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ORIGINAL PAPER

Assessing the Validity of the Law of Crime Concentration Across Different Temporal Scales

Cory P. Haberman[1] **· Evan T. Sorg**[2] **· Jerry H. Ratcliffe**[3]

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Abstract
Objectives The present study examined if Weisburd's (Criminology 53(2):133–157, 2015) law of crime concentration held across different theoretically relevant temporal scales.
Methods The cumulative percentages of Philadelphia, PA USA street blocks and intersections experiencing 25 and 50 % of street robberies by hour of the day, days of the week, and seasons of the year were compared to the bandwidth percentages established by Weisburd (2015). Different analyses were used to determine the stability of the micro-places' street robbery levels within the three temporal scales.
Results We found that the cumulative percentages of street blocks and intersections experiencing 25 and 50 % of street robberies at each of the three temporal scales closely matched the bandwidth percentages expected from Weisburd (2015) and some micro-places experienced street robberies across all temporal periods while others had more isolated temporal concentrations.
Conclusion Weisburd's (2015) law of crime concentration holds across different theoretically relevant temporal scales, and future criminology of place studies should not ignore temporal crime patterns. Further, it may be possible to refine hot spots policing approaches by incorporating spatial–temporal crime concentrations.

Keywords Law of crime concentration · Geography of crime · Criminology of place · Crime and place · Hot spots

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✉ Cory P. Haberman
cory.haberman@uc.edu

1 University of Cincinnati, P.O. Box 210389, 660H Dyer Hall, Cincinnati, OH 45221, USA

2 Rowan University, Glassboro, NJ, USA

3 Temple University, Philadelphia, PA, USA

Introduction

Researchers have consistently found that crime is disproportionately concentrated at relatively few micro-places (e.g., addresses, intersections, and/or street blocks) (Braga et al. 2010, 2011; Sherman et al. 1989; Weisburd and Amram 2014; Weisburd et al. 2004).[1] Drawing on that work and new analyses of crime concentrations from eight jurisdictions, Weisburd (2015: 138) proposed the law of crime concentration: “for a defined measure of crime at a specific microgeographic unit, the concentration of crime will fall within a narrow range of bandwidths of percentages for a defined cumulative proportion of crime” (also see Weisburd and Amram 2014; Weisburd et al. 2012). Weisburd’s (2015) analyses suggested that the “narrow bandwidth” within which crime clustered at street segments was remarkably consistent across eight conveniently sampled cities. The percentage of street blocks that accounted for 25 and 50 % of crime ranged from 0.4 to 1.6 and 2.1 to 6 % (which is consistent with past research), and the concentrations remained stable across years in the four cities where longitudinal data were available. Weisburd’s (2015: 151) validation of the law of crime concentration in multiple jurisdictions over several years led to the conclusion that “It is time for criminologists to focus their attention on place. This emphasis will enrich criminology and crime prevention”. Weisburd’s (2015) analyses, however, did not consider whether the law of crime concentration holds across different temporal scales. Crime and place scholars have long theorized that crime is concentrated in space *and* time (Cohen and Felson 1979; Felson and Eckert 2016),[2] and the empirical research reviewed below suggests spatial crime patterns can vary by time of day, day of the week, and season of the year. Therefore, this study sought to replicate Weisburd’s law of crime concentration work across different theoretically relevant temporal scales for street robbery in Philadelphia, PA, USA. After replicating Weisburd’s (2015) work across three different temporal scales, we then argue that future crime and place researchers should also incorporate time into their work and provide some avenues for future research and crime prevention policy.

Theoretical Frame

Environmental Criminology

Environmental criminology predicts that crime will be concentrated in space and time based on human movement patterns across a city. In the simplest terms, Cohen and Felson’s (1979) routine activities theory originally proposed that crime events are the result of motivated offenders converging with suitable targets lacking protection from capable guardians. Drawing on this idea, Brantingham and Brantingham (1993a, b, 1999) described how human movement patterns facilitate the convergence of Cohen and Felson’s three basic elements of crime to create crime concentrations.

Crime pattern theory considers the cityscape as a collection of nodes, or places that people travel to and from, connected to one another via pathways, such as streets and public transportation lines. Edges are formed when two distinct areas, often separated by a pathway, come together (Brantingham and Brantingham 1993b). Individuals have activity

[1] In this paper we use the phrases micro-places and street segments and intersections interchangeably.

[2] For an example of how space *and* time has been considered for operational policing see Santos and Santos (2015).

spaces that are made up of the nodes and paths that encompass their routine activities. For the most part, peoples' activity spaces consist of places where people live, go to work or school, or participate in leisure or recreational activities, as well as the streets and public transportation lines they use to travel to and from those locations (Horton and Reynolds 1971). A central premise of crime pattern theory is that offending will concentrate in and around nodes and paths that are frequented by the most people because they produce the greatest convergence of routine activity theory's three basic elements of crime (Cohen and Felson 1979). When street segments form edges and increase anonymity or concentrate features that facilitate offending, then crime will also concentrate at edges. Since places with features that facilitate opportunities are rare, crime consistently concentrates at relatively few locations, or "hot spots" of crime, in a jurisdiction.

However, human activity also varies across time and follows natural temporal rhythms (Chapin 1974; Cohen and Felson 1979; Hawley 1950). Peoples' routine activities are constrained by biological and social factors (Hägerstrand 1970; Miller 2005; Ratcliffe 2006). For example, the human body requires sleep, and the majority of Americans sleep during the nighttime and into the early morning hours. Furthermore, most people are at work or school (or childcare) during the day on weekdays. In the hours just before and after work/school, people spend time in transit (Haberman and Ratcliffe 2015). Most people then engage in discretionary activities during the evening. Some people engage in recreational activities away from their homes (e.g., jogging in parks) while others spend time at home completing household chores. After the conclusion of the work week on Friday evening, people have more discretionary time for recreational activities. Thus, people may spend more time away from home engaged in leisure activities or running errands on the weekends (or up until Sunday evening).

Routine activity patterns also change throughout the year. Generally, most people will be more active and spend more time outdoors during the fall, spring, and summer months when the weather is more pleasant, but retreat indoors during the winter when the weather becomes unpleasant. As the seasons change, students are released from schools, recreational places open (e.g., public pools), different sports seasons begin and end, and many families take vacations. In other words, specific types of activities are associated with specific seasons, and seasonal changes will impact where people spend their time. For example, many tourist locations are deserted during the winter months but bustle with out-of-towners during the summer. As a result, crime opportunities are not theorized to be uniform across hours of the day, days of the week, or seasons of the year (Felson and Eckert 2016; Ratcliffe 2006) because "[a]s the relevant actors—victims, offenders, guardians and place managers—adjust their relative densities over time and around specific places, the opportunities for crime shift and coagulate" (Ratcliffe 2010: 15).

Crime and Time Research

Temporal crime patterns have not been entirely ignored by researchers, but the analysis of spatial *and* temporal crime patterns is vastly under-researched (Ratcliffe 2010). Consider the literature on the seasonality of crime patterns. Most of these studies examine city-wide crime patterns and entirely ignore smaller spatial units (for exceptions, see Andresen and Malleson 2013; Breetzke and Cohn 2012; Ceccato 2005; Harries et al. 1984; Sorg and Taylor 2013). Additionally, many studies correlate daily or within-day weather measures and crime levels while not only ignoring space but also aggregate seasonal periods (see Lebeau 1988 for discussion on the importance of aggregate seasonal periods; for examinations of seasonality at temporal scales longer than a day see Field 1992; Hipp et al. 2004;

Landau and Fridman 1993; McDowall et al. 2012; Mares 2013; Yan 2004). In other words, even though citywide studies of daily seasonal patterns typically control for time of the day and day of the week and can tell us about within-season variation in crime (Cohn 1993; Lab and Hirschel 1988; Rotton and Cohn 2000; Tompson and Bowers 2015), they tell us nothing about within-day, within-week, or between aggregate season *spatial–temporal* crime patterns.

Not all work on temporal crime patterns, however, has ignored space. For example, Brower and Carroll (2007) found that in the City of Madison, Wisconsin, various crime categories had distinct hourly periods when they peaked. Further, the geographic location of these incidents shifted over the course of the day. For example, assaults and batteries began to increase at 11:00 p.m. and peaked at 2:00 a.m. in the section of the city with the highest bar density. Analogous results were found for violence, harassment, and disorder crime in Worcester, England (Bromley and Nelson 2002) and automobile theft in Philadelphia, PA (Rengert 1997).

Similarly, work by Martin Andresen and his colleagues has directly compared the spatial patterns of different crime types across different temporal scales. Andresen and Malleson (2013) applied Andresen's (2009) point pattern analysis to test whether there was similarity in the spatial patterns of several crimes across seasons in Vancouver, Canada. As with numerous other studies, seasonal variation arose for many crime categories: an aggregate crime index, assaults, thefts, thefts from vehicles and thefts of vehicles all had higher counts during the warmer summer months. In addition, there were also changes in the spatial distribution of crime. Specifically, during the summer months Andresen and Malleson (2013: 32) found that crime increased in Vancouver's downtown shopping area, other shopping/tourist areas, large parks and the location of Vancouver's summer fair. Andresen and Malleson (2015) also found different crime types spiked on different days of the week in Vancouver, Canada. Further, their work demonstrated that different days of the week exhibited different spatial patterns for all but two crime categories (robbery and sexual assault). In other words, not only were there differences in the volume of crimes on different days, the places where crime occurred also differed by day of week.

Finally, some studies have modeled the influence of potentially criminogenic places on crime counts across different times of the day. Haberman and Ratcliffe (2015) found that some criminogenic places only had effects on census block street robbery counts at certain times of the day. For example, neighborhood parks significantly increased street robbery during all hours outside of 9:15 p.m. to 6:44 a.m. or times when parks were likely in use, and pawn shops were only criminogenic during the afternoon when they were open and conducting business. Additional studies have found analogous results when examining the relationship between census block assault levels at different times of the day and schools (Roman 2005) or domestic violence levels and places that sell alcohol (Roman and Reid 2012). Alternatively, a few studies have not found any differences in the temporal distributions of crime in and around casinos when compared to non-casino areas (Barthe and Stitt 2009a, b).

In sum, research on temporal crime patterns have either (1) ignored space entirely, (2) compared spatial crime patterns across different temporal units, or (3) examined whether different types of places link to crime levels differently across different times of the day. The question of whether or not spatial crime concentrations hold across different temporal scales remains. Given the theoretical reasons to expect crime to concentrate in space across different temporal scales and Weisburd's (2015) elevation of crime concentrations into the first law of the criminology of place, this study examined whether the law of crime concentration holds across different temporal scales: hours of the day, days of the week, and seasons of the year. As discussed later in this paper, the extent to which crime concentrates across different temporal scales has important implications for future research and crime policy.

Data and Method

Study Site

The present study examined the law of crime concentrations across different temporal scales for street robberies in Philadelphia, PA USA. Philadelphia is the fifth largest city in the country. Philadelphia's estimated 1.5 million residents are roughly equally black and white (43 and 41 %) with approximately 12 % reporting as Hispanic/Latino (US Census Bureau 2010). Philadelphia's median income is $34,207 compared to the national median income of $50,502 (US Census Bureau 2011).

Street Robbery

The Philadelphia Police Department (PPD) provided street robbery incident data for 2009 to 2011.[3] Street robberies involve the theft of someone else's property through use of the force or the threat of force by one or more persons in public locations (mostly on the street) (see Monk et al. 2010).The PPD geocoded the street robbery data at about a 98 % hit rate. Ratcliffe (2004a, b) suggested a hit rate above 85 % was adequate for spatial analysis. Between 2009 and 2011, a total of 17,918 street robberies were available for analysis.

We chose to focus on street robbery for both theoretical and practical purposes. There are robust theoretical reasons and empirical support to expect that street robberies will vary with aggregate level routine activities (Bromley and Nelson 2002; Haberman and Ratcliffe 2015). The predatory nature of street robbery requires people to be in public in order to become victims, and people's presence in public will be determined by changing routine activity patterns (Felson 2006; Felson and Eckert 2016; St. Jean 2007; Wright and Decker 1997). Focusing on a single crime type also allows those theoretical mechanisms to be explicated more clearly (Clarke 2008; Smith et al. 2000). Further, the problems with recording the dates and times of crime events is less of a concern for street robbery since the victim is present during the act. Many other crime types, such as burglary, occur over longer time spans or occur when the victims and witnesses are not present to accurately report the event time (Ratcliffe 2000). We will return to this issue in the discussion.

Unit of Analysis

Street blocks and intersections are examined in this study ($n = 60{,}381$) (also see Braga et al. 2010, 2011). We use the term street blocks and intersections and micro-places interchangeably throughout the remainder of the study. These units were chosen for both theoretical and practical reasons. Street blocks, two street block faces between two intersections, are behavior settings in urban environments (Taylor 1997; Weisburd et al.

[3] We note that the Philadelphia Foot Patrol Experiment spanned from approximately the last day of March through the end of September in 2009 (Ratcliffe et al. 2011) and the Philadelphia Policing Tactics Experiment was implemented from July, 2010 through February, 2011 (Groff et al. 2015). Both experiments statistically significantly reduced violent crime, which included street robbery. While we are unable to quantify the extent to which this impacted the results of the present study, readers should consider the context in which the data were generated when considering the results and implications of the present study.

2012). In other words, they are places that structure recurring social behavior in cities (Wicker 1987). Street intersections also serve as behavior settings in urban environments (Anderson 1978, 1999; Liebow 1967; Moskos 2008; Simon and Byrne 1997). Therefore, both units capture the routine activity patterns of urban life. Further, in Philadelphia, approximately 68 % of analyzed street robberies were geocoded to an intersection (n = 12,176).

Temporal Scale and Periods

We previously argued routine activity patterns are structured across multiple temporal scales. The present analysis examined crime concentrations across three temporal scales: (1) within-days, (2) days of the week, and (3) seasons. Following the lead of Haberman and Ratcliffe (2015), we examined four within-day periods: (1a) morning (6:45 a.m. to 9:59 a.m.), (1b) daytime (10:00 a.m. to 4:29 p.m.), (1c) evening (4:30 p.m. to 9:14 p.m.), and (1d) late-night (9:15 p.m. to 6:44 a.m.). These periods capture within-day routine activity patterns based on an analysis of activities of average Americans on an average day from the American Time Use Survey (ATUS) (see Haberman and Ratcliffe 2015: 460–462 for more details). For example, the morning period captures morning commuting times, the daytime period encompasses the typical school/work day, the evening period is the hours when people are commuting from school/work and/or engaged in discretionary activities, and the late-night period captures when most people will be at home but also the hours when some people will be engaged in recreational activities or commuting home from them (e.g., bar closing hours). We sometimes refer to these periods as the "ATUS within-day periods" hereafter.

All analyses described below were also repeated using two additional within-day operationalizations: (1) six four-hour periods and (2) four six-hour periods. These operationalizations had the benefit of providing exposure periods of equal lengths, but were limited by the fact that their operationalization was arbitrary and not based on the actual routine activities of Americans from the ATUS. The starting time for both operationalizations was 06:00 a.m., and 4/6 h were added in an incremental fashion to bound the periods. The results of the sensitivity analyses can be found in the online supplemental material, but the substantive findings described below held regardless of how the within-day periods were operationalized.

We also examined the concentration of street robbery by day of the week. We used bifurcated weekday and weekend periods. The weekday period spanned from 6:45 a.m. on Monday morning until 4:29 p.m. on Friday afternoon. This period captured the American school/work week or when most citizens will be concentrated on commuting to and from school/work and spending a lot of time at home getting ready for the next school/work day. The weekend period spanned from 4:30 p.m. on Friday afternoon until 6:44 a.m. on Monday morning. This period captured when Americans will typically be more likely to be engaged in recreational activities in public spaces (Andresen and Malleson 2015). We sometimes refer to these periods as the "bifurcated day of week periods". Again, the substantive results described below held when the day of the week temporal scale was operationalized as seven 24-h periods (12:00 a.m. to 12:00 p.m.) (see the online supplemental material).

The concentration of street robbery was also examined by season. Fall spanned September through November. Winter spanned from December through February. Spring began on the first day of March and ended on the last day of May. Summer included the days between June 1st and the end of August. These operationalizations are consistent with previous examinations of seasons and seasonal crime patterns (Andresen and Malleson 2013; Linning 2015; Trenberth 1983). The operationalizations of seasons also represent times when routine activities shift across the year. In the fall, Philadelphia experiences pleasant weather with the average daily maximum temperature of about 66 °F during the study period. Many Philadelphians enjoy spending time walking city streets and visiting outdoor spaces. The fall also marks a time when students return to schools and universities, all collegiate and professional sports are in season, and many citywide events and festivals occur outdoors. Philadelphia winters can be harsh. During the study period, the average daily maximum temperature was about 40 °F (average daily minimum = 26 °F; average daily mean = 33 °F) and Philadelphia averaged roughly 39 days with precipitation (usually rain but sometimes snow). Given the unpleasant weather conditions, many Philadelphians remain indoors during the winter, but a few winter events, such as New Year's Eve or school/University breaks, may encourage routine activity patterns that facilitate street robberies. The weather gradually becomes more pleasant during the spring. The average daily maximum temperature across the study period was 53 °F in March, 63 °F in April, and 74 °F in May. As the weather transitions from unpleasant to pleasant, residents begin to spend more times outdoors. Finally, summers in Philadelphia are fairly hot. The average daily maximum temperature during the study period was 85 °F. Many people spend time outdoors and public events/festivals frequently occur. Philadelphia is also flooded with tourists during the summer.[4]

Analytic Plan

The extent to which crime concentrated across the three temporal scales was examined using a range of analyses. Descriptive statistics for each period's street robbery distribution were first computed. Next, we focused on replicating the atemporal cumulative percentages of micro-places that experienced 25 and 50 % of crime in Weisburd (2015) for street robberies that occurred in each period across a given temporal scale. In other words, the total number of street robberies in each period was used as the denominator to calculate the cumulative percentages of street robberies in a period while the total number of micro-places was used as the denominator to calculate the cumulative percentages of micro-places experiencing those respective cumulative percentages of street robberies.

We then examined the extent to which the places that experienced high concentrations of crime within each period were stable across the other periods of the temporal scale. Spearman rank-order correlations, which are appropriate for non-normal count variables (Corder and Foreman 2014), were computed in R (version 3.1.2) using the Hmisc (version 3.16-0) package (Harrell 2015). Scatter plots comparing street robbery counts across the different periods for each temporal scale were also examined.[5] To assist with describing the scatter plots, the street robbery counts across micro-places by periods were recoded into three categories: (1) zero street robberies, (2) one to four street robberies, and (3) five or more street robberies. The five street robbery cutoff was chosen as a reasonable threshold

[4] Daily weather data for Philadelphia between 2009 and 2011 were drawn from www.weatherunderground.com.

[5] Only one period and all of its pairwise comparisons are shown for each temporal scale in order to maximize the use of the available printing space and allow for the individual graphs to have larger plot sizes. The scatter plots were created using the ggplot2 package in R (Wickham 2009). "Jittering" and an opacity of 0.3 was used to reduce the effect over plotting given the large number of observations and discrete nature of the street robbery counts. Other graph types, such as heat maps, were considered, but they failed to provide a better visualization of the data.

for identifying street robbery hot spots, especially in Philadelphia (see Groff et al. 2015; Haberman 2015). Astute readers may have concerns the threshold is arbitrary, but the scatter plots provide the full ratio-level comparisons. Contingency tables (3 × 3) were then computed for all possible pairs of periods within each temporal scale to quantify the extent to which micro-places had "high" street robbery counts across both periods.[6] Finally, Gibbs-Martin heterogeneity indices (GMI) were computed for each temporal scale to describe the distribution of street robbery counts across nominal periods (Blau 1977; Gibbs and Martin 1962). The GMI is computed as:

$$GMI = 1 - \sum_{i=1}^{n_i} p_i^2 \tag{1}$$

The number of categories (temporal periods) examined is n_i and the proportion of cases within each category i is p_i. The GMI is bounded from 0 to $1 - \frac{1}{n_i}$. Values close to zero indicate the data are concentrated in a single category (or temporal period) and values near the maximum indicate the data are equally distributed across all categories (or temporal periods). The GMI's are displayed in scatter plots against the micro-places' overall street robbery counts, and provide as assessment of the similarity in street robbery counts across all the periods in a temporal scale relative to the micro-place's contribution to city-wide robbery levels.

Results

Descriptive statistics for all street block and intersection street robbery counts by temporal period are shown in Table 1 and measures of spatial concentration are shown in Table 2. Philadelphia street robberies follow some general temporal patterns. First, the total number of street robberies occurring in Philadelphia increases across the day, and this general pattern mostly holds after adjusting for the exposure length, or number of hours, of each period. The exception is that the evening period has the second highest street robbery count, but the highest street robbery per exposure hour rate. Overall, only about 6 % of street robberies occur in the morning hours (for a rate of 329.54 street robberies per hour) compared to roughly 48 % of street robberies occurring in the late-night hours (for a rate of 901.37 street robberies per hour). Second, the weekend period experienced more street robberies than the weekday period after adjusting the raw counts for the number of hours in each period. The weekday period experienced roughly 61 % of street robberies, but only 34.52 street robberies per hour compared to the 37.29 street robberies per hour experienced during the weekend period. Finally, Philadelphia street robberies were roughly equally distributed across all four seasons. The overall percentages of street robberies that occurred during each season ranged from about 22 (winter) to 28 (fall) percent.

After determining Philadelphia street robberies were spatially clustered, the law of crime concentration was tested. The law of crime concentration was found to hold for Philadelphia street robberies irrespective of time. Only about 17 % of all micro-places (n = 10,254) experienced a street robbery during the study period. In the context of the law of crime concentration's bandwidth percentages, roughly 1.09 % of micro-places (n = 657) accounted for 25 % of all street robberies and roughly 3.88 % of micro-places

[6] The contingency tables are not shown to conserve space since the scatter plots essentially show the same information with the full ratio-level pairwise comparisons, but are available by request from the authors.

Table 1 Descriptive statistics for street robberies by temporal periods

	Min	Max	Mean	SD	Sum	% of total SR	SR per hour
Within-day							
Morning	0	8	0.02	0.15	1071	5.98	109.85
Daytime	0	19	0.06	0.34	3844	21.44	197.13
Evening	0	15	0.07	0.35	4440	24.78	311.58
Nighttime	0	21	0.14	0.53	8563	47.80	300.46
Days							
Weekday	0	35	0.18	0.69	10,942	61.06	34.52
Weekend	0	21	0.12	0.47	6976	38.94	37.29
Seasons							
Fall	0	13	0.08	0.36	4948	27.61	0.76
Winter	0	13	0.07	0.33	3970	22.16	0.61
Spring	0	21	0.07	0.35	4224	23.58	0.64
Summer	0	21	0.08	0.37	4776	25.65	0.72
Total	0	52	0.30	1.03	17,918	100.00	0.68

N = 17,918 2009–2011 street robberies. N = 60,381 street blocks and intersections. *Min* minimum; *Max* maximum, *SD* standard deviation, *SR* street robberies

Table 2 Measures of street robbery spatial concentration by temporal periods

	Percentage of micro-places experiencing…[a]		
	Zero SRs (%)	25 % of period's SRs	50 % of period's SRs
Within-day			
Morning	98.38	0.29	0.74
Daytime	95.06	0.52	1.81
Evening	94.14	0.66	2.18
Nighttime	89.86	0.95	3.05
Days			
Weekday	88.03	0.93	3.03
Weekend	91.43	0.88	2.79
Seasons			
Fall	93.40	0.75	2.50
Winter	94.64	0.62	2.07
Spring	94.48	0.60	2.03
Summer	93.82	0.69	2.23
Total	83.02	1.09	3.88

SR street robberies

[a] Percentages of micro-places experiencing different percentages of street robberies were computed within each temporal period

(n = 2343) accounted for 50 % of all street robberies. These percentages are nearly identical to the bandwidth percentages reported by Weisburd (2015).

The law of crime concentration also held across all three temporal scales. Due to the low street robbery counts across the various temporal periods, however, the bandwidth percentages of micro-places experiencing street robbery were also lower. Recall the percentages of street robberies were based only on the total number of street robberies that occurred during each period.[7] The bandwidth percentages of micro-places experiencing 25 % of all street robberies during each of the ATUS within-day periods ranged from 0.29 to 0.95 %. The bandwidth percentages of micro-places experiencing 50 % of all street robberies during the within-day periods ranged from 0.74 and 3.05 %. On the other hand, these bandwidth percentages are similar to those reported by Weisburd (2015) for the less populous cities that experienced relatively lower levels of crime in his sample. Given this finding, it would appear that data volume may be an important predictor of bandwidth percentages.

Most micro-places also did not experience a single street robbery during either the bifurcated weekday or weekend periods (roughly 88 and 91 %, respectively). The percentages of micro-places that experienced 25 and 50 % of each period's street robberies are also within the bandwidths that would be expected if the law of crime concentration holds for the day of week temporal scale (see Weisburd 2015: 143–144). For weekdays, about 0.93 and 3.03 % of micro-places experienced 25 and 50 % of weekday street robberies and about 0.88 and 2.79 % of micro-places experienced 25 and 50 % of the street robberies that occurred during the weekend period.

Street robberies were found to be similarly concentrated in a relatively small number of micro-places during each season. Approximately 93 or 94 % of micro-places did not experience a street robbery within each season (Table 2). Across the four seasons, anywhere from 0.60 (spring) and 0.75 (fall) percent of micro-places experienced 25 % of the period's street robberies. The percentage of micro-places experiencing 50 % of a season's street robberies had a similarly small range; anywhere from 2.03 (spring) to 2.5 (fall) percent. Again, the results suggest the law of crime concentration holds at the seasonal temporal scale.

Given the law of crime concentration was found to hold across all three temporal scales, the next logical step was to examine the extent to which the same micro-places experienced crime concentrations across multiple temporal periods. Table 3 shows spearman rank-order correlations among the micro-places' street robbery counts across the periods within each temporal scale. Weak correlations were found. The maximum correlation of .30 was between the weekday and weekend periods. The correlations ranged from .15 to .24 for the within-day periods and .20 and .23 for the seasonal periods.

Representative scatter plots comparing street robbery counts among periods are shown for each temporal scale in Figs. 1, 2 and 3. In each figure, pairwise comparisons are shown only for a single period and all other periods within the temporal scale in order to maximize plot area. The scatter plots that were not displayed were similar to the displayed plots, and are still discussed throughout the results. The scatter plots that were not displayed in the figures are available from the authors upon request. The general patterns that emerged in all plots was that most micro-places were clustered in the areas with low street robbery counts during both periods and some micro-places had either relatively high street robbery counts during only one of the periods or high street robbery counts during both periods.

Figure 1 displays the ATUS within-day periods' pairwise comparisons. There was relatively minimal correspondence between the morning period street robbery counts and those from any of the other within-day periods. This was somewhat expected given the

[7] For example, per Table 1 the denominator in the percentage calculations for the morning period is 1071.

Table 3 Spearman rank-order correlations across temporal periods

	Morning	Daytime	Evening	Nighttime	Weekdays	Weekends	Fall	Winter	Spring	Summer
Morning	–	–	–	–	–	–	–	–	–	–
Daytime	.15***	–	–	–	–	–	–	–	–	–
Evening	.15***	.22***	–	–	–	–	–	–	–	–
Nighttime	.14***	.22***	.24***	–	–	–	–	–	–	–
Weekdays	–	–	–	–	–	–	–	–	–	–
Weekends	–	–	–	–	.30***	–	–	–	–	–
Fall	–	–	–	–	–	–	–	–	–	–
Winter	–	–	–	–	–	–	.20***	–	–	–
Spring	–	–	–	–	–	–	.22***	.21***	–	–
Summer	–	–	–	–	–	–	.21***	.21***	.23***	–

*** $p < .001$. N = 60,381 street blocks and intersections

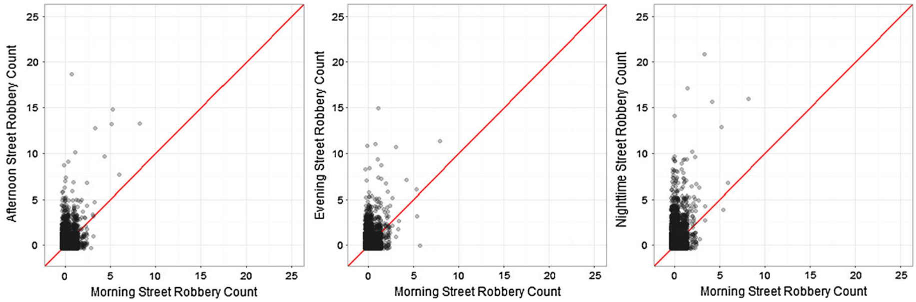
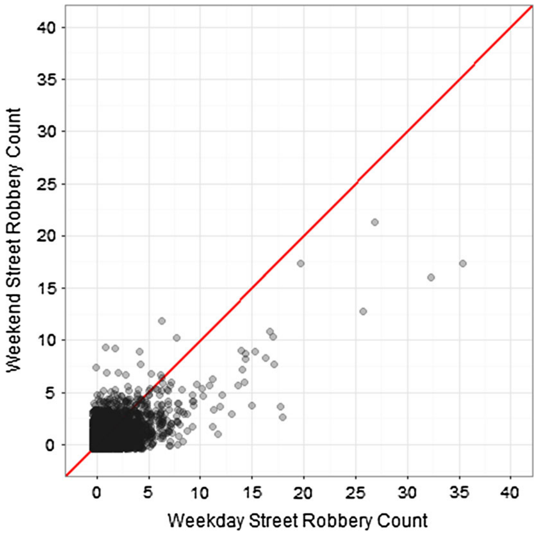


Fig. 1 Representative *scatter plots* comparing the morning period to all other within-day periods. *Notes* N = 60,381 micro-places. Jittering and opacity used to minimize over-plotting. *Scatter plots* for all other pair-wise comparisons were not shown in order to maximize the available plotting area, but are available from the authors upon request. All plots led to substantively similar conclusions

Fig. 2 Scatter plot comparing street robbery counts by day of week periods. *Notes* N = 60,381 micro-places. Jittering and opacity used to minimize over-plotting



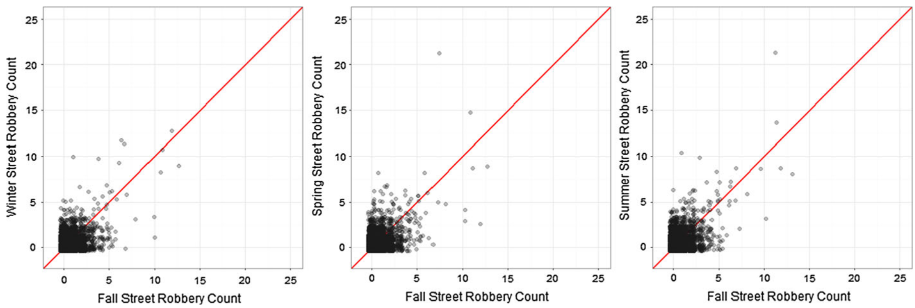


Fig. 3 Representative scatter plots comparing the fall period to all other seasonal periods. *Notes* N = 60,381 micro-places. Jittering and opacity used to minimize over-plotting. Scatter plots for all other pair-wise comparisons were not shown in order to maximize the available plotting area, but are available from the authors upon request. All plots led to substantively similar conclusions

overall low counts for the morning period compared to the other within-day periods (Table 4). The micro-places with at least five street robberies during the morning period (n = 4) also had at least five street robberies during the afternoon and nighttime period (with one exception during the nighttime). Compared to the evening period, however, two of the micro-places with at least five street robberies during the morning period had zero or only a few street robberies. When the afternoon and evening periods were compared, roughly an equal number of places singularly had five or more street robberies in only one period and fewer than five street robberies in the other period (afternoon only n = 19; evening only n = 15) as had five or more street robberies in both periods (n = 14). The comparison between afternoon and night time micro-place street robbery counts revealed a relatively large number of micro-places (n = 23) had five or more street robberies during both the afternoon and night time periods yet a fairly large number of places still only had five or more street robberies in one period but not the other. A total of 10 micro-places recorded street robbery counts above five for the afternoon period, but below five for the night time period, and 79 micro-places experienced five or more street robberies during the night time period but not the afternoon period. The evening versus night time comparison showed patterns that were substantively similar to the afternoon versus night time comparisons just discussed.

Figure 2 suggests that the similarity between weekday and weekend micro-place street robbery was also mixed. Again, most micro-places did not experience any street robberies during both the weekday and weekend periods. A total of 50,127 micro-places experienced zero street robberies during both day of the week periods. An additional 8091 micro-places experience between 1 and 4 street robberies during only one of day of the week periods and zero street robberies during the other period and 1952 micro-places experienced between 1 and 4 street robberies during both day of the week periods. Following the x-axis across Fig. 2 demonstrates the general pattern that 147 micro-places were found to have less than five street robberies during the weekend period and greater than five for the weekday period. This was somewhat expected given the differences in the exposure periods and count distributions between the two units (see Table 4), but overall suggests some places that were street robbery hot spots during the weekday were not necessarily hot spots during the weekend period. The same substantive conclusion can be drawn by examining the 22 micro-places above five on the y-axis (weekend street robbery counts), but below five street robberies on the x-axis (weekday period). Finally, examining the cases along the imposed perfect correlation line past the values of five on both axes shows the 42 micro-places that were found to have relatively high street robbery counts during both day of the week periods.

The comparisons of micro-place street robbery counts among seasonal periods revealed nearly the same patterns across all comparisons. Most places experienced less than five street robberies during both periods. Next, anywhere from 10 to 26 places experienced five or more street robberies during one season but not the other in the pairwise comparisons. Finally, anywhere from 11 to 19 micro-places experienced five or more street robberies during both seasons. Overall, there were a small number of places that were only a hot spot during one season and a roughly equal number of micro-places were hot spots during both seasons for any pairwise seasonal comparison.

The scatter plots of GMI values and total street robbery counts by temporal scale in Fig. 4 produced similar conclusions as the previous analyses. Between zero and five on the x-axis of all plots, there are a cluster of micro-places that experienced too few crimes to have the possibility of recording a GMI indicating any heterogeneity across the periods for the respective temporal scale. These are the large number of micro-places that dominated

Table 4 Distributions of street block and intersection street robbery counts by temporal periods

Count	All	Hour blocks				Days		Seasons			
		Morning	Daytime	Evening	Nighttime	Weekdays	Weekends	Fall	Winter	Spring	Summer
0	50,127	59,401	57,366	56,844	54,259	53,155	55,206	56,397	57,144	57,046	56,648
1	6864	913	2519	2950	4674	5323	4054	3355	2750	2772	3053
2	1789	56	340	423	945	1133	780	451	364	395	498
3	777	6	93	102	304	409	208	107	80	101	109
4	331	1	30	33	97	172	69	36	20	31	34
5	172	2	15	12	45	72	28	20	7	18	18
6	111	1	4	3	14	41	10	5	5	9	8
7	57	0	4	5	17	23	7	3	2	3	4
8	47	1	1	2	9	16	4	1	1	2	2
9	27	0	2	2	8	7	6	0	2	2	3
≥10	79	0	7	5	9	30	9	6	6	2	4

N = 60,381 street blocks and intersections the low values of both axes in the scatter plots. One important difference among the graphs is the cluster of points between five and ten on the x-axis of the day of week plot (center) that recorded GMI values near zero indicating those micro-places only experienced their street robberies during either the weekday or weekend periods. Next, all three graphs show that when considering the micro-places with total street robbery counts between five and approximately fifteen, there is more variability in the recorded GMI values as evidenced by the large spread of points moving up/down the y-axis. This suggests that even though these micro-places would likely be considered "hot spots" in an atemporal analysis, some micro-places experienced street robberies across multiple periods while other places only experienced street robberies during specific periods. Stated differently, the former micro-places' street robbery levels exhibit much more temporal heterogeneity than the latter micro-places. With a few exceptions, GMI values become close to the mathematical maximums for micro-places with more than fifteen total street robberies. This suggests that the highest street robbery micro-places experienced street robberies during all periods. Overall, the general pattern show in Fig. 4 is that for the micro-places that did experience street robberies, some experienced relatively high street robbery levels during only one particular period, but the micro-places with the highest street robbery levels were more likely to have experienced street robberies across all periods for each of the three temporal scales.

Discussion

This study tested if Weisburd's (2015) law of crime concentration held for Philadelphia street robbery patterns across different theoretically relevant temporal scales. It did. Four specific contributions were made. First, we extended the examination of the law of crime concentration to another city: Philadelphia. Second, we assessed the law's validity using a disaggregated crime measure: street robbery (see Andresen and Linning 2012). Third, we demonstrated for the first time in the literature that the law of crime concentration held for three different theoretically relevant temporal scales: time of day, day of week, and season of the year. Fourth, we demonstrated that some micro-places experienced street robberies consistently across different temporal scales and some micro-places only suffered street robberies during particular periods. These results have important implications for crime and place theory and research as well as crime prevention policy.

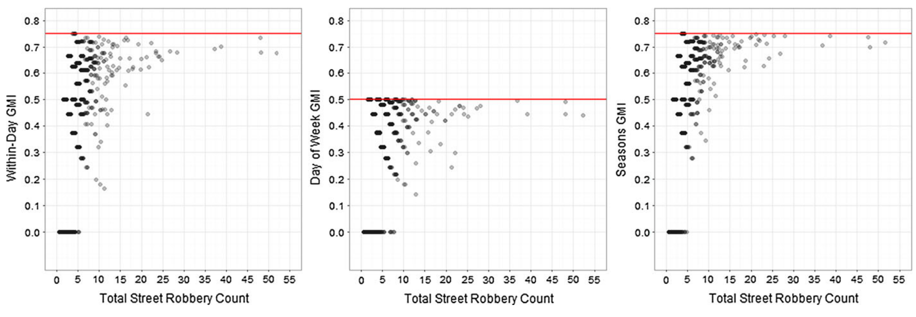


Fig. 4 Scatter plots comparing GMI values and total street robbery counts by temporal scale. *Notes* N = 10,254 micro-places with at least one street robbery. Jittering and opacity used to minimize overplotting. The *bold*, *horizontal line* indicates the mathematical maximum for the GMI

Implications for Theory and Research

Extending the law of crime concentration to different theoretically relevant temporal scales further suggests that "[t]ime should be considered a vital parameter in the crime and place research agenda" (Haberman and Ratcliffe 2015: 478). Given the lack of research on spatial–temporal crime patterns (Ratcliffe 2010), formulating research questions relating to spatial–temporal crime patterns is especially important. For example, more work is needed that investigates which independent variables predict spatial crime concentrations across different temporal scales. If time is in fact theoretically important—as it appears to be, then the hypothesized predictors of spatial–temporal crime concentrations as derived from environmental criminology should be supported empirically. On the other hand, scholars have recently suggested that theories previously used to explain spatial crime patterns at the community/neighborhood-level, such as social disorganization or collective efficacy, may also explain micro-level spatial crime patterns and should be integrated with environmental criminology theories (Groff 2015; Weisburd et al. 2014). If spatial–temporal crime patterns are important, then theoretical refinement is needed to demonstrate how community criminology's important theoretical mechanisms, such as collective efficacy, work at different temporal scales (Haberman and Ratcliffe 2015). Overall, greater theoretical specificity will be needed to develop a deeper understanding of how crime concentrates spatially across different temporal scales.

Explaining spatial–temporal crime patterns, however, is also not an easy methodological and/or statistical task. It has long been recognized that the dates and times of crimes are not always reliably reported. Further, the date and time of occurrence is often unknown to victims, such as the family who leaves for vacation to come home a week later and find their home burgled (Ratcliffe 2000, 2002). This analysis focused on street robbery because those who report robbery are more likely to know when they witnessed or experienced a robbery. Ratcliffe (2000, 2002) suggested aoristic analysis could be used to estimate the likely occurrence of crime events, yet further research assessing the validity of methods for dealing with temporal ambiguities is certainly warranted (e.g. see Ashby and Bowers 2013). Alternatively, simulation analyses might be used to examine how missing or ambiguous measures of dates/times of crime occurrences from "known" temporal distributions might impact observed temporal distributions under different scenarios. Another option might be to use agent based simulation modeling (Groff 2007, 2008) or qualitative research methods with known offenders to further understand spatial–temporal crime patterns.

Another challenge for testing theories that explain spatial–temporal crime patterns is having valid temporal measures for the independent variables that will be entered into the model. For example, if one wants to test the temporally differentiated impact of certain types of places, then knowing the exact opening and closing times for those places would be useful (Haberman and Ratcliffe 2015). Of course, we know from personal experience how difficult it can be to get valid measures of *just the locations of different types of places*. One option might be to use alternative (open) data sources, such as online business records.[8] On the other hand, knowing when places are open is different from knowing when they are actually in use and how pedestrian populations change over time (Andresen and Jenion 2010; Andresen 2010, 2011). Another option might be to use "big data", such

[8] It is important to ensure any data collected from websites does not violate the site's terms of service or any copyright laws.

as credit card transactions, cell phone usage, or social media posts (Malleson and Andresen 2015), to estimate where people are and what they are doing at different times of the day.

Another challenge with examining spatial–temporal crime problems is determining the statistical methods appropriate for study. Examining rare events, such as crime incidents, across micro-places *and* times produces a large number of zero observations and very few "high" counts. As readers of this journal will know, researchers need to be careful about ensuring the selected probability distribution for their model, such as the negative binomial distribution, is adequate for their data. Further, researchers should question if there is enough variance on their dependent variable to have something interesting enough and capable of being explained. In other words, how interesting (and practically useful) would it be to explain why some places have zero crimes and some places only have one crime (a hypothetical maximum) during a given time? It probably depends on the question being answered, but it is a reasonable concern when examining spatial–temporal crime patterns. Additionally, many advanced statistical techniques, such as dynamic panel models, may not be available "out-of-the box" in popular statistical programs for count outcomes and researchers will need advanced programming and statistical skills to implement those routines. In certain contexts, Bayesian space–time models may be an option to deal with rare count outcomes (Law et al. 2014). Overall, while the analytical challenges will be research question and data specific, the takeaway point is that modeling rare crime counts across space and time will present analytical challenges that the readers (and future authors) of this journal will need to resolve. Perhaps this explains the dearth of research examining spatial–temporal research questions.

Another important issue for future research is to determine how best to choose temporal scales and operationalize temporal periods (see Taylor 2015). Haberman and Ratcliffe (2015) used the American Time Use Survey to inform their operationalization of within-day periods, and ultimately their temporal units were still quite intuitive. This paper drew on those temporal periods, but ultimately incorporated sensitivity analyses of other operationalizations to ensure the results were robust.[9] Perhaps other data sources on routine activity patterns (e.g., cell phone GPS tracking data) can be used to inform this issue. It may also be that temporal units should be different by location. For example, researchers might choose to expand their late-night/early-morning periods in cities where bars and night clubs that stay open later when examining within-day periods. Other considerations may arise for astronomical/meteorological considerations (e.g., see Tompson and Bowers 2013). Overall, the extent to which the modifiable temporal unit problem will impact spatial–temporal studies of crime remains unknown.

Despite these methodical/statistical challenges, given the law of crime concentration at places, relevant theorizing, and our findings here, important research questions regarding spatial–temporal crime patterns remain and deserve investigation. Answering these questions requires crime and place scholars to carve out research agendas that more deeply consider time.

Implications for Crime Policy

Finding that the law of crime concentration held across different temporal scales has important policy implications. First, the present findings should interest proponents of hot spots policing. One of the current challenges facing police departments after the economic

[9] We thank the anonymous reviewer who encouraged us to do so for providing comments that improved the quality of this manuscript.

recession is how to police effectively with minimal resources, particularly lower numbers of officers. The law of crime concentration suggests that police do not have to 'put a cop on every corner' but rather simply focus on the small percentage of micro-places that account for a large proportion of crimes. Police may even be able to spend as little 15 min once every 2 h in crime hot spots to generate crime reduction effects (Koper 1995; Telep et al. 2014). Our findings suggest that police may benefit even further by moving down the *temporal* "cone of resolution" (Brantingham et al. 1976). Our results show that some micro-places had fairly stable street robbery patterns across all times while other micro-places had street robbery patterns that were limited to specific times. Therefore, police departments may be able to triage their hot spots policing efforts and adjust their hot spots policing strategies to use their resources more efficiently by accounting for the temporal patterns of individual hot spots (also see Ratcliffe 2004a, b).

Further, both critics and proponents of hot spots policing have argued the police should do more than just be present or conduct enforcement activities in crime hot spots (Rosenbaum 2006; Braga et al. 2014; Haberman et al. 2016; Sorg et al. 2013; Telep and Weisburd 2012). Improving our understanding of crime concentrations by recognizing the importance of time provides additional theoretical avenues for understanding crime hot spots and developing crime prevention tactics specifically tailored to the hot spot in question (Goldstein 1979). The basic research recommended in the previous section will provide conceptual tools for helping practitioners develop a deeper understanding of crime concentrations and develop more holistic crime prevention tactics (Clarke and Eck 2005). That pursuit should be followed by applied research evaluating the effectiveness of those approaches.

In conclusion, this study found that the law of crime concentration proposed by Weisburd (2015) held when street block and intersection street robbery counts were examined across different temporal scales. Additionally, some micro-places, the highest street robbery locations, experienced street robbery consistently across different temporal periods while others had more isolated temporal patterns. Given the lack of research on spatial *and* temporal crime patterns, the present study should be viewed as a starting point. These findings will need to be replicated in other locations for other crime types. Then additional research is needed to develop our theoretical understanding of why crime concentrates in micro-places at specific time of the day, week, and year. From there, a new series of applied studies will be needed to develop an evidence-base for crime control strategies designed to address spatial–temporal concentrations of crime.

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