Crime at places and spatial concentrations: Exploring the spatial stability of property crime in Vancouver BC, 2003-2013

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Objectives. Investigate the spatial concentrations and spatial stability of criminal event data at the micro-spatial unit of analysis in Vancouver, British Columbia.

Methods. Geo-referenced crime data, 2003 – 2013, representing four property crime types (commercial burglary, mischief, theft from vehicle, theft of vehicle) are analyzed considering crime concentrations at the street segment and street intersection level as well as through the use of a nonparametric spatial point pattern test that identifies the stability in spatial point patterns in pairwise and longitudinal contexts.

Results. Property crime in Vancouver is highly concentrated in a small percentage of street segments and intersections, as few as 5 percent of street segments and intersections in 2013 depending on the crime type. The spatial point pattern test shows that spatial stability is almost always present when considering all street segments and intersections. However, when only considering the street segments and intersections that have crime, spatial stability is only present in recent years for pairwise comparisons and moderately stable in the longitudinal tests.

Conclusions. Despite the crime drop that has occurred in Vancouver, there is still spatial stability present over time at levels suitable for theoretical development. However, caution must be taken when developing initiatives for situational crime prevention.

Keywords: crime at places; spatial stability; spatial point pattern test

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1. INTRODUCTION

The spatial stability of crime patterns is important for the development of theory and the application of policy. If spatial stability is not present, all data analyses are literally historical without contemporary relevance and cannot be used in a meaningful way to test/refine/develop theory or make applicable crime prevention policy.

Research in spatial criminology over the past 25 years has shown that crime is incredibly concentrated, most often having 50 percent of criminal activity accounted for in 5 percent of micro-places, or street segments (Sherman et al., 1989; Weisburd & Amram, 2014). Though this high degree of crime concentration implies that spatial stability is present, this may not be the case; rather, crime may be highly concentrated but there still may be enough spatial shifting in the other 50 percent of crime to cause problems for theory and policy.

As reviewed below, the body of research regarding crime at places and spatial concentrations of crime is growing, but this literature is still relatively new and early in its development (Weisburd, 2015). Though research that investigates these phenomena in different places and at different times is important (one of the contributions of this paper), there are unanswered questions that must be investigated to advance the crime at places literature. For example, what is the importance of the spatial stability of crime patterns? There is indirect evidence for the presence of spatial stability through the use of traditional trajectory analysis, but more information is required to understand this stability. If a large percentage of any given city is “stable” with regard to its crime patterns, what can the lack of stability in the small percentage of that city tell us? Only when spatial stability is directly measured can such investigations be considered. Also, is the law of crime concentration at places just a manifestation of the concentration of human concentrations, in general (Weisburd, 2015)? If this is the case, we should find greater concentrations of crime where we know there are greater concentrations of human activity.

In this paper we investigate the presence of spatial stability in municipal level crime patterns in order to begin to fill these gaps in the crime and place literature. We use an open source crime data set with four crime types (commercial burglary, mischief[4], theft from vehicle, and theft of vehicle) and an open source spatial point pattern test that allows for the identification of similarity in spatial point patterns: we compare the similarity of spatial point patterns over time within each crime type. We find that despite the significant crime drop that has occurred in this municipality, a common phenomenon around the world over the past 25 years (Farrell et al., 2011, 2015; Tseloni et al., 2010), spatial patterns of crime and concentrations of crime have remained relatively stable. The importance of these results is discussed in the context of theoretical development and crime prevention policy.

[4] Mischief most often represents some form of property damage or graffiti, but may also include disorder. This crime type is also the most sensitive to police reporting and patrol activities and should be interpreted with caution.

2. SPATIAL STABILITY: ITS IMPORTANCE AND RECENT EVIDENCE

Spatial stability, sometimes referred to as ecological stability, is a concept that is implicitly assumed when considering the relevance of spatial analyses of crime. This is particularly the case when researchers analyze one year of data, or average a small number of years of data. If the spatial patterns do not have spatial stability, then it is impossible to make predictions with regard to crime levels at other times or in other places. Without spatial stability, research only tells one about historical relationships.

The importance of spatial stability was recognized in the context of social disorganization theory. Shaw et al. (1929) and Shaw and McKay (1931, 1942, 1969) stated that neighborhoods maintained their relative rankings with regard to juvenile delinquency (spatial stability) despite the changes in ethnic composition over time. These researchers were able to make this claim because they had data that spanned many years. However, a lot of the research in social disorganization theory that followed did not. Because of the changing nature of cities through the process of gentrification (Lees et al., 2007), the assumption of spatial stability was difficult to justify and led to social disorganization falling out of favor in criminological research (Bursik, 1988). It is important to note spatial patterns may be persistent despite changes in the urban environment, this assumption could just not be tested. But does a lack of spatial stability at the neighborhood level correspond to a lack of spatial stability at micro-places? This is an important question within the crime and place literature, to test the law of crime concentration at places (Weisburd, 2015).

Many years passed before a data set covering an entire city and multiple years would emerge again that could test the assumption of spatial stability. In a longitudinal study of crime patterns in Seattle, Washington, Weisburd et al. (2004) investigated the stability of crime concentrations at the street block level of analysis. Over a 14-year period, they found that one-half of the crime in Seattle occurs in 4-5 percent of the street blocks and that all crime took place in approximately 50 percent of the street segments. In order to investigate the spatial stability of crime patterns, Weisburd et al. (2004) used trajectory analysis at the street segment level and found that the overall majority of all trajectories generated remained relatively stable over their 14-year period. Moreover, they found that the changing crime rate trends (decreasing over time) were accounted for by only a small percentage of the street segments in Seattle.

Weisburd et al. (2009) and Groff et al. (2010) replicated the Seattle study but in specific contexts. Weisburd et al. (2009) found that juvenile crime was spatially concentrated to a greater degree than all crime analyzed by Weisburd et al. (2004): less than one percent of street segments accounted for one-half of the juvenile criminal incidents in Seattle and all crime was attributed to 3-5 percent of street blocks over a 14-year period. Groff et al. (2010) found strong evidence for spatial stability over a 16-year study period and found that different trajectories tended to be spatially close to one another. This is not evidence counter to spatial stability, but shows the importance of micro-spatial units of analysis.

In a 29-year longitudinal study in robberies in Boston, Massachusetts, Braga et al. (2011) found that only 12 percent of street segments had one robbery incident between 1980 and 2008, and one-half of robberies in Boston occurred in 8.1 percent of street blocks during that same time period—remarkable stability for such a long time period. In their temporal analyses, Braga et al. (2011) found that chronic street segments remained chronic over time, providing strong evidence for spatial stability.

In an analysis of three years of data spanning 10 years (1991, 1996, and 2001), Andresen and Malleson (2011) were the first to explore multiple crime types, individually, for the same location over time. Their analyses of assault, burglary, robbery, sexual assault, theft, theft of vehicle, and theft from vehicle in Vancouver, British Columbia at three levels of analysis (census tracts, dissemination areas, and street segments) found that one-half of all crime could be accounted for by 1-8 percent of street segments. Moreover, approximately one-half of all street blocks in Vancouver experienced none of the crime types with strong evidence that spatial crime patterns remained relatively stable throughout the years of data examined.

Most recently, Curman et al. (2015) undertook an independent replication of Weisburd et al. (2004) over a 16-year time period in Vancouver, British Columbia. In their analyses of crime, 1991 – 2006, Curman et al. (2015) found very similar results to that of Weisburd and colleagues: approximately 40 percent of Vancouver was without any crime reported to the police and the vast majority of trajectories were classified as stable or with very little change over time.

Despite the strengths within all these studies, they are not without their limitations. First, aside from Braga et al. (2011), these more recent investigations of spatial stability have not considered criminal activity that occurs at street intersections. This is particularly problematic for Curman et al. (2015) because 25 percent of the crime data had to be excluded from their study. Such a large proportion of data could change spatial patterns—according to Weisburd (2015), crime at intersections can be as low as 0 percent, but as high as 33 percent. Second, as evident in the actual trajectories shown in Weisburd et al. (2004) and Curman et al. (2015), though trajectories may be stable from a statistical perspective they may still be increasing or decreasing by a small degree. Consequently, over longer time periods it is still possible that actual spatial patterns are changing in meaningful ways—the spatial trajectories may actually be different. The exception to this is Andresen and Malleson (2011), but they restricted their analyses to three individual years and only considered pairwise comparisons.

In this paper, as stated above, we investigate the spatial stability of crime patterns for Vancouver, British Columbia considering four property crime types. We employ a spatial point pattern test that allows for two types of tests for spatial stability. First, year-to-year comparisons can be undertaken such that spatial stability can be compared for pairwise successive years as well as pairwise comparisons over longer time spans, 2003 to 2013, for example. Second, a longitudinal version of this spatial point pattern test that considers all years under analysis for the consideration of spatial stability, the spatial trajectory. This allows for a test of spatial stability that is more specific than previous research.

This more direct test of spatial stability allows for better information regarding the degree of stability and to know the degree of instability in spatial crime patterns. Additionally, through a comparison of highly concentrated human activities (commercial land use and mixed land use for the presence of commercial burglary) and more ubiquitous human activities (the presence of vehicles and their associates thefts: theft of and theft from vehicle) we can begin to know if the law of crime concentration at places is a particular manifestation of the concentrations of human activities, more generally.

3. DATA AND METHODS

The City of Vancouver is contained within Metro Vancouver, collectively the third largest metropolitan area in Canada. The Vancouver Census Metropolitan Area (CMA) is the largest metropolitan area in western Canada, with a population of just over 2.3 million people. Since 1991, the Vancouver CMA has seen significant population growth. Most often, this population growth has been linked to the 1986 World Exposition on Transportation and Communication. After this time, the Vancouver CMA has seen a lot of international investment and subsequent development. The World Exposition in 1986 brought worldwide attention to the Vancouver CMA that has only increased because of the relatively recent 2010 Winter Olympics held in this area.

With regard to crime, the Vancouver CMA has the highest level of crime rates among the three largest metropolitan areas in Canada: 6897 criminal code offences per 100 000 persons in 2013, more than double the rate in Toronto (2941 per 100 000 persons) and 70 percent greater than the rate in Montreal (4072 per 100 000 persons); the same ranking was present for the violent crime rate in 2013 for Vancouver (1023 per 100 000 persons), Toronto (749 per 100 000 persons), and

Montreal (903 per 100 000); and, similarly, for property crime in 2013 for Vancouver (4642 per 100 000 persons), Toronto (1936 per 100 000 persons), and Montreal (2657 per 100 000). However, it should be noted that with the international crime drop that began in the early 1990s, the reported differences in crime rates has decreased in recent years (Boyce et al., 2014; Kong, 1997; Savoie, 2002; Silver, 2007; Wallace, 2003, 2004). Overall, the crime drop that these CMAs have been of a large magnitude over the study period, 2003 – 2013: 47 percent (Vancouver), 42 percent (Toronto), and 35 percent (Montreal). Needless to say, an investigation into the spatial stability of these crime patterns is in order with this substantial drop in crime for Vancouver.

3.1. Crime Data and Spatial Units of Analysis

The crime data for Vancouver are police incident data that were retrieved from the Vancouver Open Data Catalogue.[5] These data contain information pertaining to location and month of occurrence of four crime types over an 11 year period, 2003-2013. The crime types include: commercial break and enter, mischief, theft from vehicle and theft of vehicle. Though this is a more restricted data set for Vancouver than used in previous analyses with regard to crime types, these data were the most current available crime data at the time of data gathering, whereas previous research using Vancouver data is almost a decade old with its most recent data point. As such, we chose to conduct a more temporally relevant analysis rather than attempting to obtain access to the older data for Vancouver.

[5] http://data.vancouver.ca/datacatalogue/crime-data.htm

The nature of the geographic locations provided with these data is the street intersection or the 100-block[6]; no specific addresses are provided because these are open data. The street intersections are easily geocoded, but these data are problematic in their raw form for geocoding the street addresses. For example, the address 123 Main Street would be provided as 1xx Main Street. Because of this, and the need to geocode the data to a street network for subsequent analysis, a random number generator was used to create a set of numbers ranging from 1 to 99. This number replaced "xx" in the original data file. An obvious limitation of these data and this approach for geocoding is that no inference can be made at the specific location geocoded for each criminal event. However, as discussed below, all of our analyses are undertaken at the street block level so there are no issues in regard to the ecological fallacy and inappropriate inference. With the data recoded, the geocoding hit rate percentages ranged from 96.3 to 97.1 percent for all four crime types and all 11 years. This is well above the minimum acceptable hit rate of 85 percent set by Ratcliffe (2004).

The spatial units of analysis for this research, as mentioned above, are street segment, or 100-blocks, and street intersections. In Vancouver, there are 11,730 street segments. Because of the presence of street intersections in our data and a desire to retain as much of these data as possible to avoid spatial bias, street intersections were created using the street segment file. A buffer was set around the street segments in order to create overlap of the street segments—7 meters was

[6] The 100-block is both sides of the street in between two intersections, the same definition for the street segments used by David Weisburd and his colleagues.

found to be sufficient. This overlap was then used to create unique polygons representing intersections. The resulting total number of spatial units of analysis is 18,445: 6715 street intersections and 11,730 street segments.

In the crime and place literature, criminal events occurring at street intersections range from 0 to 33 percent (Weisburd, 2015). In the early years of our data, 2003 – 2005, criminal events at street intersections comprised of 4 – 6 percent of the data. However, in the latter years of the data set, criminal events at street intersections comprised of 10 – 12 percent of the data. It is important to note that these criminal events should not be considered as actually occurring within the street intersections. Rather, the street intersection is considered to be a better spatial reporting location to the officer than a street address: a vehicle (stolen or having property stolen from it) that is parked at the intersection. In fact, there are even some commercial burglaries that occur at "intersections". Upon inspection of these locations, these are locations at which street vendors commonly operate. As such, these commercial burglaries are burglaries with the street vendor stand as the target. Given the notable percentage of criminal events in our data and the fact that these locations are not at random (the street intersections appear in a rather systematic manner), they should be included in the analysis in order to avoid spatial bias (Ratcliffe, 2004).

3.2. Spatial Point Pattern Test

In order to assess the spatial stability of crime patterns in Vancouver, 2003 – 2013, a statistical technique is necessary that is able to identify any spatial change that is statistically significant. One obvious methodology, as outlined above, is trajectory analysis. This technique allows for the identification of different trajectories for street segments and intersections. Therefore, if the vast majority of the trajectories are stable one can assume that the crime patterns are spatially stable. But this is an assumption. However, there is another test that allows for the identification of stability of spatial patterns, when considering multiple points in time. The spatial point pattern test developed by Andresen (2009) can be used to identify spatial stability through the identification of similarity between multiple spatial point pattern datasets. To date, this test has been used in a variety of contexts. The initial application of the test was an investigation of the similarity of spatial patterns across crime types (Andresen, 2009), but the test has also been used to investigate: changing patterns of international trade (Andresen, 2010), the stability of crime patterns (Andresen and Malleson, 2011), the spatial impact of the aggregation of crime types (Andresen and Linning, 2012), the spatial dimension of the seasonality of crime (Andresen and Malleson, 2013a; Linning, 2015), the impact of modifiable areal units on spatial patterns (Andresen and Malleson, 2013b), the role of local analysis in the investigation of crime displacement (Andresen and Malleson, 2014), and the comparison of open source crime data and actual police data (Tompson et al., 2015).

The spatial point pattern test is summarized as follows, initially considering a pairwise test for simplicity. The first step is to identify one point-based data set as the base (2003 mischief, for example) and calculate the percentage of points within each spatial unit under analysis (street segments and street intersections, for example); second, the other point-based data set is deemed the test data (2013 mischief, for example), and randomly sampled with replacement for 85 percent of the test data (this allows for the calculation of the percentage of points within each spatial unit under analysis and 85 percent is based on the research by Ratcliffe (2004)); third, repeat this sampling process 200 times;[7] fourth, calculate the 200 percentages, rank them, and remove the top and bottom 2.5 percent to generate a 95 percent confidence interval; fifth, if the value within a spatial unit of analysis for the base data set (2003 mischief, for example) is within the 95 percent confidence interval, that spatial unit of analysis is similar; and sixth, repeat this last step for all spatial units of analysis. Further details are available in Andresen (2009) and Andresen and Malleson (2011).

A global statistic can be calculated using the output from the statistical testing, outlined above. This statistic measures the degree of similarity between the two datasets, the similarity index, *S*. The similarity index ranges between 0 (no similarity) and 1 (perfect similarity), calculated as follows:

$$S = \frac{\sum_{i=1}^{n} s_i}{n} \tag{1}$$

where s_i is equal 1 if the pattern of two datasets are similar and 0 otherwise (this similarity is defined by step 5 described above), and *n* is the number of areas.

[7] Often in the spatial analysis literature 50 repeated samples are used (Davis & Keller, 1997). However, early research on Monte Carlo experiments by statisticians showed that as few as 20 repeated samples would provide good results (Hope, 1968). We use a 200 repeated random sample for the purposes of being conservative and to provide convenient cut-off values for the confidence interval.

Consequently, the similarity index measures the percentage of areas that share a similar pattern. In the literature that has used this spatial point pattern test, a rule of thumb has emerged to indicate the point at which S indicates similarity. This rule of thumb is similar to rules of thumb relating to multicollinearity in a regression context. The variance inflation factor (VIF) is often used as a regression diagnostic to indicate levels of multicollinearity that can cause issues with inference, most often when the VIF is in the range of 5 to 10 (O'Brien, 2007). Though the VIF can be calculated with many explanatory variables, the range of 5 to 10 is equivalent to a bivariate correlation of 0.80 to 0.90. As such, an S-Index value of 0.80 is considered to represent two spatial point patterns that are similar. Though not practical with over 18,000 spatial units under analysis, it is important to note that the results of this test can be mapped showing the local level results, s_i (Andresen, 2009). We used the graphical user interface (GUI) that was developed for the application of this spatial point pattern test that can perform the pairwise version of this spatial point pattern test.[8]

The nature of the spatial point pattern test, as described and executed in the GUI, undertakes pairwise comparisons of spatial point patterns. Though instructive, as shown below, such pairwise tests are limited with regard to the investigation of spatial stability. For example, subsequent pairwise comparisons (2003-2004, 2003-2005, 2003-2006, and so on) may indicate high degrees of similarity, $S >= 0.90$. However, if the 10 percent of non-similar spatial units changes with every pairwise

[8] https://github.com/nickmalleson/spatialtest

comparison, by the time 10 years have passed spatial similarity will actually be quite low.

In order to address this limitation of previous research using this spatial point pattern test, we contribute to this literature through an expansion/extension of Andresen's (2009) spatial point pattern test by making it longitudinal in order to properly assess the stability of spatial trajectories. This is done by allowing for multiple "test" data sets. In the current analysis, 2003 is still considered the base data set. However, all other subsequent years are independently considered test data sets, repeatedly randomly sampled, and used to calculate confidence intervals for statistical testing—a confidence interval is generated for each year to be compared to the base data set.

The possible outcomes from this longitudinal version of the spatial point pattern test are illustrated in Fig. 1. In Fig 1, each dashed horizontal line represents the base year percentage. Each of the vertical lines represents the confidence interval for each of the test data sets, years in the current analysis. Fig. 1 only shows 8 years of data (1 base year and 7 test years), so it is for illustrative purposes, not representing all of the years in the current analysis.

<Insert Fig. 1 About Here>

The first possibility of a completely stable spatial trajectory is shown in Fig. 1a. As stated above, the dashed horizontal line represents the percentage of points in the base data set that are assigned to each spatial unit (street segment or intersection in the current analysis). By definition, this percentage is considered constant for the study period because the base data set is the baseline from which any deviations in the spatial patterns are measured for each year. The vertical lines represent the confidence intervals for each subsequent test year that are generated from the repeated sampling procedure. In each case within Fig. 1a, the base data percentage is within the confidence intervals so this particular spatial unit would be considered having a stable spatial trajectory. It is important to note here that a stable spatial trajectory is not necessarily the same as a stable trajectory as defined in other crime and place research (Curman et al., 2015; Weisburd et al., 2004). In the current context, a stable spatial trajectory is one in which a spatial unit of analysis has the same percentage of points; as such, the volume of crime may be going up or down but it is changing proportionately.

Fig 1b shows the situation of crime no longer occurring on a particular spatial unit—the latter confidence intervals are only present on the *x*-axis, and made smaller, for illustrative purposes. In this particular case, crime has a stable spatial trajectory for the first few years and then crime disappears; a new level of stability is found in this case. This situation becomes important below. A volatile spatial trajectory is represented in Fig. 1c. In this scenario, sometimes the confidence intervals for the test years include the base year percentage and other times they do not. And finally, Fig. 1d shows no stability in the spatial pattern: after 2003 the percentage of points has completely changed.

From these possibilities, three new *S*-Indices are calculated. The first, S_{Absolute}, represents Fig 1a: the percentage of spatial units of analysis (street segments and street intersections) that exhibit total spatial stability. The second, S_{Zero}, is calculated in a similar manner but considers any spatial unit of analysis that exhibits the pattern in Fig. 1b to also be a stable spatial trajectory. Of course this is not true in an absolute sense, hence the names of the first two indices, but it represents the situation when crime stops occurring in a place altogether: it found a new "stability". And third, S_{Sum}, is an index that represents all of the times when the base and test values are similar most of the time. As such, this index does not "punish" a spatial unit of analysis and classify it as dissimilar when it is only dissimilar one or two times over a longer study period. This situation is represented in Fig. 1c with 5 of the 7 years being classified as similar: 5/7 = 0.71. So, such a spatial unit of analysis is not stable in an absolute sense, but is generally stable over longer periods of time.

These three indices each also take 2 forms. The first considers all street segments and street intersections whether they have crime or not. This is the closest similarity to the previous trajectory modeling in crime and place. The places that always have zero crime would be classified as low crime and stable trajectories. The second only considers street segments and intersections that actually have crime. This form of the index can identify the degree of spatial stability where crime actually occurs without being influenced by the places that never have criminal activity. In order to make these calculations the non-zero street segments and street intersections were defined as any street segment of intersection that had at least one crime over the study period; for consistency, this same definition was used for the pairwise comparisons as well. Consequently, when two or more point data sets are compared, the set of street segments and intersections is complete such that all points have a street segment of intersection to be placed on. With three indices and two forms of their calculations, each crime type will have six new *S*-Index values to be considered for their longitudinal spatial trajectories.

4. RESULTS

4.1. Descriptive accounts of crime types over time

The context of decreasing property crime in Vancouver is shown in Table 1 and Fig. 2. Table 1 shows the counts of the four different crime types (commercial burglary, mischief, theft from vehicle, theft of vehicle) as well as their aggregate. In 2003, the most common form of property crime is theft from vehicle, followed by mischief and theft of vehicle (effectively the same levels) and commercial burglary. However, by 2013, theft of vehicle has become the lowest volume property crime under analysis. Overall, the crime drop for the aggregate of these crime types is 53.9 percent, a large magnitude decrease in crime over an 11-year period. The distribution of this crime drop is not uniform across the four crime types though. As would be expected because of volume, theft from vehicle is the most similar to the aggregate, with commercial burglary also exhibiting a similar drop. Mischief, however, exhibits a notable lower magnitude crime drop (35.3 percent) and theft of vehicle exhibits a substantial drop over this time period (83.8 percent)—this drop has been confirmed through conversations with police and vehicle insurance agencies as well as with checks using other statistical sources.

This drop is further represented in Fig. 2 that shows the crime rates for the City of Vancouver, calculated using the census population and linear interpolation for intervening years. In order to facilitate a comparison across crime types, all crime rates for 2003 were normalized to an index value of 100. Because of the small magnitude population change relative to the changes in the crime counts (population increased just below 10 percent, 2003 – 2013), there are no major differences between Table 1 and Fig. 2, but the magnitude of the drop in theft of vehicle is immediately apparent. This result is interesting in and of itself, but is beyond the scope of the current analysis.

<Insert Fig. 2 and Table 1 About Here>

Turning to crime concentrations, Table 2 shows the percentage of street segments and intersections that have any events for the four property crime types. In the aggregate, only 35 percent of Vancouver had criminal events in 2003 and this fell to just over 25 percent by 2013. This shows that in 2013, essentially 75 percent of Vancouver was free from reported criminal activity for these crime types. Already this is a high degree of concentration. When considering individual crime types, this concentration becomes more apparent. Commercial burglary has remained relatively stable in the percentage of locations it occurs, 4.5 to 7 percent. However, it should be noted that commercial burglary can only occur where there is commercial land use. As such, the high degree of concentration for this crime type is at least partially "artificial" and a product of the urban landscape. However, the spatial concentration of commercial burglary will be clearly evident in subsequent tables.

Mischief has exhibited an increase in it spatial concentration over the study period of approximately 30 percent. Theft from vehicle and theft of vehicle both show increases in the spatial concentration of their criminal events, but the drop has been of a greater magnitude for theft of vehicle. In conjunction with the knowledge that there has been a substantial drop in the volume of theft of vehicle, this is an indication that theft of vehicle is no longer occurring in particular locations. Again, though beyond the scope of the current analysis, this is an intriguing spatial change.

<Insert Table 2 About Here>

Keeping in mind that all of the criminal events associated with these four crime types can be considered spatially concentrated based on the percentages in Table 2, Table 3 shows the percentage of street segments and street intersections that account for 50 percent of criminal events in Vancouver. In the aggregate, these numbers have not changed over time that is worthy of any discussion. However, with only 3 to 4.5 percent of street segments and intersections required to account for 50 percent of these criminal events, this is a high degree of spatial concentration that is in line with previous research (Sherman et al., 1989; Weisburd, 2015). Commercial burglary only requires just over 1 percent of locations to account for 50 percent of its criminal events and this percentage is stable over time. Theft from vehicle is also generally stable over time, with some variability, at approximately 3 percent. However, mischief and theft of vehicle are exhibiting decreases in the percentage of locations required to account for 50 percent of their criminal events: 3.5 to 2.5 percent and 5 to 2 percent, respectively. As such, not only are these crime types spatially concentrated, but there is a concentration within that general concentration; moreover, this latter concentration is becoming more pronounced over time.

<Insert Table 3 About Here>

In the final investigation of crime concentrations, Table 4 shows the percentage of street segments and street intersections with any crime that are required to account for 50 percent of criminal events. Such a statistic identifies concentrations within concentrations as well and accounts for land use issues for commercial burglary. Overall, for the aggregate, 11 to 14 percent of locations that have any crime are required to account for 50 percent of criminal events. This is a high degree of spatial concentration within an already small percentage of places that have any crime. There is a moderate decrease in this measure of spatial concentration, indicating that criminal events are becoming relatively more uniform over time, but this is not surprising given that the percentage locations with any crime has been decreasing. Commercial burglary and theft from vehicle show similar moderate increases in the percentage of locations with any crime required to account for 50 percent of criminal events. Mischief, contrary to the other crime types, though with some variability, has remained relatively constant at approximately 20 percent.

The largest magnitude change is with regard to theft of vehicle. The percentage of locations with any crime required to account for 50 percent of criminal events has increased from 24 to 40 percent. As such, though the percentage of locations with any theft of vehicle has decreased substantially, the spatial distribution within that spatial concentration has become very close to uniform. With fewer places theft of vehicle is occurring, however, such as result is not unexpected but interesting nonetheless.

<Insert Table 4 About Here>

4.2. Pairwise spatial point pattern results

The results of the pairwise spatial point pattern tests for spatial stability are shown in Tables 5 to 8. In each table, the upper-right triangle represents the spatial point pattern test results using all street segments and street intersections, whereas the lower-left triangle represents the spatial point pattern test results only using street segments and street intersections that have at least one criminal event in any given year. This is a sensitivity analysis that we perform because all of the zero-values may artificially inflate the *S*-Index values, indicating spatial stability when it is not present within the places that experience crime. This set of street segments and street intersections is different for each crime type under analysis, but the same for all pairwise comparisons in order to be consistent with the longitudinal analyses.

The results for commercial burglary are shown in Table 5. Though we do not want to consider the threshold value for the *S*-Index of 0.80 in a dichotomous fashion, the upper-right triangle of Table 5 clearly shows a high degree of spatial stability from year-to-year as well as over the entire study period; *S*-Index values are all greater than 0.935. This bodes well for the spatial analysis of any given year of data and making inferential statements regarding theoretical processes and the development of criminal justice policy, specifically crime prevention initiatives. The results for sensitivity analysis, only considering non-zero street segments and street intersections, is not as favorable for spatial stability, particularly for the early years in our study period. When comparing over time and year-to-year, there are very few *S*-Index values greater than 0.70, 2003 – 2006. Only in the more recent years of the study period do the *S*-Index values approach the threshold of 0.80, indicating spatial stability. Therefore, when considering the entire city there appears to be a high degree of spatial stability for commercial burglary, but when considering only those locations where crime occurs, spatial stability only emerges in more recent years. This indicates that there has been some degree of spatial change in the years of the crime drop for commercial burglary in Vancouver.

The results for mischief, Table 6, are very similar to those for commercial burglary. The S-Index values in the upper-right triangle of the table are always greater than 0.84, indicating spatial stability when considering the entire city. The sensitivity analysis does show an increasing degree of spatial stability in more recent years, but the S-Index values are greater than those for commercial burglary and approach the threshold value of 0.80 sooner, beginning in 2005.

Table 7 shows the results of the spatial point pattern test for theft from vehicle. The S-Index values in the upper-right triangle for the entire city are now mostly below the threshold value of 0.80, but still quite close so it would be difficult to argue that there is not a high degree of spatial stability from 2003 to 2013 in Vancouver. However, more similar to commercial burglary, the results of the sensitivity analysis for theft from vehicle indicate that there is not spatial stability in the set of locations that actually have criminal events of this type. With S-Index values most often below 0.70 the case for spatial stability is difficult to make, even in the more recent years under analysis.

And finally, Table 8 shows the S-Index values of the spatial point patterns test for theft of vehicle. As with the previous results, those for theft of vehicle are arguably the most interesting. When considering the entire city, the S-Index values are always greater than 0.83, indicating a high degree of spatial stability in theft of vehicle. Additionally, in the more recent years, 2010 to 2013, the S-Index values are all greater than 0.90, similar to the results for commercial burglary. As such, there is strong evidence for the presence of spatial stability at the level of the city even with the large magnitude crime drop, 2003 – 2013. When only considering the street segments and street intersections with any crime in the sensitivity analysis, the early years in the study period do not exhibit a high degree of spatial stability, but in more recent years, 2005 to 2013, there is strong evidence for spatial stability with increasing values of the S-Index. This is particularly true for 2008 to 2013. This evidence for spatial stability in theft of vehicle is particularly interesting given the large magnitude crime that has occurred for this crime type in Vancouver over the study period.

<Insert Tables 5 – 8 About Here>

4.3. Longitudinal spatial trajectories, 2003 – 2013

The overall pattern for the four crime types under investigation is relatively consistent. When considering all street segments and intersections the S-Indices are generally all above 0.80—theft from vehicle is the exception but those values are all very close to 0.80—and when considering non-zero street segments and street intersections, earlier S-Indices were moderately high (0.60 to 0.70) and approaching the threshold of similarity in the later pairwise comparisons. This latter increase in the S-Index values is likely due to the retention of all street segments and intersections in the data that have at least one criminal event in conjunction with the crime drop—the situation represented in Fig. 1b.

Despite the appearance of spatial stability, such pairwise comparisons, though instructive, may not provide an accurate representation of spatial stability over longer periods of time. In order to account for this possibility, the spatial point pattern test was also conducted in a longitudinal manner to investigate the spatial trajectories to account for the stability of crime patterns. These results are all shown in Table 9.

<Insert Table 9 About Here>

Considering all street segments and intersections to be most consistent with the more traditional trajectory analyses in the crime and place literature, commercial burglary shows a remarkable degree of spatial stability over the 11-year study period—this is not an unexpected result given that commercial land use is present in a small proportion of the city. Similarly, mischief, theft from vehicle, and theft of vehicle all surpass the threshold of 0.80 for the S_{Zero} and S_{Sum} Indices. It should be noted, however, that these two indices do not measure spatial stability in its purest sense. S_{Zero} includes places that have seen potentially dramatic crime decreases but have found a new "stability", and S_{Sum} includes places that may be sporadic but will only impact the degree of similarity when a spatial unit of analysis is generally stable with a few aberrations. As such, it is very important to also use the index that measure pure, or absolute, stability, the S_{Absolute} Index. Though the S_{Absolute} Index values are all below the 0.80 threshold for all crime types aside from commercial burglary, mischief and theft of vehicle have S_{Absolute} Index values that are approaching the threshold and theft from vehicle has a moderately high index value. Overall, particularly if one considers the crime drop leading to zero crime in some places, the spatial trajectories of these crime types in Vancouver are remarkably stable over time.

Considering the non-zero street segments and intersections, stability is not as high, showing the importance of removing the zero-values when considering the stability of crime patterns in a supplementary analysis. Street segments and intersections that do not have any crime over the study period is a form of stability. Consequently, this is an important result that needs to be identified. However, if the researcher is interested in knowing how stable spatial crime patterns are in those places in which crime actually occurs, a supplementary analysis that only considers non-zero spatial units of analysis becomes important. Considering non-zero street segments and intersections, all crime types have S_{Absolute} Index values less than 0.51 indicating a low level of stability over the study period. However, the S_{Zero} and S_{Sum} Indices are approaching the 0.80 threshold (and achieving that threshold for theft of vehicle), indicating a moderate degree of stability in crime patterns particularly if one considers the crime drop represented in Fig. 1b.

These results show that the pairwise comparisons discussed above are generally consistent with the longitudinal spatial trajectories. However, caution must be undertaken when making longer-term inferences from pairwise comparisons.

5. DISCUSSION

In this paper, we have investigated crime concentrations and the spatial stability of crime patterns for four property crime types in Vancouver, British Columbia, 2003 – 2013. With regard to crime concentrations, we find that crime is highly concentrated in few locations in Vancouver. And, in most cases, these crime concentrations have been increasing while crime volumes have been decreasing. This is a particularly interesting phenomenon that needs further investigation. In the case of Vancouver, two things are occurring. First, crime is going down almost everywhere. This overall decrease was present in previous research on Vancouver (Curman et al., 2015) and in the current data. Also, the crime types investigated in this paper have disappeared from particular street segments and street intersections. Overall for the city, 65 percent of Vancouver was free from these (police-reported) crime types in 2003 compared to 75 percent of Vancouver in 2013. With lower volumes of crime, fewer micro-places are necessary to account for 50 percent of the criminal events, as evidenced in Tables 2 and 3.

Perhaps more interesting is the consideration of Table 4. When considering all of the street segments and intersections, crime is dropping and becoming more concentrated. However, when one considers only the places in which crime is occurring, crime is becoming more dispersed—mischief is the exception. So, there is less crime, it is occurring in fewer places, but within those fewer places the distribution of criminal events is becoming more evenly distributed, particularly for theft of vehicle. Why? Consider the case of theft of vehicle. This crime type exhibited a decrease in criminal events that was approximately 84 percent, whereas the percentage of street segments and intersections (micro-places) with any theft of vehicle dropped by approximately 75 percent. At the same time, the percentage of micro-places that account for 50 percent of criminal events decreased by a little more than one-half. Given that the percentage of micro-places with any theft of vehicle decreased by a greater degree than the percentage of micro-places that account for 50 percent of theft of vehicle, the percentage of micro-places with any thefts of vehicle that account for 50 percent of thefts of vehicle must necessarily increase. There were simply fewer places for those criminal events to occur.

Consequently, those researching crime at places and spatial concentrations must be cautious to not take these statistics at face value. They are important and tell a story of changes in spatial patterns of crime, but they should not impress us at face value. This is similar to a crime type that is relatively rare, say 1000 events over the course of a year, that is counted in the context of micro-places. If there are 10,000 micro-places and one criminal event per micro-place, the minimum level of concentration over the entire city is 10 percent: 1000/10,000. Stating that 90 percent of the city is free from this crime type seems to be an impressive concentration, but such a "concentration" is actually uniform—it isn't a concentration at all. This is precisely the case for theft of vehicle in Vancouver during 2013: 1000 criminal events, approximately 20,000 micro-places and approximately 5 percent of the entire city that experiences this crime type. In fact, the most dispersed this crime type can be is being present in 5.4 percent of micro-places. Consequently, theft of vehicle is hardly concentrated at all when one considers the number of possible places it can occur; therefore, the need for 40 percent of micro-places to account for 50 percent of criminal events makes perfect sense. Yes, this crime type is incredibly concentrated within the entire city, but we must consider the nature and possibilities of that concentration given our chosen spatial units of analysis.

The flipside of these concentrations is the degree of change in the spatial patterns of crime. With 35 percent of micro-places having one of these four crime types in 2003 and only 25 percent in 2013, there is a lot of crime concentration at both points in time. However, there has also been substantial change. As shown using the longitudinal version of the spatial point pattern test (Table 9), a lot of the change can be explained considering those micro-places that cease to have criminal events (Fig. 1b): the S_{Absolute} Index versus the S_{Zero} Index. But where is the rest of the change occurring? Part of this change is occurring through the simple mathematics of places described above: crime concentrations change because there is nowhere else for the criminal events to go that will not impact the spatial stability of crime and, hence, the spatial trajectories. This does not mean that we do not need to investigate any socio-demographic or socio-economic changes that have led to subsequent changes in crime patterns, but we must recognize that a lot of the changes shown above can be understood based on simple explanations: crime just stopped occurring in particular places and became more evenly dispersed as a result. However, socio-demographics and/or socio-economics may come into play to understand *why* particular micro-places no longer had crime, but this is beyond the scope of the current paper.

Returning to the question of whether the law of crime concentration at places is simply a manifestation of the concentration of human activities more generally, we begin to shed light on this question through a comparison of the results for commercial burglary and vehicle-related crime. Vehicle-related crime can occur wherever there is the presence of vehicles, whereas commercial burglary can only occur where there is commercial or mixed land use, by definition. Consequently, if the law of crime concentration at places is simply a specific manifestation of the concentration of human activities, more generally, commercial burglary will always be more concentrated than vehicle-related crime. General support for this proposition is found in Tables 2 and 3, given that commercial burglary is always more concentrated than theft from vehicle and more concentrated than theft of vehicle in all but one case. However, because the degrees of concentration for commercial burglary and theft of vehicle are converging over time, this shows that the concentration of human activities is not enough to explain the law of crime concentration at places. This will prove to be an interesting avenue of future research, considering specific crime types and the availability of opportunities based on the general concentrations of human activities.

Overall, when considering spatial stability for the entire city, we find strong evidence for the presence of spatial stability. This bodes well for theoretical testing and development as well as the development of criminal justice policy, specifically crime prevention initiatives. When only considering street segments and street intersections that have any crime, the results for spatial stability are less promising for any general statements. Theft of vehicle shows the greatest degree of spatial stability in the sensitivity analyses, but generally speaking spatial stability in the locations that actually have crime has a shorter time horizon.

The implications for theory from these results are that there is a relatively high degree of spatial stability at the level of the city. As such, if the testing of theory and any subsequent refinements are based on city-level analyses, using street segments or census tracts as the units of analysis, for example, there are probably not going to be any difficulties. However, if local area analyses are being undertaken to investigate the nuances of theoretical predictions, then caution should be undertaken for generalizing if a longer period of time has elapsed. This is especially the case when the volume of crime is changing.

In the context of criminal justice policy, specifically crime prevention initiatives, the same general statements can be made. However, specifically in the case of situational crime prevention that is quite spatially-specific, the importance of having recent crime data is paramount. Even with S-Index values greater than 0.80 there is still a great degree of spatial change occurring: 20 percent of 18,455 spatial units of analysis is still 3689 street segments and street intersections that are exhibiting change. An argument for spatial stability can be made for the overall crime pattern, but this may not be spatially stable enough for situational crime prevention.

Though instructive, our analyses are not without their limitations. First and foremost, we are restricted to police-reported crime data and a small number of crime types. There is little we can do regarding this limitation, however. Relatedly, one of these crime types (mischief), as mentioned above, is sensitive to police reporting, citizen reporting, and police patrol activities; however, mischief does not present any results that are qualitatively different from the other crime types. Second, our data do not have specific addresses or geographic coordinates available, but we do restrict all inference to the street segment or street intersection in order to avoid the ecological fallacy. And third, our time frame is only 11 years. Though there are not many longitudinal criminal event data sets available there is little that can be done regarding this limitation aside from waiting for more years to pass, assuming more years of data will continue to be available for these cities. However, with evidence of spatial stability in the 10 years prior to this study (Curman et al., 2015), we should be able to move forward with cautious optimism with regard to spatial stability.

As with most research, our analyses raise more questions than answered and these guide future directions for research. First and foremost is the importance of further replication. In order to move forward with (social) science, our results must be replicated in other contexts: are spatial trajectories stable over time in other cities? Second, traditional trajectory analyses of these data would prove to be instructive. A comparison of the results presented here considering the spatial trajectory should be compared with the various classifications that would emerge from a traditional trajectory analysis. Are the various clusters of traditional trajectories when compared with the locations that exhibit spatial stability or not in the same places? It would be interesting to know if traditional trajectories classified as stable would include the street segments and street intersections that are classified as spatially stable using our longitudinal extension of Andresen's (2009) spatial point pattern test, and vice versa. And finally, further investigations into the changing patterns of theft of vehicle are in order. With such a large magnitude crime drop and increasingly concentrated crime types, there are most certainly interesting patterns emerging.

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Fig. 1. Spatial point pattern test, spatial trajectories

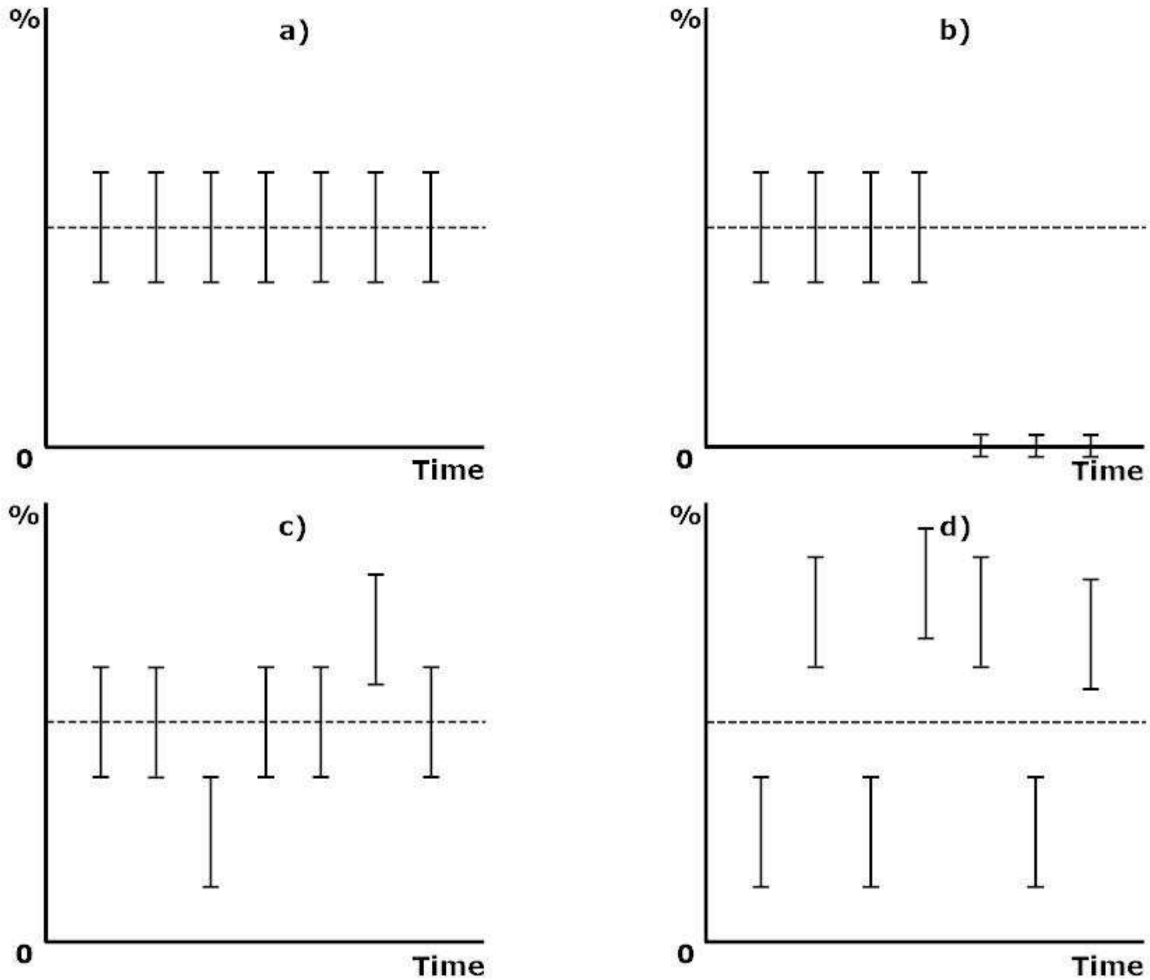

Fig. 2. The crime drop in Vancouver, 2003 - 2013

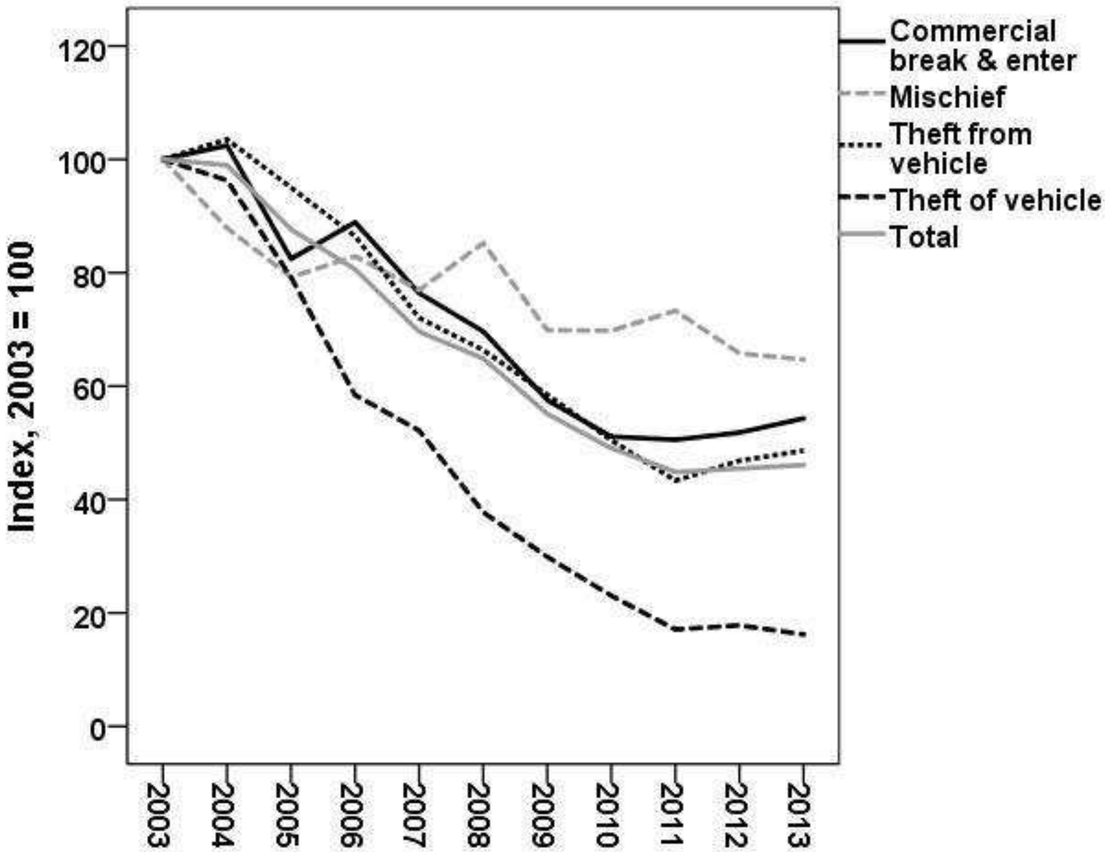

Table 1. Count of crime types, Vancouver, 2003 – 2013

	Aggregate	Commercial burglary	Mischief	Theft from vehicle	Theft of vehicle
2003	32082	3181	6270	16459	6172
2004	31754	3259	5510	17042	5943
2005	28118	2623	4968	15641	4886
2006	25860	2828	5199	14227	3606
2007	22332	2430	4825	11857	3220
2008	20816	2216	5345	10924	2331
2009	17680	1830	4380	9626	1844
2010	15729	1625	4376	8307	1421
2011	14390	1608	4596	7132	1054
2012	14585	1648	4124	7714	1099
2013	14784	1727	4057	8000	1000
Crime drop, %	53.9	45.7	35.3	51.4	83.8

Table 2. Percent of street segments and street intersections with any crime

	Aggregate	Commercial burglary	Mischief	Theft from vehicle	Theft of vehicle
2003	34.77	6.41	16.62	24.87	17.86
2004	36.58	6.81	15.89	27.05	18.77
2005	35.41	6.40	14.69	26.22	16.99
2006	32.32	6.45	15.01	23.25	13.07
2007	30.14	5.80	13.44	20.71	12.13
2008	28.24	5.59	14.53	18.64	9.28
2009	27.86	5.03	13.41	18.86	8.18
2010	27.57	4.49	12.71	19.50	6.45
2011	26.39	4.49	12.93	18.09	4.98
2012	26.50	4.90	12.29	19.01	5.13
2013	26.24	5.21	11.75	19.06	4.55

Table 3. Percent of street segments and street intersections that account for 50% of crime

	Aggregate	Commercial burglary	Mischief	Theft from vehicle	Theft of vehicle
2003	3.75	1.20	3.34	2.50	4.27
2004	4.34	1.23	3.49	3.10	4.96
2005	4.46	1.31	3.37	3.17	4.77
2006	3.68	1.26	3.22	2.50	3.59
2007	3.21	1.13	2.75	2.10	3.40
2008	2.86	1.19	2.80	1.65	2.69
2009	3.37	1.08	3.12	2.24	3.18
2010	3.85	1.01	2.68	3.12	2.60
2011	3.75	0.92	2.46	3.21	2.12
2012	3.84	1.16	2.61	3.18	2.15
2013	3.60	1.21	2.41	2.93	1.84

Table 4. Percent of street segments and street intersections with any crime that account for 50% of crime

	Aggregate	Commercial burglary	Mischief	Theft from vehicle	Theft of vehicle
2003	10.79	18.68	20.10	10.05	23.92
2004	11.87	18.06	21.94	11.47	26.42
2005	12.59	20.41	22.96	12.10	28.05
2006	11.37	19.60	21.46	10.77	27.47
2007	10.67	19.55	20.49	10.13	28.03
2008	10.14	21.24	19.25	8.87	28.99
2009	12.11	21.47	23.29	11.87	38.90
2010	13.96	22.44	21.11	16.01	40.34
2011	14.20	20.39	18.99	17.74	42.59
2012	14.48	23.70	21.22	16.74	41.97
2013	13.72	23.20	20.53	15.36	40.41

Table 5. Indices of similarity, 2003-2013, Vancouver, commercial burglary, street segments & intersections and non-zero street segments & intersections

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
2003		0.940	0.941	0.939	0.941	0.938	0.940	0.940	0.939	0.940	0.939
2004	0.678		0.937	0.939	0.938	0.942	0.939	0.947	0.936	0.943	0.936
2005	0.681	0.659		0.940	0.941	0.942	0.940	0.949	0.941	0.944	0.940
2006	0.668	0.672	0.679		0.941	0.941	0.940	0.948	0.941	0.944	0.938
2007	0.682	0.664	0.682	0.680		0.949	0.946	0.951	0.945	0.946	0.945
2008	0.681	0.691	0.690	0.686	0.727		0.949	0.952	0.949	0.947	0.949
2009	0.680	0.770	0.681	0.675	0.713	0.732		0.957	0.952	0.951	0.951
2010	0.683	0.719	0.727	0.723	0.735	0.740	0.770		0.957	0.950	0.957
2011	0.672	0.662	0.681	0.685	0.708	0.727	0.744	0.764		0.953	0.957
2012	0.675	0.694	0.702	0.697	0.706	0.725	0.739	0.729	0.750		0.954
2013	0.675	0.655	0.674	0.670	0.703	0.720	0.734	0.767	0.765	0.754	

Note. Analyses using all street segments and intersections are in the upper right and analyses using non-zero street segments and intersections (sensitivity analysis) are in the lower left.

Table 6. Indices of similarity, 2003-2013, Vancouver, mischief, street segments & intersections and non-zero street segments & intersections

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
2003		0.844	0.845	0.843	0.845	0.842	0.841	0.843	0.843	0.842	0.844
2004	0.700		0.848	0.854	0.848	0.855	0.850	0.857	0.849	0.860	0.847
2005	0.703	0.709		0.858	0.859	0.859	0.859	0.872	0.860	0.864	0.857
2006	0.696	0.720	0.728		0.855	0.857	0.857	0.858	0.857	0.863	0.857
2007	0.701	0.710	0.729	0.722		0.863	0.871	0.873	0.869	0.878	0.869
2008	0.695	0.722	0.728	0.727	0.738		0.860	0.860	0.861	0.863	0.858
2009	0.697	0.711	0.730	0.726	0.755	0.733		0.877	0.870	0.880	0.871
2010	0.701	0.728	0.754	0.728	0.756	0.732	0.762		0.878	0.878	0.877
2011	0.699	0.712	0.730	0.727	0.748	0.735	0.753	0.766		0.880	0.876
2012	0.695	0.732	0.740	0.736	0.767	0.737	0.769	0.767	0.770		0.883
2013	0.700	0.708	0.726	0.726	0.751	0.728	0.754	0.761	0.761	0.774	

Note. Analyses using all street segments and intersections are in the upper right and analyses using non-zero street segments and intersections (sensitivity analysis) are in the lower left.

Table 7. Indices of similarity, 2003-2013, Vancouver, theft from vehicle, street segments & intersections and non-zero street segments & intersections

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
2003		0.765	0.762	0.758	0.765	0.765	0.771	0.771	0.768	0.768	0.774
2004	0.629		0.749	0.744	0.747	0.779	0.755	0.768	0.753	0.767	0.756
2005	0.627	0.604		0.772	0.755	0.784	0.750	0.769	0.757	0.770	0.762
2006	0.621	0.599	0.644		0.783	0.790	0.780	0.778	0.783	0.779	0.784
2007	0.632	0.604	0.615	0.661		0.817	0.805	0.787	0.801	0.788	0.799
2008	0.631	0.653	0.661	0.671	0.715		0.825	0.790	0.820	0.792	0.818
2009	0.640	0.616	0.618	0.655	0.693	0.726		0.812	0.819	0.797	0.816
2010	0.640	0.635	0.636	0.654	0.665	0.671	0.704		0.814	0.816	0.812
2011	0.635	0.611	0.617	0.657	0.687	0.717	0.716			0.819	0.827
2012	0.635	0.634	0.641	0.642	0.667	0.673	0.682	0.712	0.717		0.815
2013	0.645	0.619	0.637	0.661	0.686	0.714	0.712	0.705	0.728	0.709	

Note. Analyses using all street segments and intersections are in the upper right and analyses using non-zero street segments and intersections (sensitivity analysis) are in the lower left.

Table 8. Indices of similarity, 2003-2013, Vancouver, theft of vehicle, street segments & intersections and non-zero street segments & intersections

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
2003		0.838	0.836	0.842	0.841	0.840	0.838	0.836	0.832	0.832	0.829
2004	0.665		0.831	0.849	0.832	0.869	0.831	0.890	0.824	0.900	0.821
2005	0.662	0.651		0.857	0.842	0.887	0.848	0.904	0.839	0.912	0.836
2006	0.673	0.686	0.703		0.877	0.893	0.882	0.914	0.877	0.927	0.874
2007	0.671	0.652	0.672	0.747		0.896	0.889	0.921	0.885	0.930	0.883
2008	0.669	0.733	0.765	0.778	0.784		0.913	0.927	0.911	0.938	0.910
2009	0.666	0.650	0.685	0.756	0.769	0.819		0.930	0.922	0.942	0.922
2010	0.660	0.772	0.801	0.824	0.837	0.848	0.855		0.939	0.945	0.936
2011	0.651	0.634	0.665	0.746	0.762	0.817	0.840	0.874		0.952	0.950
2012	0.651	0.793	0.818	0.846	0.853	0.872	0.879	0.884	0.884		0.950
2013	0.645	0.629	0.660	0.740	0.759	0.815	0.838	0.869	0.898	0.897	

Note. Analyses using all street segments and intersections are in the upper right and analyses using non-zero street segments and intersections (sensitivity analysis) are in the lower left.

Table 9. Indices of Similarity, spatial trajectories, 2003 – 2014

	All street segments and intersections			Non-zero street segments and intersections			
	S_{Absolute}	S_{Zero}	S_{Sum}	S_{Absolute}	S_{Zero}	S_{Sum}	n
Commercial burglary	0.901	0.946	0.941	0.470	0.709	0.681	3430
Mischief	0.740	0.874	0.845	0.502	0.759	0.704	9625
Theft from vehicle	0.673	0.823	0.803	0.373	0.661	0.628	9625
Theft of vehicle	0.762	0.953	0.838	0.506	0.903	0.664	8899