Vehicle Crime: Communicating Spatial and Temporal Patterns

FINAL REPORT

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Executive Summary

Previous research by the writers and others demonstrated clustering of domestic burglary in space and time. This enabled the development of a predictive mapping instrument (PROMAP) which substantially outperforms traditional crime mapping in anticipating burglaries. This report seeks to determine whether the clustering which underpins PROMAP is also evident in relation to vehicle crime, specifically Theft from Motor Vehicle (TFMV) and Theft of Motor Vehicle (TOMV). Data of recorded vehicle crime over a one year period from Derbyshire and Dorset were examined to test that proposition. Analyses demonstrated that

- TFMV clusters closely in space *and* time in both police force areas. When such an offence occurs at one location another is likely to occur nearby and soon after. To use the vocabulary of an epidemiologist, like burglary the risk of this type of vehicle crime is highly communicable.

- TOMV clusters somewhat, but not in the same way or with the same closeness as TFMV. The pattern is similar in both force areas.

- The spatio-temporal signatures of the two types of vehicle crime, as noted above, differ.This suggests different targeting or foraging strategies are employed for these two types of crime. The difference is consistent with common sense, since there is more post-offence activity implied in theft of a car (onward selling, changed identity, enjoying performance for a non-trivial period) than for theft from a motor vehicle, where the primary constraint on further offending is the offender’s carrying capacity.

- There are data limitations which have implications for the ease with which a PROMAP variant dealing with vehicle crime could be deployed operationally. These include shortcomings in the current recording of locations of vehicle crime, and the special problems in mapping crime in car parks,

Notwithstanding current data limitations, the patterning of vehicle crime in time and space is such as to encourage the view that prospective mapping could, with proper implementation, prove operationally useful in crime reduction and offender detection

Introduction

Reducing uncertainty about when and where crime is likely to occur facilitates its reduction by limiting opportunity at crime-prone times and places and by detecting offenders at work. Using techniques developed in epidemiology (e.g. Knox, 1964), it has recently been found that the risk for burglary clusters in space and time in a predictable way (e.g. Johnson & Bowers, 2004; Johnson et al., 2005; Townsley et al., 2003). This, together with the knowledge that victimisation is one of the best predictors of future offending against the *same* target (see Pease, 1998) enables accurate predictions of when and where burglary is most likely to occur (see Bowers, Johnson & Pease, 2004).

The aim of the research reported here is to determine whether such patterns are evident for vehicle crime. An initial brief literature review sets out to place the research in theoretical context. This is followed by consideration of the quality of vehicle crime data recorded by the police (in two police force areas). Next, analyses are presented to show how patterns of vehicle crime vary in space, time and in space *and* time. The final section provides a discussion of the main findings and yields recommendations for theory, research and practice.

The aims of the present research were five-fold, as follows:

- In relation to this type of analysis, are recorded crime data concerned with vehicle crime 'fit for purpose'?
- Is there a general periodicity to vehicle crime as recorded by the police by time of day, weekday and/or season?
- Is the risk of vehicle crime 'communicable', ie does vehicle crime cluster in space and time?
- If vehicle crime is clustered in space and time, over what distances and times is risk elevated?
- Are there *distinct* geographical and spatio-temporal signatures for theft of and theft from vehicle offences?

Literature Review

Over a decade of research demonstrates that prior victimisation is one of the best predictors of future risk (see Pease, 1998). Accordingly, many strategies aimed at reducing crime (in particular burglary and domestic violence) focus on preventing (repeat) victimisation by drip feeding crime reduction resources to recent victims of crime. Evaluations of such interventions demonstrate the wisdom of so doing (for a review, see Farrell and Pease, 2006), showing reductions in burglary where implementation has been adequate.

Inspired by the precepts of optimal foraging theory (for an account, see Krebs & Davies, 1987), research has recently examined whether repeat burglary victimisation is simply a special case of a more general foraging pattern. According to optimal foraging theory, when hunting for resources (e.g. food), animals aim to maximise the resources acquired whilst minimising the consequent chance of getting injured (or eaten!) and the search time and effort expended. To what extent do offenders behave like optimal foragers? And if they do, what should their targeting patterns look like?

The explanation that follows is necessarily brief and the interested reader is referred to earlier work for a fuller account (see, for example, Johnson, Bowers and Pease, 2005). According to rational choice theory (Cornish and Clarke, 1986), offenders select targets by considering the risks and rewards involved for different opportunities. Uncertainty about a particular target may lower the chance of victimisation. One prediction that flows from this line of reasoning is that the risk at a particular location (or for a particular individual) is partly a function of an offender's awareness of it. Thus, when a home is burgled the offender's familiarity with it provides him with a better basis for judging whether to return. Where returning to the same location is perceived to be likely to be rewarding with an acceptable level of risk, the goals of the optimal forager suggests return will take place. Having burgled one property, an offender increases his awareness of those nearby. Neighbouring houses typically share a variety of features, such as access routes, levels of natural surveillance and the value of goods found inside. Thus, having burgled one home a burglar may identify others nearby as candidates for future offences. Over time it is possible that the characteristics of an area may change or an offender may forget details necessary for a successful burglary, Further, the proceeds of a burglary do not meet needs (whether fiscal or pharmaceutical) for long. For both reasons, both possible change of area and swift recurrence of need, it will often be prudent and necessary for a burglar to return swiftly to nearby homes.

It was hypothesised that insofar as offenders adopt optimal foraging strategies, the risk of burglary victimisation should exhibit the defining feature of a communicable disease – it would cluster in space *and* time. Using techniques developed in the field of epidemiology (e.g. Knox, 1964) this was put to the test in our recent research.

To summarise the results to date, the risk of burglary victimisation *does* cluster in space and time. This has been found in every area analysed. These include Merseyside (Johnson & Bowers, 2004) and the East Midlands (Johnson et al., 2006) in the UK, Philadelphia and Florida in the USA, the Hague and Zoetermeer in the Netherlands, and areas throughout Australia and New Zealand (Johnson et al., 2006). To illustrate, for Merseyside the results indicated that following an initial burglary event, there was a heightened risk of victimisation to houses within 400 metres of the burgled home for a period of approximately one month. This was particularly true for houses on the same side of the street as the burgled home and in the most affluent areas (Bowers & Johnson, 2005). Thus, a burglary on a street flags an increased risk to those *proximate* for a *short period of time*.

The identification of such regularities in patterns of crime obvious has practical value. Simple models calibrated using these findings can be used to substantially improve the accuracy with which the future locations of burglary can be predicted (e.g. Bowers et al., 2004). However, an as yet unanswered question concerns the generality of the findings in relation to other types of crime. Vehicle crime shares similar motivational factors to burglary and is one of the highest volume crimes recorded by the police. The central aim of the current research was to see if, for two case study areas, patterns of vehicle crime (in space and time) conform to those observed for burglary. Before answering this question, the available data will be examined to determine its quality and scope. The results of these preliminary analyses are reported in the next section.

Data Quality

In this section, using one-year's data from each of two police force areas (Derbyshire and Dorset), an assessment is made of the timeliness with which vehicle crime data is available for analysis, the accuracy of the geographical coordinates supplied, the precision of information concerning the time of offences, and the availability and potential usefulness of recorded modus operandi and vehicle description.

Data analysed

The data analysed, supplied by Derbyshire and Dorset police, comprised incidents of theft of (TOMV) and from vehicles (TFMV: Home Office codes 4510 and 4801). This amounted to a total of 9,261 and 5,747 incidents for the two counties, respectively. For every event, the following fields of information were available for analysis:

- The earliest and latest date on which the crime could have occurred
- The earliest and latest time that the crime could have occurred
- The text address of the offence
- The geographical grid coordinate of the location of the offence, recorded as a 12 digit easting and northing grid coordinate
- Characteristics of the Modus Operandi employed
- A vehicle description

The data for Dorset police were obtained directly, while the data for Derbyshire were obtained from the County Council after it had been formatted for analysis.

Context

Before discussing the analyses, it is worth briefly discussing the areas for which data were available, particularly in relation to the crime problems experienced. In 2003/04, the number of theft from vehicle offences per 1,000 population was higher than the average for England and Wales (11.5) in both Dorset (16.4) and Derbyshire (14.7). In contrast, the rate for theft of vehicle was lower in Derbyshire (4.9) than, and in Dorset (5.6) comparable to, the national average rate of 5.6 (Source: Home Office (number of offences) and 2001 Census (population figures).

Both Derbyshire and Dorset are modern (post-1974) English counties including a mix of rural and urban areas. Derbyshire is located in the East Midlands (see Figure 1) and has a population of 734,585. Dorset is in the South West of England and its population is 390,980.[1]

Figure 1. The location of Derbyshire **and Dorset within England and Wales.**

Timely Availability of Data

In Derbyshire, Call Reception Centre staff may record a vehicle theft crime onto the police database if sufficient information is available at the time of reporting. Where this is not the case or when certain criteria are met (e.g. there are obvious suspects or the complainant is not agreeable for the report to be taken over the phone), an officer will attend the scene and enter the information into the database at a later date.

In Dorset, once a crime is reported, details about the event are added to the police database. In some cases before April 2005 and in all cases since, an incident log initially is created, and an officer is subsequently required to confirm that an incident actually took place before the data is entered onto the crime recording system. In both counties, these processes may lead to a small delay in data being added to the force IT systems.

[1] Population figures obtained from the Office for National Statistics 2001 Census.

This could affect the timely availability of (recorded crime but not necessarily incident) data for analysis. This will be important for implementation of predictive mapping insofar as the patterns for burglary are reproduced here, revealing as they do *short-term* predictability. It is less important for the research reported here.

Considering the data provided, an examination of the difference in the dates that crimes were reported and the dates on which they appeared on the force IT systems revealed that for 92% incidents of TFMV in Derbyshire , information was entered onto the force recording system within one-day of being reported to the police. In the case of TOMV the percentage was slightly higher at 94%. In Dorset, these percentages were 92% and 89% for theft from and theft of vehicle incidents, respectively. Thus, in both counties the majority of data concerned with vehicle crime is available for analysis within twenty-four hours.

Accuracy of Geographical Coordinates

For crimes such as burglary, offences are committed at fixed locations that do not (usually[2]) move and hence with the availability of a relevant gazetteer it is a straightforward process to provide accurate geo-codes to specify the locations of events. However, cars move, and the precise location of an event is not always so easily settled upon. Analyses were conducted to examine the detail of information supplied and the accuracy of geographical grid coordinates generated.

In Derbyshire a total of 574 incidents took place in car parks, 934 in Dorset. Due to the distinct contextual differences between car parks and other locations, these data are analysed separately and not included in the present analysis (for a discussion, see Box 1. They are also examined where appropriate later in the report). Of the remainder, 112 records (1.3% of the sample) in Derbyshire and 35 (0.7%) in Dorset had missing or incorrect geographical coordinates or had been (being geo-coded outside the selected areas).

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[2] Except in New Zealand where people sometimes physically move their houses, or even hotels.

Box 1. Vehicle Crime in Car Parks

Incidents that take place in car parks may differ from other vehicle crime for a variety of reasons, including the following:

- access to car parks is often restricted to specific days of the week and/or times of day. These influences could affect the results reported later in this report.
- it is usually difficult to accurately geocode the location of an offence within a car park; instead, the centroid is routinely used which may bias (to a greater or lesser extent, depending on the size of the car park) any analyses of the spatial distribution of crime
- the management and reduction of vehicle theft in car parks usually falls under the responsibility of the owner of the facility and is arguably not as directly relevant to police forces
- Multi-storey car parks bring the vertical dimension into play. Experience suggests that vehicle crime is concentrated in spates and at particular locations within car parks, suggesting that a case-by-case analysis of car parks would be informative.

On a practical note, one issue that arose from the analysis of the police data provided was that that although there was a specific MO field provided to indicate whether an incident took place in a car park, this was rarely completed. Instead, this information was more routinely recorded in one of the address fields, and usually entered in free text form. This means that the identification of vehicle crimes taking place in car parks can be difficult. However, if combined with data on the location of car parks, incidents that occur in these locations can easily be identified. Alternatively, simple data mining techniques could also be used to identify incidents of this type.

Consequently, for this part of the analysis, data were available for 8,575 events in Derbyshire and 4,778 in Dorset that took place at the road side or on drive ways. The majority of these were supplied with non-zero geographic grid coordinates. The accuracy of these was not assumed. Thus, the first step in the analysis was to establish the veracity of the coordinates provided. To do this, each record was checked manually to see how complete was the address recorded. The rationale for this was that unless a full address was supplied, the geo-coding for a particular event would probably include error, if only a small amount (e.g. within a full unit postcode boundary).

Table 1 shows that for Dorset 70% of all incidents had complete address information (house number, street and town name, and postcode). For Derbyshire the proportion was less. However, in both counties there were a large number of events for which complete address data were available.

Those events for which only partial address information was recorded were further analysed. Table 2 shows what information *was* recorded, and suggests that for around one-half of these events only street and town names were recorded. Where this was the only information provided, visual inspection of a small random sample of events suggested that the geographical coordinates provided related to the centroid of the road concerned. This level of information may be sufficient only in cases where a street is short, but probably not otherwise.

	Derbyshire				Dorset			
	Theft FROM Vehicle		Theft OF Vehicle		Theft FROM Vehicle		Theft OF Vehicle	
Included in the analysis								
Address incomplete	3,873	(59%)	917	(45%)	1,246	(30%)	194	(31%)
Address complete	2,667	(41%)	1,118	(55%)	2,896	(70%)	442	(69%)

Table 1. **Number of incidents for which the house number or name of the property, street name and postcode were provided.**

For the remainder, additional information was often supplied that might usefully allow an analyst to identify the precise location of the event, although this information was rarely stored in a format suitable for analysis using automated geocoding procedures of the kind used by the police.

	Derbyshire				Dorset			
DATA RECORDED	Theft FROM Vehicle		Theft OF Vehicle		Theft FROM Vehicle		Theft OF Vehicle	
Only town	0	(0%)	0	(0%)	36	(3%)	10	(5%)
Town and street name	1655	(43%)	435	(47%)	697	(56%)	97	(50%)
Town, street name and pointer	133	(3%)	21	(2%)	227	(18%)	34	(18%)
Town, street name and business/house name	2085	(54%)	461	(50%)	286	(23%)	53	(27%)

Table 2. Type of information provided for events with incomplete addresses

To take this analysis further, a small random sample of events for which complete (N=160) and incomplete (N=75) addresses were available were more closely examined to establish the precision of the geographical coordinates provided. To do this, OS landline data (detailed maps) were imported into a GIS and the incidents mapped against this background. These maps included “polygon” representations of houses and roads and also indicated the numbers of the houses on each road. Thus, these data allowed the location of each event, mapped using the geographic grid coordinates supplied, and the address of the crime and the address of the point on the map to be compared for reliability. Due to the time consuming nature of this task, the analyses conducted were concentrated on two residential areas within each county where crime was highly concentrated (Derby and Chesterfield in Derbyshire, and Bournemouth and Weymouth in Dorset). Thus, the areas selected for scrutiny were those in which the types of analysis reported later in this report would be most likely to be conducted, and predictive methods subsequently employed.

This analysis revealed that for events for which a full address was supplied, the geographic grid coordinates were consistently accurate, thereby suggesting that confidence in the accuracy of the geo-coding of these incidents would not be unwarranted. For those incidents where only partial address (including a postcode) information was available, not surprisingly the accuracy of the geographical coordinates was limited to being within the postcode sector for the incident concerned. Thus, even where only partial information was supplied, it is possible that the data could be useful for spatial analyses for which the exact location of events is not paramount.

An alternative approach of assessing the accuracy of the geo-coding is to examine the text addresses of events for which the geographical coordinates are the same. For Derbyshire, 8% of incidents for which complete addresses were provided had the same geographical coordinates as at least one other incident, in Dorset 13% of incidents shared the same geographic coordinates. The data for all of these incidents were checked manually and the results of the analysis are shown as Table 3.

	Derbyshire				Dorset			
	Theft FROM Vehicle		Theft OF Vehicle		Theft FROM Vehicle		Theft OF Vehicle	
Same address	216	(95%)	67	(97%)	408	(100%)	38	(100%)
Different address	11	(5%)	2	(3%)	0	(0%)	0	(0%)

Table 3. Number of vehicle crime incidents with the same geographical coordinates for which the address was the same (complete address records only).

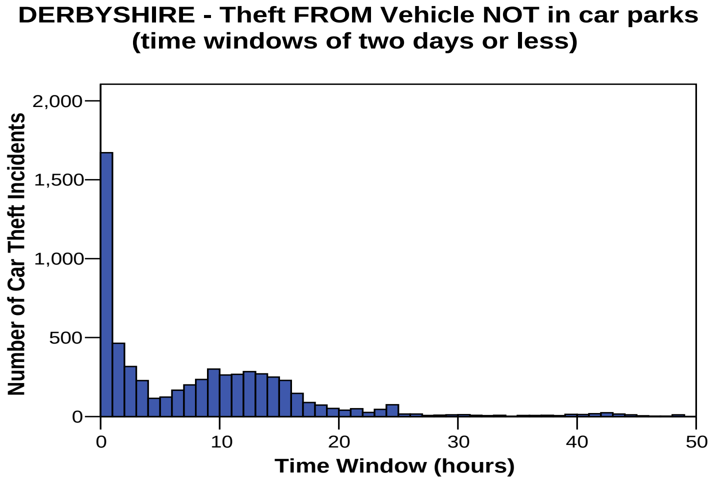
For Dorset, all such incidents were consistently geo-coded. For Derbyshire the majority (95% or more) of incidents paired in this way had the same addresses. For nine of the eleven incidents, different addresses had been recorded but the discrepancy related to the precise location on the street, all other information was the same. For these cases, the differences ranged from seven to 45 house numbers (i.e. four to 23 houses, respectively). For the remaining two incidents, the postcode had been incorrectly entered for one of them so that they both matched, despite actually being located 0.2 miles apart.

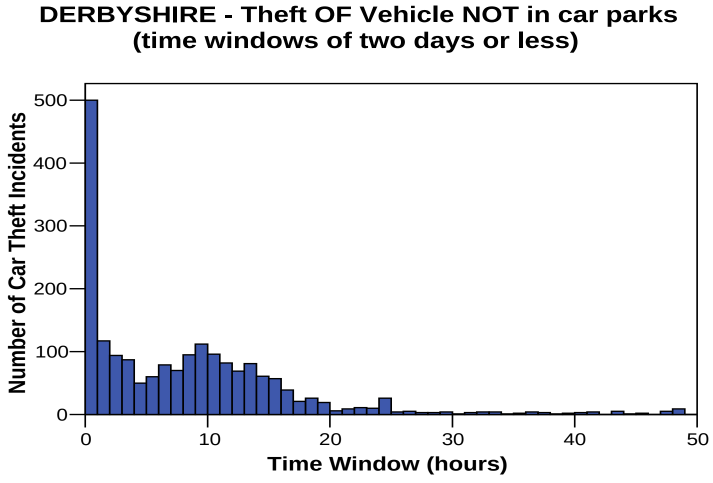
Information on the Time that Crimes Occurred

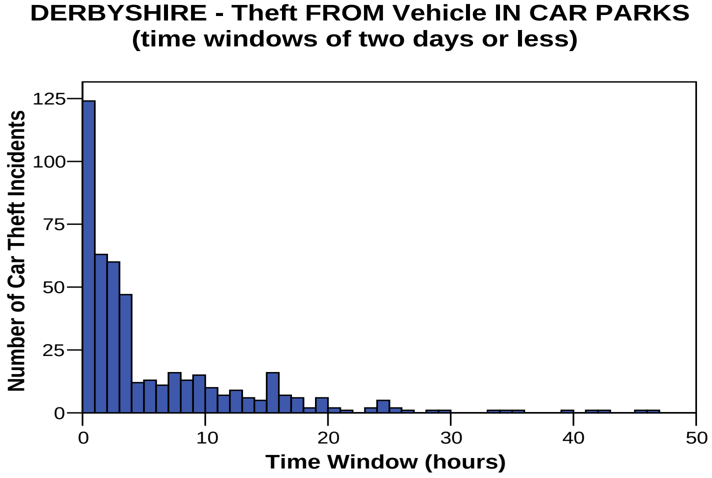
When a crime is reported, the victim does not usually know the time that it occurred. Accordingly, to estimate the timing of an offence, the police record a window of time during which the crime incident must have occurred, recording earliest and latest possible time as ‘brackets’ for the offence time. For any detailed analysis of crime patterns, consideration of the length of these intervals is important as this duration affects the degree of precision with which temporal patterns of crime can be summarised, and more sophisticated analyses performed. Thus, analyses were conducted to examine the length of these intervals.

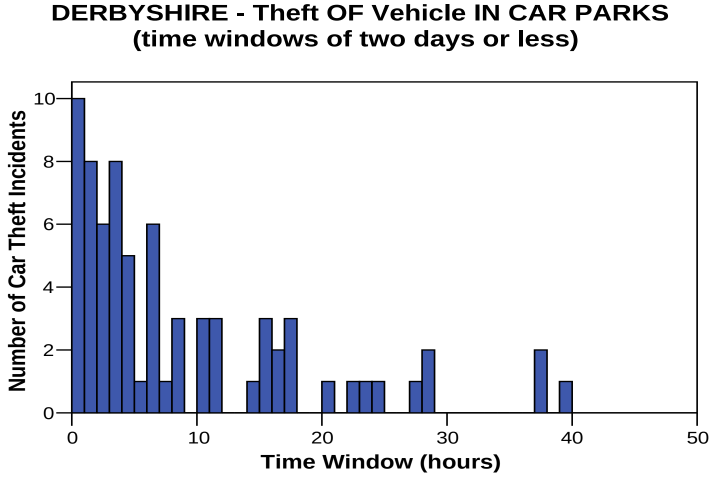
For the reasons already discussed, incidents of vehicle crime that took place in car parks were analysed separately from those that took place elsewhere. All incidents of vehicle crime for which complete data concerning the time of an offence were available were analysed, including those for which complete addresses were unavailable.

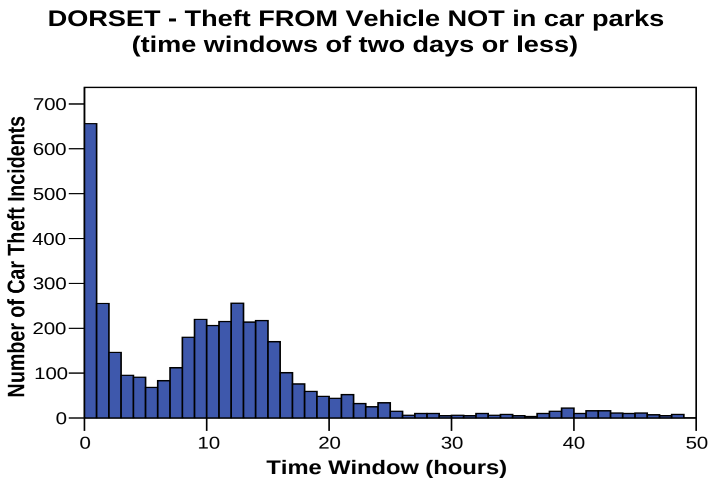
In both Dorset and Derbyshire around 95% of all incidents of TFMV occurred within a specified interval (brackets) of 48 hours. For TOMV, this proportion was similar for Derbyshire but slightly lower for Dorset (87% for crimes on the street, 84% for those in car parks). More detailed analyses are shown in the four panels below (and as summary tables in Appendix 1). To summarise, for vehicle crime that occurred on the street, the distributions tended to be bi-modal, being either one hour or less or around 10 hours, no doubt reflecting victim activities (from going to bed to getting up or from going to work to coming home). In contrast, incidents that occurred in car parks tended to have much shorter intervals, presumably reflecting the routine activity of those out shopping.

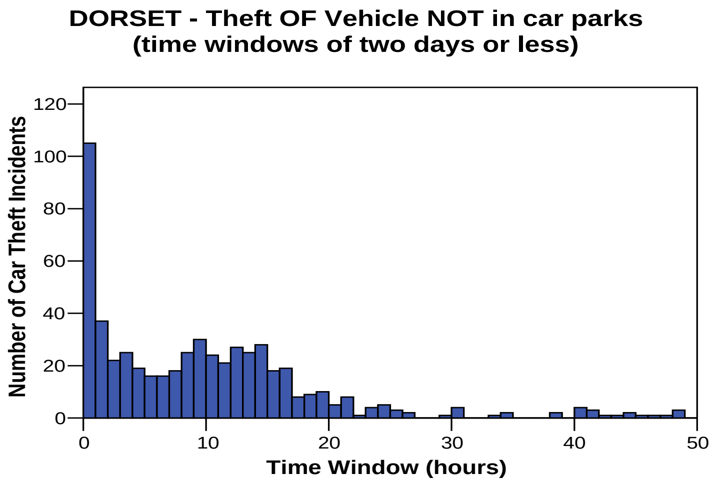

DERBYSHIRE - Theft FROM Vehicle NOT in car parks
(time windows of two days or less)
Number of Car Theft Incidents
Time Window (hours)


DERBYSHIRE - Theft OF Vehicle NOT in car parks
(time windows of two days or less)
Number of Car Theft Incidents
Time Window (hours)


DERBYSHIRE - Theft FROM Vehicle IN CAR PARKS
(time windows of two days or less)
Number of Car Theft Incidents
Time Window (hours)


DERBYSHIRE - Theft OF Vehicle IN CAR PARKS
(time windows of two days or less)
Number of Car Theft Incidents
Time Window (hours)


DORSET - Theft FROM Vehicle NOT in car parks
(time windows of two days or less)
Number of Car Theft Incidents
Time Window (hours)
0
100
200
300
400
500
600
700
0
10
20
30
40
50


DORSET - Theft OF Vehicle NOT in car parks
(time windows of two days or less)
Number of Car Theft Incidents
Time Window (hours)
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20
40
60
80
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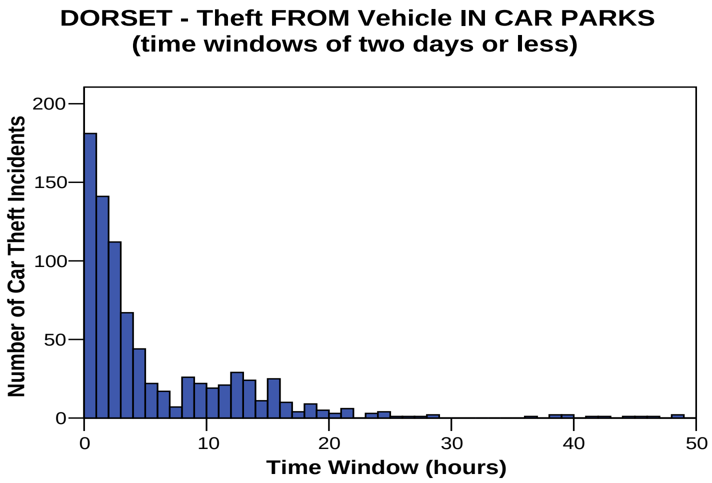
10
20
30
40
50


DORSET - Theft FROM Vehicle IN CAR PARKS
(time windows of two days or less)
Number of Car Theft Incidents
Time Window (hours)
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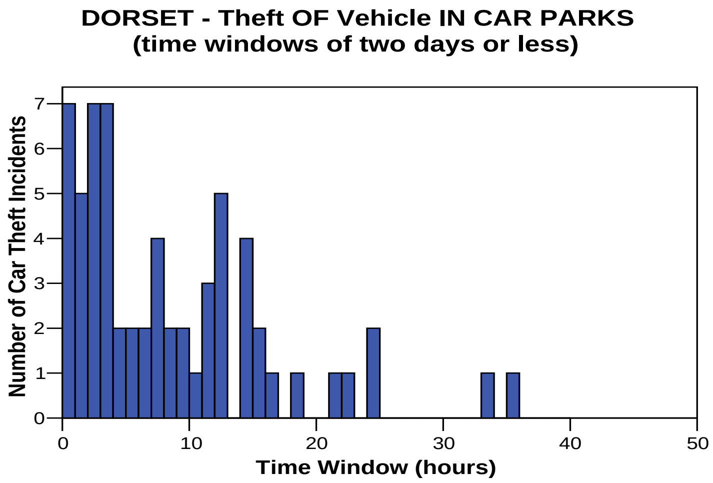
50
100
150
200
0
10
20
30
40
50


DORSET - Theft OF Vehicle IN CAR PARKS
(time windows of two days or less)
Number of Car Theft Incidents
Time Window (hours)
0
1
2
3
4
5
6
7
0
10
20
30
40
50

Modus Operandi (MO) data

In addition to when and where crimes occur, the police routinely record information on *how* they are committed. Whilst the degree varies to which these types of data are systematically recorded, they have the potential to be useful. For example, where appropriately recorded they may be used to identify frequently used MOs, with implications for crime prevention. They may also allow crimes to be identified as part of a series. As part of predictive mapping, they could be used to anticipate how as well as when and where crimes may next occur. For this reason, a simple audit was conducted to see what data is routinely recorded by the two police forces for which data were available. Both Derbyshire and Dorset police forces record MO information by assigning one or more codes to individual offences (some of which are specific to vehicle theft). As can be seen from Table 4, this was done consistently in both counties, with every incident having at least one MO code. The mean number of MO codes assigned was, however, slightly higher in Dorset.

	Derbyshire		Dorset	
	Theft FROM Vehicle (N=7,117)	Theft OF Vehicle (N=2,144)	Theft FROM Vehicle (N=5,030)	Theft OF Vehicle (N=717)
Mean	5.3	2.7	7.9	5.0
Standard deviation	1.9	1.1	2.1	2.7
Minimum	1.0	1.0	2.0	1.0
Maximum	16.0	12.0	21.0	22.0

Table 4. Descriptive statistics for number of modus operandi codes assigned.

Examples of some of the MO codes most commonly used in Dorset are shown in Table 5. Further analysis of these data was beyond the scope and aims of this report, but the analysis indicates that there are available data that could be usefully analysed in future research of this kind.

	Theft FROM Vehicle		Theft OF Vehicle		ALL Vehicle theft	
Actions following offence						
Glove box opened	435	(54%)	6	(6%)	441	(49%)
Locks damaged	82	(10%)	7	(7%)	89	(10%)
Bodywork dented	57	(7%)	11	(11%)	68	(8%)
Type of property stolen						
Vehicle accessories	1,703	(18%)	11	(1%)	1,714	(16%)
Audio-visual equipment	963	(10%)	11	(1%)	974	(9%)
Bank items and documents	843	(8%)	15	(2%)	858	(8%)
Vehicle abandoned						
Burnt out	0	(0%)	42	(59%)	42	(49%)
Other damage	6	(43%)	15	(21%)	21	(25%)
Undamaged	3	(21%)	4	(6%)	7	(8%)
Vehicle method of entry						
Passenger’s side	1,528	(14%)	13	(3%)	1,541	(14%)
Glass broken	1,531	(14%)	4	(1%)	1,535	(14%)
Driver’s side	1,344	(13%)	33	(8%)	1,377	(13%)
Vehicle parked						
Side street	1,959	(28%)	204	(23%)	2,163	(29%)
Driveway	583	(9%)	116	(13%)	699	(9%)
Car park (private)	484	(7%)	67	(8%)	551	(7%)

Table 5. Most common modus operandi codes for Dorset.

Vehicle Descriptors

As with MO data, if consistently recorded, analyses of the types of vehicles targeted in an area may help to inform crime reductive responses or help to link events in a series. For both Derbyshire and Dorset, vehicle descriptors were included as part of the crime record. This information included the make, model, colour and year of registration of the vehicle. The data were recorded in separate fields but as free text. Thus, useful data are available although they will require further processing before analyses can be conducted.

In addition to the data already discussed, the police also record Vehicle Registration Numbers (VRNs). Although not available for this research, it was possible to confirm that this information was available for the vast majority of incidents (>99%) in both police force areas. The small number of cases for which this information was missing was primarily attributable to offences against new vehicles that had not yet been registered at the time of the offence. Thus, in future research it would be possible to cross reference this data with that held by the DVLA in order to obtain further details regarding stolen vehicles that may be useful for analysis. Finally, as part of the MO data recorded, some information is also provided regarding the security features of vehicles targeted. Although not a compulsory field, an examination of the data available for Derbyshire and Dorset revealed a number of records for which this information was included. An example of some of the most commonly used security features MO codes in Dorset are presented in Table 8.

	Theft FROM Vehicle		Theft OF Vehicle		ALL Vehicle theft	
No security fitted	2,071	(40%)	301	(40%)	2372	(40%)
Security unknown	2,048	(39%)	225	(30%)	2273	(38%)
CCTV cameras covering area	269	(5%)	30	(4%)	299	(5%)
Remote alarm fitted	261	(5%)	31	(4%)	292	(5%)
Key operated alarm fitted	208	(4%)	33	(4%)	241	(4%)
Alarm failed to activate	167	(3%)	12	(2%)	179	(3%)
Immobiliser disabled	50	(1%)	41	(5%)	91	(2%)
Mechanical device	35	(1%)	47	(6%)	82	(1%)
Windows etched	48	(1%)	11	(1%)	59	(1%)
Alarm disabled	34	(1%)	12	(2%)	46	(1%)
Attempt - deterred by security	15	(0%)	4	(1%)	19	(0%)
Alarmed	4	(0%)	0	(0%)	4	(0%)
Security lights fitted	4	(0%)	0	(0%)	4	(0%)
Guard dog present	1	(0%)	1	(0%)	2	(0%)
Window locks fitted	2	(0%)	0	(0%)	2	(0%)
Over 25 sticker	1	(0%)	0	(0%)	1	(0%)

Table 8. Most common security features modus operandi codes for Dorset

Summary

At this point it is worth summarising the results of the analyses so far carried out. For the two areas considered, there was some variability in the proportion of events for which complete address information was provided. In the case of Dorset, complete data was available for a high proportion of events. Detailed analyses of the accuracy of a sample of events suggested that where complete addresses were supplied the geographical coordinates were almost always accurate, and that where only partial addresses were provided the accuracy varied ranging from a full unit postcode boundary to being somewhere along a street.

In relation to when crimes occurred, the window of opportunity during which most events were reported to have taken place was rarely more than two days, and for 50% of events between one and eight hours. Perhaps not surprisingly, these intervals varied systematically depending on whether an event occurred on the street or in a car park, being shorter for the latter.

Considering other data, useful information was recorded concerning the types of vehicle stolen and the MOs used by offenders. Whilst the latter data will not be further analysed here, it was audited during the research to help identify data that might be usefully examined in further research.

In the sections that follow, temporal, spatial and space-time patterns of vehicle crime will be considered. To begin, general temporal trends will be explored.

General Temporal Trends

Before exploring how the risk of vehicle crime varies in space and time it is useful to summarise how risk changes in time alone. Where rhythms emerges these can be useful for predicting the times of the day, days of the week or months of the year in which risk might be elevated. Figures 4 and 5 show how the risk of vehicle crime varies in Derbyshire and Dorset throughout the week and by the interval of the day for crimes that occur on the street. To estimate the time of day that an event occurred, the midpoint of the window of time during which the event could have occurred was computed. To increase the reliability of the analyses concerned with the time of day of victimisation, any events for which the interval considered was more than 12 hours were excluded from the analysis.

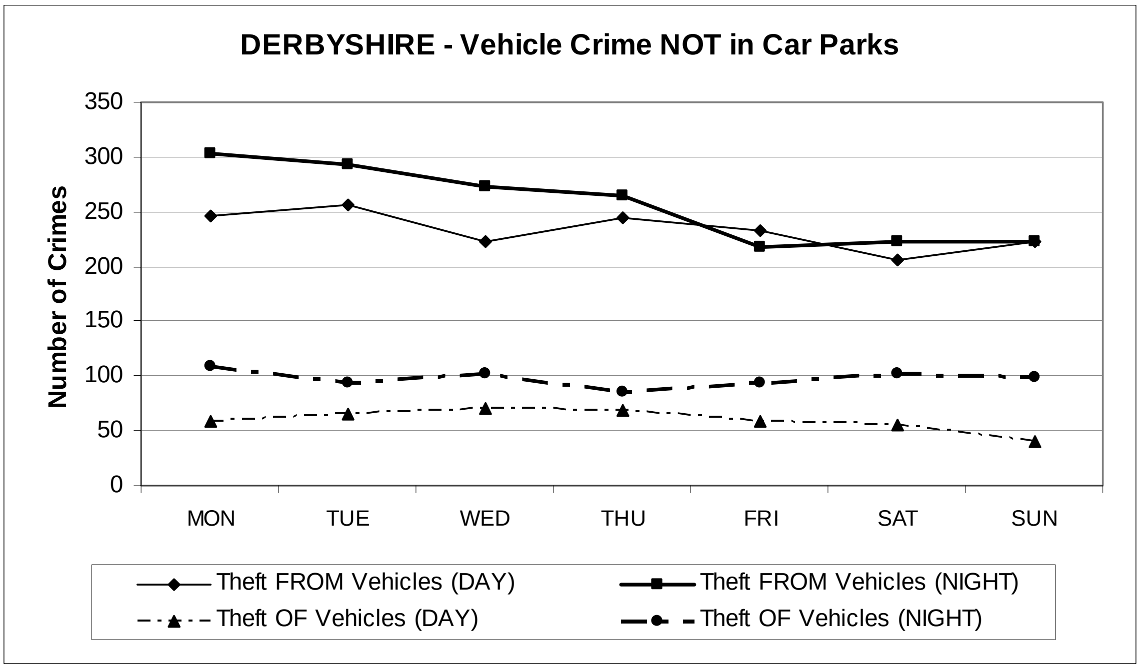


Figure 4 Daily patterns of vehicle crime on the street or on drive ways in

It is evident that both TFMV and TOMV occur mostly during the night. Further analyses (not shown) which included all incidents also suggested that TFMV is slightly less frequent during the middle of the week. These data are consistent with analyses of the British Crime Survey.

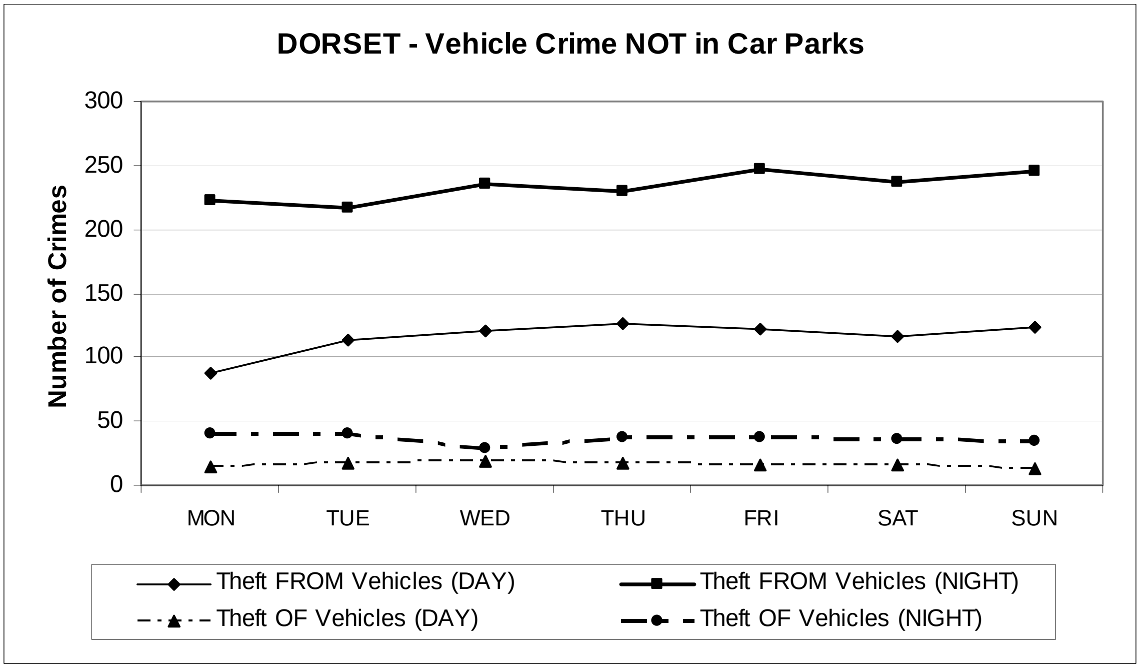


Figure 5 Daily patterns of vehicle crime on the street or on drive ways in Dorset

Considering vehicle crime that occurred in car parks, as shown in Figure 6 a different pattern emerged in Derbyshire. In this county, it generally appears that the risk of both types of crime were greater during the day.

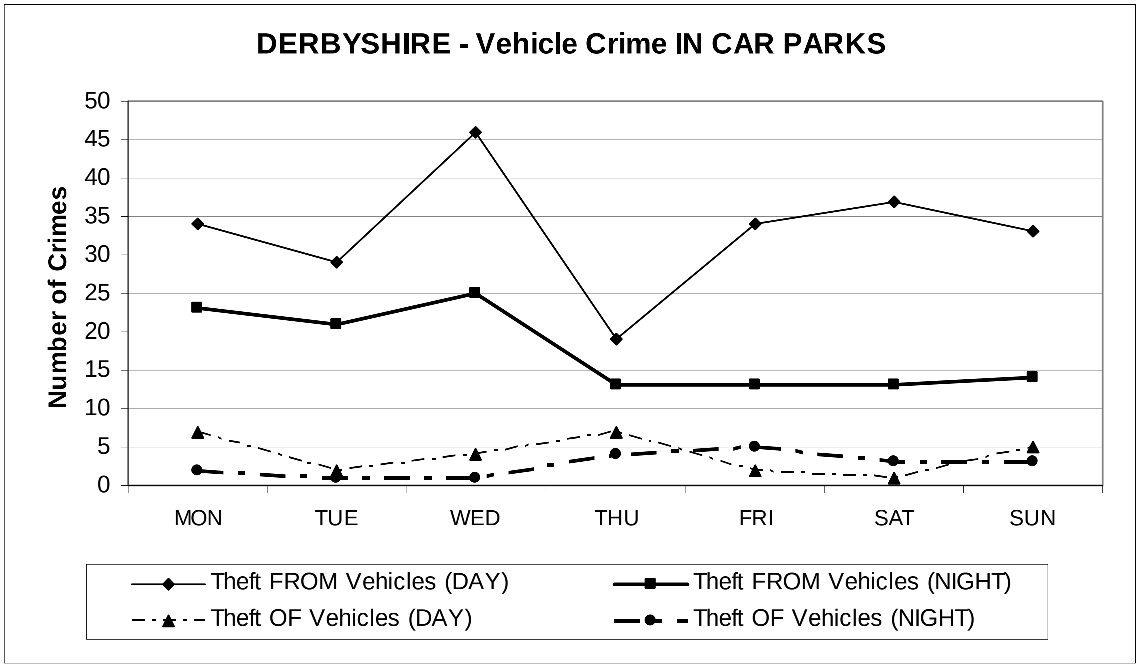


Figure 6 Daily patterns of vehicle crime in car parks in Derbyshire

In Dorset, as shown in Figure 7, the patterns observed in car parks were similar to those observed on the street and elsewhere. The risk of TFMV was greatest in the evening, but there was no systematic trend associated with the day of week. For TOMV, the small sample size precludes any meaningful interpretation of the results.

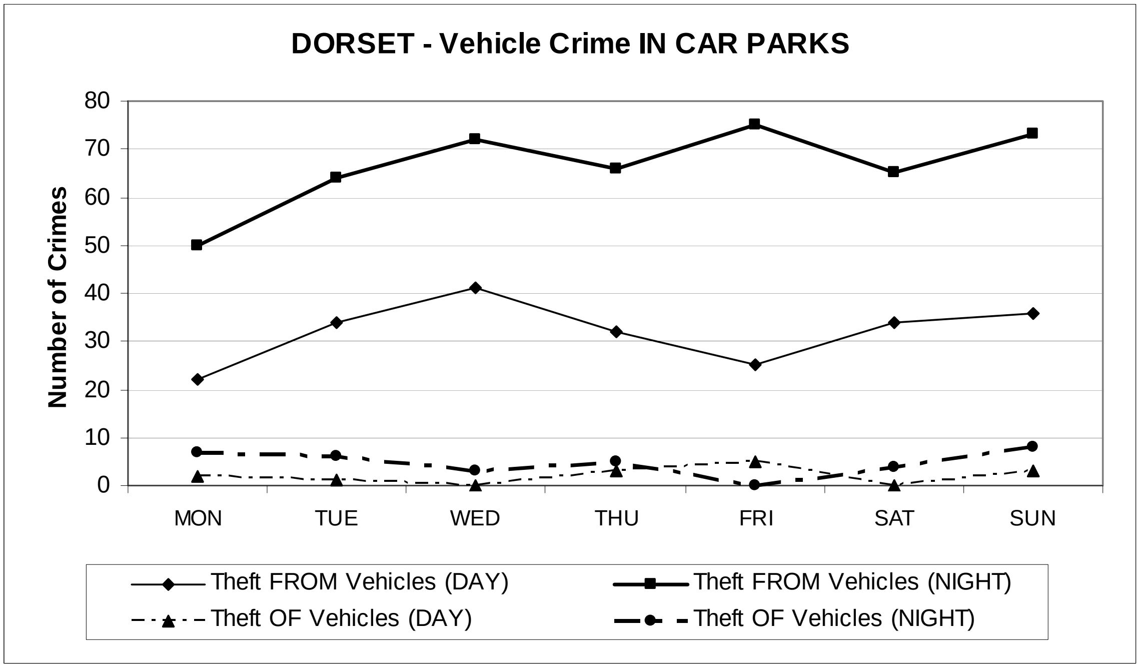


Figure 7 Daily patterns of vehicle crime in car parks in Dorset

Considering seasonal patterns, as only data for one-year were here analysed, it is not possible to establish whether any patterns revealed extend to other years or simply reflect the patterns for this period alone, although the similarity to BCS data where possible suggests robustness of the trends across years. Nevertheless it is instructive to consider the patterns observed for crimes that occurred on the street and those that occurred in car parks. Figures 8 and 9 show the relevant results for Derbyshire.

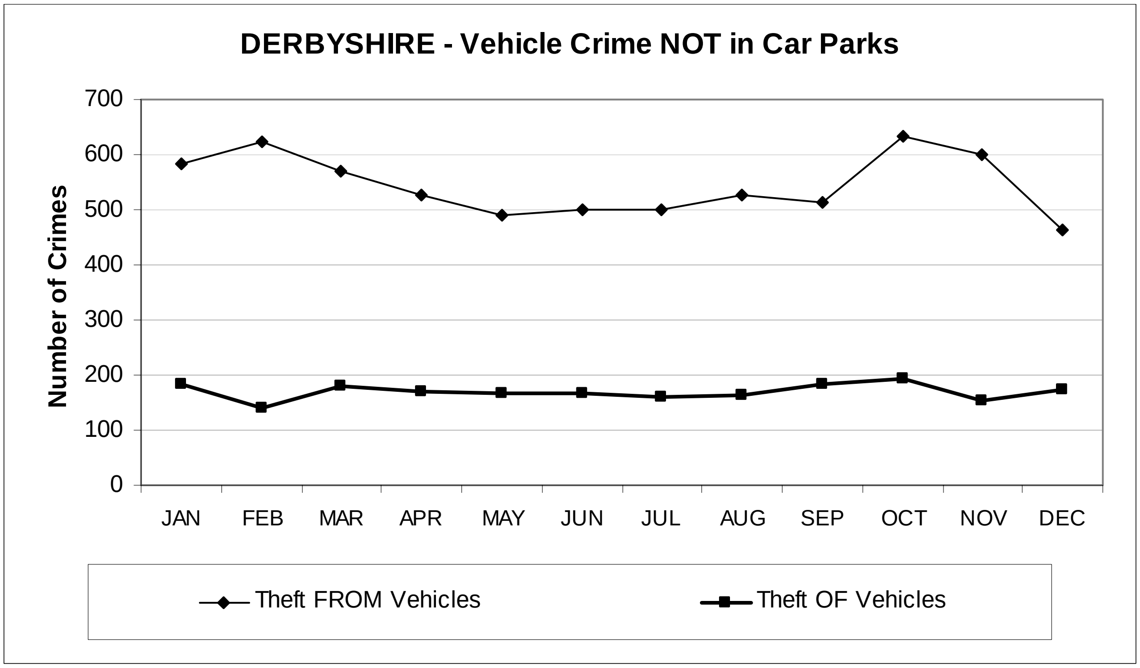


Figure 8 Seasonal patterns of vehicle crime on the street or on drive ways in Derbyshire

Figures 8 and 9 suggest that the risk of TOMV remains fairly constant over the course of the year. However, it appears that for the year considered the risk of TFMV on the street peaked during the autumn and winter months.

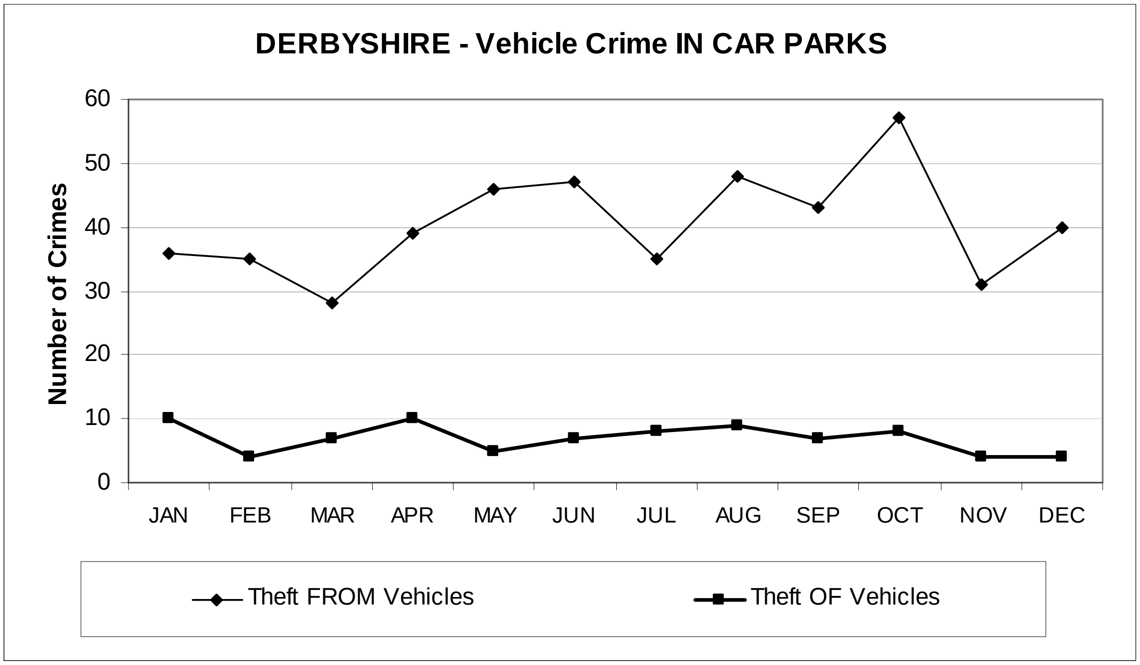


Figure 9 Daily patterns of vehicle crime in car parks

The results for Dorset, shown in Figures 10 and 11, suggest a similar pattern of results for TOMV, but for incidents of TFMV committed on the street, the pattern in Dorset is a little different to that for , emphasising the importance of context in crime analysis.

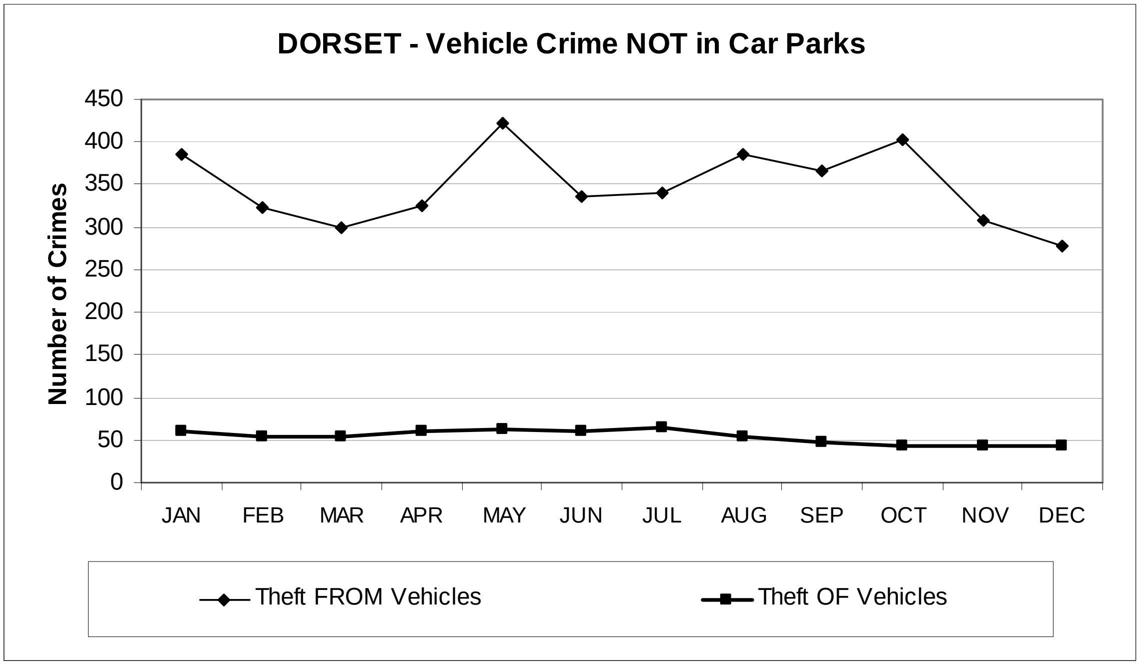


Figure 10 Daily patterns of vehicle crime in not car parks in Dorset

As was the case for , the pattern of results for vehicle crime in car parks in Dorset did not reveal any particular trends that would immediately inform methods of crime prediction.

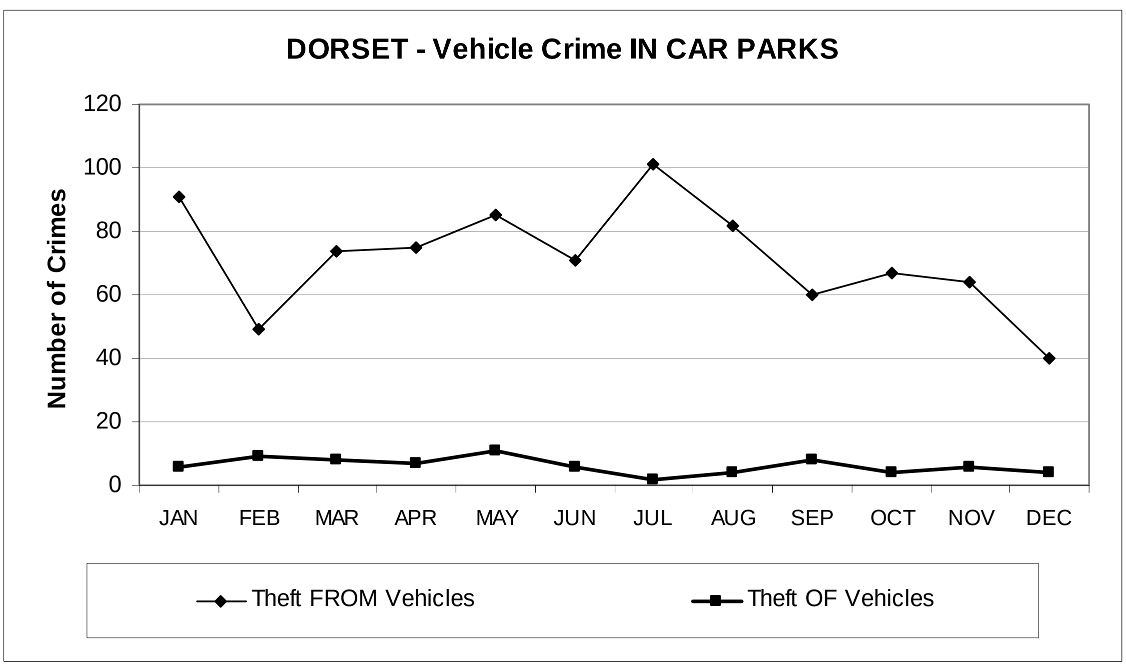


Figure 11 Daily patterns of vehicle crime in car parks in Dorset

Is Vehicle crime Spatially Concentrated?

To determine whether each type of crime was spatially concentrated and thus formed geographic hotspots of crime a nearest neighbour analysis (nna) was conducted. This is a simple diagnostic test of spatial randomness for which the null hypothesis is that crime is evenly distributed across the area considered. This analysis was conducted using a freely available program, CrimeStatIII (Levine, 2004). The output generated by the programme includes descriptive statistics which indicate the average distance between each event and the nearest neighbour to it (the next nearest neighbour, and so on), along with a Z-test and associated p-value for the 1st order nearest neighbour. For the Dorset PFA, and for incidents of TFMV for which a full address was available (N=2,696), the average nearest neighbour of 163m was statistically significant (Z=-76.0, p<0.0001), ie TFMV was spatially concentrated. Similarly, analyses confirmed that TOMV (N=391) was spatially concentrated (Z=-24.61, p<0.0001) more than would be expected on the basis of chance, but that the mean nearest neighbour distance of 626m was substantially larger than that for TFMV.

Having established that for this area, vehicle crime was spatially concentrated, a simple hotspot map was generated using Kernel Density Estimation (KDE). This was also generated using CrimeStatIII and then displayed in a Geographic Information System (GIS). Figure 12 shows the KDE hotspots for both types of crime along with the BCU boundaries for Dorset. The areas shaded red are those for which the density of crime was highest, those not shaded hosted no crime. The different quantiles used to determine the shading were calibrated using a natural breaks function and the data for the TOMV KDE hotspot. Thus, the two maps allow the reader to compare not only where crime is most concentrated but also to see spatial patterns in the differences in risk intensity across the two maps.

Two things should be clear from the maps. First, the risk of TFMV is greater than TOMV, and that both types of crime are particularly concentrated in the two BCUs in the South East of Dorset, these being Bournemouth and Poole (the dividing boundary between the two is unclear from the map). This will not come as a surprise to Dorset police officers. The same analyses conducted for Derbyshire revealed a similar pattern of results, namely that both TFMV (mean 1st order nn distance =175.08 , Z=-70.3, $p<0.0001$, N=2,466) and TOMV (mean 1st order nn distance=318.8, Z=-42.9, $p<0.0001$, N=1,096) were spatially clustered. Figure 12, constructed in exactly the same way as Figure 12 shows the spatial distribution of vehicle crime for this county.

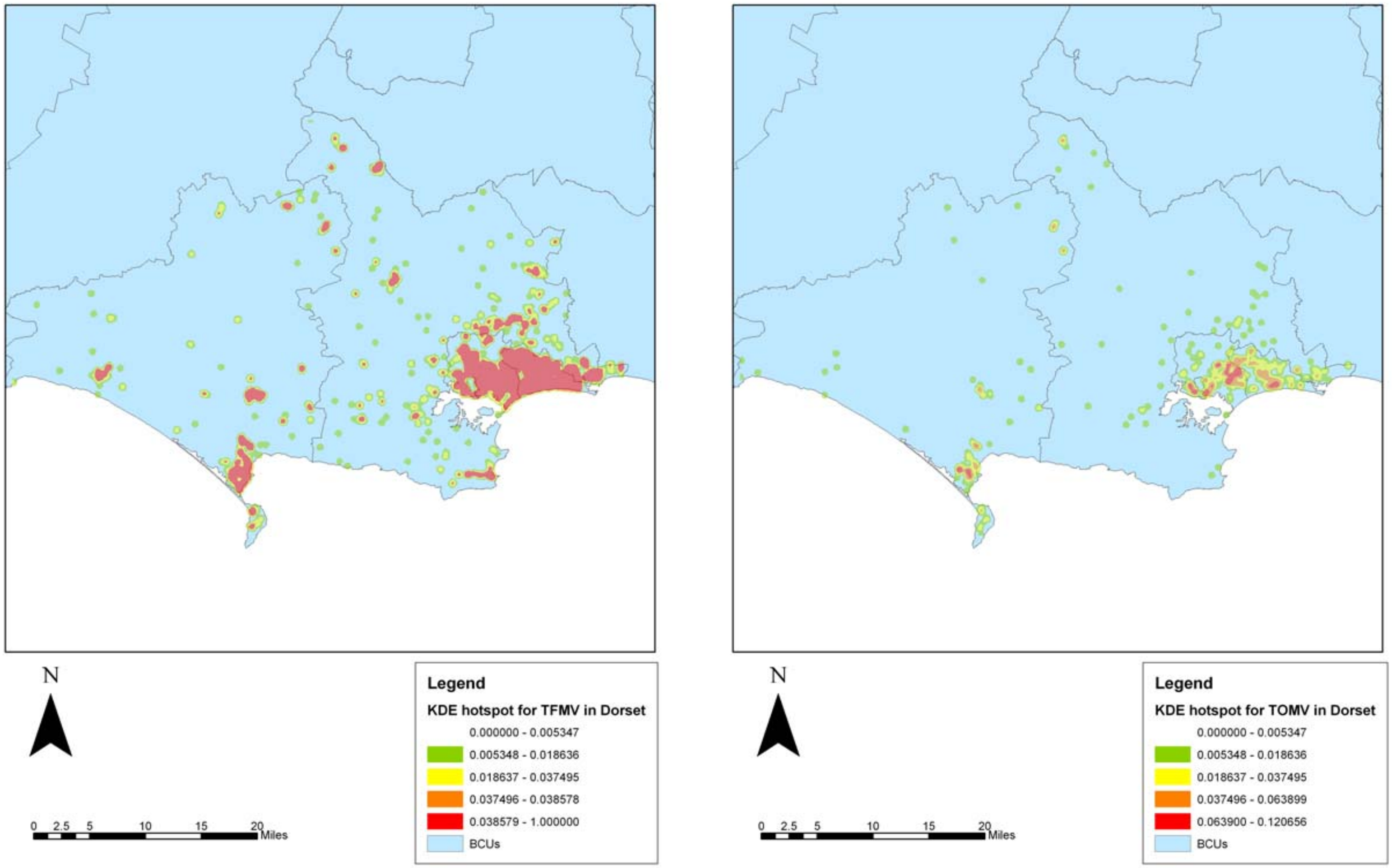


Figure 12 Kernel Density hotspot maps for Dorset (Left Panel: TFMV, Right Panel: TOMV)

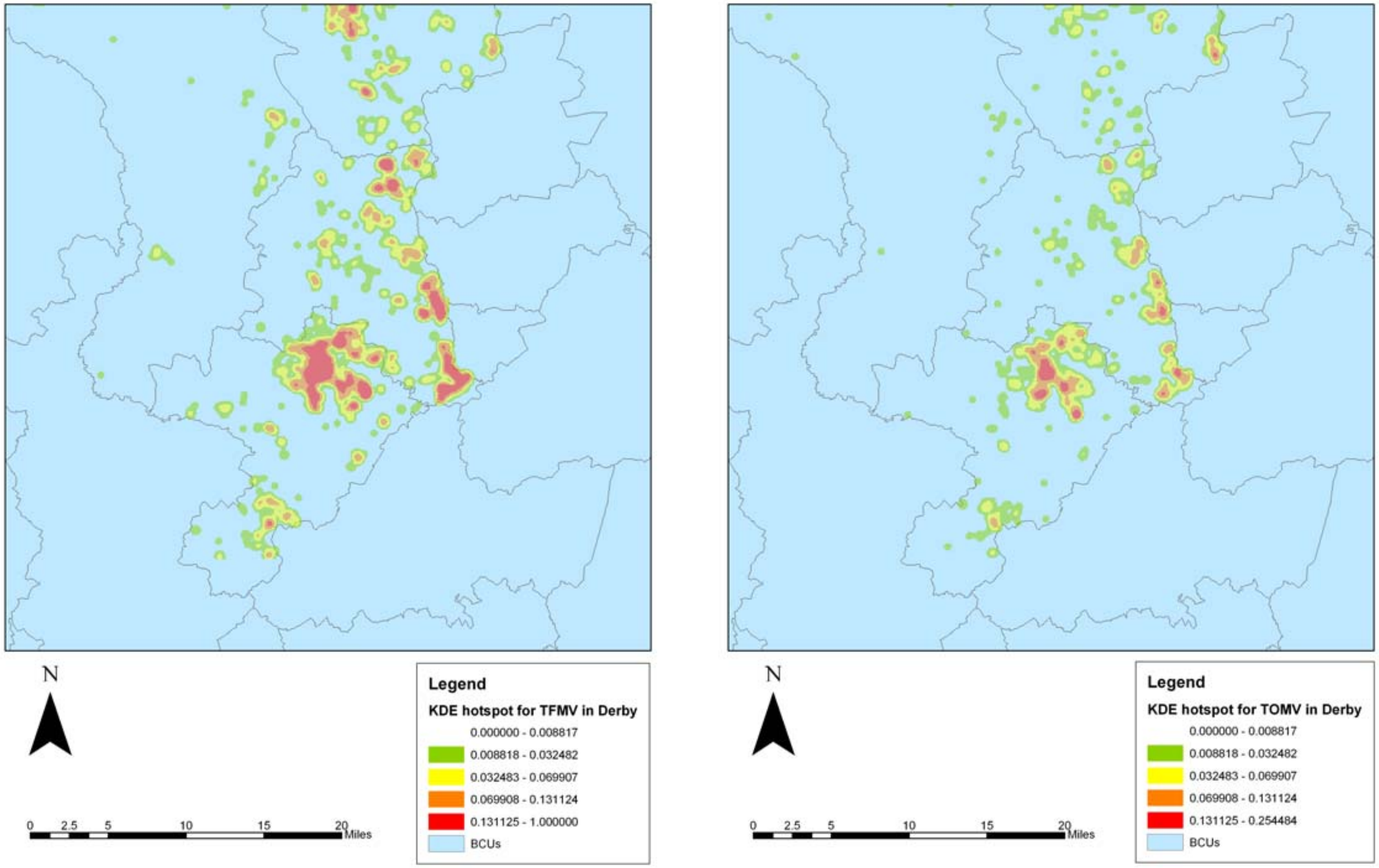


Figure 13 Kernel Density hotspot maps for Derbyshire (Left Panel: TFMV, Right Panel: TOMV)

Does Vehicle crime Cluster in Space and Time? Descriptive Analyses

The above analyses demonstrate that vehicle crime is clustered in space, a finding which has useful implications for generic crime reduction strategies for which the timing of implementation is perhaps not so important. However, in and of itself this is not necessarily of practical value for day-to-day operational policing or other crime reduction interventions whose effectiveness requires a rapid response. For such approaches, the targeting of resources needs more precisely to follow (or ideally anticipate) the rhythm of victimisation. For example, knowing that vehicle crime occurs with greater probability in one area than another is not helpful unless it is also known *when* it is most likely to occur. As noted in the introduction, the finding that burglary clusters in space and time facilitates accurate predictions of when and where it is most likely to occur. Is the same true of vehicle crime.

One simple descriptive way of exploring the patterns of vehicle crime is to calculate what percentage of events occurred near to an antecedent in both space *and* time. That is, how many incidents of vehicle crime occurred within say 400m and one week of a previous event? This provides an easy to understand estimate of the extent to which crime clusters in space *and* time. The latter is, as already discussed, important as we already know that crime clusters in space and follows a temporal trend, but the central question is whether crime clusters in both these dimensions. A methodological difficulty associated with this approach concerns the cut-offs used to define what is considered to be near in both space and time. Thus, an alternative is to vary the definition for one dimension (e.g. distance) at a time and plot the results. This allows the reader to draw their own inferences from a range of possibilities. For this analysis patterns are considered at the county level to provide the reader with a general picture of the results across these areas, whereas in a later section the analyses will be at the BCU level.

Theft From Motor Vehicle (TFMV)

Figure 14 shows the percentage of incidents of TFMV in Dorset which occurred within 400m of an earlier event, plotted as a function of the time elapsed between the two. In this analysis, the first three months of data were used as a temporal buffer period to allow all proximate events that occurred up to three months apart (around 90 days) to be identified. Accordingly, the denominator used in the analysis (N=2,055) was less than the total volume of crime for the one-year period for which data were available.

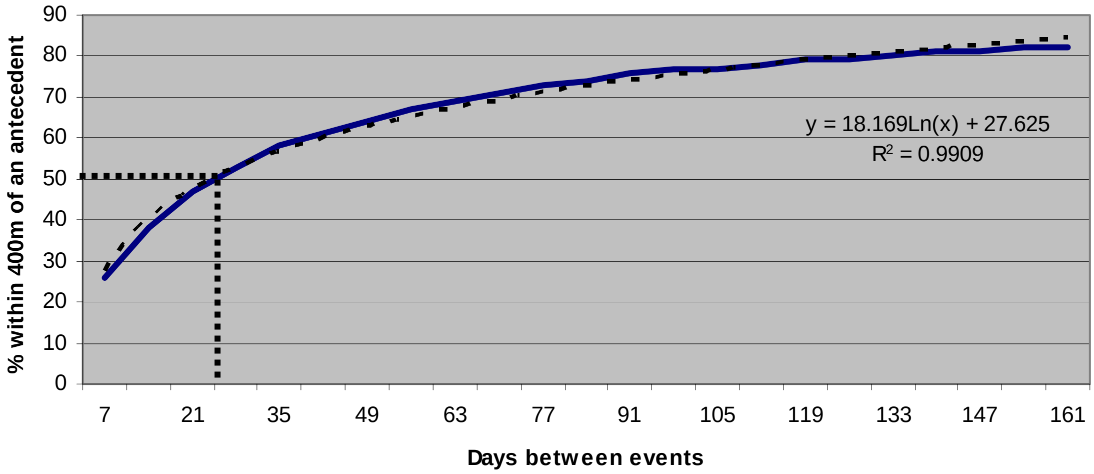


Figure 14 Cumulative percentage of TFMV events that occurred within 400m of an antecedent in Dorset

Figure 9 indicates that a high proportion of events occur within 400m of other incidents relatively quickly. For example, just under 40% of events took place within 14 days and 400m of an earlier event, one-half in less than 28 days. A simple regression analysis of the trend revealed that a logarithmic function fitted the data well, thereby confirming the observed trend in the data- that when events occur near to each other in space they tend to do so quickly, and are ever less likely to occur as time elapses. As many events occurred within one-week of a nearby incident (28%) a natural question that arises is whether most took place on the *same* day. If this were the case then there would be no window of opportunity for crime reductive responses. A follow-up analysis revealed that only 5% of incidents took place on the same day as a nearby event, about the same proportion (5.5%) took place a day later. Thus, although many do take place on the same day as each other, most do not. There is time to take some preventive action for the bulk of predictable events.

Figure 15 shows the same analysis for Derbyshire (N=2,428). A similar pattern emerges although the pattern is slightly less concentrated. For example, around 30% of all events occurred within 14 days of an antecedent and one-half of all incidents of TFMV occurred within 400m and six weeks of an earlier event. Again, a follow-up analysis was conducted to see how many events occurred on the same day as a previous event. In

Derbyshire just over 6% of incidents occurred on the same day and within 400m as an antecedent event (another 4% a day later) thereby meaning that the window of opportunity for preventing incidents of TFMV in Derbyshire , as in Dorset, is unlikely to be too short to inform crime reduction activity.

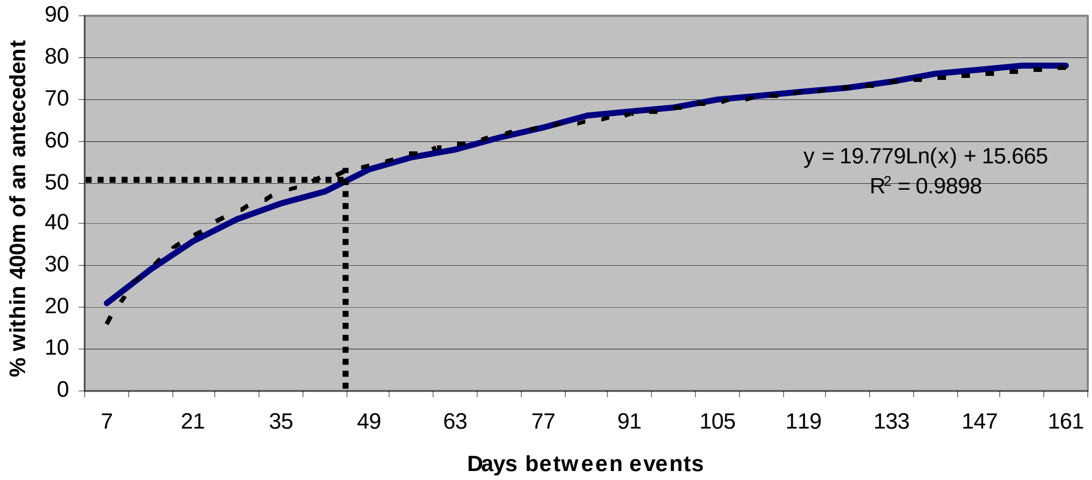


Figure 15 Cumulative percentage of TFMV events that occurred within 400m of an antecedent in Derby

Figure 16 shows a similar analysis, but in this case the propinquity of events that occurred within one-week of each other is considered. In this case only a one-week temporal buffer period was required (N=2,503). This reveals that around one-half of all incidents of TFMV in Dorset occurred within one-week and 800m of each other. The logarithmic trend in the data suggests that when events occur swiftly they tend to occur near to previous incidents.

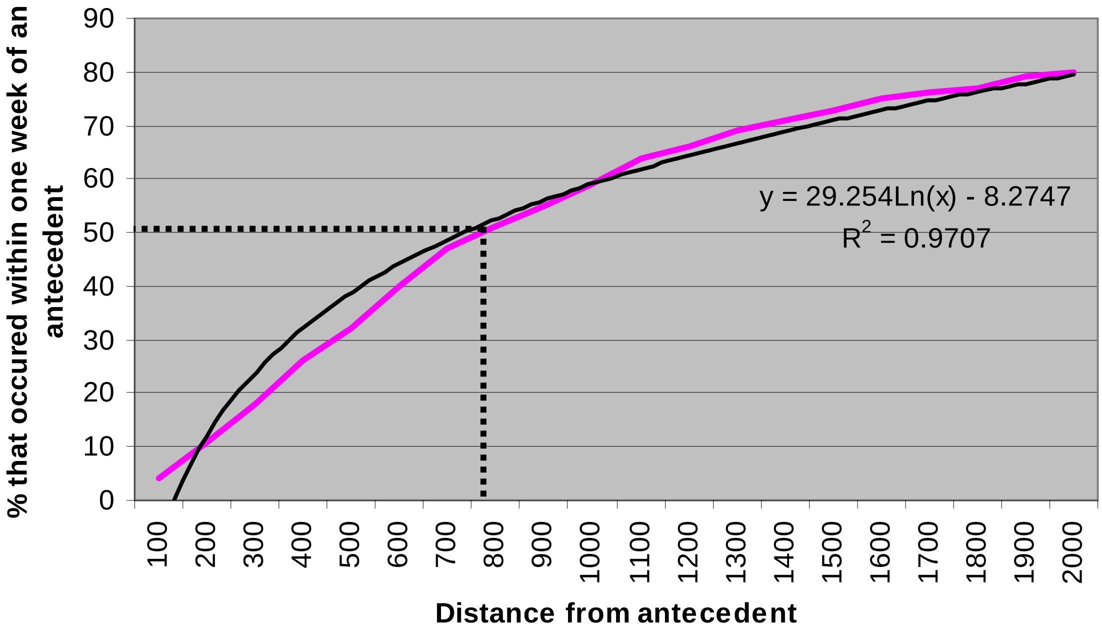


Figure 16 Cumulative percentage of TFMV events that occurred within one-week of an antecedent in Dorset

Figure 17 shows the same analysis for Derbyshire. A similar pattern emerges, although the gradient of the curve is less acute indicating that the events were slightly more spatially and temporally diffused. Taken together, the results suggest that in both Dorset and Derby incidents of TFMV cluster in both space *and* time. However, while such results provide a useful diagnostic function, they are merely descriptive and do not demonstrate that the patterns observed are statistically reliable. To do this more complex analyses discussed in a subsequent section are required. Readers less concerned with the statistical niceties and more with practical application may prefer to skim the two sections which immediately follow.

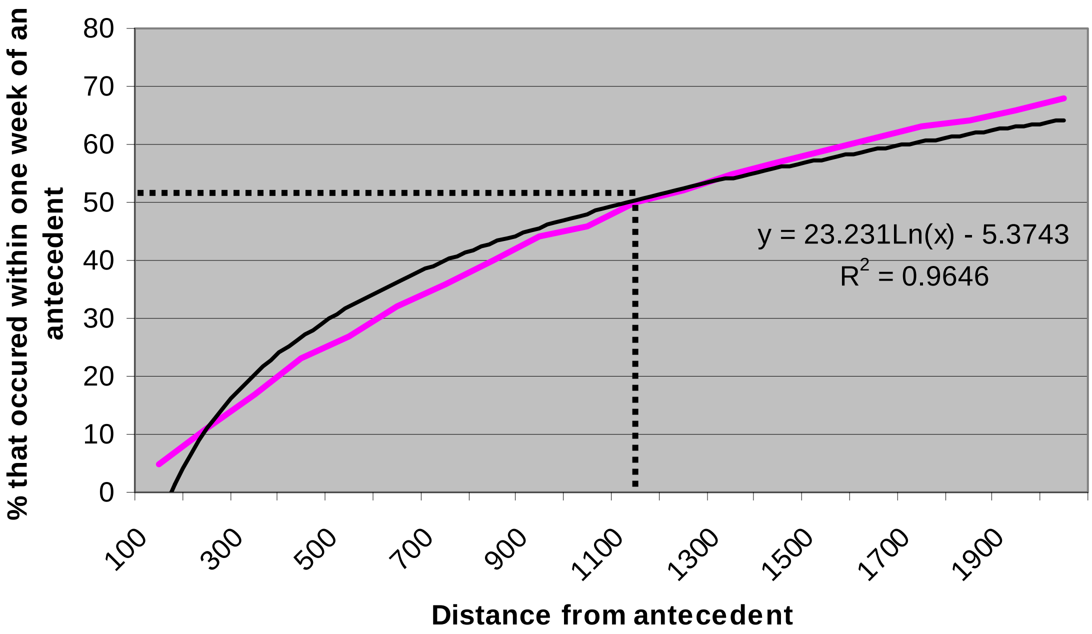


Figure 17 Cumulative percentage of TFMV events that occurred within one-week of an antecedent in Derby

Theft of Motor Vehicle (TOMV)

The same analyses were conducted for TOMV. The results for Dorset are shown as Figures 18 and 19. Figure 18 shows that this type of crime is less concentrated than TFMV. Considering those events that occurred within 400m of each other, a much smaller proportion occurred rapidly. For example, only 10% occurred within 14 days of a previous event (compare to 40% for TFMV for the same area). Regression analysis confirmed that a linear trend fitted the data best, suggesting that any elevation in risk within the area of a previous event was time invariant.

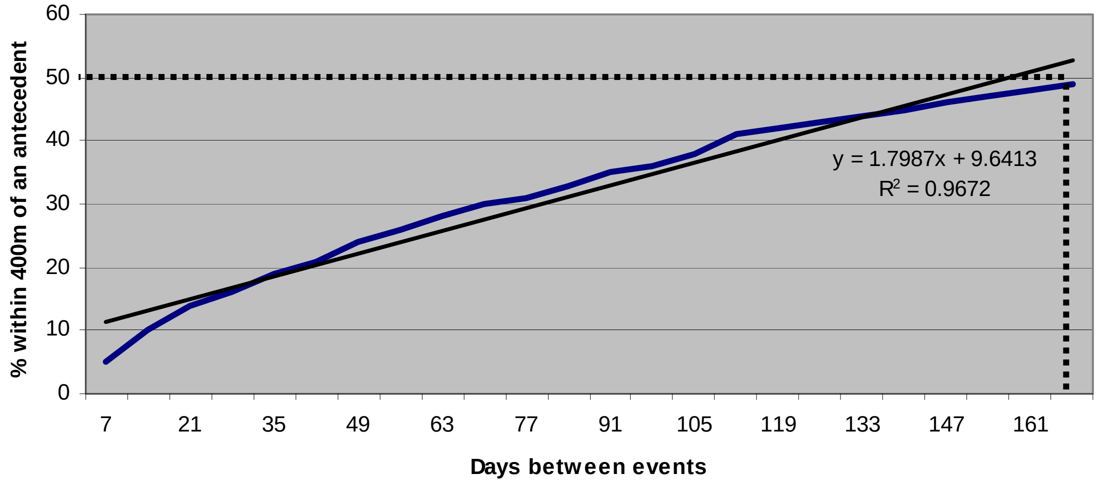


Figure 18 Cumulative percentage of TOMV events that occurred within 400m of an antecedent in Dorset

Figure 19 shows the same analysis for Derbyshire, and indicates a more pronounced trend, with around 25% of all incidents occurring within 400m and hour weeks of another. Although the pattern is much less concentrated than for TFMV, unlike the pattern observed for Dorset, the trend for this type of crime in Derbyshire was not quite so linear. In fact, a logarithmic function provided a better fit of the data.

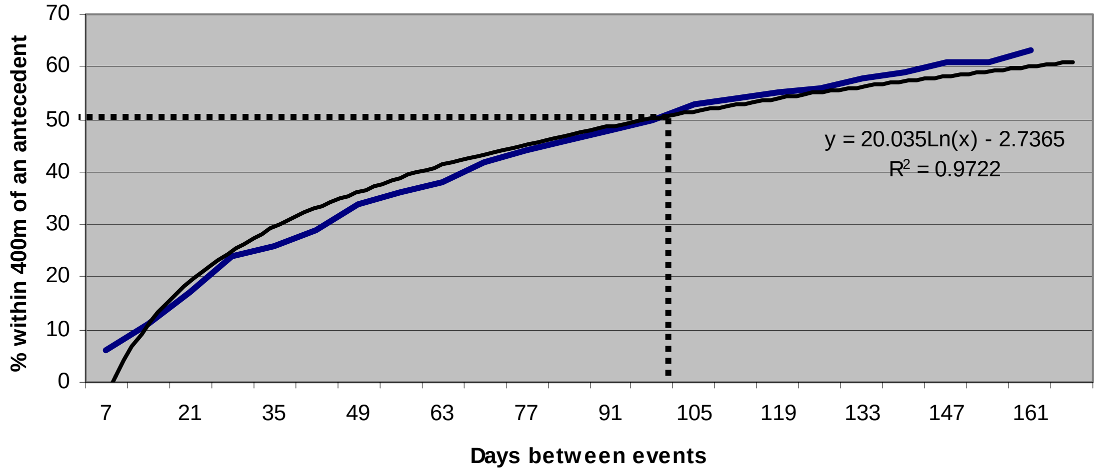


Figure 19 Cumulative percentage of TOMV events that occurred within 400m of an antecedent in Derbyshire

Figure 20 reveals that a much smaller proportion of events of TOMV occurred within one-week and near a previous event. By way of a comparison, around 13% of incidents of TOMV occurred within 800m and one-week of a previous event (compare to 50% for TFMV for the same area). Only 25% of events occurred within one week and less than 1500m of an antecedent.

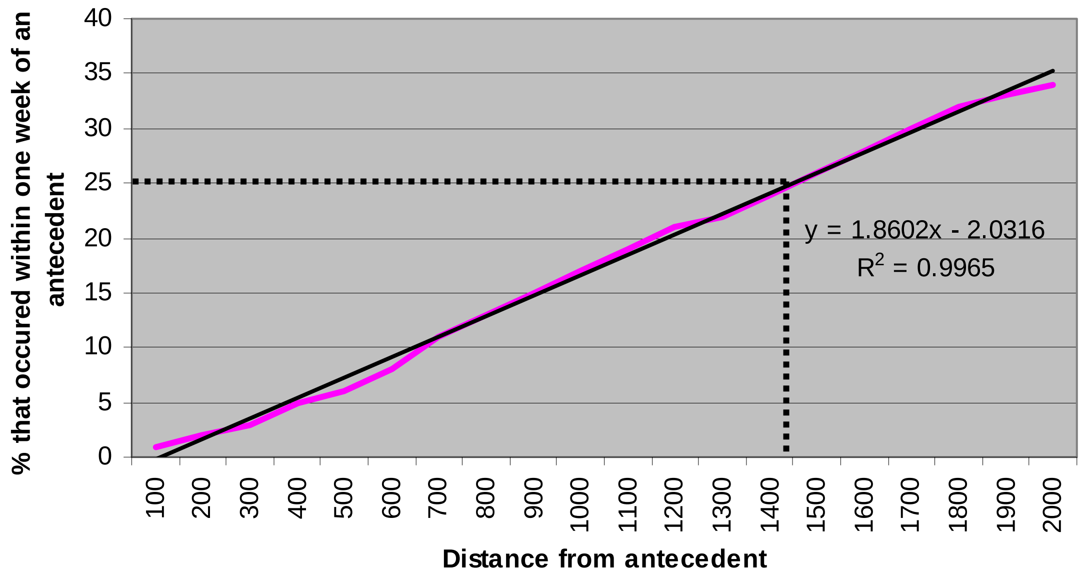


Figure 20 Cumulative percentage of TOMV events that occurred within one-week of an antecedent in Dorset

A similar pattern of results emerged for Derby, although as shown in Figure 21, the coefficient of the trend line was somewhat larger, thereby indicating that events which occurred within one week of each other on average tended to occur nearer together. For example, in Derbyshire, 25% of incidents occurred within 1,100 m of an earlier event (compared to 1500m for Dorset). Nevertheless, it is clear that TOMV is much less concentrated in space *and* time than TFMV.

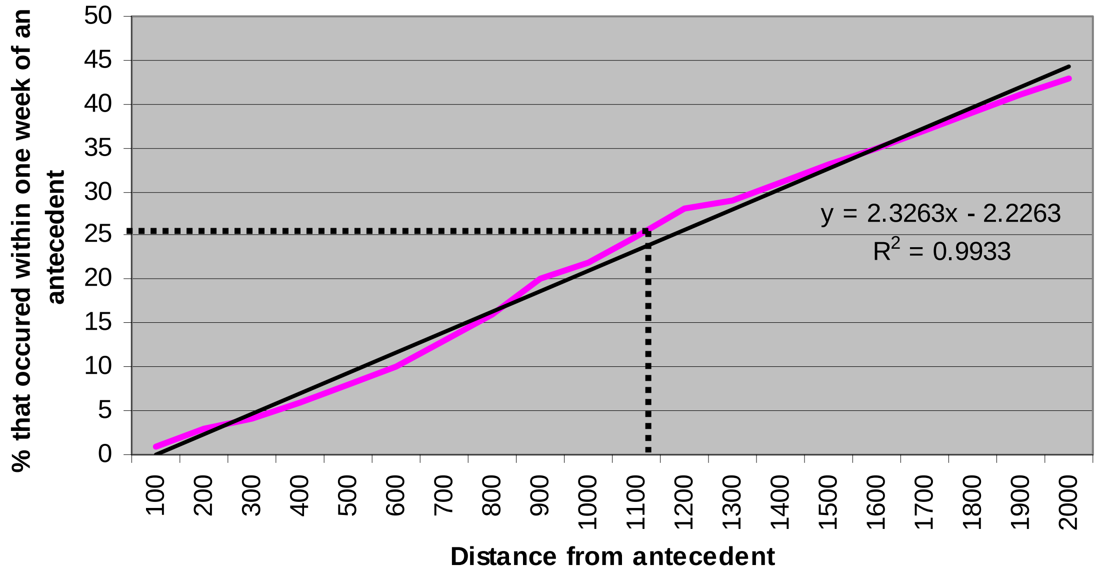


Figure 21 Cumulative percentage of TOMV events that occurred within one-week of an antecedent in Derbyshire

Testing the statistical significance of Space-Time Clusters of Vehicle crime

Empirical research concerned with the space-time clustering of events was first conducted by Knox (1964) to study epidemics of childhood leukaemia. Being a rare disease with an aetiology largely unknown, it was hypothesized that there was an element of communicability involved in the disease. Knox derived a method to detect the communication of risk using epidemiological data on the times and places of disease onset. The rationale underlying the Knox test is to determine whether more events 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, such as shown in the table below, with i columns and j rows is then populated. For example, cell n_{11} would give the number of event pairs that occur within 14 days and between 1-100 meters of each other[3]. The spatial and temporal increments (or bandwidths) used in the rows and

[3] The focus of the current study was on proximate events, and hence pairs of incidents which occurred at the same address (repeats) were excluded from the analysis. The inclusion of such

columns can be arbitrary, although they should be so defined as to allow specific hypothesis informed by the underlying theory to be tested. For instance, in the case of crime the question is over what distance does crime risk propagate, and for how long does this endure? Ideally, the bandwidths selected should have relevance to operational policing.

	14 days	28 days	42 days	…………..
100m	n_{11}	n_{21}	n_{31}	
200m	n_{12}	n_{22}	n_{32}	
300m	n_{13}	n_{23}	n_{33}	
400m	n_{14}	n_{24}	n_{34}	
……..				

Once the contingency table (hereafter, the Knox table) has been generated, the cell counts can be compared against the expected cell values computed under the assumption that the time-distance and the space-distance are unrelated (the null hypothesis). In the case of communicability, the observed counts will be significantly higher than the expected counts in the cells for which events occurred both close in space and time. One complication is that the assumption of independence of observations, a common criterion for most inferential statistical methods, 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, Knox suggested that in the absence of a space-time interaction, the statistical distribution of the expected values for the cells of the contingency table would conform to a Poisson distribution and could be computed in the same way as a Chi-Square test, using the marginal totals of the table.

events would have skewed the results. Of course, in such cases both incidents would still be compared with all other events occurring at different addresses.

Monte-Carlo Simulation

An alternative approach, for which the independence of observations is not a requirement, may also be computed. 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 Monte-Carlo Knox test, the dates are randomly shuffled using a pseudo-random number generator, whilst the spatial locations remain fixed[4]. This process of generating permutations is repeated a number of times, say 999 iterations, and a new contingency table generated each time which is compared with the contingency table for the observed distribution. The hypothesis is that if there is statistically significant space-time clustering in the data then there should be more events occurring close in space and time for the observed data than for 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 following formula (see North, 2002):

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

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

In the current research the data are analyzed using the Monte-Carlo method. Different temporal bandwidths could be used to examine the patterns of space-time clustering, but intervals of 14 days are used here. In relation to the spatial parameter, intervals of 100m are used. The results focus on intervals up to and including 365 days, and 1km. This produces a contingency table 26 by 10 with 260 cells.

In addition to calculating the statistical significance of the results, estimates of the effect size may also be derived. One simple method was illustrated above, but calculating this metric takes no account of what would be expected on the basis of chance, given the

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[4] Although in terms of relativity, one might argue that the spatial coordinates are shuffled and the dates remain fixed.

actual spatial and temporal distribution of exploited opportunities for crime. An alternative is to compute for each cell of the contingency table the ratio of the observed count and the mean or median of the expected counts, derived using the Monte-Carlo Simulation[5]. The latter approach is used here. To illustrate the Monte-Carlo approach and the results generated in a little more detail, an example for one cell of one contingency table will first be considered. For the Bournemouth BCU in Dorset, there were a total of 1,094 incidents of TFMV for which complete addresses were available. For these data, there were a total of 111 pairs of crimes that occurred within 14 days and 100m of each other. The (median) expected value of 74 (mean=74.3) was significantly lower (for every iteration of the simulation and thus $p<0.001$) and the observed to expected ratio was 1.50. Thus, there were observed around 50% more pairs of events of TFMV that occurred within 100m and 14 days of each than would be expected if there was no regularity to the timing and location of events (taking account of when and where the crimes did actually occur).

A particular challenge with this type of research is of how to display the results. Contingency tables could easily be presented but for (ease of interpretation and) parsimony in this paper we present a risk surface for one area in each county. In relation to this issue, it is possible to compute the results for each county considered as a whole, but the problem with this analytic strategy is that different areas within the counties are likely to have different profiles due to variation in the spatial constellation of opportunities across the county and the different offenders that operate within them. Consequently, aggregating the data for too large an area (such as the PFA) may distort the patterns, reflecting the profile of none of the individual areas. Determining how to disaggregate the areas for analysis is somewhat arbitrary and any classification is open to the Modifiable Areal Unit Problem (MAUP: Openshaw, 1984) whereby changing the boundary used may have an impact upon the results observed. However, while changing the boundaries used is likely to affect the precise results (e.g. the exact value of each odds ratio and p-value) it is unlikely to affect the general findings unless any patterns are specific to only a few areas.

For simplicity, and for practical purposes in relation to operational policing, it was decided that a sensible approach would be to complete the analyses separately for one police Basic Command Unit (BCU) in each county. Other possibilities exist, but this criterion seemed to offer a compromise between producing the results for too large an

[5] The authors would like to thank Wim Bernasco (NSCR) for this suggestion.

area that would fail to reflect the patterns within the smaller areas that it comprised, and generating the results for small areas in which the volume of crime would perhaps be too low to ensure the reliability of the patterns observed.

Theft from Motor Vehicle

Figure 21 shows the results for TFMV for the Bournemouth BCU in Dorset using only data for which a full address was available (N=1,094). Points on each line which have a symbol represent statistically significant odds ratios.

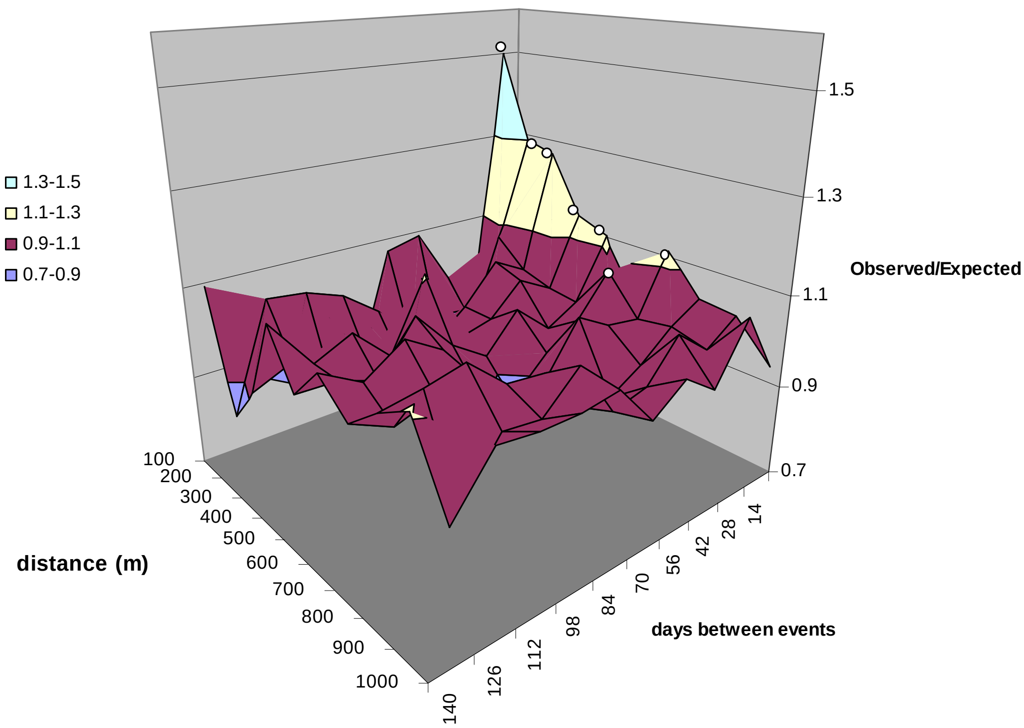

Figure 21 Surface of observed to expected numbers of pairs of TFMV events at different spatio-temporal intervals for the Bournemouth BCU in Dorset (white dots indicate statistical significance, p<0.01)

It is immediately apparent from the results for Bournemouth that the risk of TFMV clusters in space and time, as the odds ratios are greatest for pairs of events which occurred shortly after and near to each other. There is consequently a clear pattern of distance decay whereby the value of the odds ratios are more extreme (and statistically significant) for pairs of events that occurred closest to each other in both space and time. Although not shown, similar results were observed for other BCUs in Dorset.

The same analysis, shown as Figure 22, was completed for Division A BCU in Derby and a similar pattern of results emerged. However, in this area the patterns were less acute, a finding which chimes with the descriptive analyses presented above. Thus, there were observed significantly more events that occurred swiftly at somewhat greater distances as well as nearby. When interpreting this pattern, it is important to consider not only to the level of significance observed but, and perhaps more critically, the effect size. With this in mind, it is clear that for both areas for TFMV there was clear evidence of distance decay in relation to the effect sizes observed. This profile appears to be fairly typical of those for the other BCUs in Derby (not shown).

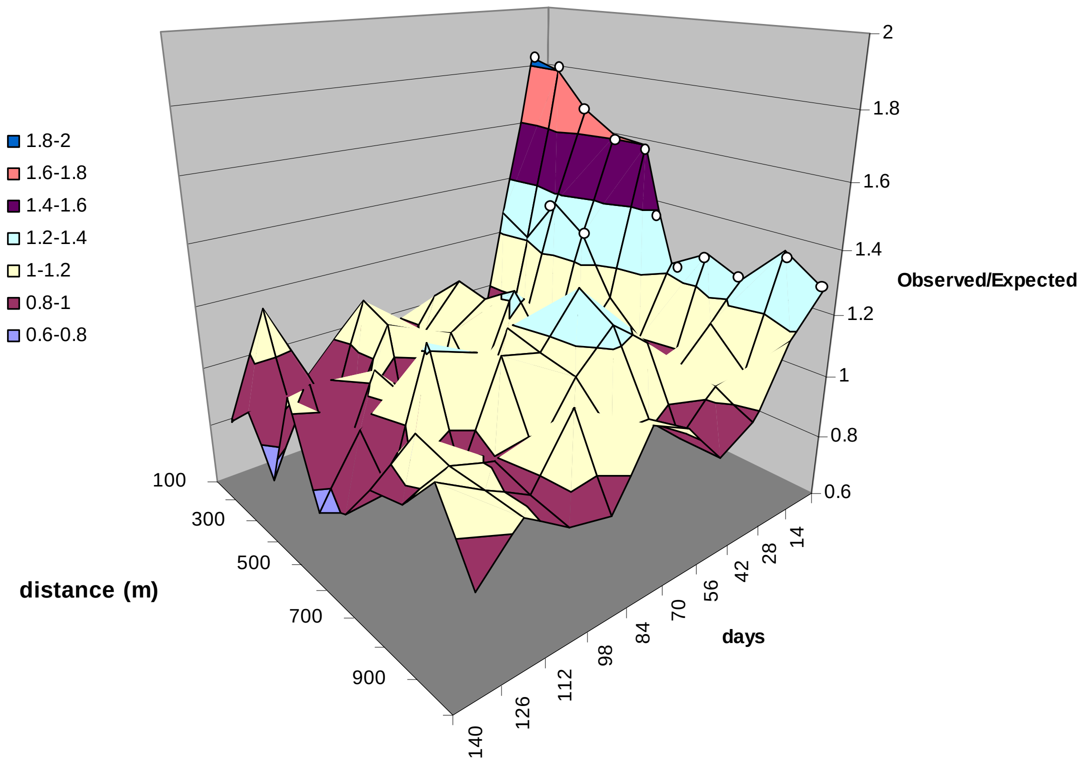

Figure 22 Surface of observed to expected numbers of pairs of TFMV events at different spatio-temporal intervals for Division A BCU in Derby (white dots indicate statistical significance, p<0.01)

Theft of Motor Vehicle

Unfortunately, for Dorset the small sample size precluded a meaningful analysis using the Monte-Carlo approach. This is because the cell values were so small that any inferences drawn would be at best weak. However, for Derby the numbers were somewhat larger and thus an analysis was conducted. Division D had the greatest volume of crime for which complete addresses were available and hence the analysis was conducted for this area. The results, shown as Figure 23, demonstrate that there was no real pattern. Although not shown (they are not visible due to the shape of the surface), only two of the Odds ratios were statistically significant at the 1% level, and these were randomly located within the contingency table. This suggests that, in Derby at least (the same pattern was evident for Division A), the risk of TOMV is not communicable.

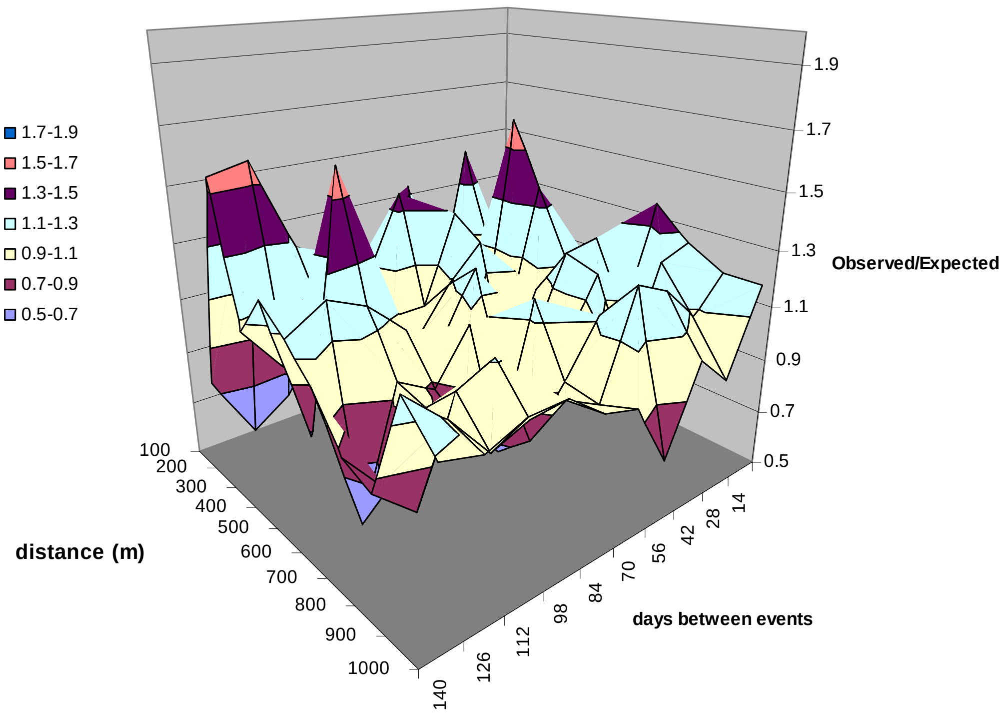

Figure 23 Surface of observed to expected numbers of pairs of TOMV events at different spatio-temporal intervals for Division D BCU in Derbyshire

Summary and Conclusions

To recapitulate, the findings demonstrate that:

- For the two study areas, complete addresses were available for a fairly high proportion of incidents of vehicle crime, particularly for TFMV. However, addresses were better recorded in one area than the other.

- There are distinct temporal patterns for vehicle crime, with this type of crime being greatest in the evening.

- This type of crime is spatially concentrated leading to the formation of geographical hotspots

- Importantly, TFMV was shown to cluster in both space *and* time. That is, when an event occurs at one location another is likely to occur soon after. To use the vocabulary of an epidemiologist, like burglary the risk of vehicle crime is communicable.

- The finding that TOMV does not cluster in the same way as TFMV demonstrates that there is evident selectivity to the spatio-temporal signatures of these two types of vehicle crime. This may suggest different targeting or foraging strategies are employed for these two types of crime

It is suggested that the distinct patterns observed for TFMV enable prospective mapping- the prediction of the future locations of crime. In addition to the data here analysed, each force recorded useful information concerning the Modus Operandi used for each offence. Further research may seek to determine the potential usefulness of these data for crime linking or for refining predictions about when, where and how future crimes might occur (see Bowers and Johnson, 2005; Johnson and Bowers, 2006). A further obvious next step would be to see if the spatio-temporal distribution of one crime affects that of another. For example, does a burglary victimisation at one location increase the risk of vehicle crime nearby? The evident versatility of offenders (e.g. Scheider, 2005; Deane, Armstrong & Felson, 2005) is one reason for hypothesising that this may be the case.

One issue with respect to the above analyses is that by only including events for which full addresses were available, the results of the analyses may be biased and have implications for only this sub-sample of events. It is plausible that those events that were excluded from the analyses differ from those analysed in systematic ways. One obvious difference is that no events that took place within car parks were considered in the analyses of space time clustering. The reasons for the exclusion of these types of events should be obvious, but it is useful to rehearse them here. For car parks, the problem is that the grid references supplied typically correspond to the centroid of the facility. Thus, there is little spatial precision in the data, and in some cases the car parks are large with the coordinates of an offence varying not only in terms of x and y coordinates but, in the case if multi-storey car parks, also on the z-axis. Nevertheless, this does not mean that the data for events that took place in car parks are unhelpful. In fact, even this level of data means that useful analyses can be performed to see if there exist patterns in the timing with which events occur at particular car parks, or nearby. In a sense, and in particular, events which occur at the same car park can be thought of as a special case of repeat victimisation. Thus, further research is suggested.

Also excluded were crimes for which a complete address was unavailable. The problem with such events is that they introduce a level of uncertainty into the analysis with respect to the spatial distribution of events. This uncertainty could distort the results in two ways. First, if the error is random and quite substantial then any real patterns in the data may be diluted or even masked by white noise. And, second, if there is a systematic pattern to the errors (for example if the midpoints of a series of long roads are frequently used when in fact the events occurred at different points along them) this may inflate the patterns creating an illusory effect or overemphasising those patterns which are representative of the true space-time distribution of crime.

Thus, the inclusion of these events could have a number of different detrimental effects on the inferences made, increasing the likelihood of false positives or of decreasing the identification of real patterns. Moreover, and importantly, it is worth making the point that even if the patterns described do not generalise to all incidents of vehicle crime, if they are representative of the sub-samples considered and regularities such as those described exist, then the findings still have clear implications for a substantial proportion of the problem, in the case of Dorset at least 70% of vehicle crime recorded by the police and in Derby for around 50% of such crimes. If it were possible to predict the location of 50% of only these incidents, then substantial reductions in these types of crime might be realised or detections potentially facilitated.

Only superficial analyses concerned with temporal patterns of vehicle crime were presented here. Further analyses are desirable. Research concerned with burglary victimisation (Sagovsky and Johnson, 2006) has shown that repeats at the same address and those that occur nearby (Johnson et al., 2006) tend to occur during the same time of day as an antecedent event, and thus determining whether similar patterns are evident for vehicle crime would be a useful next step. In addition, time series analyses, such as the Box-Jenkins approach to forecasting, could be incorporated into models of next event prediction to refine estimates of when the probability of crime is greatest, or to estimate the likely volume of crime for a particular place and time.

As a tentative explanation for the extended clustering observed in Derby for TFMV, we suggest that this may be explained at least partly by simultaneous clustering over geographical ranges of this order. Consider (for example) that a number of offenders or teams of them may operate within a larger area, each committing a series offences that form a distinct space-time cluster. If a series of such clusters emerge at (say) 1000m from each other, then this would easily generate the patterns observed. It is important to emphasise the selectivity of the patterns- the effect sizes were greatest for events that occurred closest to each other.

To conclude, the prediction of the precise future locations of crime has received relatively little attention within the research literature or in front line policing. Research such as that presented here suggests that this is a worthwhile enterprise. Further research that aims to identify factors that might facilitate or impede the communication of risk would aid in the development of predictive systems of increasing efficacy. The next step is to move from describing patterns in the data to generating predictive models, such as those developed by Bowers et al. (2004) and others.

References

Besag, J. & Diggle, P.J. (1977). *Simple Monte Carlo tests for spatial pattern*. *Applied Statistics*, 26, 327-333.

Bowers, K.J., Johnson, S.D., & Pease, K. (2004). Prospective Hot-spotting: The Future of Crime Mapping? The *British Journal of Criminology,* **44**(5), 641-658.

Bowers, K.J., & Johnson, S.D. (2005). Domestic burglary repeats and space-time clusters: the dimensions of risk. *European Journal of Criminology*, **2**(1), 67-92.

Bowers, K.J., & Johnson, S.D. (2004). A Test of the Boost explanation of Near Repeats. *Western Criminology Review*, **5**(3), 12-24.

Cornish, D. and Clarke, R.V. eds. (1986), *The Reasoning Criminal.* NewYork: Springer-Verlag.

Deane, G., Armstrong, D.P., and Felson, R.B. (2005). An Examination of Offense Specialization Using Marginal Logit Models. *Criminology*, 43(4), 955-988.

Farrell, G., and K. Pease. 2006. 'Preventing Repeat Residential Burglary: A Review' in B. C. Welsh and D. P. Farrington (Eds.) *Preventing Crime: What Works for Children, Offenders, Victims, and Places* Dordrecht: Springer*.*

Forrester, D.; Chatterton, M. & Pease, K. (1998). The Kirkholt burglary prevention project, Rochdale. *Police Research Group Crime Prevention Series 13*. London: Home Office.

Johnson, S.D., & Bowers, K.J. (2004). The burglary as clue to the future: The beginnings of prospective hot-spotting. *European Journal of Criminology*, **1**(2), 237-255.

Johnson, S.D., Bowers, K.J., Young, C.A. & Hirschfield, A.F.G. (2001). Uncovering the true picture: Evaluating crime reduction initiatives using disaggregate crime data. *Crime Prevention and Community Safety: An International Journal,* ***3****(4), 7-24.*

Johnson, S.D., Bernasco, W, Bowers, K.J., Elffers, H., Ratcliffe, J., Rengert, G. & Townsley, M.T. (2006). The diffusion of risk: A cross national assessment of residential burglary victimization. In Submission.

Johnson, S.D., Birks, D, Bowers, K.J., McLaughlin, L., and Pease, K. (2005). Prospective Mapping Technical Report. Submitted to the Home Office.

Johnson, S.D., and Bowers, K.J. (2006). Burglary Prediction: Theory, Flow and Friction. In Graham Farrell, Kate Bowers, Shane Johnson and Michael Townsley (Eds.), *Imagination for Crime Prevention: Essays in Honour of Ken Pease, Crime Prevention Studies,* in press.

Johnson, S.D., Bowers, K. and Pease, K. (2005). Predicting the Future or Summarising the Past? Crime Mapping as Anticipation In Melissa Smith and Nick Tilley (Eds.) *Crime Science: New Approaches to Preventing and Detecting Crime,* 145-163. London: Willan.

Knox, G. (1964). The detection of space-time interactions. *Applied Statistics*, **13**, 25-29.

Krebs, J.R. & Davies, N.B. (1987). *An Introduction to Behavioural Ecology*, 2nd ed. Oxford: Blackwell.

Levine, N. (2004). *CrimeStat*: A Spatial Statistics Program for the Analysis of Crime Incident Locations (v 3.0). Ned Levine & Associates, Houston, TX, and the National Institute of Justice, Washington, DC. May.

North, B.V., Curtis, D. and Sham, P.C. (2002). “A note on the Calculation of Empirical P Values from Monte Carlo Procedures.” *American Journal of Human Genetics*, 71/2, 439-441.

Openshaw, S. (1984). The modifiable areal unit problem, *Concepts and Techniques in Modern Geography* , **38**: 41.

Pease, K. (1998). Repeat victimisation: Taking stock. *Crime detection and Prevention Series Paper 90*. London: Home Office.

Sagovsky, A., and Johnson, S.D. (2006). Patterns of Repeats: Long- and Short-term Temporal Patterns of Repeat Burglary Victimisation. In submission.

Schneider, J. (2005). The link between shoplifting and burglary: The booster burglar. *British Journal of Criminology*, **45**(3), 395-401.

Townsley, M., Homel, R. and Chaseling, J. (2003). “Infectious Burglaries: A Test of the Near Repeat Hypothesis.” *British Journal of Criminology*, 43/3: 615-633.

Appendix 1 Summary of the time windows over which incidents of vehicle crime were reported to have occurred

The patterns are summarised using simple descriptive statistics to indicate the intervals for the 25% of incidents with shortest time windows (1st quartile), the median interval, and the duration of the time windows for the 75th percentile.

Inter-quartile ranges for vehicle theft (all incidents).

	Derbyshire		Dorset	
QUARTILES (hours)	Theft FROM Vehicle (N=7,061)	Theft OF Vehicle (N=2,135)	Theft FROM Vehicle (N=4,989)	Theft OF Vehicle (N=699)
1st quartile	1.0	1.1	2.0	2.5
Median	7.7	7.5	9.7	9.7
3rd quartile	13.8	13.3	14.8	16.7

Inter-quartile ranges for vehicle theft (no car parks).

	Derbyshire		Dorset	
QUARTILES (hours)	Theft FROM Vehicle (N=6,572)	Theft OF Vehicle (N=2,051)	Theft FROM Vehicle (N=4,134)	Theft OF Vehicle (N=625)
1st quartile	1.0	1.0	2.5	2.5
Median	8.0	7.5	10.5	9.8
3rd quartile	14.0	13.0	15.0	16.7

Inter-quartile ranges for vehicle theft (only car parks).

	Derbyshire		Dorset	
QUARTILES (hours)	Theft FROM Vehicle (N=489)	Theft OF Vehicle (N=84)	Theft FROM Vehicle (N=855)	Theft OF Vehicle (N=74)
1st quartile	1.0	2.3	1.0	2.9
Median	2.8	6.6	2.8	8.8
3rd quartile	9.4	18.3	10.0	16.9