nontraffic Crime Related Events (for example, weapon offenses, violations, warrants, domestic disputes, missing persons, juvenile-related offenses, threats and alarms)</td>
<td>16.6%</td>
</tr>
<tr>
<td>Traffic-related (hit and run, drunk driving, accidents with injuries)</td>
<td>4.7%</td>
</tr>
<tr>
<td>Unknown</td>
<td>1.0%</td>
</tr>
<tr>
<td>Total</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

Figure 1. Seattle Street Segment Crime Trends
Examined year by year our data confirm findings from prior studies that indicate a strong concentration of crime in "hot spots" (see Figure 2). Moreover, they suggest that the general concentration of crime in hot spots follows a consistent pattern over time. Sherman et al. (1989) report that over a year 50.4 percent of all calls for service in Minneapolis occurred at 3.3 percent of all addresses and intersections and that 100 percent of such calls occurred at 60 percent of all addresses. Very similar findings for all reported incidents are found for each of the 14 years observed in Seattle (see Figure 2). Between 4 and 5 percent of the street segments account for about 50 percent of incidents in our data in each of the years examined. All incidents are found in between 48 and 53 percent of the street segments.

Figure 2. Crime Concentration in "Hot Spots"

A simple review of our data also suggests a significant degree of stability of crime concentrations over time. In Figure 3 we report the percentage of street segments in each year with a specific number of incident reports. Though there is variability, the overall distribution is fairly similar from year to year. For example, the percentage with no recorded crime varies between 47 percent and 52 percent. Similarly, the proportion of street segments with one to four incidents varies only
slightly, between 34 percent and 35 percent. The proportion with more than 50 recorded crime events in a year is approximately 1 percent across all 14 years.

Figure 3. Crime Concentration Stability across Seattle Street Segments

Though the proportions of street segments with a specific threshold of crime activity remain fairly consistent year to year, it may be that the specific segments within each of these thresholds change. Accordingly, it is important to identify not only the general patterns over time but also how each of the 29,849 street segments’ crime frequencies changed. This descriptive exercise on the aggregate data leads to two key questions. First, is the stability evidenced in our simple descriptive analysis of the proportion of places with a specific threshold of crime in a specific year replicated if we examine the developmental patterns of offending of places over time? Second, are there different patterns of crime over time for different groups of street segments?

TRAJECTORY ANALYSIS

We are unaware of any available technique in use in the criminology of place that would allow us to answer these questions, but such a technique—group based trajectory analysis—has been used in developmental social science more broadly (Nagin, 1999, in press; Nagin and Land, 1993). This technique and related complementary growth curve
techniques such as hierarchical linear modeling (Bryk and Raudenbush, 1987, 1992; Goldstein, 1995) and latent curve analysis (McArdle and Epstein, 1987; Meredith and Tisak, 1990; Muthen, 1989; Willet and Sayer, 1994) are designed to allow developmental researchers in the social sciences to measure and explain differences across population members as they follow their developmental path. The need for such techniques arose in the 1980s as psychologists, sociologists and criminologists all began to turn to the study of developmental processes rather than to static events or states (see Bushway et al., 2001; Hagan and Palloni, 1988; Laub et al., 1998; Loeber and LeBlanc, 1990; Moffitt, 1993).

The group-based trajectory model, first described by Nagin and Land (1993) and further elaborated in Nagin (1999, in press), 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; Nagin and Tremblay, 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 an individual to a group based on their highest probability.

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 is one such case where this group-based trajectory approach is justified: not everyone participates in crime, and people appear to start and stop at very different ages (Muthen, 2001; Nagin, 1999) or Nagin (in press).

8. For an overview of these methods, see Raudenbush (2001), Muthen (2001), Nagin (1999) or Nagin (in press).

9. 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 parametric assumptions in random effects model (Bushway et al., 2003). For a different perspective on this issue, see Eggleston et al. (2003).
TRAJECTORIES OF CRIME AT PLACES

Nagin, 1999, in press; Raudenbush, 2001). Given that we have no strong expectation about the basic pattern of change, the group-based trajectory approach is an excellent choice for identifying major patterns of change in our data set.\textsuperscript{10}

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).\textsuperscript{11} We chose Proc Traj. When estimating trajectories of count data, Proc Traj requires that we make three decisions: 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).\textsuperscript{12} 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 because conventional 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). 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 (McLachlan and Peel, 2000). In the final analysis, the utility of the groups is determined by their ability to identify distinct trajectories.

\textsuperscript{10} Those interested in a more detailed description of the group-based trajectory approach should see Nagin (1999) or Nagin (in press).

\textsuperscript{11} The procedure, with documentation, is available at www.ncovr.heinz.cmu.edu.

\textsuperscript{12} 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).
the number of units in each group, and their relative homogeneity (Nagin, in press).

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 nineteen groups. We were unable, despite repeated attempts, to estimate the twenty-group solution and interpret this failure to mean that such a solution is not viable. The nineteen-group solution had a better BIC score than the eighteen-group, but proved very unstable, meaning that it did not converge to the same solution in multiple attempts with similar starting values. In each case, the model simply divided a larger group into two parallel curves. In contrast, the eighteen-group model found the same solution in at least four attempts from different starting values, and created a new group with a different shape than we found in the seventeen-group analysis. We therefore chose the eighteen-group model with a BIC score of -626,182.42.

Figure 4 illustrates the final eighteen trajectories we obtained with the percentage of segments that fall within each trajectory. The figure presents the actual average number of incident reports found in each group over the 14 year time period. The main purpose of trajectory analysis is to identify the underlying heterogeneity in the population. What is most striking, however, is the tremendous stability of crime at places suggested by our analysis. Looking at the trajectories, it is clear that although many have different initial intercepts in terms of the level of criminal activity observed, most evidence relatively stable slopes of change over time.

This finding can be interpreted more easily if we classify our trajectories into common patterns. To simplify our description and to focus our discussion more directly on the question of stability of crime at place across time, we divided the trajectories from Figure 4 into three groups: stable, increasing and decreasing trajectories (Figures 5, 6 and 7, respectively). To aid in this classification, which does not depend on the quadratic term in the fitted trajectories, we fit a linear curve to the average number of offenses at each time point for each group. This created eighteen linear trend lines that were either basically stable, declining or

13. It is worth noting that this model was extremely complex because of the large number of segments. As a result, the model estimation was time and computer intensive. For example, the eighteen-group model took 8 hours and 15 minutes to converge using an AMD Athlon (TM) 2100 1.73 GHZ machine with 1.00 GB of RAM.
Figure 4. Eighteen Trajectory Solution for Seattle Street Segments

Note: The percentages in parentheses represent the proportion of street segments that each trajectory accounts for in the city of Seattle.
increasing. Under each figure, we provide the fitted linear slope and intercept for each trajectory.\footnote{We justify our use of a fitted linear trend to curves estimated using a quadratic functional form in the present case because we are primarily interested in differentiating between the simple direction of the trend, and not the shape of the downward or upward trend. Use of the simple linear slope makes this classification easier to present than if we provided the parameters of the quadratic curves. We also use the approach of presenting the actual number of events because of the unique nature of geographic, rather than individual data. In this case, we had a number of segments that routinely reported more than fifty crimes. This seems plausible in the case of places, but is unrealistic in the case of individuals, where the most likely explanation for such outliers is over reporting or data entry error. In most analyses of individuals (see Nagin and Land 1993; Jones et al. 2001), the distribution is truncated at approximately fifty to estimate Proc Traj, a practice done without loss of generality. In this case however, presenting the smoothed estimates using the data truncated at fifty would in fact be misleading because these types of high crime places are plausible, realistic and an important part of the crime story in Seattle. To get around the shortcomings of the parametric form without harming the descriptive story, we first estimated the groupings based on the truncated distribution, but report the graphs using the untruncated, actual data. This manipulation only affected approximately 1 percent of the segments over the 14 years.}

As is apparent in Figure 5, the stable trajectories had slopes very close to 0 (ranging from between -.0779 and .1412). Eight of the eighteen trajectories we identified fit this pattern, and they represent fully 84 percent of all the segments we examined. This suggests that most of the street segments in the city did not follow the general crime decline found in Seattle as a whole. Indeed, there is a decrease of only 1,590 in incident reports between 1989 and 2002 in stable trajectories, a decline of only 4 percent. This may be contrasted with the overall decline of about 30,000 incidents in the city as a whole, a 24-percent drop.

It is important to note that these trajectories overall also had relatively low intercepts. For example, trajectories 1 and 2 account for almost half of all the street segments in the city, but may be classified more generally as "no crime" segments, given that their trajectories remain close to zero. In contrast, however, trajectory 12, accounting for about 2 percent of the street segments, shows a stable crime pattern of just over 10 incidents per year and trajectory 9, accounting for almost 4 percent of the segments, has a rate of about 7 incidents per year.

The number of street segments found in trajectories that represented noticeable increasing slopes during the study period is comparatively small. Only three trajectories of this type are identified in our study, and they account for only about 2 percent of the street segments in Seattle as a
Figure 5. Stable Trajectories

Figure 6. Increasing Trajectories
whole (see Figure 6). Nonetheless, the overall crime changes noted here are generally relatively large. Trajectory 10, though beginning with a very low rate of crime, increased its average crime rate more than four fold during the observation period to more than 20 incident reports per year. Trajectory 15 increased from about 20 to more than 40 incidents. Overall these segments accounted for a 6,507 increase in incident reports between the first and final observation years, a 42-percent increase in reported crime over the period.

![Figure 7. Decreasing Trajectories](image)

Another seven trajectories identified in our analysis account for about 14 percent of the street segments in the city and can be classified as having noticeably decreasing slopes (Figure 7). The extent of the declining slopes varied a good deal across the segments identified here (between -2.1302 to -0.2782), as did the intercepts observed. It is significant that, despite the variability of crime across these segments over time, the highest rate trajectories remain relatively high throughout the observation period, and the lower rate trajectories remain lower both in terms of their intercepts and final estimates. For example, the highest rate trajectory begins at a rate of almost 95 incidents and has at the end of our study an average rate of more than 75 incidents. This is still a higher rate than any other
trajectory in our study. Similarly, the largest declining slope (trajectory 18) has an initial estimate of over 50 incidents and falls to about 25. Again, this is still higher than the final estimates for all lower intercept decreasing trajectories we examine.

Overall, as illustrated in Figure 8 these decreasing segments appear to account for the crime drop observed in Seattle during the study period. The area at the bottom of the figure represents crime that occurred in stable trajectories, and shows that the overall number of incident reports in these segments remains relatively stable throughout the 14 years examined in our study. The increasing trajectories, represented in the next shaded area, provide for a slight increase in crime. When combining both stable and increasing trajectories, representing about 86 percent of the street segments, we identify a small increase in crime between 1989 and 2002. In contrast, we can see that the shaded area associated with decreasing segments provides a fairly consistent degree of decline in the crime rate as measured by incident reports. Indeed, the decreasing trajectories, which show a decline of about 35,000 incidents between the first and last year of observation, can be seen as more than accounting for the overall crime drop in Seattle street segments of about 30,000 events during the study period.

Figure 8. Seattle Crime Drop Analysis
THE GEOGRAPHY OF CRIME TRAJECTORIES

We think that the use of a micro place level of analysis has allowed us to examine crime trends at places with greater precision. It might be argued, however, that this choice has masked more general clustering of crime trends within neighborhoods or communities, or in terms of geographic analysis, that stable, increasing and decreasing trajectories may not be randomly distributed across space but rather exhibit some spatial dependence that might contribute to the trends. To examine this problem we developed kernel density maps for each of the three types of trajectories identified above (see Figure 9). Kernel density estimations provide a visual interpretation of the number of events across a geographic area, estimated at every point in that area. These estimates of intensity are created using a moving circular window around the region that measures the number of event locations from the center of the window outward at a specified distance, known as a "bandwidth." The intensity is measured at every point to create a "smooth" estimate of the terrain of event locations. To estimate kernel densities of segments classified within stable, increasing or decreasing trajectories, equal bandwidths for each estimation were set at 5000 map units with equal output cell sizes of 500 map units. Equalizing bandwidths and output cell sizes allows for comparison among maps.

We recognize that this is only a general estimate of the concentration of segments within each grouping. Overall, though, Figure 9 suggests that street segments of each of the three defined types are spread throughout the city. At the same time there are places of concentration. Segments classified into stable trajectories, for example (see Figure 9a), appear to have considerable diffusion across the entire city, but are especially prominent in more affluent and less densely populated areas in the north of the city.

15. Formally, the kernel density estimation function is represented by the following equation:

\[ \hat{\lambda}_t(s) = \frac{1}{\hat{\delta}_t(s)} \sum_{i=1}^{n} \frac{1}{\tau^2} k\left( \frac{s - s_i}{\tau} \right) \]

Here, the mean estimated intensity of a particular location is denoted by \( \hat{\lambda}_t(s) \). \( k(\ldots) \) is the probability density function, which is the function of intensity around a particular point, the radius of the kernel being the bandwidth, or \( \tau \) and the center of the kernel, \( s \). See Bailey and Gatrell (1995) for a full explanation of kernel density estimation.

16. While not the focus of this study, we are looking more carefully at the geography of crime trajectories in another paper (see Lum et al., in progress).
Figure 9. Kernel Density Estimations

a. Stable Trajectory Group
b. Increasing Trajectory Group
c. Decreasing Trajectory Group
Supplement to CRIMINOLOGY 42:3

ERRATUM

TRAJECTORIES OF CRIME AT PLACES: A LONGITUDINAL STUDY OF STREET SEGMENTS IN THE CITY OF SEATTLE
  David Weisburd, Shawn Bushway, Cynthia Lum, and Sue-Ming Yang

Originally published in CRIMINOLOGY 42:2

Please use this insert to replace Figure 9 on page 305.
Similarly, though a relatively small proportion of the street segments are increasing trajectories (Figure 9b), we find concentrations in most areas of the city. There is even greater spread of decreasing segments (Figure 9c), though this may be due in part to the larger number of segments in this grouping. At the same time, we do find that there are concentrations of increasing and decreasing trajectories in the urban center of the city. This is particularly interesting in part because it suggests that there may be similar causal processes underlying both types of trajectories.

**DISCUSSION**

In our introduction we argued that prior studies of concentration of crime at place do not provide a solid empirical basis for focusing either theory or practice on micro places. Even if there is tremendous concentration of crime at crime hot spots, as has been documented (see Brantingham and Brantingham, 1999; Crow and Bull, 1975; Pierce et al., 1986; Roncek, 2000; Sherman et al., 1989; Weisburd and Green, 1994; Weisburd et al., 1992), if there is little stability in such concentration across time, the underlying assumptions of this new area of research interest and practical crime prevention would be challenged. Our study enabled us to go beyond prior description of crime at micro places in two ways. First, we were able to examine assumptions about the stability of crime at place looking at a longer time series than has been available in prior research. Second, we were able to investigate whether different developmental trends are found across groups of places. Taking this approach we find strong support for the position of stability of crime at micro places across time.

Eighty-four percent of the street segments we examined could be grouped into what we defined as stable trajectories. That is, the vast majority of street segments in Seattle showed a remarkably stable pattern of crime over a 14-year period. Moreover, even in the case of the increasing and decreasing trajectories, changes in the rates of incident reports over time suggest a kind of stability of scale. For example, the two decreasing trajectories with the highest initial rates of more than fifty incident reports do not decline to fewer than twenty-five at the end of the study period—still placing these trajectories among the most active in our study. And the highest frequency increasing trajectory, which ended in an average count of more than forty incidents, still began with a rate of more than twenty.

It might be argued that the fact that trajectories that show the largest increases or decreases in the number of incident reports are also those with the highest crime frequencies to begin with, suggests that random
factors unlikely to be under the control of the police or the community might play an important part in the crime patterns found in our data. For example, "regression to the mean" could be one explanation for highly variable crime patterns. Very high levels of crime at a particular time might decline simply as part of a more general set of chance processes. While this explanation could apply to the trajectories with the very highest initial incident report rates, it does not explain why we do not find dramatic increases in incident reports over time at the very lowest rate places, which would be the other side of the regression to the mean phenomenon.

While we do not discount the workings of random fluctuations in our data (Spelman, 1995), we think the overall stability that we observe suggests that such fluctuations are much less important than systematic factors. Our data do not allow us to define directly these underlying causes of crime at place. Nonetheless, before concluding we would like to speculate on the potential mechanisms leading to the distributions we observe and discuss the types of studies that would help us to more fully understand crime trajectories at places.

Most study of crime hot spots has relied on routine activities theory (see Cohen and Felson, 1979) as an explanation for why crime trends vary at places and as a basis for constructing practical crime prevention approaches (see Eck, 1995; Sherman et al., 1989). The main assumptions of this perspective are that specific characteristics of places such as the nature of guardianship, the presence of motivated offenders, and the availability of suitable targets will strongly influence the likelihood of criminal events (see also Felson, 1994). Studies examining the factors that predict crime at micro places generally confirm this relationship (see Roncek and Bell, 1981; Roncek and Maier, 1991; Smith et al., 2000).

Routine activities theory does not necessarily predict stability of crime at place over time. Indeed, the theory was originally developed to explain changes in crime rates that were observed over long periods and that were related to changes in routine activities (Cohen and Felson, 1979). But most scholars advocating hot spots approaches have argued that the routine activities of places are likely to be fairly stable over relatively shorter periods of time such as the 14 years in this study (see Sherman, 1995; Weisburd, 2002). The availability of suitable targets, of capable guardians, and the presence of motivated offenders in this context are not expected to change rapidly under natural conditions in the urban landscape, though they are likely to change over longer periods as routine activities of offenders, victims and guardians change as well. Accordingly, the overall stability of crime at place we observe in our data is consistent with routine activities theory.
Although we can only speculate on changes in routine activities over time in Seattle, a theory of routine activities at crime hot spots (see Sherman et al., 1989) might also explain the variability in the increasing and decreasing trajectories. Those advocating hot spots approaches have assumed that the routine activities of places can be altered in the short term by interventions such as greater police presence (see Sherman and Weisburd, 1995; Weisburd and Green, 1995). Indeed, the short-term stability of crime at place predicted by routine activities theory and the assumed amenability of routine activities to change through police or community intervention is seen to provide a strong basis for crime prevention at hot spots (see Braga, 2001; Eck and Weisburd, 1995; Sherman, 1995; Sherman et al., 1989; Taylor, 1997; Weisburd, 2002). It may be that declining trajectories in our study are places where aspects of routine activities that prevent crime have been encouraged, perhaps because the police have focused more attention on them. Increasing crime trajectories could represent places where crime opportunities have increased, perhaps as a result of the introduction of new targets through urban renewal, or motivated offenders through the introduction of easy transportation access or perhaps the displacement of offenders from other crime hot spots that have been the focus of police or other crime prevention measures.

While routine activities theory has been a central feature of recent interest in crime hot spots, it is important to note that other theoretical approaches might also be consistent with our findings. Ecological theories of social disorganization used to explain the stability of crime patterns in communities (see Schmid, 1960; Shaw and McKay, 1942), for example, might also be applied to micro crime places (see Smith et al., 2000). In this case one might expect a stability of crime patterns because there is an underlying social and demographic stability at places (see Bursik, 1986). Conversely, relatively stable high crime rates at places may be explained by continuous social change that prevents the establishment of strong social bonds and community controls at the micro place level (e.g. see Shaw and McKay, 1942). Relatively high numbers of increasing and decreasing trajectories (representing on average higher overall rates of crime) in the urban center of Seattle are consistent with this perspective, as are the low rate stable trajectories showing higher concentrations in the less densely populated and more affluent northern parts of the city.

But if social disorganization variables explain the crime patterns we observe, formal social controls, such as hot spots policing, may have less potential for affecting the trajectories of crime at places. While the police may affect social disorganization at crime places by reinforcing forces of social organization and social control, the social disorganization perspective suggests emphasis on a much broader set of policies than
increased police attention. If the primary causal mechanism underlying crime trajectories can be found in factors such as single family households, racial heterogeneity and economic deprivation, all linked to the social disorganization perspective, then a much wider set of social interventions would be required to change the form of trajectories at crime hot spots. Of course, it may be that a combination of routine activities and social disorganization variables influence crime patterns at micro places (see Smith et al., 2000), and thus a complex combination of interventions might be required to have a meaningful and long term impact on crime at hot spots.

Accordingly, while we think that our finding regarding the stability of crime at place across time is a robust one and is consistent with the theoretical arguments underlying crime prevention practice at hot spots, our study suggests that more analysis of crime trajectories at places drawing from a much more comprehensive set of data is needed. Future studies should examine changes in the social and demographic characteristics of places over time, and in the characteristics of their routine activities and guardianship, including the role of police activities in altering crime trajectories. Such data would be needed to tease out the characteristics of places that encourage stability and those which lead to change in crime rates, and would provide a basis for testing directly the relevance of routine activities theory and theories of social organization for understanding trajectories of crime at micro places over time.

Because different causal mechanisms may underlie different types of crime (Clarke, 1983) examination of crime trajectories of specific types of crime might also lead to new insights. It may be for example, that homicide or robbery trajectories at places differ markedly from those we observed here, though of course such studies might encounter new problems in defining trajectories when the occurrence of such crime events is relatively rare at micro units of analysis. In turn, while focusing on general trends, such as those represented by stable, increasing and decreasing trajectories, has allowed us to examine assumptions underlying hot spots approaches, more specific analyses of specific trajectories would likely increase our understanding of the dynamics of crime at place.

Finally, while our study has examined a longer time series than has been available to other scholars, it is still relatively short when one considers the overall developmental patterns of crime at places. Theories of routine activities and social disorganization are often concerned with changes that occur over decades or even longer time periods (e.g. see Bursik, 1986; Bursik and Webb, 1982 Cohen and Felson, 1979). Our analysis accordingly, may have underestimated dynamic elements of change over the long run and thus provides only a part of the story of crime trajectories at places. Although such long-term longitudinal data
may prove extremely difficult to identify, they would provide key insights into the nature of trajectories of crime at places and the underlying theoretical mechanisms that explain such change.

CONCLUSIONS

Our analysis of crime at street segments in Seattle over a 14-year period and our use of the trajectory approach allowed us to fill an important gap in our understanding of crime at micro places. Our study confirms prior research showing that crime is tightly clustered in specific places in urban areas, and that most places evidence little or no crime. But we also are able to show that there is a high degree of stability of crime at micro places over time. This stability is evident in the vast majority of street segments in our study of 14 years of official data. Moreover, for those trajectories that evidenced decreasing or increasing trends, we still found a stability of scale with the highest rate segments generally remaining so throughout the observation period.

Our data however, also suggest that crime trends at specific segments are central to understanding overall changes in crime. The crime drop in Seattle was confined to very specific groups of street segments with decreasing crime trajectories over time. If the trends in Seattle are common to other cities, the crime drop should be seen not as a general phenomenon common to places across a city but rather as focused at specific places. Such places in our study are also street segments where crime rates are relatively high. This reinforces a public policy approach that would focus crime prevention resources on hot spots of crime (Braga, 2001; Sherman and Weisburd, 1995; Skogan and Frydl, 2003; Weisburd and Braga, 2003; Weisburd and Eck, 2004).

These observations are of course preliminary given the nature of our data. Our more general findings must be subjected to examination in other contexts and across other micro place units (for example, see Griffiths and Chavez, 2004). To understand the etiology of crime trajectories at micro places we also need more insight into the nature of such places and their

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17. One reader, Anthony Braga, has suggested that our finding that specific trajectories account for the overall crime drop in Seattle is consistent with broader trends in crime and violence across American cities. While the national trends illustrate an overall decrease in crime during the 1990s, there was a good deal of variability across cities (Blumstein, 2000; Travis and Waul, 2002). When looking at specific crimes there has also been acknowledgement of important differences across populations. For example, Cook and Laub (1998, 2002) observe that the youth violence epidemic was concentrated among minority males who resided in poor neighborhoods, used guns and engaged in high risk behaviors such as gang participation (see also Braga, 2003).
experiences across the periods of study. Nonetheless, our examination of trajectories of crime at micro places over time suggests the importance of a developmental, criminal career perspective in the study of micro crime places (Sherman, 1995; Weisburd, 1997).

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