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Testing the "Law of Crime Concentration at Place" in a Suburban Setting: Implications for Research and Practice

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Abstract
Objective To assess whether the "law of crime concentration at place" applies in a non-urban context. We test whether longitudinal trends in crime concentration, stability, and variability apply in a suburban setting.
Methods We use group-based trajectory analysis to examine trends in recorded crime incidents on street segments in Brooklyn Park, a suburban city outside Minneapolis, Minnesota, over a 15-year period from 2000 to 2014.
Results Consistent with the law of crime concentration at place, crime in Brooklyn Park is highly concentrated at a small percentage of micro-places. Two percent of street segments produced 50 % of the crime over the study period and 0.4 % of segments produced 25 % of the crime. The patterns of concentration are highly stable over time. However, the concentration of crime is substantially higher and there is much less street-by-street variability in Brooklyn Park compared to urban areas.
Conclusions We find strong support for the application of the law of crime concentration at place to a non-urban setting, suggesting that place-based policing approaches tested in cities can also be applied to suburbs. However, there are also important differences in the concentration and variability of crime hot spots in suburbs that require further examination. Our study is based on a single setting that may not be representative of other suburban and rural areas. Finally, the clustering of hot spots raises questions about the use of street segments to analyze crime at suburban micro-places.

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Background

The "Law of Crime Concentration at Place"

In his 2014 Sutherland Address to the American Society of Criminology, Weisburd (2015, p. 138) proposed a "law of crime concentration at place," which posits that a small number of microgeographic places, such as addresses, street blocks or segments (defined by Weisburd et al. (2004, p. 290) as the "two block faces on both sides of a street between two intersections"), drug markets, schools and other institutions, account for a disproportionate percentage of all the crime in a given larger area such as a neighborhood or city. This "law" is supported by a growing body of research from around the world (e.g. Andresen and Malleson 2011; Andresen and Linning 2012; Beavon et al. 1994; Crow and Bull 1975; Curman et al. 2015; Hillier 2004; Jaitman et al. 2015; Johnson 2010; Johnson and Bowers 2010; Kautt and Roncek 2007; Mazeika and Kumar 2016; Pierce et al. 1988; Sherman 1987; Sherman et al. 1989; Weisburd and Amram 2014; Weisburd and Green 1995; Weisburd et al. 2004, 2009, 2012; Wheeler et al. 2015), which shows remarkable consistency in the number of street segments producing 25 and 50 % of the crime across multiple contexts, crime types, and time periods.

For example, in Minneapolis, MN Sherman et al. (1989) reported that 50.4 % of police calls for service came from 3.3 % of addresses in a particular year. In Seattle, WA 5.1 % of street segments accounted for 50 % of the city's crime and 1.6 % produced 25 % of the crime (see also Weisburd 2015; Weisburd et al. 2004). Weisburd and Amram (2014) found similar concentrations in a non-United States setting, observing that 4.5 % of Tel Aviv, Israel's street segments produced 50 % of the crime and 0.9 % of segments produced 25 %. Weisburd (2015) brings together these studies and data from other large and small cities, concluding that the "bandwidth" of crime concentration at small places is approximately 4 % at 50 % concentration and less than 1.5 % at 25 % concentration.

A smaller number of studies have also identified considerable stability in these levels of concentration over time, strengthening the evidence for the law. Stability in these studies refers to the level of consistency in the proportion of street segments producing a particular degree of crime concentration over multiple years. In Seattle, for example, between 4.6 and 5.8 % of street segments produced 50 % of the crime over a 16-year period from 1989 to 2004 (Weisburd et al. 2004), while in Tel Aviv the range was 3.9–6.5 % between 1990 and 2010 (Weisburd and Amram 2014) and in New York between 4.7 and 6 % over 9 years (Weisburd 2015; see also Weisburd et al. (2015). Curman et al. (2015) found in Vancouver, Canada that although crime was somewhat less concentrated at street segments than in other studies (approximately 7.8 % of street segments produced 50 % of the crime), the degree of concentration was still highly stable over a 15-year period between 1991 and 2006. Importantly, this stability has been observed even despite significant overall crime drops in the cities (except Tel Aviv) during the study period (Weisburd 2015). Less often discussed in these studies is whether the concept of stability extends to the specific street segments that produce the most crime—do the same places continually appear within the 4–5 % of locations producing 50 % of the crime, or do some "cool down" and get replaced by newly hot blocks? Levin et al. (2015), for example, find that the specific street segments with the highest crime rates vary over time (see also Johnson et al. 2008). This has implications for the theoretical explanations for and practical uses of the law of crime concentration, discussed below.

Further evidence for the law is found in studies that have examined the street-by-street variability of crime hot spots—the extent to which crime rates differ from one street segment to the next. While it may be tempting to assume that the substantial degree of crime concentration exhibited at the street segment level simply represents the clustering of high crime street segments within so-called "bad neighborhoods," the research suggests that hot spots are spread throughout the city (e.g. Groff et al. 2009; Weisburd et al. 2009, 2012). Places characterized locally as "bad neighborhoods" nonetheless have substantial numbers of low-crime or crime-free street segments, while hot spots are also interspersed throughout areas residents would likely consider safe. Groff et al. (2010) find significant heterogeneity in the crime trajectories of neighboring street segments, indicating that crime patterns at the street level are not simply dictated by larger area trends. This suggests that the law is not simply a measurement artifact (see also Levin et al. 2015)—it does indeed apply at the microgeographic level specifically, and there is something substantively different about these street segments. The distribution of motivated offenders, suitable targets, and capable guardians—the elements of routine activity theory (Cohen and Felson 1979)—at each street segment predict this variability (e.g. Felson 1987; Roncek and Maier 1991; Smith et al. 2000), as do environmental (e.g. Brantingham and Brantingham 1995) and social (e.g. Weisburd 2012) features of places.

The existence of the law of crime concentration at place is not only a matter of academic interest. It also forms part of the theoretical mechanism explaining the effectiveness of focused police patrol and problem solving at high-crime microgeographic places, or "hot spots" (e.g. Braga and Bond 2008; Braga et al. 1999, 2014; Groff et al. 2015; Lum et al. 2011; Ratcliffe et al. 2011; Sherman and Weisburd 1995; Skogan and Frydl 2004; Telep et al. 2014; Weisburd and Eck 2004; Weisburd and Green 1995). These strategies are hypothesized to work primarily by changing the opportunity structure for crime through increased formal guardianship and/or modifying the situational characteristics of places. However, the pattern of crime concentration at specific micro-places in many cities also allows police to direct these strategies more efficiently, thus maximizing their effectiveness. Furthermore, the high level of street-by-street variability in crime rates may explain why there is little evidence that focused policing efforts displace crime to neighboring street segments (e.g. Bowers et al. 2011; Braga et al. 2014; Weisburd et al. 2006).

Crime Concentrations in Suburban Areas

While there is good evidence that the law of crime concentration at place applies in larger urban cities, much less is known about how crime concentrates in non-urban environments such as suburbs and rural areas. We cannot assume that the patterns observed in cities will hold in the same way in these settings. First, the layout of streets in suburban and rural areas does not always follow the same pattern of relatively short and uniformly-sized street segments laid out on a grid, as is common in urban cities in the United States. Street segments have been the key unit of analysis in research on crime at microgeographic places because they are theorized to act as "behavior settings" (Barker 1968; Wicker 1987) within which social activity is organized (e.g. Appleyard 1981; Brower 1980; Felson 1987; Jacobs 1961; Smith et al. 2000; Taylor 1997; Taylor et al. 1984; Unger and Wandersman 1983). Over time, the routine activities of people who use the street segment lead to the development of standing patterns of behavior, shared norms, and familiarity, regulated within the tight physical boundaries of the block (Taylor 1997; Weisburd et al. 2016; 2012). As such, street segments on which individuals live, work, and socialize become key components of their "activity spaces" (Felson and Boba 2010). It is not clear whether these patterns also exist on the often longer and nonlinear street segments that exist in suburbs. For example, how does the length of the segment between its two intersections impact the theoretical assumptions about awareness and activity spaces?

Second, the opportunity structures that shape crime in suburbs and rural areas may differ from those found in cities. Environmental features such as transportation hubs and networks, roadways, and land use (e.g. residential vs. commercial) affect the probability of crime at a location (e.g. Brantingham and Brantingham 1995). Suburbs often differ substantially from cities in terms of the presence of public transportation services and mixed-use land developments, population density, and population transience. In turn, these features also affect the routine activities of individuals who use the space. Furthermore, features and opportunities that attract certain types of people to a place at specific times of day may also differ between suburban and urban areas. Andresen (2006) finds that crime concentrations are better predicted by characteristics of the ambient rather than residential population. For example, suburbs typically lose a substantial proportion of their residents during the work day, while the populations of cities temporarily increase.

Finally, related to the points above, the street layout itself is also strongly correlated with crime (Hillier 2004). Street layouts in many suburban areas differ from their urban counterparts, which subsequently affects crime risk. For example, Beavon et al. (1994) note that more complex street networks with higher number of limited-accessibility streets are associated with reduced opportunities for crime. Similarly, Johnson and Bowers (2010) find that more permeable street segments are at increased risk for burglary compared to cul-de-sacs, which offer fewer access and escape routes for offenders. In suburban areas, which may not be laid out on a consistent grid and have more non-permeable streets, the types of places more conducive to crime may be more highly concentrated, affecting the applicability of the law of crime concentration.

The small amount of research on crime at micro-places in suburban and rural locations that has been conducted suggests that these environmental differences may indeed alter the law of crime concentration at place in these settings. In fact, as noted above, crime may be even more highly concentrated than it is in cities because opportunity-generating places are less evenly distributed across the geographic space. For example, Hibdon (2013) found in Fairfax County, VA, a largely suburban jurisdiction with some rural pockets, that 50 % of the crime was concentrated at just 2.1 % of street segments, compared to the 4–5 % found in urban areas. Furthermore, 100 % of crime was concentrated at 20.3 % of street segments in the county overall, and in just 9.1 % of rural segments. Hibdon also discovered that there was much less variability in the locations of these hot spots across the county. Rather than being spread throughout the county, they tended to cluster around major roadways and commercial areas, which were found less frequently and in more specific places in the suburban environment. Weisburd (2015) found very similar concentrations of crime in two small suburban cities in California, Redlands and Ventura, where 50 % of the crime was found at 2.1 and 3.5 % of street segments respectively. He also found that the concentration of crime in Brooklyn Park, MN—another suburban city and the focus of the present study—exactly matched that of Fairfax County and Redlands.

Why is it Important to Examine Crime Concentration in Suburban areas?

Just as there is little research on crime concentrations in suburban and rural areas, most of the evidence-based policing literature discussed above has also been generated in larger urban cities. However, Weisheit et al. (2006) note that most of the U.S. population is concentrated in suburban or rural, not urban, locations. Furthermore, over 70 % of U.S. police agencies serve populations of under 10,000 people and almost 95 % of agencies employ fewer than 100 sworn officers (Reaves 2015). We know very little about the translation of place-based policing studies to these settings (e.g. Lum and Koper 2013; Lum et al. 2011). As previously discussed, different routine activities and opportunity structures in these areas may produce unique crime patterns and problems that require different police responses (see also Kuhns et al. 2007; Weisheit et al. 2006). Suburban-rural police departments have different features, such as a higher ratio of sworn officers to civilian staff and special challenges in terms of police-community relations and legitimacy (e.g. Lum and Koper 2013). The lower population density in suburban and rural environments also requires police agencies to spread their resources across a wider geographic area. The challenges of translating research into practice may therefore be even greater in smaller agencies (Lum and Koper 2013; see also Lum 2009; Rojek et al. 2012; Telep and Lum 2014).

Thus, police leaders in smaller agencies may be skeptical that effective place-based policing practices that have been tested in urban environments are relevant or feasible in their jurisdictions. The theory and research behind hot spots policing and related practices are predicated on common patterns in the concentration, stability, and variability of high-crime urban places and may not hold outside of these contexts. In the absence of program evaluations of hot spots policing in suburban and rural areas, an assessment of whether the "law of crime concentration at place" applies in such locations could provide some empirical basis for the use of these practices outside of large cities.

The Present Study

The purpose of this study is to examine the application of the law of crime concentration at place and its stability and variability in a suburban setting. We replicate the approach of Weisburd et al. (2004), who used group-based trajectory analysis (GBTA) to identify distinctive developmental trends in crime concentrations in Seattle, WA. The present study is the first that we know of to use GBTA with data from a suburban jurisdiction, allowing us to extend the prior work on suburban crime concentration by Hibdon (2013) and Weisburd (2015) by also examining crime stability and variability. We also consider whether the street segment is an appropriate unit of analysis outside the urban context. Finally, we conclude with a discussion of whether we need to adjust our policy recommendations from crime and place research for suburban police agencies.

Methodology

Study Setting

Our study examines crime trends over a 15-year period in Brooklyn Park, Minnesota. Brooklyn Park is a suburban city with a population of approximately 78,000 people over 26 square miles. It is the second-largest suburb in the Minneapolis-St. Paul metropolitan area and the sixth-largest city in the state.

As a city in its own right, Brooklyn Park does share some features with more urban locations. The land is 85 % developed and contains a mix of residential and commercial properties, and the population density is high at almost 3000 residents per square mile (2010 Census).[1] The population of Brooklyn Park is highly diverse. Twenty-five percent of residents are foreign-born and almost 50 % are non-White. Twelve percent of residents are below the poverty line.[2]

However, Brooklyn Park has traditionally been a "bedroom community" for nearby Minneapolis and the layout and land use are more traditionally suburban. For example, it lacks a true downtown area, has few public transit links, and there is clear separation between residential and commercial areas. Much of the population is concentrated in large one- or two-bedroom apartment complexes in the southwestern portion of the city (Fig. 1).

Brooklyn Park is the location of an ongoing collaboration between the Brooklyn Park Police Department (BPPD) and the Center for Evidence-Based Crime Policy at George Mason University, funded by the Smart Policing Initiative of the Bureau of Justice Assistance, to develop and test using a randomized controlled trial a police-led collective efficacy building and problem-solving program in hot spots (see Weisburd et al. (2016).[3] According to BPPD, the city's crime rate is the highest among Minneapolis-St. Paul suburbs with 50,000 or more residents.

Description of the Data

Data on crime and disorder incidents (crime events in which a police report was taken) occurring in Brooklyn Park between 2000 and 2014 were provided by the BPPD as part of the Smart Policing Initiative project. We geocoded incidents and associated them with their respective street segments ($N = 2937$), which is the geographic unit of analysis for this study.[4] The geocoding hit rate for these data is 97.9 %, which is higher than the 85 % minimum threshold for reliability suggested by Ratcliffe (2004). We excluded incidents recorded as occurring at intersections because they could not be linked to a specific segment (Curman et al. 2015; Dario et al. 2015; Telep et al. 2014; Weisburd et al. 2006, 2012).[5]

In total, 222,585 incidents occurring on street segments are included in our analysis. Of these, 42.6 % were disorder (e.g. disturbing the peace, abandoned vehicle, code enforcement complaints); 13.6 % were crimes against persons (e.g. assault, robbery, homicide); 23.0 % were property crimes (e.g. burglary, arson, vehicle theft); 1.2 % were drugs/prostitution-related (e.g. solicitation, narcotics), and 19.5 % were other crime types (e.g.

[1] This population density is similar to the small cities examined by Weisburd (2015), Ventura, CA (3316 people per square mile) and Redlands, CA (1887 people per square mile), which were shown to have similar levels of crime concentration. Information retrieved from U.S. Census Bureau American FactFinder (http://factfinder.census.gov/) and Interactive Population Search (http://www.census.gov/2010census/popmap/ipmtext.php).

[2] U.S. Census Bureau. 2009–2013. State and County QuickFacts. http://quickfacts.census.gov/qfd/.

[3] http://www.smartpolicinginitiative.com. BJA award number 2013-DB-BX-0030.

[4] A street segment is defined as the two block faces on either side of a street between two intersections. The average length of a street segment in Brooklyn Park is 596 feet.

[5] Incidents occurring at intersections accounted for a total of 6.5 % of all incidents over the study period. Of these, 19.5 % were disorder incidents, 8.8 % were crimes against persons, 5.0 % were property crimes, 10.5 % were drugs/prostitution-related, and 56.2 % were other crime types.

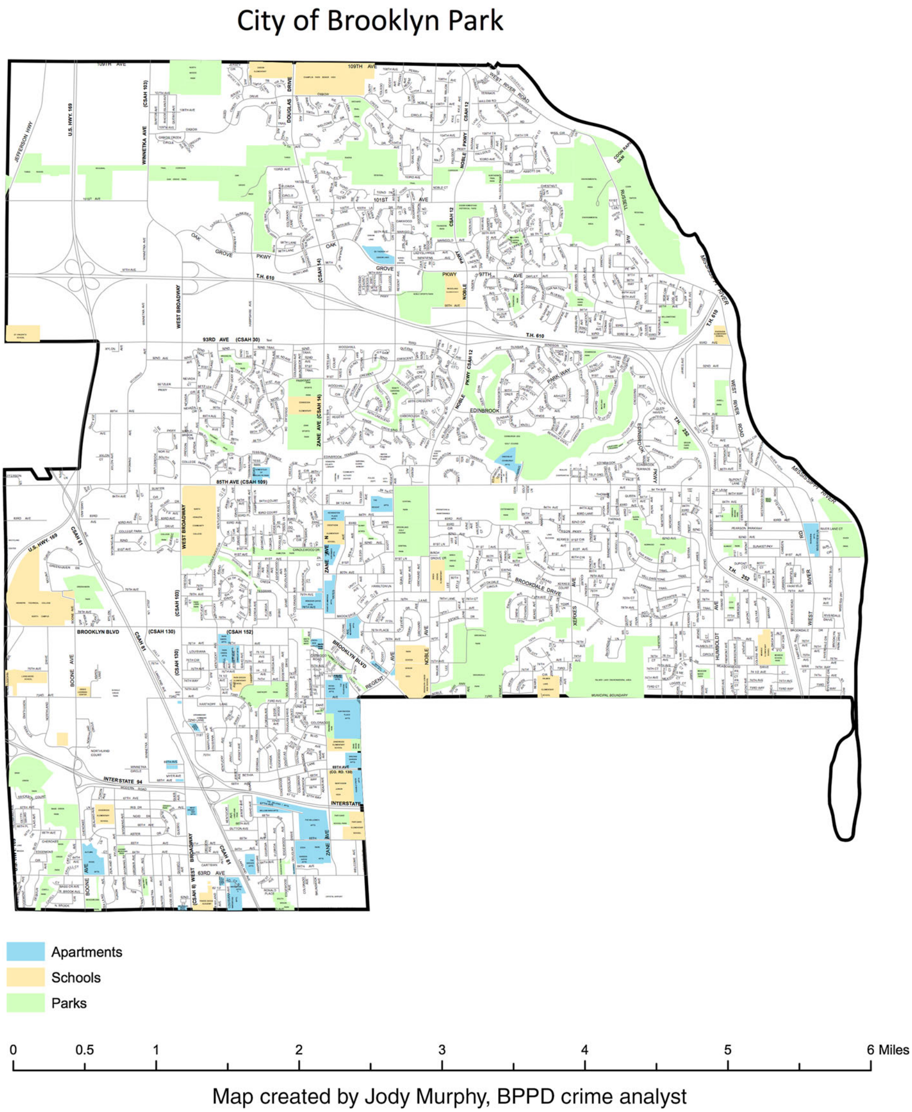


Fig. 1 Land use in Brooklyn Park, MN

suspicious activity, juvenile-related incidents, weapons). The mean number of incidents per street segment in a given year is approximately 5.1 ($SD = 27.1$).

Analytic Strategy

We use GBTA to explore the underlying heterogeneity in the population of street segments in Brooklyn Park in order to assess the stability and variability in high crime locations over time. GBTA statistically identifies distinct and unknown subgroups within a population by examining the evolution or “developmental trajectory” of an outcome over time (Nagin and Land 1993). GBTA is widely used in criminology, particularly in developmental and life-course research to identify individuals who follow similar offending patterns over time (Blokland et al. 2005; Bushway et al. 2009; Erosheva et al. 2014; Haviland and Nagin 2007; Kreuter and Muthén 2008; Nagin and Odgers 2010; Nagin et al. 1995). More recently, scholars have extended the use of this methodology to isolate and better understand heterogeneity in crime at places over time (Curman et al. 2015; Griffiths and Chavez 2004; Groff et al. 2010; Weisburd et al. 2004, 2009, 2012, Wheeler et al. 2015; Yang 2010).

GBTA is ideal for testing whether distinct patterns exist in the data and is suitable for examining questions pertaining to the shape of the developmental course of the outcome of interest over time (Nagin 1999, 2005). Hierarchical modeling (Bryk and Raudenbush 1987, 1992) and latent growth curve analysis (McArdle and Epstein 1987; Muthén 1989) can also be used to analyze and explain differences in developmental processes, but these complementary approaches may be distinguished from GBTA by the technical assumptions they make about the distribution of the trajectories in the population. Unlike GBTA, these modeling techniques assume a continuous distribution of trajectories so they are more suited to explaining individual differences in terms of variation about the population mean and examining questions pertaining to predictors of the outcome's developmental course (Nagin 1999, 2005). A further advantage of GBTA is that its findings can be presented in a manner that is easily understood by both technical and nontechnical audiences.

There are a number of approaches to identifying trajectory groups in a population. The method most frequently employed in criminological research focusing on street segments is based on a finite mixture model that has been adapted for a Poisson distribution (e.g. Jones and Nagin 2007; Nagin and Tremblay 2001):

$$\log\left(\lambda_t^j\right) = \beta_0^j + \beta_1^j Year_{it} + \beta_2^j Year_{it}^2 + \beta_3^j Year_{it}^3,$$

where λ_t^j is street segment i's logged rate of crime incidents at time t conditional on membership in group j. Note that the model coefficients are superscripted by j to signify a vector of parameters and the equation is specified in terms of a polynomial function of time, so that the coefficients are able to vary freely across j groups and have a distinct shape.

GBTA requires the researcher to select the number of trajectory groups and the shape of each trajectory manually. Nagin (2005) provides guidance on selecting this overall model. The goal is to select a model that minimizes within-group differences and maximizes heterogeneity between groups. This entails testing all possible combinations of numbers of groups and polynomial order (linear, cubic, and quadratic[6]). Since the variable of interest in our analysis is based on count data (number of annual crime incidents) and the degree of crime concentration suggests a nontrivial number of street segments experiencing zero crime incidents, we used a zero-inflated Poisson model for this process.[7] The cubic model

[6] The process began with fitting a two-group model and each model was explored sequentially up to a twenty-eight-group model. The upper limit on j was selected based on goodness of fit as (1) the BIC suggested that increasing the number of groups resulted in a poor model fit, (2) the parameters began to lose statistical significance, and (3) increasing the number of groups did not provide useful and meaningful information.

[7] Trajectories were calculated in Stata 12.0 using the *traj* plug-in and the zip command for the zero-inflated Poisson model (Jones and Nagin 2013). Due to the inability of the *traj* plug-into accommodate extreme outliers (see also Curman et al. 2015; Weisburd et al. 2004), we truncated cases at 60 in the analysis. A total of 40 cases were truncated, representing 1.4 % of all street segments. These cases were assigned to trajectories 16 (n = 1) and 18 (n = 39).

was consistently a better fit over the linear and quadratic models. Ultimately, we selected an 18-group solution for this study.[8]

We used several different analytical tools to arrive at this solution. First, we used the Bayesian Information Criterion (BIC) to select the optimal trajectory solution (Kass and Raftery 1995; Raftery 1995; Schwarz 1978). The BIC is specified as follows:

$$\mathrm{BIC} = \log(L) - 0.5k\log(N),$$

where L is the maximized likelihood of the model, k is the number of model parameters (determined by the number of groups and polynomial order of trajectories) and N is the sample size. A larger BIC is more desirable in selecting the solution. BIC generally improves as the number of groups increases, but it can be penalized if adding more trajectories or increasing the model's complexity does not also substantially improve model fit (Nagin 2005). The BIC for the 18-group solution was higher than all solutions with fewer groups, but it began to decline once more than 18 groups were included.

We also used posterior probabilities of group membership to assess the quality of model fit. These probabilities measure street segment i's likelihood of belonging to each J trajectory group (Nagin 1999). For the 18-group solution, the minimum average posterior probability of membership in each group was 0.84, which is higher than the 0.7 cut-off proposed by Nagin (2005). Finally, we noted that increasing the number of trajectories did not provide additional useful information, and in fact began to simply divide existing groups into parallel trajectories. Conversely, the 18-group solution revealed a new group with a different shape that was not present in the 17-group solution. A description of the final 18-trajectory model is provided in the results section below.

Results

Concentration of Crime in Brooklyn Park

Figure 2 shows the trend of crime incidents in Brooklyn Park from 2000 to 2014 and the extent of crime concentration during this period (see also Weisburd 2015). The data support the findings from prior studies described above, which indicate that there is significant clustering of crime at microgeographic units of analysis and that this concentration is consistent over long periods of time. Furthermore, consistent with the findings of Hibdon (2013) and Weisburd (2015), crime in Brooklyn Park is substantially more concentrated than crime in large urban cities such as New York and Seattle. Over the 15 years in our dataset, 50 % of crime incidents in Brooklyn Park was found at about 2 % of street segments (ranging from 1.5 to 2.6 % year by year), while just 0.4 % of street segments (ranging from 0.3 to 0.5 %) produced 25 % of the crime. Brooklyn Park experienced two minor crime waves during the observation period, but overall there was a 29.5 % decline in the number of recorded incidents from 2000 to 2014.

Trajectory Model

Figure 3 illustrates the annual average number of crime incidents for each of the 18 trajectory groups in Brooklyn Park. We present descriptive statistics for each trajectory in Table 1. As in prior studies, we find that a group of high-crime places drives a majority of

[8] The selected model has a BIC of −75,216.22.

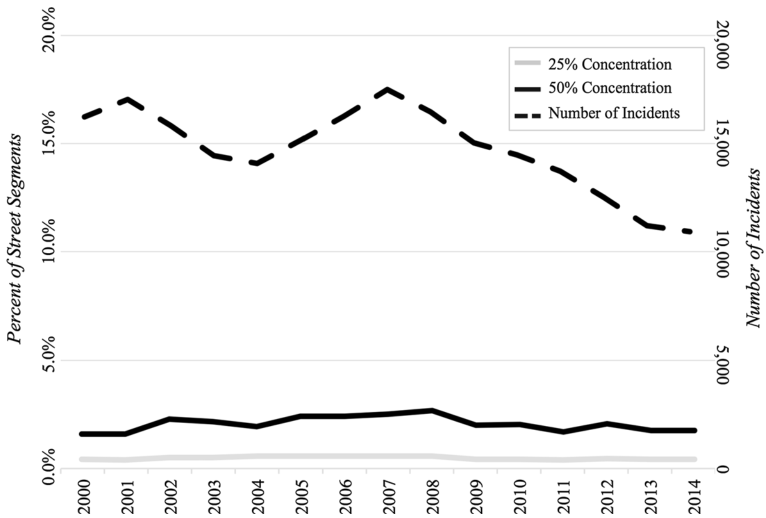


Fig. 2 Trends in crime and disorder incidents and crime concentration in Brooklyn Park, MN, 2000–2014

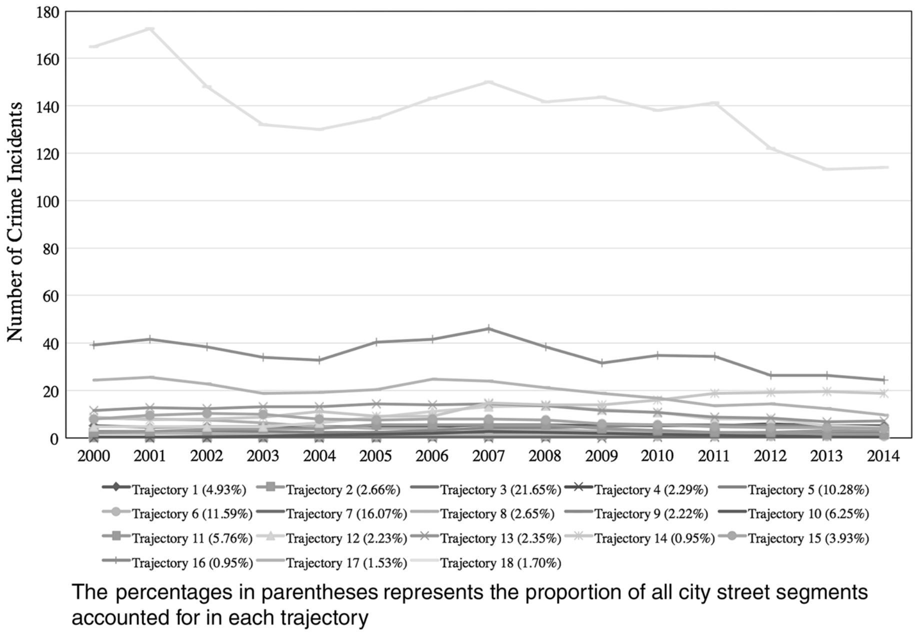


Fig. 3 18-trajectory solution for crime at street segments in Brooklyn Park, MN, 2000–2014

the crime. Trajectory Group 18, which contains just 1.6 % ($N = 50$) of the city's street segments, accounted for almost half (46.9 %) of total crime incidents in Brooklyn Park. Overall, the data show remarkable stability in the number of crimes at each street segment over the 15-year period. While the trajectories have varying initial intercepts, they have relatively similar slopes. The uniformity of the longitudinal trends for the majority of street segments is notable given that Brooklyn Park experienced a substantial crime drop during

Table 1 Descriptive statistics for 18-trajectory solution; Brooklyn Park, MN street segments

Trajectory group	N of street segments in trajectory	Average length (Ft)	% of all street segments	Posterior probability of group membership	% of property crime	% of personal crime	% of disorder	% of total crime
1	145	823.99	4.93	0.89	4.74	4.68	4.96	4.98
2	75	593.92	2.66	0.88	0.67	0.55	0.53	0.60
3	673	494.69	21.65	0.94	0.15	0.06	0.09	0.12
4	56	476.11	2.29	0.86	0.15	0.08	0.06	0.10
5	303	589.28	10.28	0.87	4.99	3.86	4.09	4.67
6	328	490.69	11.59	0.86	3.21	1.63	2.23	2.69
7	467	439.42	16.07	0.89	1.80	0.79	1.04	1.41
8	78	705.48	2.65	0.87	1.89	1.90	2.26	2.16
9	65	719.47	2.22	0.92	1.28	1.45	1.49	1.43
10	176	445.20	6.25	0.84	1.70	1.17	1.41	1.55
11	171	679.66	5.76	0.86	3.91	3.87	4.13	4.14
12	66	823.36	2.23	0.93	3.16	3.82	3.70	3.56
13	67	946.71	2.35	0.98	4.61	5.28	5.34	5.22
14	28	862.92	0.95	1.00	2.43	2.79	2.56	2.48
15	116	958.89	3.93	0.91	4.78	4.96	5.98	5.53
16	28	1007.56	0.95	1.00	7.40	5.69	6.59	6.67
17	45	1158.51	1.53	1.00	6.37	5.26	5.50	5.79
18	50	1063.90	1.70	1.00	46.77	52.18	48.03	46.91
Total	2937	596.32	100.00	Min: 0.84	100.00	100.00	100.00	100.00

The average street segment length in the Total row reflects the mean length where each street segment is given equal weight

the analysis period. This also suggests that the slight crime increase in Brooklyn Park in the early to mid 2000s and the overall crime drop between 2000 and 2014 can both be explained by crime trends at a very small proportion of street segments. Figure 4 shows the same analysis with the highest-crime trajectory group (Group 18) excluded so that trends over time in the remaining groups can be more easily visualized.

A review of crime trends by type suggests that the crime increase in the mid-2000s is attributable to a spike in crimes against persons (assault, robbery, etc.) among street segments in Trajectory Group 18. The most substantial decline in crime is observed for disorder-related incidents (particularly in Trajectory Groups 8 and 18), while property crimes experienced modest declines. There is variation in the mean number of crime incidents by type across each trajectory group (see Table 2), but the distribution of types of crimes within trajectories is very similar, with disorder-related incidents being most prevalent followed by property and personal crimes.

To simplify the description and focus the discussion on the stability of crime at street segments over time, we categorized the trajectories into four groups: stable, increasing, decreasing, and increasing–decreasing (Fig. 5a–d respectively).[9] Figure 5a shows the

[9] Following Weisburd et al. (2004) and Curman et al. (2015) we used the slope of the trajectory to determine the category. A slope of −0.2 or less was classified as decreasing; greater than −0.2 to +0.2 as

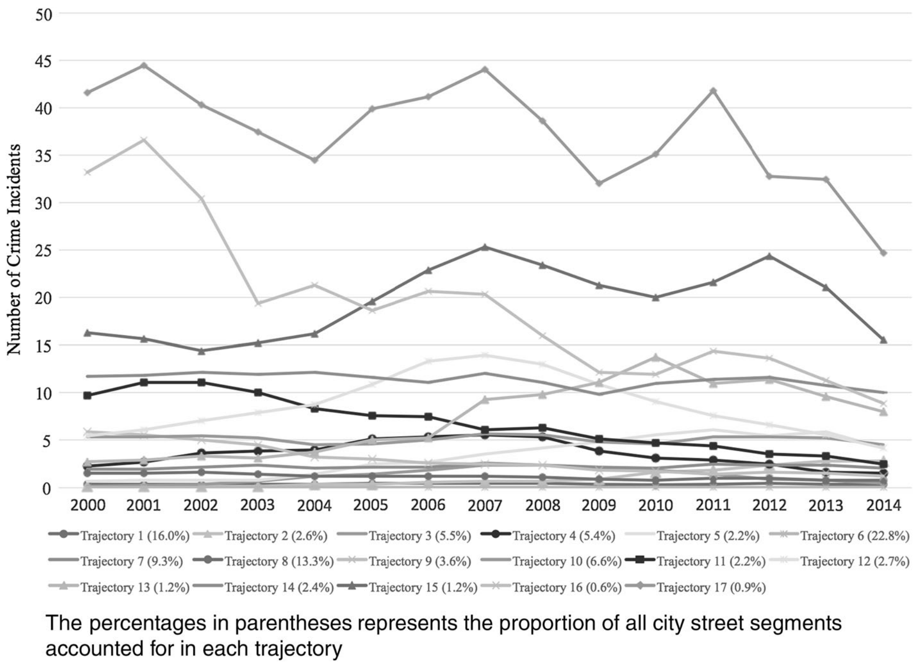


Fig. 4 18-trajectory solution for crime at street segments in Brooklyn Park without high declining group

seven trajectory groups that had stable crime trends over the 15 years. These stable trajectories had slopes relatively close to 0, ranging from −0.08 to +0.19. These groups contain 2047 street segments—the majority (69.7 %) of streets in Brooklyn Park. Street segments in stable trajectories were relatively at 522 feet on average. As indicated by Table 1 (Trajectory Groups 1–7), just 14.6 % of crime in the city came from stable segments, with an average of 1.5 crimes per year across trajectories in this group. As noted above, this indicates that most of the street segments in the city did not follow the general crime decline in Brooklyn Park.

The temporal crime trend in the declining trajectory groups is presented in Fig. 5b. These groups contain 384 street segments and have noticeably decreasing slopes during the study period, ranging from −3.64 to −0.31. As depicted in Table 1, the overall length of the declining segments is considerably longer than street segments in Brooklyn Park overall (946 feet for the declining group vs. 596 feet citywide).[10] Even though these trajectory groups contain only a small proportion of street segments in the city (13.1 %), they account for the majority of the crime (72.3 %; Table 1, Trajectory Groups 8, 13, 15–18). This is predominantly driven by the 50 street segments in Trajectory Group 18. However, while these street segments had a substantially higher number of crime incidents per year (139 on average) than any other trajectory group, they also experienced the most

Footnote 9 continued
stable; and greater than +0.2 as increasing. We determined the increasing–decreasing trajectories by a qualitative assessment.

[10] Detailed information on street segment length (mean, standard deviation, minimum, and maximum for each trajectory) in Brooklyn Park is available in Table A1 in the online appendix.

Table 2 Mean number of annual crime incidents by trajectory group

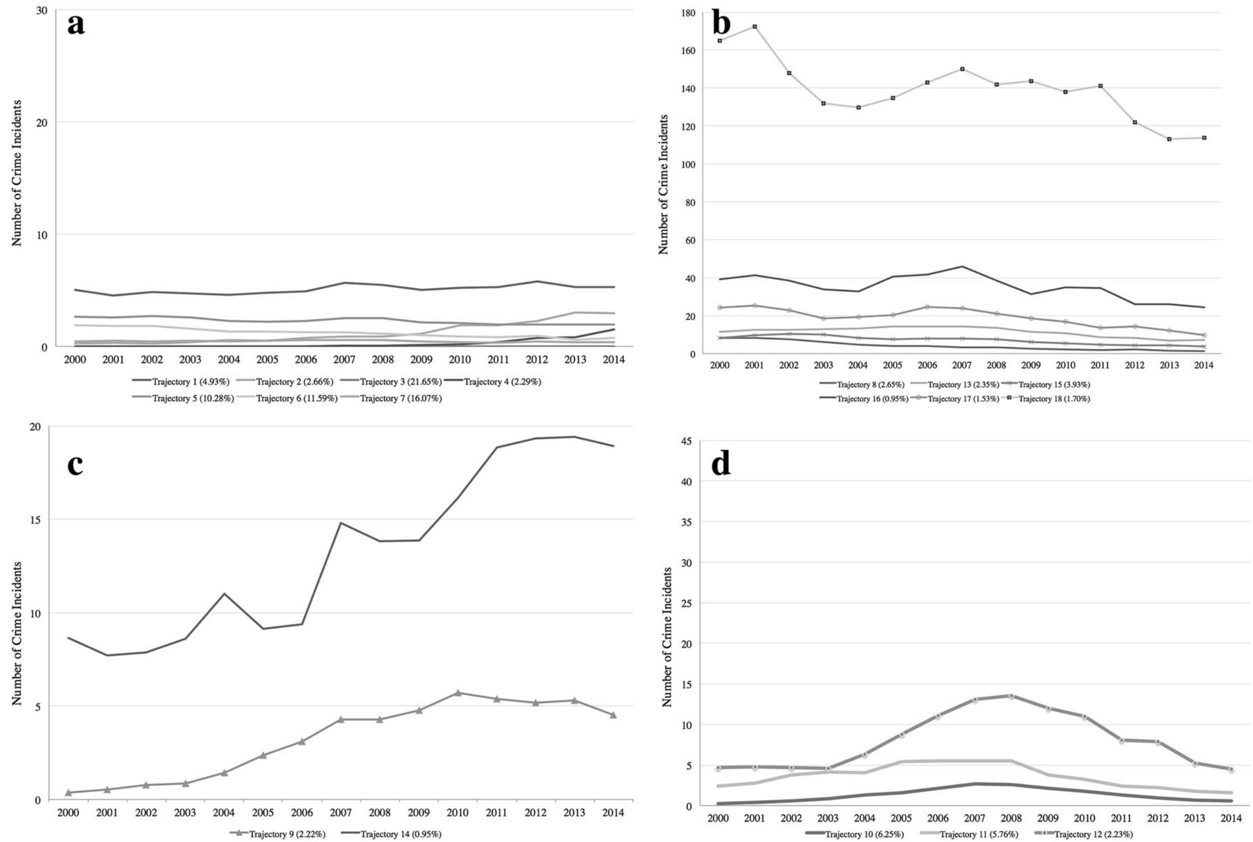
Trajectory group	Trajectory type	Property	Personal	Disorder	All incidents
1	Stable	1.42	0.59	2.05	5.09
2	Stable	0.36	0.13	0.43	1.19
3	Stable	0.01	0.00	0.01	.03
4	Stable	0.08	0.03	0.06	.26
5	Stable	0.71	0.23	0.81	2.29
6	Stable	0.42	0.09	0.41	1.22
7	Stable	0.17	0.03	0.13	.45
8	Decreasing	1.07	0.44	1.74	4.11
9	Increasing	0.83	0.40	1.38	3.26
10	Increasing–decreasing	0.42	0.12	0.48	1.31
11	Increasing–decreasing	1.01	0.41	1.45	3.59
12	Increasing–decreasing	2.13	1.05	3.36	8.00
13	Decreasing	3.03	1.43	4.78	11.55
14	Increasing	3.69	1.80	5.48	13.16
15	Decreasing	1.80	0.78	3.09	7.08
16	Decreasing	11.54	3.69	14.12	35.35
17	Decreasing	6.21	2.12	7.33	19.10
18	Decreasing	40.33	18.93	57.61	139.21
Total		1.47	0.62	2.04	5.05

A category for crime incidents classified as “other” (e.g., incidents related to suspicious persons, weapons/explosives, counterfeit/forgery) is not presented above but these incidents are included in the mean of all incidents. The Total row reflects the mean number of crime and disorder incidents where each street segment is given equal weight

noticeable crime drop—30.9 % over the study period. Thus, a large crime drop across fewer than 2 % of hot spot street segments explains the overall crime decline in Brooklyn Park.

Figure 5c shows the two trajectory groups classified as having increasing crime trends. These groups include 93 street segments, or 3.2 % of all segments in the city. Their slopes ranged from 0.30 to 0.74. Street segments in these groups were longer than average (762 feet) but shorter than those in decreasing trajectory groups. However, although crime was increasing at these locations, these segments produced just 3.9 % of the city’s crime. Nonetheless, it is notable that these segments experienced a crime increase of more than 200 % over the 15-year period (albeit from low base rates). For example, segments in Trajectory Group 9 had 0.4 crimes per year on average in 2000, but this had increased to 4.5 crimes by 2014. Similarly, the average number of crimes in Trajectory Group 14 was 8.6 in 2000 and 18.9 in 2014. A web search for the addresses of street segments in these groups revealed significant environmental changes in some locations, including a new outdoor mall built in 2005 and several new townhome communities built in the mid to late 2000s, that likely explain these substantial increases in crime.

A larger proportion of street segments experienced increases in crime in the early-to-mid 2000s followed by a crime drop (Fig. 5d). Their trajectory groups are categorized as ‘increasing–decreasing’ and contributed 9.3 % of the crime in Brooklyn Park. Street



The percentages in parentheses represent the proportion of all city street segments accounted for in each trajectory

Fig. 5 Crime trend by trajectory: **a** stable, **b** decreasing, **c** increasing, **d** increasing–decreasing segments in this group were slightly longer than average at 603 feet. There are 413 street segments in these groups, approximately 14.0 % of the total. Segments in Trajectory Group 12 experienced the most substantial crime spike, peaking in 2008 with 13.6 crimes on average. While this group had an overall decline in crime of 3.2 % over the full study period, its street segments experienced a 191.4 % increase between 2000 and 2008 followed by a 66.8 % decline between 2008 and 2014.

These trends across trajectory groups and the amount of crime contributed by stable, increasing, decreasing, and increasing–decreasing trajectories are more clearly depicted in Fig. 6. The number of crime incidents on stable street segments appears at the bottom of the chart, which shows a fairly consistent crime rate despite the overall crime drop during the study period. Just as Weisburd et al. (2004) found in Seattle, even though the majority of street segments fall within the stable trajectories, a relatively small portion of citywide crime occurs there (in part because many of these segments are both stable and crime-free). The majority of crime in the city is occurring on street segments with a decreasing crime trajectory, and these segments explain the overall crime drop. In contrast, the spikes in crime observed in the increasing and increasing–decreasing trajectory groups were not sufficiently substantial to impact overall crime rates.

Finally, we provide a visual examination of the street-by-street variability in Brooklyn Park's hot spots. Figure 7 maps the locations of the 50 street segments that comprise the chronic high crime Trajectory Group 18. The extent to which these segments are clustered in the southwestern and central portions of the city is striking. While it does not appear that there is a so-called "bad neighborhood" in Brooklyn Park, in the sense that the majority of segments in the southwest are not chronic high-crime places, the clustering appears much more substantial than it was in Seattle (Groff et al. 2009, 2010; Weisburd et al. 2012) and cannot be attributed to the different environmental features of a central business district or downtown area, which did influence some clustering in those prior studies.

In this study, we lack qualitative data that would allow us to comprehensively assess the factors underlying the clustering of crime hot spots in Brooklyn Park. Based on our experience of working in the city, we suggest that the uneven distribution of Brooklyn Park's population may be associated with the clustering of hot spots in specific areas. While the city's population density is high overall, many of the residential street segments consist of single-family or duplex homes. There are a few areas, mainly in the southwestern part of the city, where larger apartment complexes with as many as 1000 units are clustered. Based on the research suggesting that the ambient population and street "busyness" impact crime (Andresen 2006; Beavon et al. 1994), it is possible that these locations may produce more crime relative to areas that attract fewer people. At least by a visual inspection, street segments in our chronic high crime trajectory group cluster where large apartment complexes are also concentrated (Fig. 7). In the absence of specific data on the population at each segment we examined census tract-level population data from the American Community Survey (ACS),[11] but did not find any striking differences in population across trajectory groups. It is likely that micro-level variability is lost when the population is aggregated across a larger unit such as a census tract.

Our experience has also suggested that markers of social disorganization, such as high residential turnover, may drive crime in Brooklyn Park's apartment complexes. While we could not examine this directly, the ACS data indicate that the high-crime segments assigned to Trajectory Group 18 are more likely to be located in census tracts with a higher

[11] See Table A2 in the online appendix for full information. We are grateful to an anonymous peer reviewer for suggesting this additional analysis.

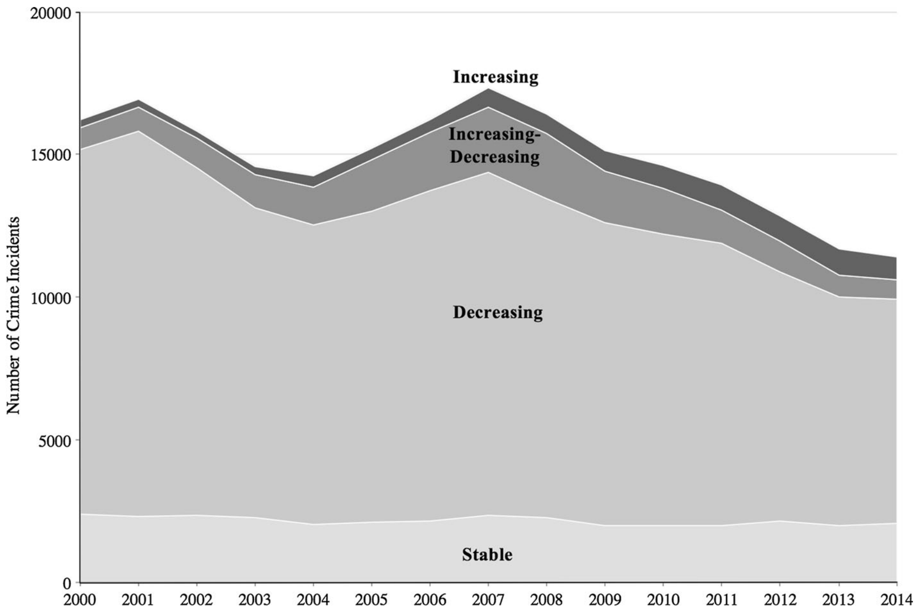


Fig. 6 Total crime in Brooklyn Park by trajectory trend, 2000–2014

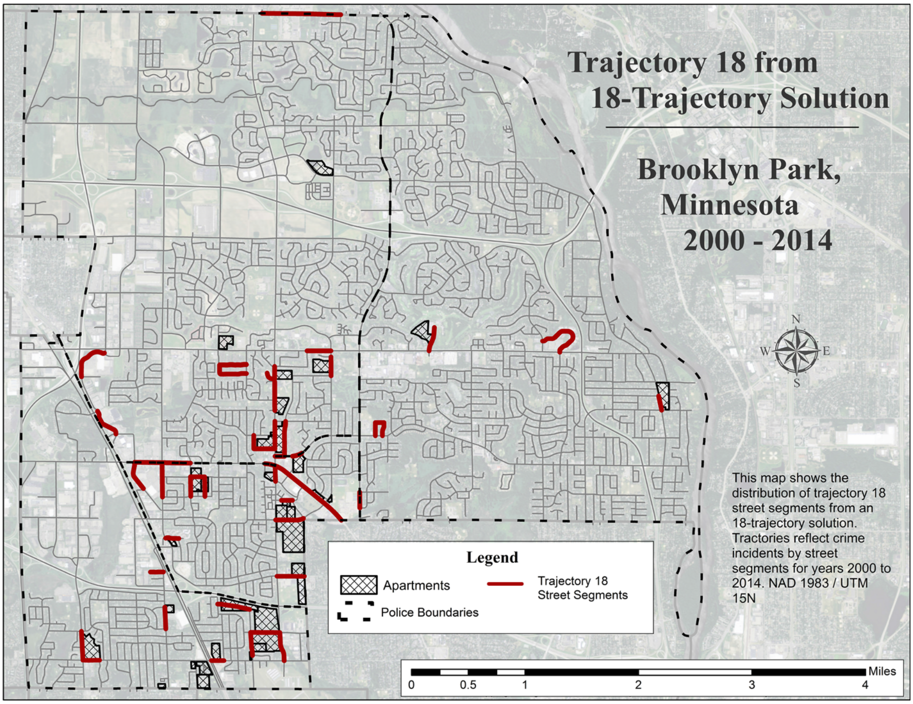


Fig. 7 Location of hot spots in trajectory group 18

percent of African-American (34 vs. 21 %) and Hispanic (10 vs. 5 %) residents, more female headed households (20 vs. 13 %), and a lower median age (31 vs. 34 years of age) on average in comparison to all census tracts in Brooklyn Park.

Discussion

In this study, we replicated the GBTA model used by Weisburd et al. (2004) and others (e.g. Curman et al. 2015; Levin et al. 2015; Wheeler et al. 2015) to assess the patterns of crime concentration, stability, and variability at microgeographic places (street segments) in the suburban city of Brooklyn Park, Minnesota. While there is a substantial and growing body of evidence for a "law of crime concentration at place" (Weisburd 2015), this study is the first to examine its applicability to a suburban setting.

Our findings lend strong support for the law of crime concentration at place. The patterns we observed over a 15-year period in Brooklyn Park are remarkably consistent with the prior research. First, a very small number of microgeographic places contributed a substantial portion of Brooklyn Park's crime. A total of 50 % of the city's crime over this period occurred at 2 % of places on average, or 59 of the 2937 total street segments, and 25 % of the crime was found at 0.4 % of places—just 12 street segments.

Second, consistent with findings from Seattle (Weisburd et al. 2004) and Vancouver (Andresen and Malleson 2011; Curman et al. 2015), these patterns of crime concentration were highly stable over the study period. Furthermore, a single group of chronically high-crime street segments ($N = 50$) contributed almost half of all of the crime incidents occurring in Brooklyn Park during this time, despite experiencing a considerable crime drop. Thus, our study not only adds to the evidence for the existence of the law of crime concentration of place but also indicates that it holds beyond the context of large urban cities.

However, our findings also highlight some key differences in crime concentrations and trends compared to larger cities. Notably, crime is much more heavily concentrated in Brooklyn Park than in urban cities (as it is in other suburban cities—see Hibdon 2013; Weisburd 2015). We also observed considerably less street-by-street variability in Brooklyn Park compared to that found in Seattle (Groff et al. 2009, 2010; Weisburd et al. 2009). The chronic high-crime segments identified through our trajectory analysis are heavily clustered together in specific areas of the city. This is consistent with Hibdon's (2013) findings in Fairfax County, Virginia.

Implications for Practice

We caution that our study only presents findings from one suburban location that may not be generalizable to other suburban or rural areas. We lack detailed qualitative information about the environmental features and patterns of routine activities at the chronic hot spots we identified. Furthermore, there remains a dearth of evidence on the applicability of evidence-based policing practices in suburban and rural areas (Hinkle et al. 2013; Lum and Koper 2013; Lum et al. 2011). However, the consistency of our findings with prior research from large cities suggests that interventions that leverage the logic of the law of crime concentration could also be effective in a suburban setting. This may alleviate any concerns of police leaders who believe these interventions do not translate to their smaller agencies. Of course, these practices must still be tested in suburban and rural locations and modified if necessary to account for the unique environmental features and challenges of these settings.

The increased concentration and lower variability of crime in suburbs suggests that the efficiency of hot spots policing may in fact be even greater in these settings. Just twelve street segments in Brooklyn Park accounted for 25 % of the crime. To the extent that their resources and personnel are more limited compared to urban police agencies, smaller departments likely need to be much more creative with their personnel and resources. The ability to experiment with hot spots policing at just a handful of street segments potentially offers a low-risk, high-payoff approach to crime control. However, the higher degree of crime concentration also means that these agencies must be even more careful to balance focused crime prevention efforts at a small number of chronically hot street segments with the desire of tax-paying community members across the city to see the police in their neighborhoods.

On a related point, our study also highlights the importance of looking at the long-term crime trend when selecting hot spots for police intervention, whether in a research study or practice. We found fewer increasing patterns in Brooklyn Park's crime trajectories compared to other locations, and the places that contributed the most crime nonetheless appear to be cooling off—in fact, the highest crime trajectory contributed substantially to an overall crime drop across the city during the study period. In the places where crime was increasing over time, the change in trend seemed to be driven by significant changes to the built environment and routine activities that will likely shape the nature of crime at those locations for years to come. This suggests that although the pattern of crime concentration remains consistent over time, that crime may not necessarily be coming from the same street segments each year (see also Levin et al. 2015). To this point, we found overall consistency but some shorter-term instability in Brooklyn Park. The top 1 % of street segments with the highest crime over the entire study period ranked among the top 1 % of highest crime street segments on average each year 86 % of the time, ranging from 77 to 93 % in any given year.

We therefore suggest that the identification of hot spots for research or intervention should be based on longitudinal trends and trajectories rather than short-term data. GBTA better identifies street segments that have similar crime patterns over time and as such are "repeat offenders," even if those places experience some short-term fluctuation (see also Levin et al. 2015). This helps to ensure that police resources are directed toward consistently chronic locations rather than hot spots that would have disappeared in a year or two anyway (Rosenfeld, personal communication, 2015), further increasing the efficiency of hot spots policing. The extent to which high crime locations may be experiencing a crime drop should also be accounted for in these assessments. In the case of Brooklyn Park we think it makes sense for police to continue to focus on the chronic high crime trajectory despite its decreasing crime trend because it still contributes such a significant portion of the city's crime. Effective police tactics in these locations may hasten a naturally declining pattern. However, assessing longitudinal trends may also prevent police departments from overlooking groups of places where crime is not yet concentrated but crime is steadily rising, such as the two increasing trajectories identified in our analysis. Proactive prevention efforts in these locations that target emergent risk factors could prevent them from becoming the chronic hot spots of the future. Thus, future research efforts could explore how to bring the methods of trajectory analysis to police departments in a manner that is accessible to crime analysts regardless of whether or not they are trained in advanced statistical methods (as is the case in most departments; see Santos 2013).

Implications for Further Study

While our findings support the existence of the law of crime concentration at place, they also add to a small but growing body of research suggesting that crime is much more concentrated at suburban street segments than urban ones, and that there is more clustering of hot spot street segments in specific areas (Hibdon 2013; Weisburd 2015). In Seattle, despite overall variability in the locations of hot spots, there was considerable clustering of hot segments in the downtown business district (Weisburd et al. 2012, 2009), which can be explained by the greater concentration of crime opportunities—stores, businesses, bars and nightclubs, transit hubs, and the rhythms and routines of the thousands of people who pass through at different times of the day. However, Brooklyn Park, like many other suburban-rural areas, lacks a true downtown area with similar features. In this study we lacked data that would allow us to assess the factors that determine the location, clustering, and variability of hot spots in the suburbs. Our assessment of ACS data at the census tract level provided limited information because of the level of aggregation. Thus, our findings highlight a need for more qualitative research on risk factors for suburban crime concentration, such as systematic social observation (e.g. Mastrofski et al. 2010; Sampson and Raudenbush 1999) to document conditions at suburban hot spots and identify patterns.

As we discuss in our Results section, variability in population density associated with different types of land use may be a more important crime driver in suburbs than the opportunities created by the land use itself (for example, the availability of desirable goods in commercial areas). Suburban hot spots in Hibdon's (2013) study were also heavily clustered in areas that draw large numbers of people, but in that case these were commercial areas and transportation links, in line with findings from larger cities (Weisburd et al. 2012). In Brooklyn Park our chronic hot spots appear to be associated with residential population density in large apartment buildings (in contrast to the findings of Andresen 2006). Social disorganization associated with this land use may also play a role. Many of these apartments are one-bedroom and typically house individuals or families who stay for short periods of time. Thus, it is possible that low collective efficacy may also influence entrenched crime problems at these locations. Residential mobility is related to informal social control, which is a key determinant of collective efficacy, the "willingness [of residents] to intervene for the common good" (Sampson et al. 1997, p. 919, see also Bursik 1988; Kubrin and Weitzer 2003; Sampson and Groves 1989). It may be difficult to develop cohesion and shared values between residents of an apartment building when large numbers of people are frequently moving in and out. Weisburd et al. (2012) find that informal social control and collective efficacy are highly variable even at the street segment level, lending further support to the possibility that even in suburban and rural areas where there may be higher collective efficacy overall (e.g. Weisheit et al. 2006), there may be highly concentrated pockets of social disorganization that drive overall crime rates.

Nonetheless, while crime in Brooklyn Park is clustered in a specific sector of the city, there is still considerable street-by-street variability within that area. This supports the conclusions of Steenbeek and Weisburd (2015), who contend that crime is generated by both macro- and micro-level trends but not those in administrative units such as census tracts.

The lower level of street-by-street variability in Brooklyn Park also raises questions about the relevance of street segments as the unit of analysis in suburbs. While prior micro-place research does allow for the possibility that crime problems could be linked across multiple street segments (e.g. Weisburd et al. 2004, pp. 290–291), the theoretical assumption behind the street segment as a unit of analysis is that individual blocks function as behavior settings in which unique standing patterns of behavior and routine activities develop (Appleyard 1981; Brower 1980; Felson 1987; Jacobs 1961; Smith et al. 2000; Taylor 1997; Taylor et al. 1984; Unger and Wandersman 1983). However, in Brooklyn Park this is not necessarily the case. We do not know whether there is heterogeneity across the clustered street segments in terms of the specific crime problem on each block or the factors that drive the crime, but it is clear that the larger area of the city in which the hot spots are clustered has its own features and processes that attract chronic problems. Thus, we recommend that future research pay closer attention to the unique nature of micro-geographic units in suburban and rural areas.

Importantly, street segments in suburban and rural areas are typically substantially longer and may be less uniform than those in urban grid-based street networks. For example, in urban areas included in Weisburd's (2015) study the average length of a street segment was 365 feet, whereas in the suburban cities (including Brooklyn Park) segments were almost twice as long at 652 feet on average. Hibdon (2013) found that street segments in Fairfax County, VA were 480 feet long on average, but the average length in rural areas was 907 feet. The average length of a street segment in Brooklyn Park is 596 feet (Table 1), and segment lengths in the city vary substantially from 0.08 to over 7500 feet.[12] In addition, many of these street segments are nonlinear (see Fig. 1). These features affect the role of the street segment as a "behavior setting" and individual activity/awareness space (Felson 1987; Felson and Boba 2010; Taylor 1997; Weisburd et al. 2016). On a short, urban street block people may be aware of activity on either side of the street but not what is going on around the corner or on the next block. Here, the street segment is therefore a convenient unit of analysis that aligns well with routine activities theory. However, in a suburban or rural area, parts of a street segment could in fact be around the corner, or otherwise outside one's immediate awareness space, and different patterns of behavior may apply. In the highest crime trajectory in Brooklyn Park street segments were twice as long as the average. Such segments may attract a larger population, who may be operating in different awareness spaces at different points along the segment but attract crime simply by their greater number (see also Andresen 2006). Routine activity theory (Cohen and Felson 1979) also suggests that a larger population increases the probability that motivated offenders, suitable targets, and capable guardians will converge in ways that impact the local opportunity structure.

Brooklyn Park's large apartment complexes also complicate the role of the street segment. They are often set back away from the street, and comprised of multiple buildings, floors, and courtyards connected by an intricate network of walkways, driveways and corridors. The structure and layout of these internal areas are important to the theories of routine activities, behavior settings, and activity spaces that underlie the choice of unit of analysis in studies of crime at microgeographic places (Hillier 2004). As we discussed above, these complex and often non-permeable networks are likely to have different crime patterns and may even be associated with a lower risk of certain types of crime (Beavon et al. 1994; Johnson and Bowers 2010). In a study of Swedish suburbs, where there are similar complexes with multiple buildings organized around courtyards, Gerell (2015) found that residents on a particular floor, stairwell, or building exhibited high levels of collective efficacy but knew very little about the people or activities in other stairwells or buildings that they did not frequent.

Furthermore, from an analytic perspective these internal paths are not officially designated streets and buildings do not always have separate addresses, so crime incidents are often coded to the nearest street segment. In some cases, incidents occurring at very large apartment complexes in Brooklyn Park could be coded to one of several different street segments, and this was not always a systematic decision. In others, incidents might code to a specific street segment because the official mailing address of the complex fell on it, but

[12] See Table A1 in the online appendix.

the incident could have occurred in an area of the complex that was actually closer to another segment.

In our Smart Policing Initiative project we initially identified hot spots based on street segments, but due to the extensive clustering of hot spots and the challenges of pinpointing specific crime locations in the types of places described above our final target sites represent a mix of both traditional street segments and polygons drawn around small clusters of street segments in ArcGIS mapping software in places where we believed crime problems at adjacent street segments may be linked (see also Weisburd et al. 2004). This has largely been an effective compromise, as BPPD's crime data is coded to the specific point on the land parcel where the crime occurs so the polygons also pick up incidents occurring away from street segments but within the same apartment complex or strip mall. However, we have run into some challenges in understanding the exact nature of the "activity spaces" of residents and other space users in our target areas.

In one example, officers who were attempting to engage the community in problem solving on a relatively short, traditional street segment initially found little evidence of the problems that had made the segment eligible for our experiment. On further investigation they found that many of the crimes were occurring in a large space behind a strip mall on the block. It is unlikely that this area would have been on the radar of most people using the street, but crime was nonetheless coded to the street segment because the address of the land parcel was not clear. We discovered that some of the crimes occurring in this space were also coding to a perpendicular street segment that was not part of the experiment.

In another illustration, we used a polygon to identify a large apartment complex of over 800 units divided across eight separate buildings that was subsequently randomly assigned to our treatment group. The complex was initially identified as a potential target site because the police believed that a large amount of crime coding to adjacent street segments was attributable to the apartments. Officers assigned to this hot spot initially struggled to focus their problem-solving efforts due to its size and complexity. They subsequently learned that much of the crime in this complex could be attributed to just one or two buildings. There were situational and design differences in these buildings, shaped by decisions of place managers.

These issues have implications for both researchers and practitioners. There is clearly a need to think beyond the street segment in some contexts, while still maintaining the microgeographic focus that allows the police to focus their resources most efficiently. We call for more research to understand how residents of suburbs and rural areas perceive their activity and awareness spaces. Qualitative methods may be most appropriate here; in particular, the use of cognitive maps (e.g. Coulton et al. 2001; Hibdon 2011). However, like all crime and place research, the feasibility and utility of these approaches are influenced by the data capacity of the police department (as well as the relative expense of large-scale qualitative data collection). In Brooklyn Park, crime analysts are able to code incidents to specific parcels and even buildings within apartment complexes (to the extent that officers are recording accurate locations), but not all departments are collecting information at this level of precision. Furthermore, for researchers the street segment is often the most logical and practical unit for collecting data on crime and its correlates place (Braga and Clarke 2014; Curman et al. 2015; Weisburd et al. 2004).

Finally, we call for further study of the applicability of the law of crime concentration at place at truly rural hot spots and in non-urban locations outside the United States. While our study represents an important new contribution to the study of crime at microgeographic places, a key limitation is that the setting is a "suburban city." While there are clear differences between Brooklyn Park and larger urban cities, in other ways its layout and land use are much more comparable to urban rather than rural areas or less populous suburbs. This is also true of the handful of other suburbs (Ventura, Redlands, and Fairfax County) that have been studied to date. Thus, some of the differences we identify between Brooklyn Park and urban areas may be caused by different mechanisms than the type of setting. This is particularly true of our observation that the lower street-by-street variability in crime in Brooklyn Park may be a feature of suburban land use and layout. While our speculation on the causes of that variability are based in theory, more research is needed in this area and some researchers have found similar results in urban areas (e.g. Curman et al. 2015; Wheeler et al. 2015).

Truly rural areas have much lower population density, substantially fewer and longer street segments, and "non-traditional" crime problems in places that are difficult to measure. For example, the Center for Evidence-Based Crime Policy has recently begun a study of rural hot spots in Appalachian Kentucky in collaboration with Partners for Education at Berea College, funded by the Bureau of Justice Assistance's Byrne Criminal Justice Innovation program,[13] where the project target area has a population of just 210,000 in almost 3000 square miles. There are no population centers of 10,000 or more residents and we are learning through qualitative research that crime places are often inaccessible by road (such as mountain hollows and strip mines), moving targets (for example, school buses, on which youth can spend 3–4 hours per day in remote areas), or virtual (social media use is prevalent and serves as a platform for anti-social behavior).[14] In the present study our geocoding rate was 97.9 %, indicating that almost all crime locations could be tied to a street address.[15] Thus, our findings are unlikely to apply to extremely rural settings.

The implications for practice in these areas are also substantially different. Rural police departments often have to cover hundreds of square miles with a smaller number of officers. In these circumstances it is even more important for the police to know where to focus their efforts in order to have the maximum impact on crime control, but the logistics of doing so may be extremely challenging. Furthermore, suburban, rural, and even some urban locations outside the United States have substantially different street networks, built environments, cultures, and police practices, which may differentially impact crime risks and concentration (e.g. Johnson and Bowers 2010; Mazeika and Kumar 2016). We encourage more examination of the generalizability of the law of crime concentration at place and its policy implications to these settings.

Conclusion

Our study of crime trends in Brooklyn Park, Minnesota over a 15-year period from 2000 to 2014 is the first to assess longitudinal crime patterns in a suburban setting using GBTA. In line with previous longitudinal research in urban areas we found a very high level of concentration of crime at a small number of microgeographic places—specifically, around 2 % of street segments in Brooklyn Park produced 50 % of the crime during this period, and just 0.4 % produced 25 % of the crime. Our findings therefore extend the evidence for the "law of crime concentration at place" to a non-urban context. While research is still needed to assess whether evidence-based policing strategies that rely on the "law" apply to

[13] http://programs.lisc.org/csi/byrne_criminal_justice_innovation_(bcji)/index.php. BJA award number 2015-AJ-BX-0007.

[14] This research is not yet published; however, the first author can provide information on request.

[15] With the exception of crimes at intersections, which were excluded—see Footnote 5.

suburban and rural agencies, it is promising to observe that the underlying theory holds in these places.

We also found, consistent with prior research, high stability in crime concentration. Just 50 chronic high-crime places drove a substantial portion of the city's crime over 15 years. However, while other studies have found that this chronic group contributes a stable amount of crime over time, in Brooklyn Park there was a steady decline in crime in these "hot" places during the study period. In fact, the cooling of hot spots in Brooklyn Park has almost single-handedly driven the city's substantial crime drop of nearly 30 % since the early 2000s.

However, we also observed some important differences in crime trends in Brooklyn Park compared to urban areas. The much higher level of crime concentration in this suburb suggests that more attention needs to be paid to the characteristics of suburban hot spots. Which features of land use, routine activities, and social processes shape the development and persistence of chronic hot spots in suburbs? We also found that Brooklyn Park's hot spots are much more clustered together rather than being spread throughout the city. This not only lends more support for our call for more research into the features of suburban hot spots and whether those features determine why they cluster, but also raises questions about the appropriateness of the street segment as the unit of analysis for place-based research in suburbs. This clustering is somewhat at odds with the theoretical assumption that individual street segments act as unique behavior settings.

We caution that our conclusions are preliminary, given that much more research is needed on the nature of crime in suburban settings. Our findings are only based on one location, which may not be representative of other suburban areas. We lack qualitative data about the specific nature of the chronic high crime places, and we do not know how or why hot spots in Brooklyn Park seem to be cooling over time. Furthermore, Brooklyn Park is a suburban city, larger and in some ways more comparable to urban areas than to other suburbs in the United States and elsewhere, and certainly to rural areas (including tribal lands). We need to understand more about longitudinal crime trends in such areas and how they affect the translation of evidence-based policing practices to these very different settings. Nonetheless, our study represents an important first step in not only extending the law of crime concentration at place to non-urban environments, but also raising the questions that will guide the suburban-rural crime and place research agenda in the future.

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