Proceedings Paper:

Adepeju, MO orcid.org/0000-0002-9006-4934 and Evans, A orcid.org/0000-0002-3524-1571 (2017) Comparative analysis of two variants of the Knox test: Inferences from space-time pattern analysis. In: Gervasi, O, Murgante, B, Misra, S, Borruso, G, Torre, CM, Rocha, AMAC, Taniar, D, Apduhan, BO, Stankova, E and Cuzzocrea, A, (eds.) Lecture Notes in Computer Science. 17th International Conference on Computer Science and Its Applications (ICCSA 2017), 03-06 Jul 2017, Trieste, Italy. Springer Nature , pp. 770-778. ISBN 978-3-319-62407-5

https://doi.org/10.1007/978-3-319-62407-5_59

Comparative analysis of two variants of the Knox test:

Inferences from space-time crime pattern analysis

[1]Monsuru Adepeju (0000-0002-9006-4934) and [2]Andy Evans (0000-0002-3524-1571)

[1,2] School of Geography, University of Leeds, LS2 9JB, United Kingdom

[1]M.O.Adepeju@leeds.ac.uk
[2]A.J.Evans@leeds.ac.uk

Abstract. This paper compares two variants of the Knox test in relation to space-time crime pattern analysis. A case study of burglary and 'stolen-vehicle' crime data sets of San Francisco city is presented. The comparative analysis shows that while one variant is designed to detect the sizes of the spatio-temporal neighbourhoods at which clustering (hotspots) is prominent within a data set, the other variant is able to reveal the spatial and temporal windows/bands at which crime events are frequently repeated to form clusters (hotspots) across an area.

Keywords: Knox test, space-time, crime, repeat pattern, critical distances.

1 Introduction

The Knox test (Knox, 1964) is ubiquitous in the analysis of spatio-temporal patterns of crime data (Johnson and Bower, 2007). The Knox test offers an interesting means of determining whether there are more instances of observed pairs of events within a defined spatio-temporal neighbourhood than would be expected on the basis of chance. In the literature, two variants of the Knox test can be identified (Townsley et al., 2003). They are fundamentally distinguishable by the way in which the spatio-temporal neighbourhoods are defined. We have, one, an enclosed neighbourhood, in which the event count is conducted within a space, formed by a reference point r and the critical distances (CDs), measured along the spatial and the temporal dimensions (Fig. 1a). Two, we have a binned neighbourhood, in which the event count is conducted within the space formed from subtracting two CDs measured along

ICCSA, p. 1, 2017.

each dimension (Fig. 1b), relative to a reference point r. As a revised version, the binned neighbourhood is intended to filter out anomalous highs which are less likely to result from interactions due to r.

The Knox test has been widely used for the purpose of understanding the space-time pattern of crime data sets, particularly the repeat and near-repeat (RNR) pattern (Farrel and Pease, 1993). The RNR is the concept that if a location is the target of a particular crime type, such as burglary, the houses within a relatively short distance of it have an increased risk of being burgled over a period of a limited number of weeks (Bowers and Johnson, 2004). While both variants of the Knox test have been used to describe the RNR patterns, there is yet to be any empirical studies that compare such results, and further, to highlight their relationship with regards to the space-time patterns displayed by the data set. Therefore, the purpose of this study is to address this research gap. For a comprehensive comparison, each variant of the Knox test will be used to examine the space-time pattern in relation to two different crime types, using a list of neighbourhood values.

2 The Knox test and the space-time neighbourhood definition

The Knox test looks at the relationships between all pairs of events in a spatio-temporal dataset, generating a test statistic ($n_{\delta,\tau}$,) that is larger when, for example, short space-time distances appear more frequently than would be expected by chance (indicating RNR behaviour). The test statistic is generated from a table where spatial and temporal distances are binned and pairings allocated to the cells. Rather than testing all $n(n-1)/2$ possible combinations, it is usual to pass a moving window repeatedly over the data point-by-point, varying the critical spatial (δ) and temporal (τ) widths, measured from the moving reference point, r; the variation size corresponding to the bins in the table. This allows only events within a reasonable space/time distance of r to be taken, improving calculation speeds. Structuring the window to remove sections allows for more complicated distance filters, as is the case in the "binned" windows discussed here.

As the full test is still computationally laborious, a close analogue of the full test can be implemented in a programming environment by constructing two 'closeness matrices'. A closeness matrix describes the closeness of all pairs of events, either in space or in time. Thus, one matrix X is created for closeness in space and the other Y for closeness in time. For the first matrix, an X_{ij} will have an entry 1 for the cell $[i, j]$ if event i occurred within some spatial distance δ of the event j and 0 otherwise. The spatial closeness is calculated by the 2D Euclidean distance measurement. Similarly for the second matrix, a Y_{ij} will have an entry 1 for the cell $[i, j]$ if the event i occurred within some temporal distance τ of the event j and 0 otherwise. The temporal closeness is calculated by the difference between the times of occurrences of any pair of events. Both matrices would have a dimension $n \times n$, where n is the total number of point events. For both matrices, if $i = j$, then the entry is 0. The test statistic $n_{\delta,\tau}$, is then formulated by the cross-product:

$$n_{\delta,\tau} = \frac{1}{2}\sum_{\mathrm{i}=1}^{\mathrm{n}}\sum_{\mathrm{j}=1}^{\mathrm{n}-1} X_{ij}Y_{ij} \tag{1}$$

$$X_{ij} = \begin{cases} 1, & \text{if the distance between cases i and j} < \delta \\ 0, & \text{otherwise} \end{cases}$$

$$Y_{ij} = \begin{cases} 1, & \text{if the distance between cases i and j} < \tau \\ 0, & \text{otherwise} \end{cases}$$

If $n_{\delta,\tau}$ is large enough, the null hypothesis of no space-time interaction may be rejected. A number of approaches have been used to derive the point distribution under the null hypothesis. These include the chi-square approach (Ohno et al., 1979), standardised residual analysis (Agresti and Finlay, 1997), and the Monte Carlo (MC) simulation approach (Mantel, 1967). The MC simulation approach has become very popular due to the greater processing power of modern computers. Moreover, it has the advantage of minimising the impacts of the edge effect of the Knox test (Johnson et al., 2007), compared to the other available approaches. The MC involves randomising the time attributes of the cases, while the spatial attributes are kept constant. The process is repeated multiple times (usually 999), so that a pseudo p-value can be calculated as $P = (1 + n_e)/(n_s + 1)$, where n_e is the number of times that the expected count, based on MC, was exceeded by the observed count and n_s is the number of simulations. Here we utilise this MC process. The MC process is extremely computationally intensive, thus, a parallel computing approach, in which multiple analyses are run simultaneously, was used.

2.1 Types of space-time neighbourhoods

The parameters δ and τ described above can be referred to as the spatial and temporal neighbourhoods, respectively, within which events that fall inside are considered to be 'close'. This is the original version of the Knox test, as proposed by Knox (1964). In this study, this was referred to as an *enclosed* neighbourhood variant. In other words, an *enclosed* neighbourhood involves counting events within a region defined by critical spatial (δ) and a critical temporal (τ) distances, measured from a reference point r (Fig. 1a). A revised neighbourhood definition was later proposed (Knox 1963), in which event counts are conducted within a region, which are created by the subtraction of the two distances measured along each dimension. In this version of the Knox test, the resulting neighbourhood is referred to as the *binned* neighbourhood (Fig. 1b).

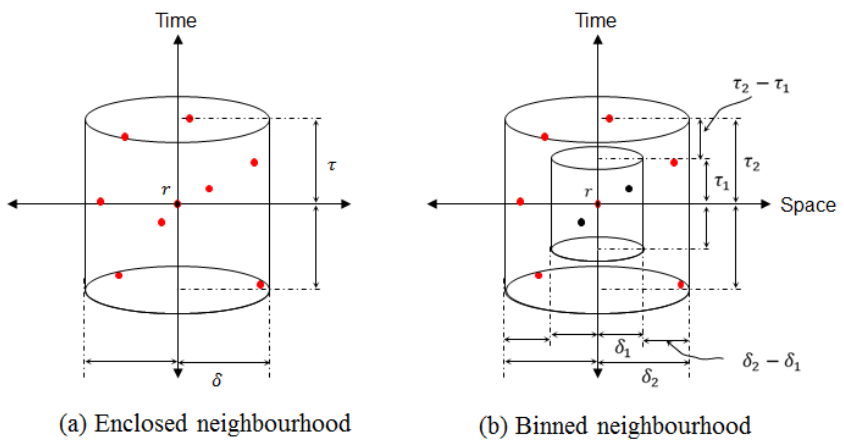

Fig. 1. Two types of neighbourhood definitions for the Knox test. (a) Enclosed neighbourhood, (b) Binned neighbourhood: each dimension requires two of δ and τ to form the region (i.e. {δ_1 and δ_2} and { τ_1 and τ_2}, respectively). The cases count in (a) is 8, while the cases count in (b) is 6 (Diagram from: Adepeju et al., 2017).

Thus, for the *binned* neighbourhood, two critical distances {δ_1 and δ_2} and { τ_1 and τ_2} are defined for the δ and τ, respectively.

The above two neighbourhood definitions, that is, the *enclosed* neighbourhood and the *binned* neighbourhood, underlie the two variants of the Knox test and will be used in this study.

In the crime domain, a contingency table is usually created in which the Knox test is repeatedly run using different values of δ and τ, and the contingency table is populated accordingly. The values of δ and τ are usually set arbitrarily. Although most studies often justify the value they use from a theoretical and/or practical point of view. In this study, the primary focus is to compare the two variants as regards to long-term local neighbourhood crime prevention. Therefore, the values of δ and τ will be made to vary at 30 day interval and 200m in the temporal and spatial dimensions, respectively. In the case of the binned variant, the inner bin is set such that the neighbourhood created with the outer bin is of 30 days and 200m in the temporal and spatial dimensions, respectively.

3 Case study of San Francisco crime data sets

3.1 Data sets

The data for this study are the burglary and 'stolen-vehicle' crimes in San Francisco, CA, U.S.A, for the year 2015. During this year, the city had some of the highest rates of burglary and 'theft-of-motor-vehicles', at approximately 20% and 150%, respectively, higher than the national average. The burglary and 'stolen-vehicles' data contains 4,267 and 4,970 records, respectively. From January to September, the monthly count of burglary crime looks very similar, with the exception of May, which is ~15% higher than the monthly average (Fig. 2a). On the other hand, 'stolen-vehicle' crime shows a continuous rise for monthly counts and peaks in May, yet immediately falls to its lowest frequency in September. The remaining three months have roughly the same crime count, while in the case of burglary, the crime level rose above the average level.

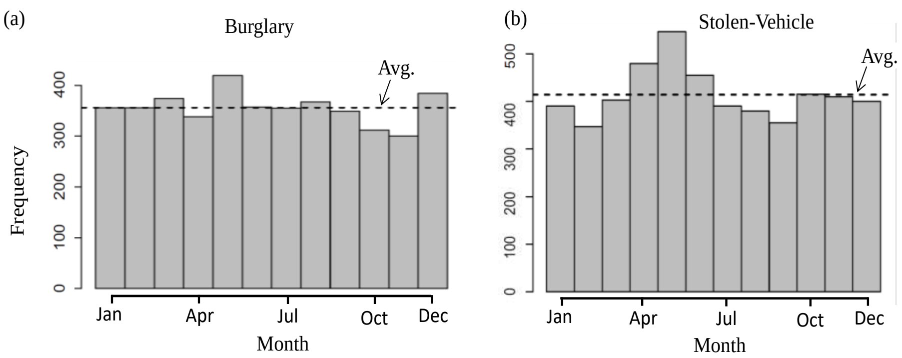

Fig. 2. Monthly crime count

3.2 Profiles of events' repeat patterns

In crime pattern analysis, a common approach for visualising the repeat and near repeat (RNR) pattern in crime data sets is to draw the repeat pattern profile (Johnson et al., 1997). The profile is drawn by counting the number of crimes occurring within a space and time lapse. The profile usually provides a picture of how events are repeated within a time window in a defined neighbourhood size, across the entire area. This same idea underlies the Knox test, except that the Knox test incorporates the statistical significance evaluation. Examples of repeat pattern profiles are shown in Fig. 3.

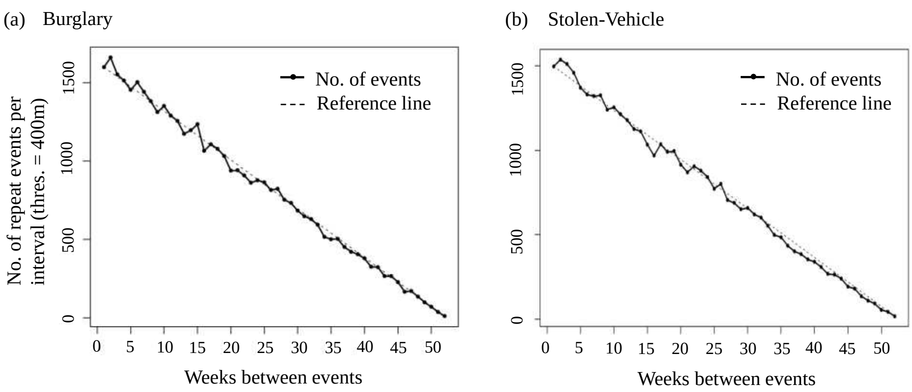

Fig. 3. Repeat pattern profile. (a) and (b) are the repeat pattern profiles of burglary and 'stolen-vehicle' profiles, respectively, within a radius of 400m of every event.

Fig. 3 shows the repeat pattern of the data set, measured within a neighbourhood of 400m in radius of an initial event. A relatively high level of repeats is indicated by the undulations in the profiles. A reference line is created in order to make the undulations (repeats) more visible by joining the first and last event. In Fig. 3a, it can be observed that the repeat pattern is more prominent in the first five months of burglary crime, while the repeat extends up to the sixth month in the 'stolen-vehicle' data. Thus, it can be easily be inferred that the repeat of crimes is prominent in the first five months for both crime types. However, the statistical quantification is missing in this type of analysis. This is where the Knox test plays an important role.

4 Results and Discussion

Table 1 and Table 2 shows the results of the two variants of the Knox test for the burglary and 'stolen-vehicle' crimes respectively. The results for the enclosed neighbourhood variant and binned neighbourhood variant are presented in table labelled (a) and (b). Highlighted values indicate where the pseudo p-value is smaller than 0.05, meaning that the likelihood of it occurring by chance is less than one in 20.

Table 1a: The *enclosed* neighbourhood variant Knox test: Burglary crime

days / mts	0 - 30	0 - 60	0 - 90	0 - 120	0 - 150	0 - 180	0 - 210	0 - 240
0 - 200	0.005	0.004	0.003	0.043	0.069	0.103	0.081	0.197
0 - 400	0.006	0.013	0.002	0.042	0.089	0.245	0.250	0.201
0 - 600	0.018	0.008	0.003	0.086	0.188	0.162	0.266	0.324
0 - 800	0.004	0.002	0.002	0.065	0.094	0.102	0.131	0.204
0 - 1000	0.002	0.005	0.014	0.104	0.145	0.109	0.112	0.179
0 - 1200	0.010	0.018	0.510	0.123	0.223	0.194	0.166	0.205
0 - 1400	0.081	0.110	0.079	0.194	0.310	0.304	0.214	0.278
0 - 1600	0.721	0.074	0.073	0.188	0.280	0.253	0.209	0.220
0 - 1800	0.060	0.081	0.081	0.163	0.253	0.229	0.150	0.152
0 - 2000	0.051	0.082	0.060	0.142	0.234	0.173	0.134	0.211

Table 1b: The *enclosed* neighbourhood variant Knox test: Stolen-vehicle

days / mts	0 - 30	0 - 60	0 - 90	0 - 120	0 - 150	0 - 180	0-210	0-240
0 - 200	0.031	0.035	0.202	0.448	0.466	0.515	0.663	0.85
0 - 400	0.002	0.001	0.003	0.026	0.615	0.762	0.65	0.744
0 - 600	0.001	0.001	0.002	0.039	0.397	0.638	0.488	0.503
0 - 800	0.001	0.001	0.003	0.059	0.394	0.621	0.55	0.631
0 - 1000	0.001	0.021	0.005	0.117	0.465	0.625	0.556	0.593
0 - 1200	0.009	0.042	0.128	0.436	0.834	0.801	0.678	0.72
0 - 1400	0.036	0.061	0.249	0.574	0.829	0.798	0.664	0.727
0 - 1600	0.054	0.054	0.371	0.558	0.845	0.803	0.635	0.684
0 - 1800	0.059	0.071	0.438	0.677	0.859	0.832	0.643	0.712
0 - 2000	0.097	0.136	0.543	0.771	0.911	0.827	0.665	0.736

In Tables 1a and 1b, representing the results of the enclosed neighbourhood variant of Knox test, all the cells with statistically significant values are arranged close to one another. In both cases, as the statistically significant cells extend in temporal sizes from 30 to 120 days, the corresponding spatial sizes decreases. This pattern indicates that significant levels of events are much closer in space at much smaller temporal sizes than at larger temporal sizes, larger distances and times being associated with events which blend with background noise. The relative closeness of events, simultaneously in both space and time, is generally referred to as space-time clustering (Diggle and Chetwynd, 1995). Considering the construct of the enclosed neighbourhood, as shown in Fig. 1a, it is argued that this variant of the Knox test is suited to the detection of events' concentration and its extensions in both space and time. In other words, we can say that space-time clustering of events is being detected (Diggle and Chetwynd, 1995). Specifically, it detects the critical spatial and temporal distances at which events' concentrations are statistically significant, and thus, form space-time clusters (hotspots). These critical spatial and temporal distances can then be described as the spatial and temporal scales of the most prominent clusters within the data set.

Table 2a: The *Binned* neighbourhood variant Knox test: Burglary crime

days / mts	0 - 30	31 - 60	61 - 90	91 - 120	121 - 150	151 - 180	181 - 210	> 210
0 - 200	0.005	0.040	0.917	0.418	0.081	0.425	0.967	0.968
201 - 400	0.108	0.038	0.567	0.691	0.966	0.720	0.066	0.723
401 - 600	0.107	0.248	0.736	0.528	0.017	0.973	0.919	0.643
601 - 800	0.017	0.117	0.402	0.201	0.212	0.342	0.992	0.997
801 - 1000	0.252	0.081	0.854	0.351	0.057	0.123	0.805	0.976
1001 - 1200	0.294	0.304	0.476	0.886	0.727	0.004	0.583	0.852
1201 - 1400	0.938	0.693	0.165	0.617	0.567	0.042	0.643	0.573
1401 - 1600	0.126	0.313	0.278	0.673	0.337	0.054	0.774	0.634
1601 - 1800	0.341	0.293	0.232	0.234	0.004	0.017	0.811	0.999
1801 - 2000	0.363	0.042	0.416	0.481	0.030	0.720	0.402	0.342

Table 2b: The *Binned* neighbourhood variant Knox test: 'Stolen-vehicle crime

days / mts	0 - 30	31 - 60	61 - 90	91 - 120	121 - 150	151 - 180	181 - 210	> 210
0 - 200	0.034	0.766	0.809	0.498	0.590	0.699	0.882	0.201
201 - 400	0.001	0.577	0.607	1.000	0.863	0.097	0.432	0.653
401 - 600	0.022	0.169	0.906	0.684	0.935	0.125	0.426	0.710
601 - 800	0.014	0.579	0.671	0.866	0.837	0.724	0.713	0.951
801 - 1000	0.129	0.375	0.733	0.931	0.407	0.225	0.770	0.832
1001 - 1200	0.479	0.999	0.924	0.978	0.031	0.016	0.200	0.208
1201 - 1400	0.560	0.856	0.745	0.664	0.385	0.053	0.815	0.671
1401 - 1600	0.577	0.693	0.247	0.844	0.464	0.065	0.624	0.985
1601 - 1800	0.459	0.884	0.982	0.702	0.387	0.001	0.837	0.502
1801 - 2000	0.921	0.380	0.975	0.943	0.029	0.021	0.841	0.533

In Tables 2a and 2b, representing the results of the binned neighbourhood variant of the Knox test, all the cells with statistically significant values are disjointed and distributed within four temporal bands, namely: {0-30 days}, {31-60 days}, {121-150}, and {151-180}. The critical spatial distances of the cells against their corresponding critical temporal distances can be described as the spatial and temporal windows at which there are more interactions or repeats in the data set. Two events interact when they are at a distance from one another in space and time different from that which would be expected on aggregate on the basis of chance. In both crime types, events are clustered within the first 2 months and also within 5 to 6 months of one another, which may be translated as the short-term and long-term repeat patterns. The ability to this variant of the Knox test to clearly isolate repeat patterns in terms of their temporality constitutes its major improvement over the events' repeat profile of Fig. 3.

Comparing the general distribution of the significant cells in all the tables, it can be observed that the patterns at smaller spatial and temporal bands/neighbourhoods (i.e. between 0m and 800m) are much stronger, and thus persist across the two variants. On the other hand, the significant cells in the distant bands for the binned variant were not reflected in the enclosed variant, and are thus tagged as weak patterns.

Crime clusters (hotspots) are formed as a result of many crimes interacting within a common neighbourhood. In practice, while the results of the binned neighbourhood variant of the Knox test can be used to identify the spatial and the temporal lags at which the next set of crimes are likely to occur, the results of the enclosed neighbourhood variant of the Knox test can be used to investigate the sizes of the spatial and temporal windows (neighbourhoods) to target during crime intervention over a coherent period after the event. This has advantages in terms of both public fear of crime and utilisation of householders fresh commitment to target hardening. While the Knox test is relatively simple and efficient to calculate, a more locally detailed answer as to the structure of short-term spatio-temporal clustering may be obtainable by employing a local clustering test, such as space-time scan statistics (STSS) (Kulldorff et al., 2005). An STSS is able to detect and isolate the specific space-time regions that contribute to the overall clustering derived by a global test such as the Knox test.

5 Conclusions

This study presents a comparative analysis of two variants of the Knox test, distinguished by the manner in which the space-time neighbourhoods (i.e. critical distances) are defined. These two neighbourhood definitions were referred to here as the *enclosed* and *binned* neighbourhoods. The goal was to compare the results generated by these two variants in relation to the same data set, as well as to describe their relationships from both theoretical and practical perspectives. The data set used for the analysis was the burglary and 'stolen-vehicles' crime dataset for the city of San Francisco.

The results reveal that the *enclosed* variant helped to detect the sizes of the spatio-temporal neighbourhoods at which clustering (hotspots) was prominent within the dataset. The *binned* variant, on the other hand, revealed the spatial and temporal windows at which crime events were repeated more broadly to form clusters (hotspots) across an area.

The Knox test has been widely applied in many different geographical domains, such as epidemiology, ecology and forestry, in order to study phenomena that are peculiar to each domain. In most of these applications, usually only one variant of the Knox test is used at a time. It is proposed in this study that the utility of the two variants of the Knox test may facilitate the revelation of new meanings and inferences in relation to the space-time pattern of the data under study.

References

1. Adepeju, M., 2017. Modelling of Sparse Spatio-Temporal Point Process (STPP) – an application in Predictive Policing. A PhD thesis submitted to the University College London (2017).

2. Agresti, A. and Finlay, B.: Statistical Methods for the Social Sciences, 3rd edn. New Jersey: Prentice Hall (1997)

3. Bowers, K.J. and Johnson, S.D.: Who commits near repeats? A test of the boost explanation. Western Criminology Review, 5(3), 12-24 (2004).

4. Diggle, P.J., Chetwynd, A.G., Häggkvist, R. and Morris, S.E.: Second-order analysis of space-time clustering. Statistical methods in medical research, 4(2), 124-136 (1995).

5. Farrell, G. and Pease, K.: Once bitten, twice bitten: Repeat victimisation and its implications for crime prevention. (1993)

6. Johnson, S.D., Bernasco, W., Bowers, K.J., Elffers, H., Ratcliffe, J., Rengert, G., Townsley, M.: Space-time patterns of risk: a cross national assessment of residential burglary victimization. J Quant Criminol, 23, 201–219 (2007)

7. Kleinman, K.P., Abrams, A.M., Kulldorff, M. and Platt, R.: A model-adjusted space–time scan statistic with an application to syndromic surveillance. Epidemiology and Infection, 133(03), 409-419. (2005).

8. Knox, G.: Detection of Low Intensity Epidemicity Application to Cleft Lip and Palate. British journal of preventive & social medicine, 17(3), 121-127 (1963).

9. Knox, G.: Epidemiology of Childhood Leukaemia in Northumberland and Durham. Brit. J. of Prev. and Social Med, 18, 17-24 (1964).

10. Mantel, N.: The detection of disease clustering and a generalized regression approach. Cancer Res., 27, 209–220 (1967).

11. Ohno, Y., Aoki, K. and Aoki, N.: A test of significance for geographic clusters of disease. International Journal of Epidemiology, 8(3), 273-281 (1979).

12. Townsley, M., Homel, R. and Chaseling, J.: Infectious burglaries: A test of the near repeat hypothesis. The British Journal of Criminology, 615-633 (2003).