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Space-Time Patterns of Risk: A Cross National Assessment of Residential Burglary Victimization

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Suggested running head: A cross national comparison of space-time patterns of burglary risk

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ABSTRACT

Using epidemiological techniques for testing disease contagion, it has recently been found that in the wake of a residential burglary, the risk to nearby homes is temporarily elevated. This paper demonstrates the ubiquity of this phenomenon by analyzing space-time patterns of burglary in 10 areas, located in five different countries. While the precise patterns vary, for all areas, houses within 200m of a burgled home were at an elevated risk of burglary for a period of at least two weeks. For three of the five countries, differences in these patterns may partly be explained by simple differences in target density. The findings inform theories of crime concentration and offender targeting strategies, and have implications for crime forecasting and crime reduction more generally.

Key words Burglary risk, space-time clustering, cross national comparison, Monte Carlo simulation

1. Introduction

A large body of research demonstrates that crime is unevenly distributed among offenders, places and victims respectively (Blumstein et al, 1986; Sherman et al, 1989; Pease, 1998). A case in point is the research concerned with repeat victimization. This literature reveals that victims experience an elevated risk of crime in the months that follow an initial event (Farrell, 1995; Pease, 1998), which has implications for crime prevention (Forrester et al., 1988). More recently, research concerned with burglary has explored whether repeat victimization is a special case of a more general phenomenon, whereby risks cluster in space and time (Johnson and Bowers, 2004; Townsley et al., 2003). Using epidemiological techniques for testing disease contagion, it was found that in the wake of a residential burglary, the risk to nearby houses is temporarily elevated, a phenomenon that is well captured by the term 'communication of risk'. Of course there is no suggestion that a burgled home exudes a burglary bacillus, but that burglar behavior, and hence space-time patterns of burglary risk, may make it look that way.

The aim of this paper is to advance this research agenda by examining and comparing patterns of burglary risk across a range of urban environments in different countries. We review the literature extant, with a particular focus on spatio-temporal patterns of crime, and then analyze spatio-temporal burglary patterns for two different areas in each of five countries. Regularities in these patterns will be considered as will a tentative explanation for variations between them.

1.1 The Theoretical Domain of Spatio-Temporal Clustering

Past research has established that crimes cluster in time (Ratcliffe, 2004b; Rengert and Wasilchick, 2000) and in space (Block et al., 1995; Ratcliffe and McCullagh, 1998; and Sherman et al., 1989). What is less well understood is what gives rise to these spatial and temporal crime clusters, and how crime varies simultaneously in these two dimensions. The pattern of clustering in time and space has significant implications for the extent and choice of crime prevention measures as well as the value of any predictive work that could influence detection activity. It determines the degree to which crime reduction measures can be focused.

Hot spots or spaces have been identified using Spatial and Temporal Analysis of Crime (STAC), kernel density analysis or similar techniques (Block, 1995; Ratcliffe, 2004a; Robinson, 2003). These hot spots commonly cover many city blocks incorporating more than one census tract. At the other extreme we have repeat victimization where one address is attacked multiple times (Johnson et al., 1997; Pease 1998, Polvi et al., 1991; Sherman et al., 1989). Between these extremes we have near repeats which take place in an area no more than three or four city blocks in extent (Bowers and Johnson, 2005). Lersch (2004) refers to repeat victimization as a “hot place” and combines hot spots and near repeats into “hot space.”

Temporal clusters can be categorized in a variety of ways. In macro-level terms, Cohen and Felson (1979) pick up on the work of Hawley (1950) and provide examples of behavior as having a *rhythm* (the periodicity at which events occur), a *tempo* (the rate at which events occur) and *timing* (the coordination or overlap of activities). Ratcliffe

(2004b) describes a classification of crime hotspots based on a combination of spatial and temporal characteristics, with three spatial classifications (dispersed, clustered, hotpoint) and three temporal classes (diffused, focused, acute). In general however, our understanding of offenders' localized use of time and space together is underdeveloped (though Rengert and Wasilchick (2000) is a welcome exception).

1.2 Hot Spaces: Theories of Opportunity and Social Disorganization

Theoretical analysis of the nature of spaces that have high crime rates has an extensive history. Guerry (1831) offered an explanation of why property crime was concentrated in high income areas while violent crime was concentrated in low income areas of France. This was an early development of *opportunity theory* that reasoned that crime rates will be highest in locations that contain the best opportunity for crime. Recently, Bernasco and Luykx (2003); Bernasco and Nieuwbeerta (2005) and Rengert (1989) used the same reasoning to explain variation in crime rates within metropolitan communities. An important finding in this body of research was that criminals did not travel far to exploit opportunities for crime (Wiles and Costello, 2000; Rengert et al., 1999; Rossmo, 2000), a nod to the least effort principle (Zipf, 1949).

The idea that the vast majority of offenders did not travel far from their homes to commit crimes is associated with a renewed interest in the nature of communities that house criminals. There are many theoretical explanations of what type of person is likely to commit crime and why their residences tend to be clustered in space (Blau and Blau, 1982; Bursik and Grasmick, 1993; Byrne and Sampson, 1986; Shaw and McKay, 1969).

Much of this research can be traced back to seminal work completed in the *Chicago School* (Shaw and McKay, 1969), which focused on the characteristics of communities that allowed youth to engage in a wide variety of behavioral choices, especially criminal behavior. These were socially disorganized communities that lacked *collective efficacy* (Sampson et al., 1997) to develop control over the behavior of their residents and of others who visit the area.

From the above, it is apparent that *opportunity theory* focuses on the location of crime in space while *social disorganization* focuses on the location of criminals in space. Both approaches deal with spatial location as one of generalized space, rather than of localized place. The beginnings of a more unified approach occurred when the above two perspectives coalesced in the form of *routine activity* theory (Cohen and Felson, 1979). This theory explicitly detailed that a crime would not take place unless a motivated offender comes into contact with a suitable target (opportunity for crime) in the absence of a capable guardian (often, though not always, within a socially disorganized community). Originally a macro-level explanation for crime patterns, more recent development of routine activity theory (see for example Eck, 1995; Felson, 1998) made possible by a higher degree of precision and accuracy in recorded crime data enabled criminological theory to move into the domain of the *place* – a more micro-level of criminological examination. This more recent work (see also Block and Block, 1995) goes some way to addressing the concerns of Cornish (1993), who identifies as a substantive issue in criminology the need for adequate micro level theories of human action. In other words, a focus on place rather than space.

Sherman et al. (1989: 30-32) also point out the importance of place over space: "The most important contribution of routine activities theory is the argument that crime rates are affected not only by the absolute size of the supply of offenders, targets, or guardianship, but also by the factors affecting the frequency of their convergence in space and time….the most appropriate unit of analysis for the routine activities approach would seem to be places." Crime therefore had a specific time and location associated with its occurrence. Yet as noted later in their article (Sherman et al., 1989: 33): "The implied premise of routine activities theory is that such concentrations are not random… But to our knowledge, that premise has never been examined across an entire city with place as the unit of analysis." We agree that place has received little systematic attention in the criminological literature. Before we go on, the nature of these places requires further theoretical discussion.

Routine activity theory left unanswered how routine behavior became established within an environmental milieu. *Pattern theory* (Brantingham and Brantingham, 1993) illustrated how the environmental *backcloth* influenced, if not determined, the routes taken to nodes selected as locations for routine activities (such as school, work places, shopping, etc.). In other words, whether criminal or victim, the location of routine activities and the routes selected to travel to these locations determined the opportunities available to the criminal unless the criminal explored space beyond their usual activity space. Cromwell et al. (1991); Maguire, (1982); and Rengert and Wasilchick (2000) determined that spatial exploration is very rare in criminal spatial behavior. Most criminals commit crimes in areas with which they are already familiar.

Brantingham and Brantingham (1993: 273) note that crime becomes a routine activity for repeat offenders who reinforce and change their initial templates: “The feedback loops may have less importance for the analysis of aggregate crime patterns, but they are very important for understanding what happens during the commission of the initial crimes by both those who will be repeat offenders and those who will be ‘scared’ off crime by the experience.” The fact that crime victims do not constitute a representative sample or an unbiased cross-section of the general population indicates that criminals do not choose their targets at random (Budd, 1999; Lauritsen, 2001). This suggests an important area of research: how criminals choose their targets and the criteria they use in such selection (Fattah, 1993). There are many opportunities for crime within a typical criminal’s awareness space. How does the criminal choose among these?

The *rational choice* perspective (Cornish and Clarke, 1986) entails two important points—both opportunities for crime and criminal motivation vary in space and time. Crime takes place when the offender has the necessary level of motivation and encounters a suitable target in space and time. The completion of a criminal act therefore requires not only an opportunity to present itself (or to be sought out by the offender), but also that the offender will be suitably motivated to take advantage of the opportunity.

1.3 The Rationality of the Communication of Burglary Risk

Once a crime has been committed, it becomes easier to repeat that crime than to identify a new location and/or a new criminal act (Pease, 1998). This does not mean that the criminal will always return to the exact same locations to commit the same crime but that this is likely. In fact, Ericsson (1995) found that 76 percent of the burglars he interviewed had gone back to a number of houses after a varying period of time to burgle them between two and five times. Similarly, Everson (2003) found that no fewer than 37 percent and potentially 94 percent of all offences against a particular target are committed by the same offender.

However, in the case of residential burglary within wealthy residential areas, the opportunity for crime may not be the same once a crime has been committed at that location. As noted by Farrell and Pease (1993: 14): "…where, with money little object, and work obligations less rigid…the householder can stay at home for a few days, …swift security uprating and other improvements will reduce the rate of immediate revictimization." In other words, the home owner is likely to expend money to harden the property so that repeat victimization is less likely. This may explain Ratcliffe and McCullagh's (1999) finding that while the risk of burglary was fairly uniform across different neighborhoods in parts of Nottinghamshire (UK), properties in more deprived areas were at a significantly greater risk of repeat victimization.

The use of counter-measures against revictimisation may make neighboring properties easier to invade than the original house burglarized. This reasoning would lead to a *near-repeat* (a concept coined by Morgan, 2000) rather than a repeat burglary, and thus be an example of crime displacement (Hesseling, 1994) at a small geographical scale. This idea is supported by the work of Bowers and Johnson (2005) who found that near-repeat burglaries were more likely in wealthy housing areas and repeat burglaries in low income housing areas.

The hardening of properties in affluent communities after a burglary is not the only explanation for near-repeat burglaries in such areas as opposed to repeat burglaries in less affluent areas. An alternative explanation is provided by Bowers and Johnson (2005) who argue that repeats are more likely in less affluent areas since they are likely to be closer to the home of the burglar while crime in more affluent areas is more probably a planned affair where near repeats are more likely. In other words, repeat victimization may be more of a spur of the moment decision where the first opportunity near the home of the offender is exploited while a near-repeat victimization is more likely to be planned in advance where the criminal travels farther to exploit more remunerative targets. On the other hand, Townsley et al. (2003: 615) argue that in some suburban areas:

> Little or no housing diversity, in terms of the type of physical construction and general appearance of dwellings, serves to restrict the extent of repeat victimization. Housing diversity allows offenders a choice of targets, and favored targets will be 'revisited' by burglars. Near identical targets usually present no motive for an offender to favor one property over another.

An exception would occur if the burglar did not take all the property when the house was first burglarized and returned to obtain goods passed up on the first offence.

If offenders return repeatedly to the same areas to commit their crimes, this leads to a *hot spot* of criminal activity. Sherman et al. (1989) argue that determining the locations of these hot spots is important to crime control. Hot spot policing forces police administrators to focus resources where need is greatest. With repeat and near-repeat concepts in mind, a small number of places (households) experience a disproportionate amount of crime and by focusing prevention efforts on these repeat victims, the impact on crime will be greater than if entire communities are targeted. This returns us to the initial point of this section: the range of ways to determine the areal extent of a crime cluster. With regard to focused police patrol, attention generally cannot be given to a single property except in the case of a stake-out. Police patrols cover an area and so the question turns to how small an area and for how long should the police maintain their focus.

Everson (2003) found that the most prolific (detected) offenders were also those who committed repeat crimes on the same street and, that victimized houses within a street were located very close to each other. Shaw and Pease (2000) discovered that 68 percent of burglaries on the same street occur on the same side (see also, Bowers and Johnson, 2005). If this is the case, then focused police attention on a city block (or even on one side of the block) could positively impact a city's crime rate. One aim of this paper is to quantify the spatial and temporal limits of the near repeat phenomenon across a range of study areas, in order to address this important limitation of crime prevention.

There is one piece of information missing that is central to determining whether focused police patrol can be effective in hot spot policing, and by corollary, the value of the phenomenon that forms the basis of this paper. This is the temporal characteristics of the local crime cluster. For example, if a sniper kills five or six people in a restaurant in a ten minute period, this location may be identified as a hot place of violent crime. Yet focused police attention is unlikely to lower the city's violent crime rate since this episode is unlikely to reoccur with or without focused police attention.

On the other hand, ten or twenty crimes may occur on a street segment throughout the year. If they are scattered evenly throughout the year, focused police attention would lead to very bored police officers as this crime would not occur 340 or more days out of the year. For operational policing purposes, it is thus not only important to know where a crime is likely to take place, but also when.

Research on repeat and near-repeat victimization gives us this information. This research has determined how soon after an offence a similar offence (in time and place) is likely to occur (Farrell and Pease, 1993). The probability of a similar crime in the same location is very high directly after the original offence has been committed. However, this risk decays exponentially over time allowing the reallocation of resources. Similarly, Griffith and Chavez (2004) model the spatial and temporal variation of violent crime within individual neighborhoods (census tracts) of Chicago across 1980-1995 and show that whilst violent crime concentrates spatially, neighborhood risks can change over time. The determination of the timing of victimization is important if we are to efficiently allocate public resources. We need to know when resources should be focused on a place and at what point benefits do not justify this focused response. Given the added dimension of the near-repeat phenomenon, this requires us to know when resources are best allocated to an individual location and for how long (repeat victimization prevention), and when resources should be allocated to the local area, and for how long. The latter allocation of resources requires practitioners to know how large an area is appropriate, and for how long treatment is required.

The ideal situation from a crime prevention perspective would be to anticipate an elevation in risk for those as yet unaffected. Prescient clarity of this kind could, in concert with the appropriate police strategies, help reduce the number of first time as well as repeat victimizations. The scope for such an approach does, of course, depend upon the empirical validation of the existence of spatio-temporal clusters of crime.

Since research on crime patterns at the micro level have generally focused on a single city, we do not know if cities differ in their patterns of crime at the micro level. This is particularly the case for patterns of crime at the micro level of place rather than at the neighborhood level of analysis. The nature of places vary substantially and we do not know how such heterogeneity influences patterns of offending. For example, many British urban areas were laid out in medieval times, or even earlier, while the Australian capital, Canberra, was planned in the early 1900s. A number of US cities were designed to facilitate the smooth flow of motorized traffic, while the street pattern in some European urban areas was designed with the horse and cart in mind.

In the present analysis, two areas in each of five different countries that differ in such important factors as population density, availability of public transportation, and urban infrastructure are examined to determine whether near-repeat victimization is similar in these varying urban infrastructures. If the processes underlying spatial and temporal crime patterns are really universal, then the phenomenon of near repeat victimization should exist in many different cities and regions around the world. The analysis that follows tests this proposition.

2. Data and Analytical Strategy

This section describes the data used to answer the research questions outlined in the preceding section. Due to the large number of data sets involved, and for the sake of brevity, only an overview of each data set and how it was processed will be provided here. More detail is available from the authors upon request. Each data set included the following fields of information: 1) a unique crime reference number; 2) the date of the offence; and, 3) the geographic grid coordinates of the property victimized, accurate to a resolution of one meter.

All data sets were provided by the police force responsible for the area in question. Most police information systems record the date of a burglary in a similar manner, using a window of opportunity rather than a single date. This is because houses are routinely unoccupied during an offence, and consequently victims can only provide an estimate of the period during which a burglary could have occurred. For the data analyzed, the time window was usually only a few hours, occasionally one or two days and in rare instances a matter of weeks. In all cases one of the two dates was consistently used. Duplicate records and those for which geographical grid coordinates were unavailable were removed from all data sets either by the police department who provided the data or by the authors. The key features of the ten data sets are summarized in Table I.

INSERT TABLE I HERE

With the exception of Pompano Beach, all data are concerned with residential burglary. For Pompano Beach, it was not possible to distinguish between burglaries which took place at a residence, business or conveyance. The authors also acknowledge that definitions of residential burglary may vary from place to place, as might the way in which incidents are recorded. Notwithstanding these issues, the data were considered to be comparable for the purposes of the current investigation.

Empirical research concerned with the space-time clustering of events was first conducted by Knox (1964) to study epidemics of childhood leukemia[1]. Being a rare disease with an etiology largely unknown, it was hypothesized that there was an element of contagion involved in the disease. Knox derived a method to detect contagiousness using only data on the times and places of disease onset. The rationale underlying the Knox test is to determine whether there are more observed pairs of events that occur close in space and time than would be expected on the basis of a random distribution, if time and place of onset were completely independent. To do this, each event for a particular dataset is compared with every other and the spatial and temporal distance between them recorded. For n cases, this generates $\frac{1}{2}n(n-1)$ pairings (e.g. for 1000 events, 499,500 comparisons). A contingency table with i columns and j rows is then populated. For example, the first cell might give the number of event pairs that occur within two weeks and between 1-100 meters of each other (for a more detailed discussion, see Johnson and Bowers, 2004; Townsley et al., 2003). The spatial and temporal increments (or bandwidths) used in the rows and columns are selected to allow

[1] Earlier work concerned with diffusion processes which used a different methodology is acknowledged (e.g. Morrill, 1965)

a detailed analysis of the distance over which disease onset, or in this case crime risk has an impact, and for how long this endures.

Once the contingency table (hereafter, the Knox table) has been generated, the observed cell counts can be compared against the expected cell counts (computed under the assumption that the time-distance and the space-distance are unrelated - the null hypothesis). In the case of contagion, the former will be significantly higher than the latter. To date, all of the published studies concerned with crime (Johnson and Bowers, 2004; Townsley et al., 2003) have followed the approach originally developed by Knox, which assumes that in the absence of contagion, the statistical distribution of the expected values for the cells of the Knox table would conform to a Poisson distribution, and can be computed using the marginal totals of the table. One complication is that the assumption of independence of observations is violated. This is because the unit of analysis in this case is crime pairs and each crime event contributes to n-1 of the pairs considered.

However, an alternative approach, for which the independence of observations is not a requirement, may also be taken. This approach uses permutations of the observed data to generate an expected distribution, rather than using the marginal totals (Besag and Diggle, 1977). To do this, the data are permuted, in effect mixing up the dates and locations across the events. Because even for moderately sized datasets a full permutation is virtually impossible to calculate, a Monte Carlo simulation is used to draw a random sample from all permutations. For the Knox test, the dates are randomly shuffled using a pseudo-random number generator, whilst the spatial locations remain fixed. This process of generating permutations is repeated a number of times, say 999.

For each permutation a new Knox table, which enumerates how many burglary pairs occurred within each space-time interval of each other, is generated and compared with the Knox table for the observed distribution. A further contingency table is produced to record the results of these comparisons. The null hypothesis is that the observed cell counts (for the shortest space-time intervals, such as those up to 100m and 14 days) could have occurred on the basis of chance. Consequently, the null hypothesis may be rejected if more events occurred close in space and time than for a large percentage (95% or 99%) of the random permutations generated. The probability that the observed value for each cell occurred on the basis of chance may be calculated using the formula shown in equation 1 (see North et al., 2002):

$$p = \frac{n - rank + 1}{n + 1} \qquad (1)$$

Where *n* is the number of simulations, and *rank* is the position of the observed value in a rank ordered array for that cell

Importantly, because the expected distribution is derived from the actual data, this approach explicitly takes account of the particular crime patterns (the burglary rate, spatial concentrations, or temporal fluctuations) for each area analyzed. This means that any patterns observed cannot be explained by more general factors such as area level rates of crime.

In addition to the significance tests computed, to aid interpretation, a measure of effect size is also used, in this case the ratio of the observed to median expected count for every cell (hereafter, the Knox ratio). The median value was used as a denominator as the use of this measure of central tendency required that no assumptions about the distribution of the permutations for any of the cells be met[2]. The resulting ratio provides the reader with an understanding of the size of the effect observed which compliments the associated p-value.

With respect to the Knox tables generated, different temporal bandwidths could be used, but intervals of 14 days are here used. For some of the areas considered, data were only available for a period of 12 months which has implications for the reliability of the effect sizes and p-values derived. To elaborate, where data are available for shorter intervals (e.g. 12 months), this means that very few burglaries could occur near to (or far from) each other in space but far away from each other in time, which generates a temporal edge effect. This problem is minimized by the use of the Monte Carlo procedure as the edge effect is also a feature of the expected distribution, but where small numbers are involved the results may be compromised. To minimize the effect of this here, the maximum interval considered between any two events is six months.

In relation to the spatial parameter, intervals of 100m are used. Intervals up to and including 183 days, and 2km, are considered which produces a contingency table of 13 by 20 = 260 cells. All incident pairs that represent repeat victimization of the same property (with distance zero) are excluded from analysis. Their inclusion in the lowest spatial interval considered would result in mixing up repeat victimization and near repeat victimization, and thereby obstruct the proper testing of the research question. An

[2] Given the number of cells considered in each table and the number of areas for which the analysis was considered, it was clearly beyond the scope of the research to check the distributions for every cell.

alternative approach would have been to analyze repeat victimization separately from near repeat victimization by dedicating a single column to it in the Knox table[3]. However, given the comprehensive empirical literature extant concerned with repeat victimization (for a recent review, see Farrell, 2005), another empirical confirmation of the phenomenon and discussion of the findings was considered superfluous, and the available journal space better utilized by focusing on near repeat victimization.

To illustrate the Monte-Carlo approach and the results generated in a little more detail, an example for one of the areas will be considered, in this case the Wirral, UK. The simulated distributions for every cell are independent of each other and hence for each of the (260) space time combinations we can construct a separate curve for the expected distribution. Figure 1 shows the results of 999 iterations for burglary pairs that occurred within 14 days and 1-100m of each other.

The vertical line shown in Figure 1 indicates the value of the observed frequency (366). This is much larger than the expected mean and is located in the extreme right tail of the distribution. Comparing this to the expected median value of 296, the Knox ratio measure of effect size for this cell in the contingency table was 1.24. Apropos statistical significance, the results of the permutation test indicate that none of the simulated pairings had a higher value than the observed data. Accordingly, the likelihood of achieving the observed value on the basis of chance is (1/1000) one-tenth of one percent (0.001), or (999 – 999 + 1)/1000 = 1/1000 using equation 1. This is strong evidence to

[3] The results of this approach are available from the authors upon request.

suggest that the observed pair frequency for this space time combination was not the function of a random process.

INSERT FIGURE 1 HERE

For this example, the results demonstrate a tendency for burglaries to cluster in both space and time. This suggests that houses proximate to burgled homes experience a temporary elevation in risk.

3. Results of the International Comparisons

The example illustrated above demonstrates the methodology for a single space time combination (i.e. 100 meters and 14 days) for one data set; that is, one cell of the contingency table for one area. Attempting to summarize the 260 space time combinations (20 (100m intervals) by 13 (14 day intervals)) across ten different datasets is a considerable task. Whilst the results illustrated in the above figure are available for each of the cells for every dataset, henceforth, for parsimony, we will focus on a more simple measure. Different measures and methods of presentation have their own advantages, but it is critical that the trends identified are tested for significance in the usual manner to establish their validity. Similarly, a measure of effect size is always useful when interpreting results for which particular patterns are anticipated (such as a pattern of distance decay). As a consequence, in the following section the findings for each area are summarized using a combination of the Knox ratios and the p-value for each space time combination. Note that in all cases the p-values are determined by the rank of the observed pair frequency compared to the expected distribution. For each space time combination the expected distribution comprises the 999 simulated frequencies and the observed frequency. It is important to note that this is a one-tailed test which considers the extent to which more (and not less) burglary events occur within particular distances and times of each other.

The permutation simulation results show that for the ten data sets available, all of the areas exhibited significant space-time clustering of burglary at short temporal and spatial intervals, though the specific patterns varied. As a minimum, for every dataset, there was an over-representation of burglaries occurring within 100 meters and two weeks of each other for every area. Thus, across all the areas, following an initial incident of burglary, further events were more likely to occur within two weeks and 100 meters of the initial incident than would be expected if the times and places of burglaries were independent. Moreover, the Knox ratio for this cell was consistently the largest in the contingency table for every area analyzed. This demonstrates the ubiquity of the near-repeat phenomenon at the shortest spatial and temporal bandwidths examined. This is an important finding as it confirms an *a-priori* hypothesis rather than representing an inductive test.

To examine the specific patterns for each area, a series of figures were generated to facilitate their comparison. Figure 2 shows a 20 by 13 grid for each data set. Distance is represented along the abscissa and time along the ordinate, with the shortest distances and times being placed at the bottom left of the grid. The cells within the grid are shaded to reflect the size of the Knox ratio. The darker the shading, the larger the effect size. To communicate the statistical significance of the patterns, only those cells for which the p-value was less than 0.05 are shaded. Those for which more than five-percent of the permutations exceeded the observed cell count are left blank.

INSERT FIGURE 2 HERE

Visual inspection of the grids gives an instant impression of the extent to which the risk of victimization appears to communicate[4] in space and time across the different areas. For instance, in both Australia and the Netherlands, burglary risk appears to communicate over longer distances. In contrast, the effect appears to be more localized in the USA. There are also some areas where the communication of risk appears to persist over longer periods of time, notably Canberra, the Hague and Philadelphia. In the other cases, the pattern appears to be limited to a two week period.

There are some areas for which the patterns are striking. This is particularly true in the cases of the Hague and Canberra. In contrast, Palmerston North in New Zealand shows a diffuse pattern of communicability- there are a large number of cells in the bottom left that are significant but these are not necessarily contiguous. Lastly, it is worth commenting on the level of 'noise' in the different data sets. That is to say, where there is an overrepresentation of burglary pairs that occur in cells that would not be anticipated on the basis of the theory discussed in the introduction. For instance, in all cases there are some cells in the centre of the grid for which the p-values are less than 0.05. In some

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[4] Recall that the use of the term 'communication' is used to describe emergent patterns in the data, but is not intended to suggest that the same mechanisms operate in the transmission of a disease and crime risk. For example, disease pathogens infect new hosts following direct contact and the communication of the disease is made possible through microbe replication. In the case of burglary, the thesis is that the same burglar swiftly victimizes a series of nearby homes. Thus, different causal mechanisms are believed to be involved but the outputs of these, measured in space and time, may have similar signatures.

cases, there are a limited number of such occurrences, or the level of significance is relatively low (Auckland, Beenleigh, Florida and the Hague). There are other data sets where the level of 'noise' is moderate, but there is no pattern to the cells that exhibit significance (Bournemouth, Wirral and Zoetermeer). In the two remaining cases, Philadelphia and Canberra, there is some evidence of a clustering of significant results elsewhere in the grid, other than the bottom left corner. The reasons for this pattern are unclear. One possibility is that it is due to an artifact referred to as reciprocal clustering, whereby an over-representation of pairs at short times and distances naturally could go hand-in-hand with an over-representation of pairs at longer times and distances. A further factor is that for any grid in Figure 5, there are 260 p values displayed, some 13 of which could be less than 0.05 on the basis of chance alone. In relation to this point, whilst the cells in the bottom left of the grid are statistically significant for all countries, there is no evident regularity across data sets for cells located elsewhere in the grid. Moreover, and as noted above, the Knox ratios are consistently highest in the bottom left cells for each area considered; only rarely does the Knox ratio for cells located elsewhere in the grids exceed a value of 1.1.

To provide a more general picture of the results, boxplots were generated to summarize the apparent trends in the Knox ratios for the cells of most relevance to the hypothesis tested. That is, for the shorter space-time intervals. A variety of approaches are possible, but we decided to produce two box plots. One for which the interval of time considered remained constant, and a summary of the patterns evident for the different spatial bandwidths was displayed and, one for which the reverse was true. The results are shown as Figure 3. Rather than displaying the data using traditional box plots, to maximize the data to ink ratio of the graphics (see Tufte, 2001) a minimalist approach was used. The black dot in the middle of each plot represents the median value, whereas the grey lines indicate the interval between the most extreme values and the top and bottom of the inter-quartile ranges. Thus, the inter-quartile range is indicated by the absence of ink rather than a large box of arbitrary dimensions.

INSERT FIGURE 3 HERE

Considering how risk diffuses in space in the aftermath of a burglary, the results suggest that there is a clear pattern of distance decay. Risk is greatest nearest to burgled homes and decays thereafter. With respect to how the diffusion of risk changes over time, the same pattern emerges. When burglaries occur at homes proximate to previously victimized houses, they tend to do so swiftly, with the risk of victimization to nearby households decaying as a function of time.

However, the results shown in Figure 3 represent the aggregate patterns observed and consequently do not indicate whether the overall picture is representative of the patterns observed for each area considered. To examine this issue, graphs were initially constructed to explore the trends but it was decided that a more parsimonious approach to summarizing the patterns would be appropriate here. Thus, Kendall's measure of concordance (*W)* was computed to assess the extent to which the rank order of the Knox ratios across areas was preserved for the different (space or time) intervals considered. This statistic, which varies from zero to one, provides an index of the degree to which observed rankings are consistent for three or more variables. To ease interpretation, Hays (1981) recommends converting W to $\bar{r}_s$, the average Spearman correlation computed on the rankings of all combinations, and it is this approach that we adopt here.

The results indicated that for the diffusion of risk in space (for the 14 days after an initial event) there was a high degree of consistency in the rankings ($\bar{r}_s$=0.79); those areas that had the largest Knox ratio for one spatial interval tended to have them for the others. Expressed in a different way, considering the curves observed as regression functions, whilst there is a change in intercept across areas, the change in slope was generally consistent.

In contrast, considering how the diffusion of risk within 100m of a burgled home changed over time, there was little consistency in the observed rankings ($\bar{r}_s$=0.04). Thus, the areas with the highest Knox ratios for the first interval were not necessarily those that had the highest Knox ratios for the others. A variety of post-hoc hypotheses may explain this finding. For example, differences in police priorities or the celerity of police response times to calls for service across the different areas may truncate (or extend) the communication of burglary risk. In the absence of the appropriate data, however, such hypotheses remain speculative and await appropriate testing.

3.1 The Communication of Risk and target density

The results so far discussed demonstrate that while there is some consistency in the overall profile of the communication of burglary risk across countries, there is variation between areas in terms of the precise extent to which the risk of burglary diffuses in space and time. One simple hypothesis regarding these differences is that they may be generated by differences in target density. Where houses are more spatially concentrated, we might expect a shorter spatial extent of the communication of risk and vice versa. In fact, in some sparsely populated rural areas, there may be no other dwellings at all within 100 or 200 meters, so that risks could only communicate, if at all, over longer distances. At the same time, the underlying explanation suggesting that space-time clustering is generated by offenders returning to places of previous offences, would not be particularly convincing in cases where the shortest distance between houses is substantial. Offenders cannot easily learn about the neighbors of their victims if the neighbors live a kilometer or more away. To test the hypothesis that areas with high housing densities have relatively high levels of space time clustering, data concerned with housing density were acquired for each area[5]. Table II summarizes this information and cross-references the densities with the patterns of space-time clustering. For the purposes of this exercise, the degree of space-time clustering for each country has been summarized into an approximation of the time and distance over which the communication of risk is significant[6].

INSERT TABLE II HERE

To summarize, while the communication of risk was evident across all areas, the relationship with housing density was mixed. For three of the five countries (UK, Australia and New Zealand), in line with the above hypothesis, the communication of

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[5] If the aim is to control for variations in target density, an alternative test is the k-nearest neighbor test (Jacquez, 1996). This uses the (asymmetric) nearest-neighbor relations as distance measures between all events, and thus assumes that physical spatial distance is irrelevant to the contagion process. Our aim was not to control for target density, but to study its relation to space-time clustering.

[6] This task was completed by identifying the largest cluster of contiguous cells in the bottom left of each grid with the criterion that 95% of the cells in the cluster should be significant at the 5% level or less.

risk extended over longer distances for the area with the lower target density. In contrast, however, for the US the pattern was reversed and in the Netherlands there was no housing density relationship.

4. Conclusions

The central aim of this paper was to test the hypothesis that near-repeat victimization is a ubiquitous phenomenon. Using techniques developed in the field of epidemiology, patterns of burglary in two different areas in each of five separate countries were explored, and a confirmatory set of results emerged. Simply put, for every data set analyzed, more burglaries occurred close to each other in space *and* time than would be expected on the basis of chance, and the size of the effect typically conformed to expectation. It is important to note that the results do more than confirm that burglary clusters in space. They also demonstrate that when a burglary occurs at one location, a further burglary is likely to occur nearby and that it will do so swiftly. As time elapses, this communication of risk decays.

The findings have implications for our understanding of crime patterns, and the processes underlying them. The ubiquity of the phenomenon across different places and times is striking, and suggests a common underlying process. Given the physical and social heterogeneity of the different areas studied, one explanation for this relates to offender foraging behavior. There is a consensus of opinion amongst some criminologists that offenders have preferences, internalized as cognitive scripts (Cornish, 1994), for the types of properties they consider suitable. The prevalence of repeat victimization as narrowly conceived, arguably a special case of the phenomenon examined in this paper, provides support for this idea showing that offenders express a desire to return to the exact same homes already burglarized. Selecting the same household on multiple occasions is, of course, the most consistent an offender could be in terms of target selection. Thus, near-repeat victimization may be an expression of a more general foraging behavior for which the aim is to target households which most closely approximate an ideal template. In the same way an offender learns about burgled homes as a consequence of committing an offence, much can also be learned about properties nearby, particularly where households in the vicinity share similar access routes and other features. In contrast, little is learned about homes outside of an offender's awareness and hence why target those?

This may explain why offenders would target households near to those previously burgled, but perhaps not why they would do so swiftly. A number of plausible explanations for this exist. First, the characteristics of an area can change over time, either because of a maturation process whereby residents react to an existing crime problem, or because of intervention from those responsible for crime reduction. Such change, actual or simply perceived, may discourage an offender from subsequently targeting the neighborhood. Equally, an offender's memory for particular features of a burgled home and those nearby may decay over time, with implications for targeting decisions or even their awareness of properties located outside of their immediate neighborhood. Testing such hypotheses would require the analysis of convicted offenders' targeting patterns, or interviews with offenders that probe interviewees about how their target choices, particularly where they choose to commit burglary, are affected by successful (and unsuccessful) antecedent events.

A further finding evident from the current study was that the distance over which the risk of victimization appears to communicate varied across locations in both spatial and temporal dimensions. Across all countries, housing units within 200m of a burglarized home were more likely to be victims of the same crime for a period of up to 14 days than would be expected if patterns of crime were strictly random. However, in Canberra (Australia) the spatial range of the phenomenon was far greater, although the size of the effect conformed to a pattern of distance decay. One *a-priori* hypothesis was that differences in the dimensions of risk would to some extent be determined by the configuration of the urban backcloth, particularly the spatial distribution of targets. The results presented provide partial support for this hypothesis, but it is clear that housing density is not the only factor. This is not surprising. Different cities vary in many other ways including the type and availability of public transport. In the Netherlands, for instance, cycling is a favored mode of transportation, especially for juveniles, whereas in the other countries considered it is not.

The availability of transportation may impact not only upon general patterns of crime, but also how these vary over the course of a day or week. For instance, public transportation in many countries is available throughout the day and evening, but much more limited overnight. This may affect an offender's mobility and rhythm of offending (see Felson and Poulson, 2003). For example, some areas may only appear suitable during the day when public transport is available, which will affect a criminal's range. In support of this, Ratcliffe (2002) shows how spatial hotspots of crime vary by time of day in Nottingham, UK. Additionally, the availability of transportation would influence not only the areas that could be traveled to, but the distance that can easily be traveled more generally, which could plausibly impact upon patterns of near-repeat victimization throughout a typical day.

Besides housing density and transportation infrastructure, the communication of risk may also be influenced by social, demographic and physical factors that characterize residential areas. For example, at a lower level of spatial aggregation than analyzed here, Townsley et al. (2003) studied between-neighborhood variation in near-repeat victimization, and found that areas characterized by homogeneous housing (i.e. many identical properties) had more near-repeats, apparently because in these neighborhoods the lay-out of previously burglarized homes were identical to many prospective targets.

A further factor that might affect the communication of risk is that of barriers, physical or otherwise. For example, using data for convicted offenders, Bernasco and Nieuwbeerta (2005) have shown that an offender's decision of whether to commit crime in a neighborhood co-varies with the ethnic heterogeneity of the area. More homogenous neighborhoods appear to generate impedance. Yet, we do not know the effect of crossing an ethnic barrier on the likelihood of targeting the same or nearby homes. We do not know the effect of operating in a familiar neighborhood (the same ethnicity as the offender) on the likelihood of a repeat or near-repeat crime. Logic may imply that a criminal operating in a more threatening environment may try to reduce risks by returning to a property exploited previously. Conversely, they may not want to return to a neighborhood where they stand out physically and perhaps be recognized as the person who was there when a home was burglarized. These are issues that require further analysis perhaps of an ethnographic nature.

In sum, within and between cities there are many ways in which the urban backcloth varies, and there may indeed be important local differences in spatio-temporal burglary patterns within each of the sites studied in this paper. Burglaries in deprived areas of Philadelphia, for example, occur against a completely different backcloth than those that take place in the suburbs. While local variations between communities across the city deserve more attention in future research, the point of central importance is that we find strong evidence for burglary contagion despite variations within and between the study sites.

In relation to the generality of the patterns observed, a natural question is whether the same is true for other types of crime. Other acquisitive crimes such as theft from automobile are likely to share motivational factors with burglary and are committed with a high enough frequency to warrant study. In a recent study, which involved an extensive data cleansing exercise to check the accuracy of the geocoordinates analyzed, Johnson et al. (in press) found affirmative evidence of space-time clustering for the crime of theft from automobile in the UK. Similar findings, albeit with very different space-time parameters, have also emerged for the more serious crime types of gun crime in Philadelphia (Ratcliffe and Rengert, in press) and insurgent attacks in Iraq (Townsley et al., in press). Though the specific theoretical explanations for expecting these patterns across these very different types of crime differ, one unifying theme relates to human behavior and the temporal and spatial constraints that influence it (see Ratcliffe, 2006).

The consistency with which these patterns occur in other places is unknown and thus the exploration of patterns for other types of crime in other areas is a next logical step, as is the question of whether patterns for one type of crime inform those of another. For example, given the evident versatility of offenders with respect to acquisitive crime (e.g. Deane et al., 2005), does a burglary increase the likelihood of theft from automobile nearby for a short interval of time?

Future research of the kind discussed may have important implications for crime prevention. A more thorough understanding of which factors affect the communication of burglary risk and how they do so may lead to advances in our capability to better predict the future locations of, and ultimately prevent, burglary. For instance, recent work (Bowers et al., 2004) grounded in the theory that risk communicates in space and time, has refined contemporary methods of crime prediction. Similarly, an understanding of how risks communicate across different types of crime could enable the prediction of future events of one type of crime based on recent patterns of another.

International comparisons of crime patterns that use the same statistical methods are rare. Thus, the current study offers a useful glimpse into the consistency of crime patterns in different countries. Demonstrating the external validity of crime patterns is important as it helps in the formulation, testing and refinement of criminological theories. The current findings aid our understanding but also unlock a series of corollary hypotheses, some of which have been articulated above.

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Table I Summary of key attributes of the ten data sets

Country	Location	Number of months	Number of offences	Area covered (km^2)	Units of analysis at risk	Target density (dwellings/km^2)
Australia	Canberra	12	4992	696	126,330	181.5
	Beenleigh [a]	58	3082	45	11,551	256.7
Netherlands	Hague	24	7388	68	225,500	3316.2
	Zoetermeer	24	951	35	45,000	1285.7
New Zealand	Auckland	12	3556	91	44,949	494.0
	Palmerston North	12	1507	920	22,464	24.4
United Kingdom	Wirral	12	2545	255	133,338	523.0
	Bournemouth	12	1271	47	72,199	1536.0
USA	Pompano Beach	12	974	57	47,652	836.0
	Philadelphia	12	8079	372	661,958	1779.5

Note:a With the exception of Beenleigh, geocodes were available for between 98.8 to 100 percent of burglaries in every area. For Beenleigh (N=3,626) the rate of geocoding varied according to whether events occurred in urban or rural locales. Geocodes were available for all burglaries that occurred in urban areas (85% of all events) and consequently events that occurred in rural areas were excluded from the analysis.

Table II Summary of risk communication findings and target density in each area

Area	**Summary of risk communication**	**Target density (households per km^2)**
Wirral (UK)	500 meters, 2 weeks	523.0
Bournemouth (UK)	300 meters, 2 weeks	1536.0
Palmerston North (NZ)	400 meters, 2 weeks	24.4
Auckland (NZ)	200 meters, 2 weeks	494.0
Canberra (Australia)	1200 meters, 4 weeks	181.5
Beenleigh (Australia)	600 meters, 2 weeks	256.7
Zoetermeer (Netherlands)	600 meters, 2 weeks	1285.7
Hague (Netherlands)	600 meters, 4 weeks	3316.2
Pompano Beach (USA)	200 meters, 2 weeks	836.0
Philadelphia (USA)	200 meters, 8 weeks	1779.5

Fig. 1 Sampling distribution for Wirral (UK) data, number of burglary pairs within 100 meters and 14 days. Dashed line indicates number of pairs actually observed.

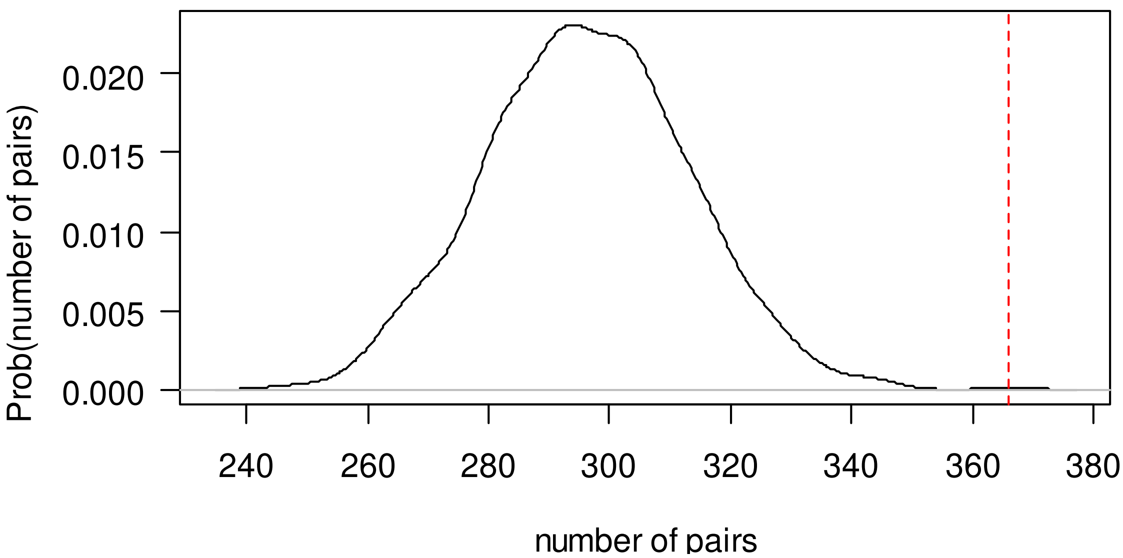

Fig. 2 Comparison of the communication of burglary risk in space and time across ten data sets (shading indicates Knox ratios significantly above 1)

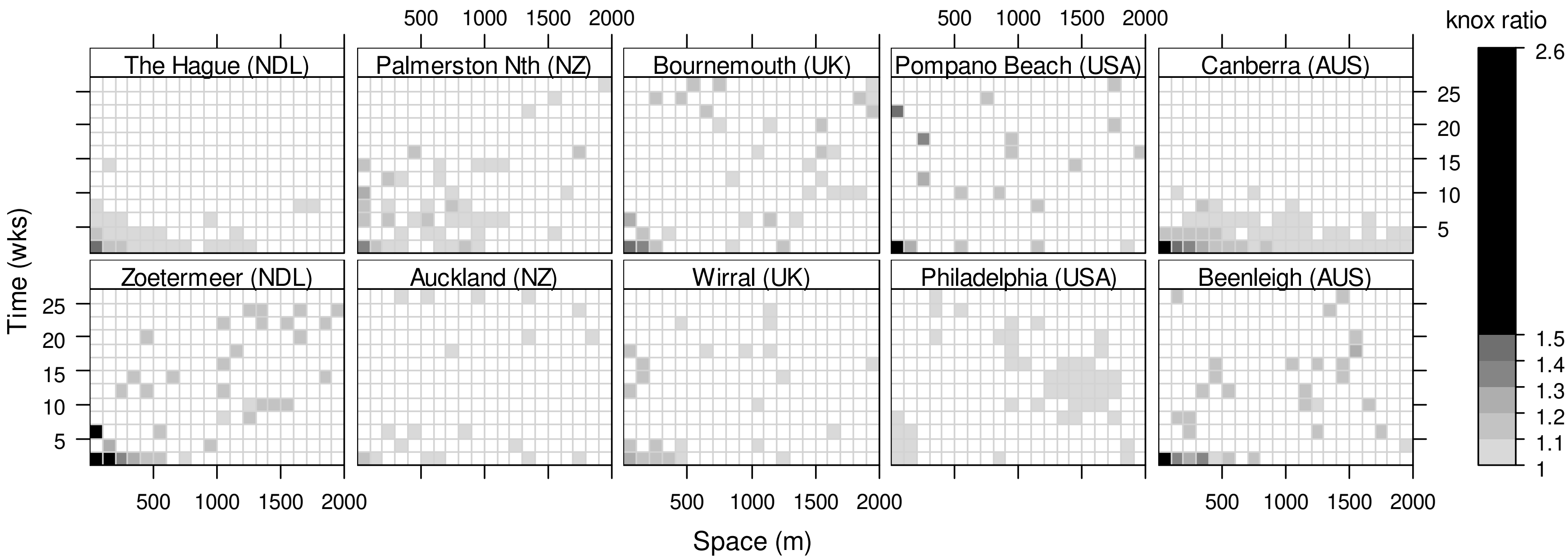

Fig. 3 Boxplots of the distributions of Knox ratios for all areas (a = time held constant at 14 days; b= space held constant at 100m)