

Domestic Burglary Repeats and Space–Time Clusters

The Dimensions of Risk

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ABSTRACT

Predicting when and where crimes are likely to occur is crucial for prioritizing police resources. In a companion paper (Johnson and Bowers 2004), we showed that burglaries clustered within 1–2 months and up to 300–400 metres of a prior burglary, i.e. a domestic burglary could profitably trigger time- and space-limited resource deployment around the burglary. Research is here presented which refines the priorities that should be given in such deployment. It demonstrates that (a) whereas repeat victimization proper tended to occur in more deprived areas, space–time clustering was more evident in affluent areas, (b) houses next to a burgled home were at a substantially heightened risk relative to those located further away, particularly within one week of an initial burglary, (c) properties located on the same side of the street as a burgled house were at significantly greater risk compared with those opposite, even when corrections are made for differences in linear distances between homes, (d) houses with probably identical layouts (e.g. houses two, four, six, etc., doors away from a burgled property) were slightly more at risk than those with the reverse layout, but these differences are too slight to inform crime reduction practice. Taken together, these patterns may be used to prioritize attention within the two months after, and up to 400 metres from, a prior burglary identified by Johnson and Bowers (2004) as encompassing homes at elevated burglary risk.

Introduction

Criminological research can contribute to the burglary reduction enterprise by providing three things:

1. An understanding of the demographic and other attributes that are associated with high rates of burglary, so that priority targets for crime prevention work can be set in advance of victimization;
2. An understanding of the distance in time and space across which victimization has an impact;
3. An understanding of the changes in burglary risks that are contingent on prior victimization.

Item 1 has been substantially (though far from exhaustively) addressed by Budd (1999). Item 2 has been clarified in Johnson and Bowers (2004). Item 3 will be covered in this paper.

The crime event provides a natural starting point for crime reduction effort, in that it is already the primary trigger for police action, and the information detailed below can be used to shape responses so that they coincide more precisely with levels of presenting risk. A full understanding of all three factors listed above would lead to three kinds of police action:

1. Routine attention would be given to burglary risks in as yet unburgled places, on the basis of household or householder characteristics (e.g. lone-parent households, recent movers).
2. After a burglary, attempts would be made to prevent both repetition and victimization of homes in the range of time and space for which elevated risks persist. If, as Johnson and Bowers (2004) demonstrate, risks endure over 300–400 metres and two months, this defines the scope of prudent post-burglary action.
3. After a burglary, the list of local risk characteristics would be revised, at least temporarily. The evidence base for such revision forms the body of the present paper.

As mentioned above, our previous research established that domestic burglaries cluster in time and space (when space is measured as linear distance). This was done using techniques first developed to examine the communicability of diseases (e.g. Mantel 1967; Knox 1964). Here we were interested in what other factors might influence the risk of victimization and the specific patterning of burglary events across different types of area. Furthermore, since the geography of built-up areas is unavoidably influenced by road layout, we wanted to see how the patterning of events was manifested at the street level. This involved using the number of doors apart, rather than linear distance, as a measure of distance.

Previous work has demonstrated a linear relation between levels of deprivation and repeat victimization (Johnson et al. 1997) – a pattern that is presumably at least partly explained by the fact that offenders tend to

live, offend and perform their routine activities within more disadvantaged neighbourhoods (Wiles and Costello 2000; Hirschfield and Bowers 1998). However, the extent to which burglaries cluster in space and time may not be highest in the same areas. For instance, given that offenders are less likely to frequent affluent areas during their routine activities, the likely effort involved in offending within these areas should be increased. Thus, it is possible that many burglaries committed within affluent areas are the result of planned journeys. For this reason, to maximize their investment in terms of travelling and the potentially elevated risk of apprehension, one might expect to observe evidence of predictable and efficient targeting strategies within more affluent areas – the areas in which repeat victimization is lowest.

In relation to specific target selection, insights gathered from interviews with offenders suggest that, across a series of events, offenders frequently target similar properties owing to the intelligence that each subsequent burglary provides regarding that type of property (Ashton et al. 1998). Thus, it is possible that the victimization of a particular type of residential housing will lead to an elevated risk for the most similar properties in the near vicinity. It is likely that offenders will also gather the most detailed intelligence on properties directly adjacent to those burgled and on those on the same side of the street as the victimized property. On the basis of the above findings, we hypothesize that:

- The relative importance of repeat victimization and near victimization will vary by type of area and type of housing, with affluent areas and more prestigious housing types experiencing greater space–time clustering, and poorer areas greater rates of repetition.
- Burglaries will cluster in space and time when space is measured as the number of houses separating successive burglaries in the same street.
- Properties on the same side of the street as other burgled properties will be at greater risk than those on the other side of the street.
- For semi-detached housing, the internal layout of properties that are an odd number of doors apart (e.g. next door, next door but two) tends to be the mirror image of the property considered. Thus, if offenders favour properties with the same internal layout as those they have already burgled, then houses an even number of doors from a burgled home, which will share its internal layout, may be at heightened risk compared with those an odd number of doors from a burgled home.

Data

Recorded crime data were obtained from Merseyside Police. Unless otherwise stated, data for a period of six years and six months were analysed (1

April 1995–30 September 2001). These provided a total of 75,101 records of domestic burglary. Each record contains the following fields:

- Unique crime reference number
- Address of the offence
- Grid reference of offence (x and y coordinates)
- Date of offence
- Victim's name (stored as a phonetic code to protect anonymity)
- Time of offence
- Type of property victimized (e.g. terraced house)

The data concerning the address of the offence location, in this case the address of the property burgled, were stored in a free-text field. The data were cleaned and reformatted using a FORTRAN program.

With respect to the analyses conducted at the street level, it was assumed that a property's house number would give some indication of the similarity between that house and a second house (particularly in combination with data about property type). For instance, it was reasoned that, for semi-detached housing in particular, house number 3 would have a more similar layout to house number 7 than to house number 5. Clearly, it is not possible to infer the internal layout of different numbered flats in the same way. Therefore, for the street-level analyses only, all data relating to burgled flats were excluded. Where the address contained the word 'Flat' or where the number of the house was immediately followed by a character (e.g. 1C) or where modus operandi (MO) data indicated that the property was a flat, all records were removed from the data set. For the linear distance analyses, records relating to flats were not excluded because only the grid references (and not addresses) were considered in these analyses. The strengths and weaknesses of the data used here are discussed in Johnson and Bowers (2004).

Measuring the space–time clustering of burglary

An important element of the research presented here concerns the measurement of the clustering of burglaries in space and time, and then comparing the observed distribution with what would be expected on the basis of chance. This method compares all burglaries with all others, making the total number of comparisons $n(n - 1)$ when there are n burglaries being considered. Since each burglary is compared with all others, there is statistical dependence in the data. This precludes the use of traditional statistical tests. The method used in the analysis described below is based on a test developed by Nathan Mantel (Mantel 1967) to analyse disease

communicability; it is discussed more fully in Johnson and Bowers (2004).

In the research reported here, Mantel z -scores were produced for local authority wards with a range of sociodemographic characteristics. z -scores were also generated for individual streets and sides of streets. In brief, high z -scores (≥ 1.96) show significant evidence of space-time clustering of burglary at both the ward and the street level.

Evidence of space-time clustering of burglary

Ward-level analysis

Analyses were conducted for each of the 118 local authority wards located in Merseyside for the one-year period 1 April 1999 to 31 March 2000. Wards are a good areal unit to use because each contains enough incidents in one year to enable meaningful analysis of burglary clusters at the ward level. Conveniently, ward boundaries are coterminous with census Enumeration Districts, the areal units for which sociodemographic data are available from the UK census.

For each of the 118 local authority wards, the following data were generated:

- A Mantel z -score to measure space-time burglary clustering
- Number of burglaries committed within that ward
- Number (and percentage) of incidents of repeat burglary committed within that ward
- Number of households contained in the ward
- Percentage of houses that were terraced
- Percentage of houses that were semi-detached
- Percentage of houses that were detached
- Percentage of houses that were flats
- Percentage of households without a car
- An index of residential segregation,¹ which is a measure of how isolated or segregated the housing types were
- An index of housing heterogeneity,² which is a measure of how mixed the housing types were

Heterogeneity reflects the number of different housing types, segregation the degree to which different housing types are separated. Crime counts

¹ For a full definition of this index, see e.g. Hirschfeld and Bowers (1997).

² For a full definition of this index, see Blau (1977).

included the total number of burglaries that had been committed at *each type* of house within each ward (this information was extracted from the MO field). An index of *victimized* housing heterogeneity was also produced for each ward. These further variables were therefore:

- Number of burglaries committed in terraced housing
- Number of burglaries committed in semi-detached housing
- Number of burglaries committed in detached housing
- Number of burglaries committed in flats
- An index of the heterogeneity of the houses that were burgled (an indicator of how mixed the victimized locations were)

The mean Mantel z -score for the 118 wards was 2.79 ($SD = 3.15$; range = -0.67 to 14.41). A one-sample t -test confirmed that the mean score indicates significant clustering ($t(99) = 2.13$, $p < 0.05$, two-tailed).³ This meant that, on average, there was a significant degree of space–time clustering of burglary within wards. Thus, individual wards suffered burglary spates. Further inspection of the data revealed that 50 percent of the wards had a z -score of 1.96 or more, and a further 12 percent had a value between 1.00 and 1.95. The clustering over a large area revealed by Johnson and Bowers (2004) is thus apparent in a significant proportion of smaller areas (in this case, wards). This is an important finding. Deploying crime reduction attention in the wake (time) and vicinity (space) of a burglary is appropriate in some but not all areas. Thus, further analyses were conducted to determine in which types of area clustering was most apparent.

To examine the associations between the census variables relating to housing composition and the degree to which burglaries clustered in time and space, bivariate correlations were computed. These are shown as Table 1. Before discussing the individual correlations, it is worth noting that both within-ward clustering and repeat victimization were positively correlated with the burglary rate. The association was closer for repeat victimization ($r(118) = 0.81$, $p < 0.001$, two-tailed) than for the degree of clustering ($r(118) = 0.19$, $p < 0.05$, two-tailed). Calculating a z -score using Fisher's (1921) transformation confirms that the two correlations were significantly different ($z = 7.12$, $p < 0.0001$, two-tailed).

Both clustering and repeat victimization are associated with the general burglary rate. This means that associations between, on the one

³ Because the data were skewed, before testing the sample mean against the required value of 1.96, the sample was trimmed and the data transformed using a square root transformation.

hand, clustering and repeat victimization and, on the other, area characteristics could be spurious. To exclude that possibility, correlations were calculated that partialled out the effect of the area burglary rate. These are presented, alongside simple bivariate correlations, in Table 1. Scrutiny of Table 1 makes it clear that the bivariate and partial correlations were almost identical. Thus the links between clustering, repeat victimization and area characteristics identified below are not an artefact of the method of analysis. Put simply, Table 1 shows that the relative importance of clustering and repeat victimization varied by housing type and area characteristics.⁴ The sign of the correlation coefficient linking census variables with the degree of clustering was almost always opposite to that linking them to repeat victimization. The two forms of concentrated victimization reflect distinct forms of offender targeting. Table 1 shows that the importance of clustering was greatest where the targets tended to be detached or semi-detached homes in areas with many such homes and with high rates of car ownership. Conversely, repeat victimization was of greatest importance where the targets tended to be terraced homes or flats in areas with many such homes and in areas with low rates of car ownership.

Considering the indices of segregation, which measure the extent to which different types of housing cluster together, although five of the (eight) relevant correlations were non-significant, it was apparent that for each index of segregation the sign of the correlation coefficients was opposite for the two types of concentration. Of the correlations that were significant, it appeared that clustering (in contrast to repeat victimization) was greater in wards where terraced housing was more segregated. There appeared to be no relationship between clustering and the degree to which different housing types were mixed within an area. In order to corroborate the findings of these analyses, a series of regression analysis were also performed. The results from these were entirely consistent with the correlation analysis and hence will be discussed no further.

Taken together, the results of the correlation and regression analyses suggest the following conclusions:

1. Factors likely to influence the level of repeat victimization in an area, such as the number of burglaries committed and the level of deprivation in that area, differ from those influencing clustering, reflecting different burglar targeting strategies.
2. Although more affluent areas (or those that have a greater proportion of affluent houses) experience less burglary overall, they suffer from more burglary spates that cluster in space and time.

⁴ Consistent with this, the correlation between clustering and the rate of repeat victimization was non-significant ($r(118) = 0.07$, $p = .426$, two-tailed).

Table 1 Correlations between Mantel z-scores indicating clustering, repeat victimization and other variables for 118 wards

	<i>Simple correlations</i>		<i>Correlation partialling out effect of burglary rate^a</i>	
	<i>Clustering</i>	<i>Repeat rate</i>	<i>Clustering</i>	<i>Repeat rate</i>
<i>Segregation indices</i>				
Detached	-0.04	0.331**	-0.052	0.234**
Semi-detached	0.054	0.375**	-0.023	0.100
Terraced	0.176*	-0.097	0.164*	-0.278**
Flats	0.129	-0.019	0.131	-0.034
<i>Proportion of households</i>				
Detached	0.189*	-0.413*	0.266**	-0.286**
Semi-detached	0.190*	-0.547*	0.301**	-0.39**
Terraced	-0.175**	0.552*	-0.264**	0.482**
Flats	-0.168**	0.273*	-0.243**	0.038
<i>Proportion of burglaries</i>				
Detached	0.249**	-0.376*	0.312**	-0.304*
Semi-detached	0.027	-0.632*	0.153*	-0.404**
Terraced	-0.039	0.710*	-0.177*	0.532**
Flats	-0.249**	0.173**	-0.286*	0.087
<i>Index of housing heterogeneity</i>				
% households without a car	0.033	-0.149	0.041	-0.201*
Total number of burglaries	-0.215*	0.543**	-0.311**	0.451**
Total households in area	0.189*	0.811**	—	—
Index of target heterogeneity	0.217*	0.272**	0.148	-0.451**
	-0.071	-0.262*	-0.045	-0.251**

Notes: * $p < 0.05$ (one-tailed); ** $p < 0.05$ (two-tailed).

^a Partial correlations partition the variance explained by the area's crime rate.

In the above analyses the areas used were defined by existing administrative boundaries (i.e. local authority wards). This has a number of implications. In particular, the modifiable area unit problem (e.g. Openshaw 1995) is concerned with the reliability of analyses that are based on the aggregation of data for different areas. For instance, wards do not take into account the geography of neighbourhoods, housing types and communities. Conducting analyses at ward level may mask some of the true variance. The ideal approach would be to identify areas by selecting them on the basis of housing and area type. It was beyond the scope of the current research to undertake such an exhaustive procedure. Such problems increase the likelihood of Type II statistical error (accepting the null

hypothesis when it is false) rather than Type I error (rejecting the null hypothesis when it is true), and hence make the results somewhat conservative but reliable.

Repeat burglary, clusters and deprivation

In dispensing crime reduction funds or deploying neighbourhood renewal funds for crime reduction purposes, deprivation features prominently – almost certainly too prominently. This justifies a brief closer look at the link between deprivation (proxied by car ownership), clustering and repeat victimization. We address the question of whether, if an area is chosen for crime reduction attention on the basis of its level of deprivation, the emphasis on repeat victimization rather than clustering, hinted at repeatedly earlier in this paper, is justified. The analyses presented above revealed that both space–time clustering and repeat victimization co-varied with characteristics of the area, such as the percentage of households without a car and area housing composition (e.g. see Table 1). Further analyses were conducted that focused on the differences observed for affluent and deprived areas. Using the census data relating to the percentage of households without a car, each of the wards was assigned a code (0 = deprived; 1 = affluent) to indicate the level of deprivation in that area. Table 2 shows the mean rate of repeats and the Mantel z -scores for these two types of area. A series of one-sample t -tests confirmed that the mean z -score for each of the two areas was equal to or greater than the value of 1.96 required to indicate significant space–time clustering (differences between a score of 1.96 and the mean z -scores were tested; $t(58) = 3.51, p < 0.001$; $t(58) = 0.19, p = 0.85$, for affluent and deprived groups respectively). Interestingly, the table also shows that the mean repeat rate in affluent areas was less than half that in more deprived areas.

Table 2 Rate of repeat victimization (per 1000 households) and Mantel z -scores for deprived and affluent areas

		Mean	F-ratio	Significance
Repeat victimization	Affluent	1.0303	31.423	0.000
	Deprived	2.9734		
Clustering	Affluent	3.5583	7.383	0.008
	Deprived	2.0225		

Furthermore, one-way analyses of variance (ANOVAs), whose results are presented in Table 2, confirmed that the rate of repeat victimization was higher in deprived areas, whereas there was significantly more evidence of clustering in affluent areas.

Street-level analysis

In addition to considering how far apart burglaries were in terms of Euclidian space, a second way of thinking about clustering counts the number of houses that separated burgled properties. This allows another approach to prioritizing crime reduction, offering distinctive analyses and perhaps coming closer to mirroring the protective choices made on the street by police officers and community safety partnerships.

Identifying incidents that occurred on the same street

The first stage in this approach was (obviously) to identify all burglaries that occurred in the same street. To do this, new software, written in FORTRAN, was developed. This generates an array summarizing the original data set. This array contains one entry for each unique street or road where at least one burglary had been committed within the studied time frame. For each road thus identified, the array stores the house number at which each burglary was committed, its date and the type of house victimized. The program first reads each burglary into a dynamic array. The address data relating to the street where the burglary occurred are compared with all other entries contained within the array, to see if they match any of them. The program uses a fuzzy matching algorithm that was developed elsewhere (Johnson et al. 1997) but recalibrated for use here. This allows for spelling mistakes and the use of inconsistent recording of address data; it also permits a range of tolerance settings. Different settings were tested before arriving at the ones used here. The accuracy of the algorithm was tested by inspecting a total of 1000 address matches identified by the program. For this sample of data, the program was 98.9 percent accurate – few obviously false identifications were included. The data were also examined to search for failures to match a street correctly. The data were imported into a spreadsheet, sorted and scanned for apparent failures to match. An omission was identified if two addresses that clearly referred to the same road occurred but were not found by the software. A total of 1396 matches were examined and the program was found to be 97.9 percent accurate in this respect. In brief, the program

Table 3 Frequency of burglaries per street

<i>Number of burglaries on street</i>	<i>Number of streets</i>
1	4469
2	2186
3–5	3102
5–9	2516
10–14	1007
15–19	487
20–24	253
25–29	145
30–39	146
40+	131

proved gratifyingly efficient both in identifying address matches and in rejecting potential matching errors.⁵

For the six years' worth of data considered, a total of 14,442 streets had experienced burglaries. The average number of burglaries per street over the period was 5.47 (s.d. = 8.09, range = 1 to 302). Table 3 summarizes the data in a little more detail.

Matrices were prepared tabulating time in months along one axis and distance between burgled homes on the other. Distance was measured as the number of houses separating burgled homes. For instance, a burglary that occurred next door would be listed as occurring one door away. The matrices were produced for all types of housing and also for each housing type (terraced, semi-detached, and so on). The matrices were produced by comparing each burglary with every other burglary in the street. Additional analyses, not reported here, compared only successive incidents on each street (i.e. analyses did not compare every incident with every other incident on a particular street, but only compared them with the next incident in time). The results of these analyses were very similar to those reported here, but because the number of comparisons was smaller they will be discussed no further.

The matrices produced were somewhat large and hence, rather than displaying these, a series of simple charts were produced to illustrate the patterns observed. For clarity and ease of interpretation, the first analyses

⁵ Considering the criteria used to calibrate the matching algorithm, we adopted an a priori confidence interval of 97.5 percent or higher to conform to more conservative statistical approaches. It was envisaged that an accuracy level higher than this would be unlikely because of recording inconsistencies.

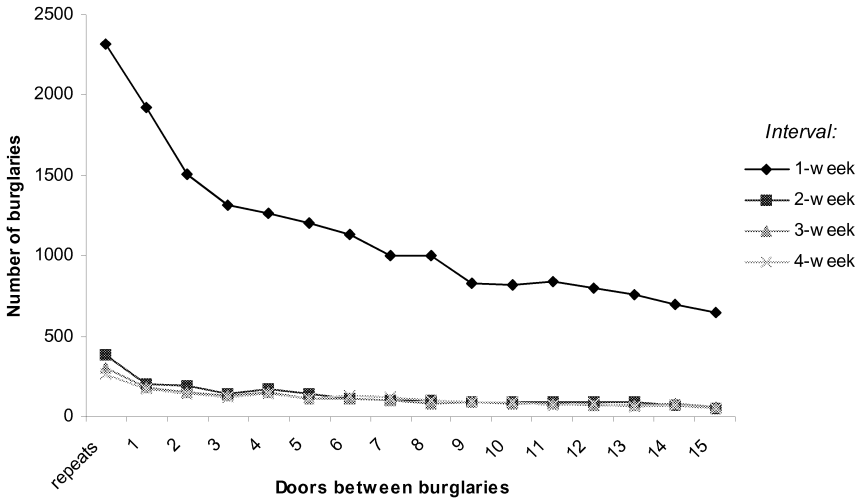


Figure 1 Neighbour effects for all housing.

consider only burglaries that occurred on the same side of the street. Figure 1 shows the number of burglaries that occurred within 1–15 doors of each other, at four intervals (1–4 weeks); it also shows the number of repeats that occurred at each interval. In contrast to research conducted by Anderson et al. (1995) (based on much smaller numbers), it is clear from Figure 1 that the risk of being burgled decreases the further a house is located from a previously victimized property. This risk decays rapidly over time.

Figure 1 suggests the value of alerting the near neighbours of burglary victims to the crime. Supplementary analysis was carried out to assess the urgency of such communication. We calculated how many burglaries occurred within close spatial proximity of another incident *and* on the same day. Looking at events within a four-week period showed that 23 percent of burglaries of immediate neighbours (houses one door apart) happened on the same day. However, the number of burglaries that occurred on the same day decayed dramatically as the number of intervening homes increased. For instance, only 10 percent of burglaries committed two doors apart occurred on the same day. For houses up to 15 doors away from another incident, 4 percent occurred on the same day. After the first day following an incident, burglaries appeared to be equally likely to occur within any of the next six days. Thus, it was clear that the risk to neighbours was not limited to the same day that an initial burglary occurred, and hence that there was a window of opportunity between related burglaries for crime prevention measures to be put in place.

We expected there to be a heightened risk for properties that share the

same internal layout as previously victimized properties. We thus expected houses an even number of doors away to show a heightened risk relative to those an odd number of doors away. Although not reported here, evidence for such a pattern was very slight. For instance, considering the risk during the three-week period following an initial event, excluding the first week (i.e. weeks 2–4), the risk to properties four doors away (457 burglaries) was higher than the risk to those three doors away (396). Further analyses for subsets of semi-detached and terraced housing showed similar patterns. Such analyses provide some evidence of an ‘identical layout’ pattern as well as of space-time clustering. However, the evidence seemed too slight to warrant further discussion or to inform crime reduction practice. On the basis of the evidence discussed here, a police officer communicating risk to homes four doors away from one recently burgled could not justifiably omit to inform the residents three doors away.

Controlling for differences in opportunity

One potential problem with the analyses presented above is that they do not take into account the variation in the number of properties located within a given number of doors from a particular property, and hence the opportunity for burglaries to occur at these distances. For instance, on a particular street, there will be more opportunity for burglaries to occur one door apart than, say, six doors apart simply because there will be more cases where properties are located one door apart from a victimized property.

To understand this better, consider a street that has five properties on one side, numbered from house 1 to house 5.

If we count the number of doors apart that a burglary could possibly be for each of these five separate locations, we get the data presented in Table 4. Property 1 has an equal likelihood of being one, two, three or four doors apart from another property on the street. However, property 3 cannot be three or four doors from any other property on the street. The total row in Table 4 shows the number of opportunities for houses to be a certain number of doors apart across the street as a whole. We can see that, in this case, there are eight opportunities for houses to be one door apart and only two opportunities for them to be four doors apart.

The distance decay effect reported above may simply reflect differences in opportunity. More burglaries may occur at houses within one door of a victimized property simply because, for a particular street, there will be more houses located at this distance than houses that are, for example, ten doors away. Further analyses were conducted that controlled for such differences in opportunity. Data concerning all properties on Merseyside

Table 4 Number of houses located 1–4 doors apart from houses 1 to 5

	Number of doors apart				Total
	1	2	3	4	
House 1	1	1	1	1	4
House 2	2	1	1	0	4
House 3	2	2	0	0	4
House 4	2	1	1	0	4
House 5	1	1	1	1	4
Total	8	6	4	2	

were acquired from an Address Point database. These data were then aggregated to street level so that the number of properties located on each street could be calculated. Figure 2 shows the distribution of the total number of properties located on streets across the county of Merseyside

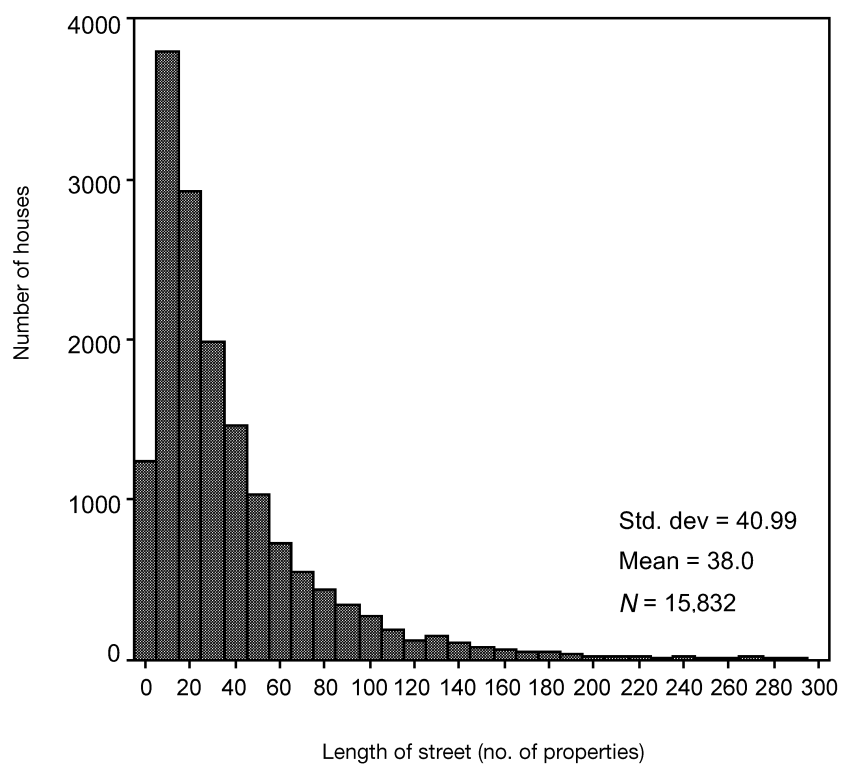


Figure 2 Number of houses on streets for Merseyside.

(this excludes outliers of streets with 300 or more properties). It can be seen that the average street on Merseyside has 38 properties.

In order to calculate the number of 'opportunity slots' for each number of doors apart, we assumed that each road would have approximately the same number of properties on each side. Using the method shown in Table 4 for each street, the number of opportunities for houses to be one door apart, two doors apart, three doors apart and so on through to 50 doors was calculated. The resulting figures were then aggregated across all streets in the Merseyside database. This produced a count of the number of opportunities for houses to be a certain number of doors apart across the whole of Merseyside. These counts, shown in Figure 3, indicate that the number of opportunities for any two properties selected at random on a street to be one door apart is far greater than the number of opportunities for them to be two doors apart, three doors apart, and so on.

Thus, the data shown in Figure 3 represent the opportunity for burglaries to occur at different numbers of doors apart from a previous incident. Using these data it was possible to re-analyse the results presented above (e.g. see Figure 1, p. 78), this time accounting for the differences in opportunity for burglaries to occur at a particular number of doors apart. This was done by using the total number of opportunities displayed in

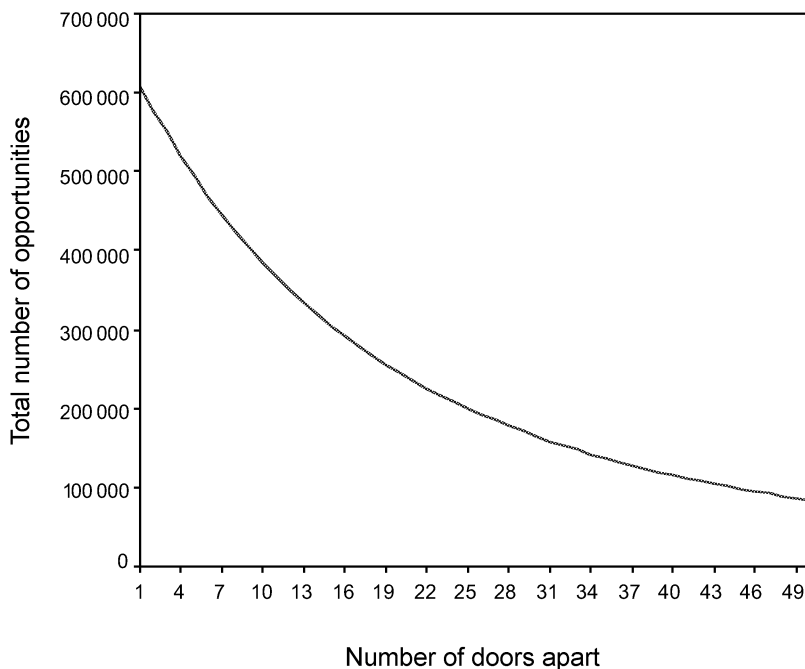


Figure 3 Number of houses n number of doors apart for the county of Merseyside.

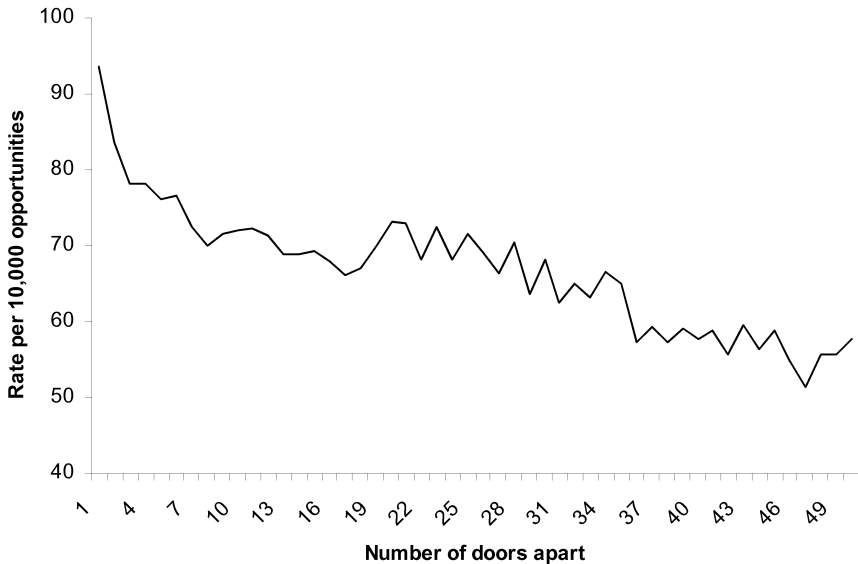


Figure 4 Neighbour effects for all types of housing (controlling for differences in opportunity).

Figure 3 as a denominator. The results for burglaries that occurred within one year of another incident, shown in Figure 4, confirm that, even when all the differences in opportunity have been accounted for, there is a distance decay effect such that properties within close proximity to a victimized property are more at risk than are those located further away.

A further analysis was conducted to examine the risk to properties within one week of an initial event. Figure 5 shows that the distance decay effect is more pronounced for this period even when differences in opportunity are accounted for. Thus, it is apparent that the results reported above were not simply the effect of differences in opportunity, but rather that homes near to a burgled dwelling are indeed at greater risk than are those located further away.

Is the same side of the street more at risk?

Curtin et al. (2001) report that, for an analysis of eight streets, the majority of burglaries tended to occur on one side (a range of 67–92 percent) of the road. However, as they acknowledge, the small number of streets included in the analysis precludes any firm conclusions being drawn. Using a larger data set and also controlling for potentially confounding factors, we aim to determine whether there is evidence of a ‘side of the street’ effect. To do this, the number of burglaries that occurred on the same side and on the

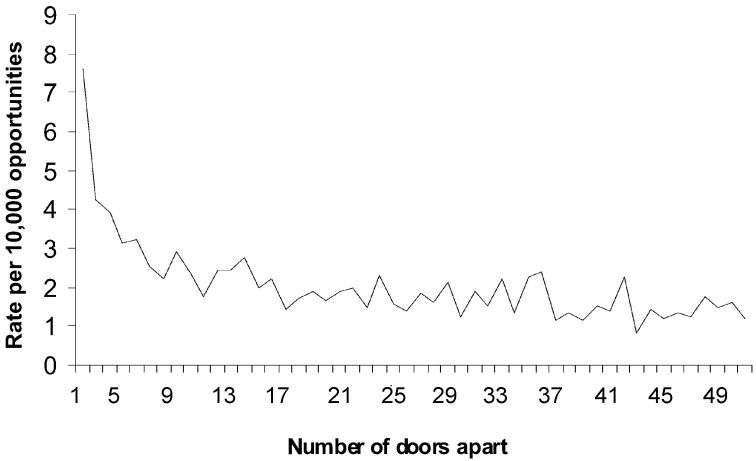


Figure 5 Neighbour effects for all types of housing for the one-week period following a reference event (controlling for differences in opportunity).

opposite side of the street within one year of another burglary was calculated. To simplify the results, the data in Figure 6 are presented as odds ratios, which represent the differences in relative risk for properties on the same and opposite sides of the street. For instance, an odds ratio of 1.5

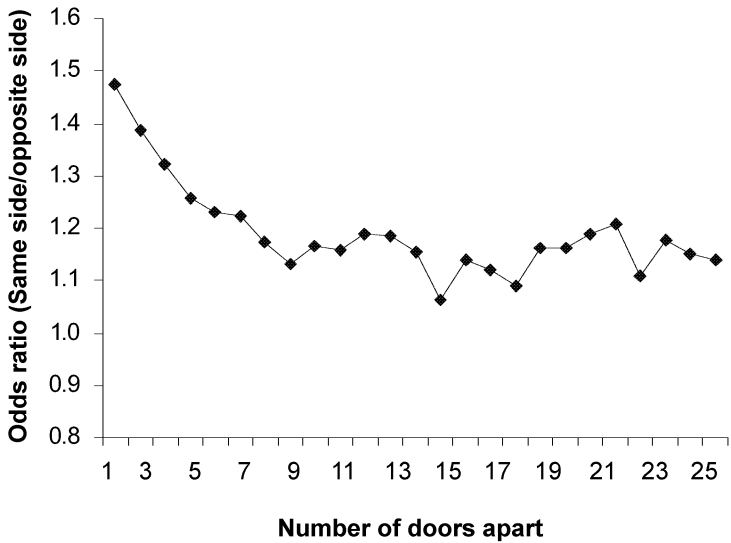


Figure 6 Odds ratios showing the relative risk to houses on the same and opposite sides of the street.

means that houses on the same side of the street (at a particular number of doors apart) are 1.5 times more likely to be burgled as are houses on the opposite side (the same number of doors apart), whereas an odds ratio of 1.0 shows that houses on both sides are at equal risk. The results (mean odds ratio = 1.19) demonstrate that neighbouring houses located on the same side of the street as a previously burgled property are at heightened risk relative to the equivalent houses on the other side of the street (e.g. those directly opposite). Furthermore, the difference in risk to houses on different sides of the street is particularly evident within four doors of a previous event, but decays over greater distances.

Figure 7 displays the risk to properties on the same side and the other side of the street for the one-week period following a burglary, this being the period of maximum risk. The pattern is similar to that of Figure 6, although the mean odds ratio is somewhat higher (1.35), reflecting the fact that the effect is particularly evident within this period.

To examine the ‘side of the street’ effect further, analyses were conducted to determine whether the apparent heightened risk was an artefact of houses on the same side of the street being physically closer to each other than those opposite. If there is a robust ‘side of the street’ effect, then the risk to properties located at the same distance should vary according to the side of the street on which they are located. Using the

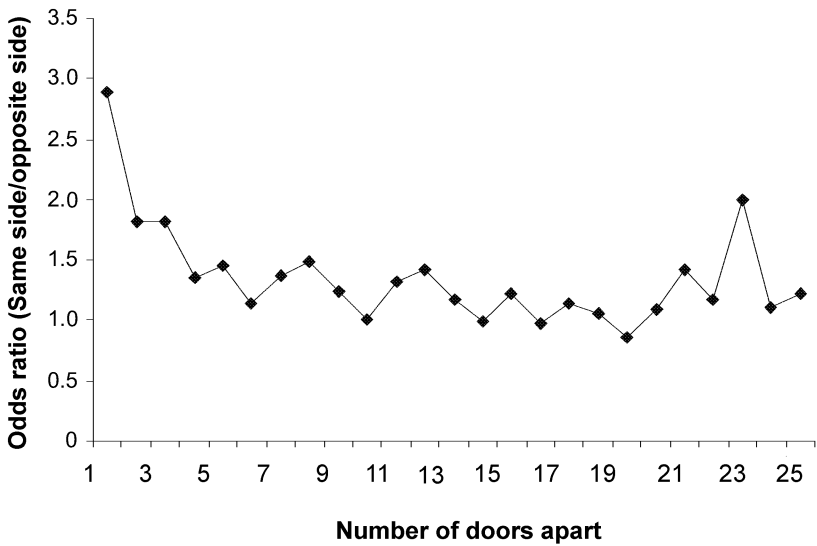


Figure 7 Number of times houses were burgled in the one-week period following another burglary.

burglary data themselves, we calculated how far apart, on average, houses that were only one door apart on the same side of the street were, how far apart houses that were directly opposite each other were, and so on. Because the most dramatic distance decay effects were observed for houses up to 10 doors apart (e.g. see Figure 1), analyses were limited to houses within this range. Next we compared distances to calculate, for instance, how many doors apart houses on the same side of the street needed to be in order to be further apart (in Euclidian terms) than the house directly opposite, the house opposite but one door down, and so on. Statistical analyses were conducted to verify the distances selected. To protect against the potential influence of outlying data, analyses were conducted using non-parametric Mann–Whitney tests. The results of the analyses conducted for houses up to ten doors apart are shown in Table 5. It is evident from Table 5 that, on average, houses located on the same side of the road as a previous burglary are closer to that property than are houses on the opposite of the road, although this effect diminishes over greater distances, since most streets are not straight.

Having established the relation between the two forms of distance (Euclidian and house numbers), analyses were conducted that compared the number of burglaries that occurred at houses on the same and opposite

Table 5 Analysis of differences in Euclidian distances for houses on the same and different sides of the street

Opposite side of road	Same side of road (doors apart)									
	1	2	3	4	5	6	7	8	9	10
1	<	<	=	>	>	>	>	>	>	>
2	<	<	<	=	>	>	>	>	>	>
3	<	<	<	=	>	>	>	>	>	>
4	<	<	<	<	=	>	>	>	>	>
5	<	<	<	<	<	=	>	>	>	>
6	<	<	<	<	<	=	=	>	>	>
7	<	<	<	<	<	<	=	=	>	>
8	<	<	<	<	<	<	<	=	=	>
9	<	<	<	<	<	<	<	<	=	=
10	<	<	<	<	<	<	<	<	<	=

Notes: = no significant difference in Euclidian distance ($p > 0.05$, two-tailed).
< houses on same side are closer than those on the opposite side ($p < 0.05$, two-tailed).
> houses on same side are further away than those on the opposite side ($p < 0.05$, two-tailed).

sides of the street that were the same Euclidian distance apart. For instance, analyses compared the number of burglaries that occurred on the opposite side of the street that were one house number apart with those on the same side of the street that were three doors apart from another event. The results (Figure 8), which used data for burglaries occurring within one year of each other, revealed a number of patterns. First, it is clear that houses on the same side of the street were burgled more frequently than were those on the opposite side of the street, even when differences in Euclidian distance were allowed for. A non-parametric Mann–Whitney test, which compared the number of burglaries that occurred on the two sides of the street for properties matched in terms of Euclidian distance, confirmed that the difference was significant ($z(9) = 1.97, p < 0.05$, two-tailed). Second, the ‘side of the street’ effect does not appear to be limited to houses that are simply the same Euclidian distance from a previous event, but rather extends to properties that are significantly further away from previous burglaries. For instance, houses up to nine house numbers (not just those three doors) away from a previous burglary on the same side of the street were burgled more frequently than were houses that were only two house numbers apart but on the opposite side of the street (see the dashed line in

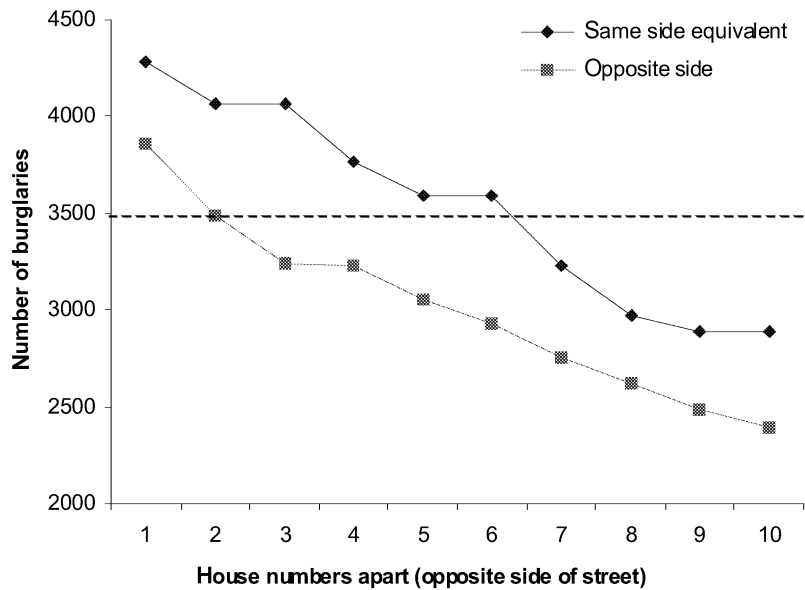


Figure 8 Number of burglaries at houses on the same and opposite sides of the street for properties at the same Euclidian distance from a reference event (up to one year after an initial event).

Figure 8).⁶ Thus, the above analyses provide clear support for the existence of a ‘side of the street’ effect that cannot be explained in terms of differences in Euclidian distances for houses on different sides of a street.

Mantel z-statistics: Examining clustering at street level

Having provided evidence that space–time clustering occurs at the street level using descriptive methods, this section will examine the extent to which space–time clustering occurs at the street level using the statistical techniques described in previous sections. Thus, Mantel z -statistics were produced for each of the streets for which burglary data were available. To do this, crime data were analysed covering the period 1 April 1999 to 31 March 2000. As with the above analyses, the x and y coordinates and the dates of all the burglaries in a particular street were submitted to the program that calculated the Mantel statistic. In all, for the one-year time period considered, data were analysed for a total of 615 streets. In order to make the Mantel test more reliable, the streets were selected on the basis of the number of incidents that had occurred on them in the one-year period; only those that suffered 20 or more burglaries were analysed. To see if there was any consistent pattern in the risk for odd and even sides of the street, further analyses were conducted that included only one side of the street. That is, each side of each street was used as the unit of analysis for the Mantel z -score. Only streets with 20 or more burglaries on the more heavily burgled side of the street over the one-year time period were used.

The results of the Mantel analysis for streets are shown in Table 6. There was some clustering, but this did not reach significance. However, there was considerable variance in the range of the Mantel z -scores, with

Table 6 Mantel z -scores at the street level

<i>Data set</i>	<i>Number of streets</i>	<i>Mean z-score</i>	<i>Standard error</i>	<i>Max z-score</i>	<i>Min z-score</i>
Complete streets	615	0.3673	0.0545	6.52	–2.05
‘Even’ side of street	149	0.3866	0.1260	6.39	–1.38
‘Odd’ side of street	164	0.6190	0.1199	7.70	–1.31

⁶ Note that, in Figure 8, the x -axis shows the number of doors separating burglaries of houses on the opposite side of the street; to see how many doors apart the burglaries occurred for houses on the same side of the street, the reader needs to consult Table 5, where the position of the equals sign shows the relationship between the number of doors apart on the same side of the street and the number of doors apart on the opposite side.

some streets having scores as high as 6.5. For the overall sample, 80 of the 615 streets showed significant clustering (high positive z -scores). This indicates that some streets but not others are prone to high levels of clustering. The 'same side of the street' analysis revealed that, when only one side of the street was used, the mean z -score was slightly higher than it was for the street as a whole, particularly for the 'odd' side of each street. However, there was no significant difference between the mean z -scores for the different sides of the street ($F(1,312) = 1.784, p < 0.183$). Although not statistically significant, therefore, there did appear to be some more evidence of space-time clustering on the odd side of the streets. Why this should be the case is unclear and we will not make any speculations here.

What type of streets have high and low Mantel z -scores?

The above analyses demonstrated that there was evidence of space-time clustering at the street level, but that this varies between streets. Hence, a complementary issue was to see if there is anything different about streets where space-time clustering is not evident. To do this, we conducted a qualitative analysis of a number of such streets. First, we selected the streets that had the 10 highest and the 10 lowest Mantel z -scores. Next we examined Ordnance Survey Landline maps that included the streets identified. The resolution of these maps enabled us to examine a number of characteristics of each of the roads – for instance, to see if they were long straight roads or if they were curved, and to see if they were made up of predominantly terraced housing or if they comprised mixed housing. In addition, orthophotographs were superimposed on the base maps, which provided further contextual information. The results of the analyses can be summarized as follows.

For the 10 streets with the highest Mantel z -scores:

- All of the streets were in the district of Liverpool
- Six of the 10 streets were fairly short straight roads of primarily terraced housing
- Three of the 10 streets were more major roads and tended to be longer
- Only 1 of the streets was not straight
- Two of the streets were neighbouring streets showing a natural cluster of roads with the same problem
- An analysis of the properties burgled on these streets revealed that, in 8 of the streets, over 90 percent of the properties burgled were of the same type, in this case terraced properties

For the 10 streets with the lowest Mantel z -scores:

- Only five of the 10 streets were in the district of Liverpool

- An analysis of the properties burgled on these streets revealed that there were no streets where over 90 percent of the properties burgled were of the same type
- There was more variation in the type of houses for these streets than for the high z -score streets: all of the streets had at least two different types of housing
- unlike the streets with high Mantel z -scores, only five of the 10 roads were straight; the others tended to be fairly highly curved, and one was circular
- The streets tended to be less continuous than the high z -score roads, containing blocks of housing interspersed with spaces and other features

In addition, a series of quantitative analyses was conducted to examine differences between streets for which there was statistically significant evidence of space–time clustering and streets for which there was not. To do this, the streets were divided into two groups: those with a Mantel z -score of 1.96 or over (the value required to be significant at the 5 percent level); and those with Mantel z -scores between 0 and 1.96 (i.e. no significant clustering). First, we examined the types of property that were victimized on the two types of street. A series of one-way ANOVAs was performed that compared the mean percentage of incidents committed at the four different types of property considered (semi-detached, detached, bungalow and terraced). The results revealed no significant differences for any of the comparisons, meaning that the streets did not appear to differ significantly with respect to the predominant type of housing that was burgled.

A further analysis looked at an index of heterogeneity; that is, the mix of the types of property burgled on each street. In contrast to the above analyses, this measure considers exactly how streets differ in terms of the homogeneity of housing *within* each street, rather than across streets. An index of 1 would mean that each of the different types of property was victimized equally and, therefore, that different types of property were equally likely to be targeted on that street. Scores close to 0 reflect an overrepresentation of one type of property. A one-way ANOVA revealed a significant difference between the mean of this index for the high Mantel z -score groups ($M = 0.2992$, s.d. = 0.1969) and the low Mantel z -score groups ($M = 0.3622$, s.d. = 0.1868) – $F(1,288) = 6.450$, $p < 0.01$. This shows that, relative to the streets with low Mantel z -scores, the types of housing targeted tended to be more similar for the streets with high Mantel z -scores. This implies that, for the streets in which there was more evidence of space–time clustering, the same type of housing was more likely to be targeted – another indication that offenders might target similar types of housing over a short period. However, it is possible that this analysis was confounded by the fact that higher numbers of burglaries were committed on some streets than on others.

For this reason, an analysis of covariance (ANCOVA) was conducted, with the total number of burglaries on each street entered as a covariate. This analysis was clearly significant ($F(1,288) = 6.941, p < 0.01$), confirming that the results were not simply an expression of the total number of burglaries committed on each street. Thus, it appears that clustering occurs more frequently on streets where offenders target similar types of property. On the face of it, this finding might appear to contradict the results reported for the area-level analyses, where there was no association between space–time clustering and the index of heterogeneity. However, a number of reasons may explain why a null effect was observed for the area-level analyses. One particular problem with area-level analyses, discussed above, is the Modifiable Areal Unit Problem. Importantly, whereas analyses conducted at the area level may be significantly affected by this problem, analyses performed at the street level will be relatively unaffected by this issue.

Conclusions

In the companion to the present paper (Johnson and Bowers 2004), we hope to have convinced readers of the appropriateness of using domestic burglary as a trigger for action at and around the burgled home for a limited time after the event. The research reported in this paper aims to refine an understanding of how such action should be organized. Put prescriptively:

- A domestic burglary should trigger preventive action in its aftermath;
- The main effort in poor areas should be aimed at preventing repeats at the same home;
- The main effort in more affluent areas should be aimed at preventing burglaries of nearby homes in the weeks following the triggering burglary;
- In all areas, there is a narrow window of opportunity, so preventive action needs to be put in place very swiftly;
- Owing to time–space clustering, the homes at greatest risk are those on the same side of the street, those of similar structure and, most of all, immediately neighbouring properties;
- Compared with the burgled home, the risk is not markedly greater for nearby homes with identical floor plans than for those with mirror-image floor plans;
- Clustering is most in evidence on straight streets with relatively homogeneous housing.

Although there is clear evidence about the appropriate crime reduction action in the wake of a domestic burglary, the next research step is equally clear. It is to articulate the changed pattern of risk flagged by a burglary event in ways that lend themselves to routine action by the police

and others. One such approach involves the preparation of prospective hotspot mapping, i.e. the preparation of maps that communicate prospectively the pattern of changed risks. This is not a trivial task, since overly complicated risk maps or surfaces will not readily translate into officer action. Trade-offs between, on the one hand, simple and clear guidance to police officers and, on the other, faithfulness to the complexities of risk surfaces will be necessary. However, the work is self-evidently worthwhile, since it deals with fine-grained patterns of risk based on the most recent data. In this, it departs from conventional hotspot analysis.

Other desirable research would involve more detailed examination of how similar burgled properties are to each other. This might include conducting physical and victimization surveys of a sample of properties.

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References

- Anderson, D., Chenery, S. and Pease, K. (1995). *Biting back: Tackling repeat burglary and car crime*. Crime Detection and Prevention Series Paper 58. London: Home Office.
- Ashton, J., Brown, I., Senior, B. and Pease, K. (1998). Repeat victimization: Offender accounts. *International Journal of Risk, Security and Crime Prevention* 3, 269–79.
- Blau, P. M. (1977). *Inequality and heterogeneity. A primitive theory of social structure*. New York: Free Press.
- Budd, T. (1999). *Burglary of domestic dwellings: Findings from the British Crime Survey*. Home Office Statistical Bulletin 4/99. London: Home Office.
- Curtin, L., Tilley, N., Owen, M. and Pease, K. (2001). *Developing crime reduction plans: Some examples from the Reducing Burglary Initiative*. Crime Reduction Research Series Paper 7. London: Home Office.
- Fisher, R. A. (1921). On the probable error of a coefficient of correlation deduced from a small sample. *Metron* 1, 3–32.
- Hirschfield, A. F. G. and Bowers, K. J. (1997). The development of a social, demographic and land use profiler for areas of high crime. *British Journal of Criminology* 37, 103–20.
- Hirschfield, A. F. G. and Bowers, K. J. (1998). The geography of crime and disadvantage: An English case study. *Japanese Journal Crime and Delinquency (Hanzai to Hiko)* 3, 77–106.

- Johnson, S. D. and Bowers, K. J. (2004). The burglary as a clue to the future: The beginnings of prospective hot-spotting. *European Journal of Criminology* 1, 237–55.
- Johnson, S. D., Bowers, K. J. and Hirschfield, A. F. G. (1997). New insights into the spatial and temporal distribution of repeat victimization. *British Journal of Criminology* 37, 224–41.
- Knox, G. (1964). Epidemiology of childhood leukaemia in Northumberland and Durham. *British Journal of Preventative and Social Medicine* 18, 7–24.
- Mantel, N. (1967). The detection of disease clustering and a generalized regression approach. *Cancer Research* 27, 209–20.
- Openshaw, S., ed. (1995). *Census users' handbook*. Cambridge: GeoInformation International.
- Wiles, P. and Costello, A. (2000). *The 'road to nowhere': The evidence for travelling criminals*. Home Office Research Study No. 207. London: Policing and Reducing Crime Unit, Home Office Research, Development and Statistics Directorate.

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