BEHAVIOURAL CASE LINKAGE IN PERSONAL ROBBERY

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by

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Abstract

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Case linkage uses crime scene behaviours to identify series of crimes committed by the same offender. The research presented here tests the underlying assumptions of case linkage (behavioural consistency and behavioural distinctiveness) by comparing the behavioural similarity of linked pairs of offences (i.e. two offences committed by the same offender) and unlinked pairs of offences (i.e. two offences committed by different offenders). It was hypothesised that linked pairs would be more behaviourally similar than unlinked pairs thereby providing evidence for these two assumptions. Logistic regression and receiver operating characteristic analyses were used to explore which behaviours can be used to reliably link personal robbery offences using samples provided by two police forces (one urban and one rural). The method of generating unlinked pairs was then refined to reflect how the police work at a local level, and the success of predictive factors re-tested. This research provided evidence supporting the assumptions with linked pairs displaying more similarity than unlinked pairs across a range of behavioural domains. *Inter-Crime Distance* and *Target Selection* emerged as the most useful linkage factors with promising results also found for *Temporal Proximity* and *Control*. No evidence was found to indicate that either the *Approach* used or the *Property* stolen were useful for linkage. The addition of extra behaviours into domains improved performance in some instances but not substantially. The potential impact of group offending on the assumptions was also tested. Although there were some differences found between group and lone robberies, the research demonstrated that case linkage remains feasible provided that the offences under examination are either group or lone in nature rather than a mixture of the two. A supplementary study gathering the views and experiences of police crime analysts regarding case linkage helped put these new quantitative findings into operational context.

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Chapter 1 : Introduction

This thesis reports new case linkage research conducted between 2007 and 2012. It is structured as follows.

Chapter 2 reviews the relevant literature. This includes a summary of key trends and patterns in personal robbery, introduces case linkage in the context of serial crime, the theoretical framework for case linkage, methods for conducting case linkage, potential barriers to accurate linkage, and a review of the evidence to date for the theoretical assumptions underpinning case linkage.

Chapter 3 presents the findings of a qualitative study which surveyed crime analysts about their views and experiences of case linkage (known as Comparative Case Analysis (CCA) in the applied setting). This study was published in the International Journal of Police Science and Management (Burrell & Bull, 2011).

Chapter 4 presents the findings of a series of quantitative studies. Study 1 of the chapter has been published in the Journal of Investigative Psychology and Offender Profiling (Burrell, Bull, & Bond, 2012) and its other studies are soon to be submitted to research journals.

Chapter 5 presents the findings of a study concentrating on group offending which explored the differences between group and lone offending and assessed the potential impact of co-offending on case linkage. This will be submitted to a research journal.

Chapter 6 discusses the key themes emerging from the new studies presented in chapters 3 to 5. This includes the potential limitations of the research and how these might impact on the findings and their applicability in an operational setting. Recommendations for directions for future research, based on the findings of the thesis, are also made.

Appendices are included where appropriate and are cited in the text. A complete list of references used is included at the end of the thesis.

Chapter 2 : Literature Review

Robbery

Robbery is the theft of property with the threat or use of force against a person. Any circumstances where the victim resists the offender or where anyone is assaulted during the offence are considered to be the use of force. Where the victim feels the offender might use force due to their language or actions, this would constitute the threat of force. Where force is targeted at the property (as in snatching a handbag, wallet, or mobile phone) rather than the person, the offence is classified as theft from the person rather than robbery (Home Office, 2012).

There are two official categories of robbery in England and Wales; business and personal. Business robberies (more commonly known as commercial robberies in the literature) are committed against companies (e.g. a bank robbery with the violence directed at bank employees) whereas personal offences are committed against individuals (e.g. 'mugging') (Home Office, 2012). The majority of robberies are personal in nature; for example, 67,920 out of 74,690 (91%) robberies recorded by the police in 2011/12 were personal (Office for National Statistics, 2012) rather than commercial. Although there may be some parallels between commercial and personal robberies – for example, both typically involve groups of offenders (Gill, 2000; Smith, 2003) and motivations for committing offences overlap (e.g. money, addiction, and excitement) – there are also differences. For example, commercial robberies are more likely to be planned, the financial rewards are usually larger and in the UK the weapon of choice is a firearm (Gill, 2000) rather than a knife (the weapon of choice in personal robberies). It is not surprising therefore that the two categories are usually separated for research purposes. Indeed, Matthews (2002) goes so far as to say that research that does not differentiate between the two categories should be interpreted with caution.

Personal robbery is commonly referred to as 'mugging' or 'street crime' (e.g. Tilley, Smith, Finer, Erol, Charles, & Dobby, 2004), and is commonly characterised as spontaneous and impulsive (Alarid, Burton, & Hochstetler, 2009: Woodhams & Toye, 2007). Numerous UK studies have linked personal robbery to street culture (e.g. Deakin, Smithson, Spencer, & Medina-Ariza, 2007; Wright, Brookman, & Bennett, 2006), and so it is not surprising that it is typically committed by small groups of young males (aged under 20) against other males (Alaird et al., 2009; Smith, 2003). Motivation for robbery ranges from material gain (Alarid et al., 2009; Monk, Heinonen, & Eck, 2010) to alleviating boredom (Tilley et al., 2004) or for the "buzz" (Alarid et al., 2009; Deakin et al., 2007; Young, FitzGerald, Hallsworth, & Joseph, 2007). It has also been noted that street robbery is associated with the desire to appear tough in front of peers (Barker, Geraghty, Webb, & Key, 1993).

Weapons are used or displayed in approximately one third of personal robberies in the England and Wales (Flatley, Kershaw, Smith, Chaplin, & Moon, 2010). Knives are commonly associated with this type of offence (Barker, et al., 1993), with evidence suggesting that they are the weapon of choice in over 20%

of robberies (Flatley et al., 2010). Definitive figures outlining the number of total offences that involve knives are not available; however, the police have recently started to record ‘knife/sharp instrument use’ for selected offences, namely homicide, attempted murder, threats to kill, actual bodily harm (ABH), grievous bodily harm (GBH), robbery, rape, and sexual assaults. In 2009/10 in England and Wales there were 33,566 offences in these categories that involved a knife or sharp instrument, almost half of which (n=15,592) were robberies (Flatley et al., 2010). Approximately 40% of robbery victims receive some kind of injury (Smith, 2003).

Small, valuable items (such as cash and mobile phones) are popularly stolen during robberies (Smith, 2003; Woodhams & Toye, 2007). This is not surprising given that these are the types of items that people commonly carry around with them. Furthermore, these items have been described as ‘hot products’ within criminology research literature (Clarke, 1999). Hot products display ‘CRAVED’ characteristics - i.e. they are concealable, removable, available, valuable, enjoyable, and disposable – making them attractive to thieves (Clarke, 1999; Clarke & Eck, 2003; Wellsmith & Burrell, 2005). Thus, the theft of items with these characteristics represents a common trend in property crime.

Robbery is a serious offence that can have a significant impact on victims (Barker et al., 1993; Dolan, Loomes, Peasgood, & Tsuchiya, 2005; Gale & Coupe, 2005; Monk et al., 2010), including loss of goods, injury, fear (Monk et al., 2010), and in some cases long-term psychological trauma (Barker et al., 1993). Furthermore, robbery typically accounts for around 2% of police recorded crime (or one offence per 1,000 population) in England and Wales per annum (Office for National Statistics, 2012), thus demonstrating the importance of identifying methods of investigating and solving such cases.

The majority of crime is usually attributable to a minority of places, situations, times, and people (Clarke & Eck, 2003; Pakkanen, Zappalà, Grönroos, & Santtila, 2012). Often this is reflected by a ‘80-20 divide’ with approximately 20% of people/situations/places etc. responsible for around 80% of crime. Robbery, like all crime, clusters in time and space (Tilley et al., 2004). For example, robbery is more concentrated in urban areas. Furthermore, in 2009/10, 62% of all robberies in England and Wales were recorded by just three (out of the 43) police forces. These forces – Metropolitan Police, Greater Manchester Police, and West Midlands Police – cover just 24% of the population (Flatley et al., 2010). In fact, the 80-20 rule applies, with this data revealing that 20% of police forces accounted for 78% of robberies. On a more local level, personal robbery tends to cluster in locations where there are high volumes of people, such as night-time economy venues (Tilley et al., 2004), shopping areas and other places where people gather. Transport hubs, in particular, are popular with robbers (Block & Davis, 1996). Moreover, robbery is concentrated on particular bus routes (Loukaitou-Sideris, 1999), and at a small number of railway stations (Burrell, 2007; Chaiken, Lawless, & Stevenson, 1974; Walsh, 1999). Commercial robberies also cluster by location with research indicating that the same companies (Overall & Day, 2008), and even individual branches/stores (Matthews, Pease, & Pease, 2001), are repeatedly targeted.

Robbery tends to be more frequent in the winter months (Field, 1992; Jammers, 1995; Landau & Fridman, 1993). This has been attributed to a range of factors including increased hours of darkness (van Koppen & Jansen, 1999), and weather conditions (i.e. colder weather means fewer people venture out thus making those who do more vulnerable to victimisation [Landau & Fridman, 1993]). Peak times for robbery are evenings and weekends (Cohn & Rotton, 2000; Smith, 2003). There are some exceptions; for example, robberies involving schoolchildren commonly occur between 3 and 4pm when they are travelling home from school and commuters using public transport are typically targeted during the evening rush hour (Tilley et al., 2004).

Robbery also clusters around people both in terms of victims and offenders. Repeat victimisation is well documented in criminology literature (e.g. Farrell & Pease, 1993; Pease, 1998), and so it is unsurprising that 14% of robbery victims interviewed by the British Crime Survey in 2009/10 had been victimised more than once (Flatley et al., 2010). Vulnerable groups – for example, elderly people, young people/schoolchildren, and students (Smith, 2003; Tilley et al., 2004) – are commonly targeted by robbers. As mentioned above, the majority of offences are attributable to a minority of offenders (Clarke & Eck, 2003; Tilley & Laycock, 2002); commonly referred to as 'prolific' offenders. Prolific offenders present a significant challenge for criminal justice agencies and there is a national effort to target the offending committed by these individuals (i.e. the National Prolific and other Priority Offenders strategy and programme). Therefore, targeting prolific offenders is often seen as central to crime reduction activity (Woodhams & Toye, 2007). For example, one of the key strands of the Street Crime Initiative (SCI), which focused on reducing robbery and snatch theft, was targeting prolific offenders (Tilley et al., 2004).

Identifying serial crime

Prolific offenders commit series of offences, and identifying the multiple offences committed by each offender is a key part of police investigation. In fact, identifying serial crime and linking offences to a single offender is a crucial part of police work (Bennell, Jones, & Melnyk, 2009; Santtila, Fritzon, & Tamelander, 2004; Sorochinski & Salfati, 2010; Yokota & Watanabe, 2002). Establishing that a number of offences are attributable to the same person supports the implementation of efficient and productive investigative strategies (Labuschagne, 2012; Santtila, Junkkila, & Sandnabba, 2005). For example, pooling information from all the crime scenes (Bennell et al., 2009) can lead to faster identification and apprehension of the offender and/or strengthening the evidential case for the courts (Woodhams, Bull, & Hollin, 2007). Linking a number of offences to one person can also be used to narrow the search (suspect prioritisation), for example by geographic profiling (Canter & Larkin, 1993; Santilla et al., 2004; Santtila, Häkkänen, & Fritzon, 2003).

Linking series of offences can be relatively simple if forensic and/or physical evidence is found at the crime scenes (Grubin, Kelly, & Brunsdon, 2001). For example, more than 1,200 links were made between crime scenes using the National DNA Database in the first few years after it was launched (Werrett, 1997). However, forensic evidence is by no means always present at crime scenes (Harbers, Deslauriers-Varin, Beauregard, & van der Kemp, 2012; Home Office, 2005). For example, Ewart, Oatley, and Burn (2005) report that such evidence is frequently absent at burglary scenes, and both Davies (1992) and Hazelwood and Warren (2003) state that no or insufficient DNA evidence is found in a significant proportion of sexual offences. Furthermore, Burrell, Bull, and Bond (2012) note that forensic evidence is often unobtainable in personal robberies due to a lack of physical contact between the offender(s) and victim. Even where forensic evidence is gathered it is expensive to process (Pakkanen et al., 2012) and/or it may not be suitable to be input onto a database (Home Office, 2005). Furthermore, a lack of searchable databases of reference samples can limit usefulness (Cole, 2010). Indeed, the UK National DNA Database (NDNAD), which has the highest rate of profiles in the UK per capita (Parliamentary Office of Science and Technology, 2006), is limited because just one per cent of recorded crimes contribute DNA profiles to the database (House of Commons Science and Technology Committee, 2005). In addition, DNA evidence might not be (fully) processed whilst the investigation is ongoing and research has found that in some cases this only occurs where a suspect has been identified (Strom & Hickman, as cited in Beaver, 2010). This means that, although forensic 'hits' might be valuable as evidence in court, they may not be available during the investigation and search for the offender. When forensic and/or physical evidence is unavailable, behavioural analysis could possibly be used to identify a linked series of offences (Bennell & Jones, 2005; Grubin et al., 2001; Hazelwood & Warren, 2003; Tonkin, Woodhams, Bull, & Bond, 2012;

Woodhams, Bull et al., 2007; Woodhams & Toye, 2007). This is known as case linkage.

Theoretical framework

Case linkage is one of a range of methods used to advise crime investigators about who might have committed an offence based on offence and victim data (Copson, 1995). In this sense it has been compared to offender profiling (Aitkin, Connelly, Gammerman, Zhang, & Oldfield, 1995). However, despite sharing some common features (e.g. both approaches are used to investigate unsolved crime), there are clear distinctions. Offender profiling makes predictions about the demographics (e.g. age, gender) of the offender based on crime scene behaviour (Copson, 1995; Davies, 1992; Rossmo, 2000), thus requiring a relationship between demographics and crime scene behaviour; it therefore assumes that offenders who display the same criminal behaviours share common demographics (Woodhams, Bull et al., 2007). This is called the homology assumption (Alison, Bennell, Mokros, & Ormerod, 2002; Mokros & Alison, 2002). Case linkage does not make this assumption; rather it aims to identify series of linked offences but makes no judgements about the type of person who committed these crimes.

Offender profiling and case linkage do, however, share the assumption that offenders are consistent in the way they commit their crimes. The offender consistency hypothesis (Canter, 1995) postulates that offenders to some extent behave consistently across their crimes, especially where the behaviour is the product of the offenders' personal attributes (e.g. personality or fantasy) rather than of the situation.

Accurate linkage also relies on the assumption that an offender's behaviour is sufficiently heterogeneous from the way in which others commit crime (Goodwill & Alison, 2006; Salfati & Bateman, 2005; Woodhams, Bull et al., 2007). Without this assumption of behavioural distinctiveness (or inter-individual variation) it would be impossible to distinguish the actions of one offender from those of another (Santtila, et al., 2005; Woodhams & Toye, 2007). Offenders must therefore commit crimes in a consistent but distinctive manner in order for case linkage to be feasible (Harbers et al., 2012; Santtila et al., 2005; Woodhams, Bull, et al., 2007).

In summary, the core underlying theoretical assumptions of case linkage are behavioural consistency and behavioural distinctiveness. The psychological literature has provided evidence in support of these assumptions; personality researchers have demonstrated that people behave consistently especially when situations are similar (e.g. Funder & Colvin, 1991; Furr & Funder, 2004), and the core literature on differential psychology and individual differences emphasises that people differ in their behaviour and strives to understand the underlying reasons for these differences (Chamorro-Premuzic, von Stumm, & Furham, 2011). The evidence base for these assumptions as provided by the case linkage literature is outlined in detail in the evidence for the theoretical framework section later in this chapter.

Methods for conducting case linkage

Case linkage focuses on identifying all of the crimes committed by an offender and often uses the offender as the starting point for analysis. Case linkage is typically conducted by crime analysts and/or police officers (Woodhams & Toye, 2007; Woodhams, Bull et al., 2007), and is commonly referred to as comparative case analysis (CCA) (Bennell & Canter, 2002). CCA is conducted at police force level on a range of offence types including robbery (Burrell & Bull, 2011). However, some of the more serious offence types are also analysed at a national level. For example, the Serious Crime Analysis Section (SCAS) receives detailed information about all serious sexual offences reported to the police in the UK (including Scottish forces and the Police Service of Northern Ireland). All information is coded into a single database called ViCLAS (Violent Crime Linkage Analysis System). SCAS analysts work to identify series of sexual offences and provide police officers with investigative advice based on their findings. This work is vital to help identify the emergence of potential serial killers and serial rapists at a relatively early stage of their serial offending. Senior analysts are able to assist in the prosecution of cases by giving specialist evidence in court.

Academic interest in the field of case linkage is nowadays apparent in the literature and more and more researchers across the world are striving to find support for the theoretical assumptions and to identify reliable linking factors. Researchers have used a range of different approaches. Salfati and Bateman (2005), for example, used a thematic approach (with behaviours categorised as expressive or instrumental) to examine if serial homicide offenders were consistent across their crimes. Some researchers seek out offences similar to a target offence and then test their linkage analysis by determining how many of these similar offences were in fact committed by the same offender (e.g. Santtila et al., 2004; Santtila et al., 2005). Other researchers assess the behavioural similarity of pairs of offences known to have been committed by a single offender and compare these to unlinked pairs (i.e. pairs of offences known to have been committed by different offenders) with the hypothesis that linked pairs will display more similarity than unlinked pairs (Bennell & Canter, 2002; Bennell & Jones, 2005; Tonkin, Grant, & Bond, 2008; Tonkin, Santtila, & Bull, 2011; Tonkin, Woodhams et al., 2012; Woodhams & Toye, 2007). The findings are then examined to identify the specific variables that demonstrate reliability as linkage factors.

Linkage research frequently uses modus operandi (MO) (i.e. the way in which the offence was committed) to identify offence behaviours for analysis (e.g. Bennell & Canter, 2002; Bennell & Jones, 2005; Ewart, et al., 2005; Yokota & Watanabe, 2002). Content analysis of these data is then used to develop a coding dictionary of offence behaviours. For example, Woodhams and Toye (2007) identified offence behaviours across four domains (target selection, planning, control, and property) in their research on commercial robbery.

MO behaviours are also utilised, alongside ritual behaviours and/or 'signature', to link offences using a case study approach (e.g. Hazelwood & Warren, 2003; Keppel, Weis, Brown, & Welch, 2005; Labuschagne, 2006). As stated above, the MO describes how the offence was committed (Rossmo, 2000), whereas ritual behaviours are ‘fantasy based’ (Hazelwood & Warren, 2003; Labuschagne, 2006). ‘Signature’ is the unique combination of behaviours displayed by an individual offender (Keppel et al., 2005), and can be made up of both MO and ritual behaviours. Signature has been described as the psychological ‘calling card’ an offender leaves at each crime scene (Keppel & Birnes, 1998; Keppel et al., 2005), and signature actions have been defined as going beyond what is necessary to commit the crime (Douglas & Munn, 1992; Keppel et al., 2005). Examples of signature behaviours include overkill, mutilation, and picquerism (Keppel et al., 2005). Furthermore, although signature may evolve over time (Rossmo, 2000), FBI Behavioural Scientists argue that the underlying core needs of the offender remain constant across their offences so the exhibited behaviours will follow a pattern (Keppel & Birnes, 1998). For example, an offender may engage in more and more post mortem mutilation as their series of murders progresses. It is not the escalation that is important in signature, but the fact that post mortem mutilation occurs. In addition, there is evidence that signature actions (such as masturbation and exhibitionism) are relatively consistent across series (Harbers et al., 2012). Therefore, unusual behaviours and/or unique combinations of behaviours could be useful to identify crimes series.

Statistical approaches

A range of statistical techniques are also used in case linkage research. Jaccard’s coefficient – a similarity measure – can be used on dichotomous variables to calculate the level of similarity between offences. Jaccard's does not take joint non-occurrences into account (Porter & Alison, 2004; Porter & Alison, 2006a; Real & Vargas, 1996), and is therefore a popular statistical test in case linkage research (Bennell & Canter, 2002; Tonkin et al., 2008) because the level of similarity does not increase if the behaviour is not reported to have occurred within an offence pair (Woodhams, Grant, & Price, 2007). This is an important issue when working with police data as the absence of a behaviour in a crime record does not necessarily mean that it did not occur (Harbers et al., 2012); only that it was not reported or recorded (Tonkin et al., 2008). The averages of Jaccard's coefficients for (a) linked and (b) unlinked pairs of offences are then compared to test behavioural consistency. This can be achieved through parametric (e.g. t-test) or non-parametric (e.g. Mann-Whitney U) tests depending on the distribution of the data (i.e. normal versus non normal respectively). Significantly higher Jaccard's coefficients in linked than in unlinked pairs provide support for the assumptions.

Taxonomic similarity is a more powerful hierarchical measure than Jaccard's and has been tested as a method of comparing linked and unlinked offences (Bennell, Gauthier, Gauthier, Melnyk, & Musolino, 2010; Melnyk, Bennell, Gauthier, & Gauthier, 2011; Woodhams, Grant, et al., 2007). Woodhams, Grant et al's. (2007) research on juvenile sex offences demonstrated that both Jaccard's and taxonomic similarity showed linked offences to be significantly more similar than unlinked offences, and that taxonomic similarity outperformed Jaccard's. Furthermore, the taxonomic similarity measure was equally or more effective at identifying linked offences when up to 20% of behaviours were removed from the analysis (even when compared to a Jaccard's analysis using the full dataset). The ability to use this more powerful measure would be beneficial for researchers who often have to rely on incomplete datasets. However, later research by Melynk et al. (2011) failed to replicate these findings with burglary and homicide data, particularly when large sample sizes were used. Woodhams, Grant, et al's. (2007) sample consisted of just 16 offences, and so it has been postulated that the sample size might be one reason for the inability of others to replicate their initial findings (Bennell, Gauthier, et al., 2010; Melynk et al., 2011). Bennell, Gauthier, et al. (2010) used adult sexual assault data to assess the impact of both sample size and data degradation on the performance of the two similarity measures. Their research revealed that Jaccard's outperformed the taxonomic similarity measure across a range of conditions.

The simple matching index (S) has also been compared to Jaccard's as a measure of similarity (Ellingwood, Mugford, Bennell, Melnyk, & Fritzon, 2012). This research found that S was only more effective than Jaccard's at discriminating between linked and unlinked pairs in one theme and that there were no significant differences between the two measures overall. Combined with the research on taxonomic similarity, these results suggest that Jaccard's is likely to continue to be the similarity measure of choice for case linkage researchers.

Regression models can be generated to examine the extent to which variables (i.e. linking factors or behaviours) can be used to discriminate between linked and unlinked offences. Given that data are coded dichotomously (i.e. 1 denoting the presence of a behaviour or action and 0 denoting the absence) this is an appropriate statistical technique. Regression has been used to search for reliable linking factors in a range of offence types including stranger rape (Scott, Lambie, Henwood, & Lamb, 2006), car crime (Tonkin et al., 2008), commercial robbery (Woodhams & Toye, 2007), and burglary (Bennell & Canter, 2002; Bennell & Jones, 2005; Markson, Woodhams, & Bond, 2010). Although heavily utilised in case linkage research, there is however a potential problem with using regression analyses. Central to regression is the assumption that the (dependent) observations are independent of each other (Field, 2006; Tonkin et al., 2008), but many studies utilise the same dataset to generate the linked and unlinked samples for analysis arguably violating such independence of the data. For this reason, previous research (e.g. Markson et al., 2010; Tonkin et al., 2008; Woodhams & Toye, 2007) has used Wilcoxon matched-pairs signed rank tests to compare the behavioural similarity of linked and unlinked crime pairs. However, this topic is one of current debate as the actual data analysed are the Jaccard's scores generated from the raw information rather than the raw information/data itself. Burrell et al. (2012) therefore elected to use an independent test of difference (the Mann-Whitney U test)[1].

Recent advances in case linkage have revealed the value of receiver operator characteristic analysis (ROC) in overcoming concerns about independence (Bennell & Jones, 2005; Bennell et al., 2009; Tonkin et al., 2008). ROC analysis

[1] The rationale for independent testing is outlined within step 2 of the statistical procedures discussed in the methodology of chapter 4 of this thesis.

is a measure of predictive accuracy and uses area under the curve (AUC) to assess the linking accuracy of the approach that gives rise to the ROC curve (Bennell et al., 2009). An AUC of 0.5 indicates chance level and an AUC of 1.0 indicates perfect discrimination – therefore the larger the AUC, the higher the predictive accuracy (Woodhams, Bull, et al, 2007). AUCs of between 0.5 and 0.7 are indicative of low levels of accuracy, 0.7 to 0.9 indicate good levels of accuracy and 0.9 to 1.0 high levels (Bennell & Jones, 2005). ROC analysis also addresses another key issue relating to traditional linkage methods, namely the lack of information about the specific degree of similarity needed for two offences to be considered to be linked (i.e. a threshold) (Bennell et al., 2009). Because the AUC represents the whole curve rather than just one point, its measure of linkage accuracy is independent of any particular thresholds adopted by the case linkage approach used (e.g. regression). Once the ROC curve has been generated, this can be used to identify a decision threshold (i.e. a point along the curve) that reflects the error rate considered appropriate under the circumstances (e.g. police officers need to find the balance of limiting the error rate to keep both false positives and false negatives to a minimum whilst still generating new lines of enquiry).

Other methods used to explore case linkage include cluster analysis techniques (e.g. Green, Booth, & Biderman, 1976, cited in Bennell et al., 2009) that sort cases (offences in this case) into groups, or clusters, using the degree of association between cases. Multidimensional scaling procedures – such as Smallest Space Analysis (SSA) – are also used (e.g. Salfati & Bateman, 2005; Santtila et al., 2005). These techniques plot variables in an n-dimensional space to provide a spatial representation of the relationship between variables. This can be used to plot behaviours or offences to demonstrate either the relationship between behaviours (the shorter the distance between the behaviours, the more likely they are to co-occur) or offences (the shorter the distance between the offences, the more similar they are and therefore the more likely they are to have been committed by the same offender).

Potential barriers to effective case linkage

There are a number of factors that could act as potential barriers to effective case linkage; for example, differing context/situation, varying opportunities in who/what presents the best target, offender adaptation/learning, and the potential impact of co-offending. Data problems and methodological limitations can also restrict the effectiveness of case linkage. It is important to consider the range of factors that might reduce the potential to accurately identify serial crime, and to ensure research findings are interpreted appropriately.

Research indicates that behavioural consistency – which is key to the identification of linked offences – is to an extent situation dependant (Furr & Funder, 2004; Sherman, Nave, & Funder, 2010). Thus, any factor that affects the degree of similarity of a situation potentially impacts on the ability to identify linked offences. One of the important issues to consider regarding case linkage is the role of opportunity. Opportunity theory (Felson & Clarke, 1998) states that trends and patterns in crime are as much determined by the physical and social arrangements of society as by the attitudes and dispositions of the population.

Thus, the trends and patterns in crime are in part due to where motivated offenders find the opportunity to commit crime. This is why crime clusters by time and location (e.g. the night-time provides a level of anonymity for offenders, and busy transport hubs provide a wide range of potential victims). The role of opportunity is a challenge in trying to link robberies, which are often characterised by a lack of specific planning by the offender(s) (Woodhams & Toye, 2007). This means that, although offenders might intend to commit a robbery, the specific person targeted, and the time and location, will depend on how, where, and when opportunities present themselves. This means that factors such as location might not be useful to link offences. Furthermore, some locations present multiple opportunities and will be popular with lots of offenders. Therefore, clusters of robberies in, say, a particular secluded subway might not indicate that these offences are linked. Instead, it could be that this location attracts a number of different offenders because of the potential opportunities to successfully rob people. Furthermore, victim characteristics might also need to be excluded from linkage analysis as victim selection is likely to be based on who uses the subway rather than the type of person offenders might usually target. Most offenders make rational choices (Cornish & Clarke, 1986) about how they commit crime in order to maximise their rewards whilst minimising their chances of detection and apprehension (Clarke & Eck, 2003). These choices can be centred on the locations offering pre-disposed offenders the best opportunities to commit crime.

General psychological research indicates that some people behave more consistently than others (Bem & Allen, 1974), which could pose a problem for case linkage researchers, as it suggests that some offenders may change their behaviour across their offences, thereby undermining the offender consistency hypothesis.

Offender learning also presents a challenge to linkage analysis because modus operandi (MO) evolve over time (Yokota & Watanabe, 2002), as offenders learn what is effective (Keppel, 1995) and gain confidence (Douglas & Munn, 1992). Many offenders learn from the mistakes that led to their capture; for example, if a rapist is caught through semen left at the scene, he might wear a condom in future offences to try to evade detection (Tonkin, Woodhams, et al., 2012). The offender might also adjust his/her MO to deal with problems faced in earlier crimes such as now binding the victim to minimise resistance (Douglas & Munn, 1992). Unfortunately, offender expertise has been found to negatively impact on the consistency of offending behaviour over time as Grubin et al. (2001) found that the overall likelihood of displaying similar behaviours decreases as the number of offences in a series increases. It is therefore not surprising that Douglas and Munn (1992) recommend analysts focus on ritualistic and fantasy-based behaviours, which are less susceptible to change as they are personality rather than situation driven, when linking offences. However, it is questionable whether fantasy plays a role in all crime types (e.g. robbery) given the differing nature and motivation of different offences (Woodhams, Hollin, & Bull, 2007).

Positively, research has found that not all aspects of the MO are subject to change; for example, if an offender finds that a certain behaviour works well for them (e.g. it helped them successfully abduct a victim) then it is likely that this behaviour will be replicated in future crimes (Hazelwood & Warren, 2003). Furthermore, Grubin et al. (2001) found that certain types of behaviour (e.g. control behaviours) remained more consistent over time. In addition, Tonkin et al. (2008), who examined the impact of expertise on behavioural consistency in their study on vehicle crime, found that there was no significant difference between the behaviours displayed in the first two offences in a series compared to the last two offences in a series. Later work by Davies, Tonkin, Bull, and Bond (2012) also failed to find evidence of expertise in car theft. This could also be due to the limited time period this study covered (three and a half years) which arguably leaves limited time for offenders' behaviour to noticably evolve. Alternatively, it might be vehicle offenders are less likely to change their MO compared to other offenders (there are only so many ways you can steal a car). However, it could also be reflective of offenders more generally, particularly given the recent findings of Harbers et al. (2012) who (conversely to Grubin et al. [2001]) reported that serial sex offenders were more likely to behave consistently as they progressed through their crime series.

Offenders can adapt their MO in response to crime prevention measures (Clarke & Eck, 2003; Tilley et al., 2004). For example, the introduction of electronic immobilisation and other security features on cars has led to a shift in the MO of car thieves. Cars are harder to steal and so offenders need to access the keys to complete the theft. This has led to offenders breaking into houses to access the car keys (Donkin & Wellsmith, 2006). Offenders also adapt their offending to take advantage of new opportunities for crime. For example, copper theft increased from 78 incidents in 2004 to 1,570 thefts in the first ten months of 2007 corresponding with a large increase in the value of copper which rose from $2,864 to $7,190 per ton over the same period (Sidebottom, Belur, Bowers, Tompson, & Johnson, 2010). Thus, it is clear that there are a number of factors that can influence an offender's decision about where, when, and how to commit crime. Variations in MO could have a significant negative impact on the ability to link crimes particularly if examining crimes from the same offender that have occurred over a long period of time.

In addition a large proportion of personal robberies are committed by groups (Alarid et al., 2009; Smith, 2003). However, the impact of group dynamics on behavioural consistency is not well understood (Alarid et al., 2009; Smith, 2003). The robberies an offender commits with a group might differ from those they commit alone, potentially making their crimes more difficult to link. However, research on behavioural coherence has demonstrated the existence of thematic similarities (e.g. an aggressive approach) between offenders committing multiple crimes within the same group (Porter & Alison, 2004; Porter & Alison, 2006a). Thus, co-offending might not impact on behavioural consistency so long as all the offences in the series are committed by the same group[2].

Limitations are not confined to the characteristics of crime. Academic case linkage research currently must rely upon police crime records – particularly MO information and witness statements – to test the theoretical assumptions (of

[2] See chapter 5 for a more in depth discussion of group offending and its potential impact on case linkage.

behavioural consistency and distinctiveness) and to develop methods to assist the investigative process. This approach retains some ecological validity as it utilises the same data that are available to analysts and police officers working to link offences in operational settings. However, there are often a number of limitations when using police data that act to inhibit the success of case linkage. Firstly, attaining high levels of accuracy in case linkage is dependent on accessing good quality data. However, in practice, the quantity, quality, and completeness of information varies widely from case to case (Santtila et al., 2005). Furthermore, the crime record is not necessarily a complete record of the offence as it is often based on the victim's account of the event. Furthermore, the victim account can be adversely affected by a range of factors including the trauma possibly experienced by the victim during the offence and/or poor recall (Woodhams, Bull, et al., 2007). In some, perhaps many, cases the victim account will be limited due to a lack of interaction with the offender (e.g. in burglary cases) or because there is no victim statement at all (e.g. murder cases). The quality of the data can also deteriorate at the recording stage as the selective questioning of the police officer may result in details they deem to be irrelevant not being asked about or omitted from the report (Canter & Alison, 2003, cited in Woodhams, Bull, et al., 2007; Tonkin et al., 2008). Furthermore, the presence of multiple offenders can create an abundance of information, perhaps contradictory. In such cases, the behavioural data can become confused as the victim tries to attribute the correct actions to each offender.

The spatial distribution (i.e. location) of offences can limit the scope of case linkage work. Crime analysts work within specific geographical areas governed primarily by police force boundaries. However, offenders often operate across multiple areas (Woodhams, Bull, et al., 2007), sometimes deliberately to evade detection. Cross 'border' offending therefore results in different analytical teams having information on only a portion of the series. Without the ability to cross reference findings across neighbouring areas analysts can struggle to identify the whole crime series. The identification of series becomes even more challenging when taking into account the simple fact that not all offences will be reported to the police and so even the most comprehensive police datasets are likely to be incomplete.

It can be difficult to identify crime series in high volume offences (e.g. vehicle crime) due to the volume of data under examination. Although this will not impact on research per se due to the methodologies used (e.g. comparison of pairs of linked and unlinked offences), it has implications for the development of techniques that are applicable in real life settings as analysts need to be able to filter through large numbers of irrelevant crimes to identify the crimes in their series.

Limitations can also arise as a result of the methodologies used in case linkage. The primary issue relates to the use of solved offences. In order to adequately test how consistently offenders behave across their crimes it is necessary to identify their offences so that these can be compared. However, it is possible that offences are solved because they display higher levels of behavioural consistency and distinctiveness than unsolved cases, thus introducing a potential positive bias boosting consistency scores (Bennell & Jones, 2005;

Santtila, Pakkanen, Zappalà, Bosco, Valkama, & Mokros, 2008; Tonkin et al., 2008). To circumvent this issue it has been suggested that future research uses unsolved cases that have been positively linked using forensic evidence (e.g. DNA) (Woodhams, Bull et al., 2007). Recent work using this approach is promising (Woodhams & Labuschagne, 2011), however, forensic/DNA evidence may be unavailable (Harbers et al., 2012; Home Office, 2005) limiting the scope of this approach. Furthermore, it should also be considered that solved offences make up a small sample of total crime and it cannot be assumed that results arising from using solved offences represent the cases that have not been reported, recorded, or solved (Aitken et al., 1995).

Rare behaviours are sometimes removed from datasets prior to analysis. For example, Woodhams and Toye (2007) removed all behaviours that occurred in less than ten per cent of cases as these unusual behaviours were not considered to be useful discriminators. Although this is beneficial in terms of identifying overarching behavioural domains that act as reliable linking factors, the omission of rare behaviours at individual case level can be detrimental as it may be this very rare behaviour that distinguishes the offender from others (Aitken et al., 1995). In fact, removing such behaviours could mean removing the signature actions within the offence, which have been shown to retain consistency across the series (Keppel et al., 2005).

The ability to generalise findings may be limited by factors including small sample sizes (e.g. Salfati & Bateman, 2005; Scott et al., 2006) and geography. For example, Tonkin et al. (2008) caution against assuming their findings for a rural police force area in the UK can be transferred to more urban areas. The value of replicating studies in different areas and with different datasets is consistently recommended in the literature (e.g. Bennell & Jones, 2005). Furthermore, researchers reinforce that case linkage research needs to be undertaken with a range of offence types to examine whether universal, reliable indicators of linkage can be identified (Bennell & Jones, 2005; Bennell et al., 2009; Tonkin et al., 2008; Woodhams, Bull, et al., 2007).

Evidence for the theoretical assumptions

Evidence of behavioural consistency has been found in both non-criminal (e.g. Funder & Colvin, 1991; Furr & Funder, 2004; Sherman et al., 2010) and criminal contexts (e.g. Bennell & Canter, 2002; Bennell, Gauthier et al., 2010; Bennell & Jones, 2005; Davies et al., 2012; Ellingwood, et al., 2012; Grubin et al., 2001; Harbers et al., 2012; Melynk et al., 2011; Salfati & Bateman, 2005; Santtila et al., 2004; Santtila et al., 2005: Tonkin et al., 2008; Tonkin, Santtila, et al., 2011; Tonkin, Woodhams, Bull, Bond, & Palmer, 2011; Tonkin, Woodhams, et al., 2012; Woodhams, Grant et al., 2007; Woodhams & Toye, 2007).

Personality researchers have demonstrated that people generally behave consistently, particularly when situations are similar (Funder & Colvin, 1991; Furr & Funder, 2004; Sherman et al., 2010). Furthermore, it has been proposed that the greater the similarity of the situation, the more consistent the behaviour (Furr & Funder, 2004; Woodhams, Hollin, & Bull, 2008). This indicates the importance of taking situation into account when searching for offences that might have been committed by the same offender. It also suggests that it might be more challenging to link offences by the same offender if these are from different offence categories (i.e. in theory it should be easier to link two burglaries by the same offender than one burglary and one robbery by the same offender). However, some research had found evidence of cross situational consistency (e.g. Funder & Colvin, 1991) and recent research (albeit not on crime linkage) has demonstrated that personality characteristics predict behavioural consistency even after controlling for situational similarity (Sherman et al., 2010), indicating it might be possible to link across offence type. In fact, recent work by Tonkin, Woodhams, et al. (2011) has demonstrated that it is feasible to link across offence type, although the behavioural similarity scores were slightly lower when linking across crime type compared to linking within the same crime type.

Some behaviours (e.g. speaking loudly and/or quickly) are more consistent than others (e.g. expressing interest in fantasy or daydreams) (Funder & Colvin, 1991). In the context of case linkage research, this suggests that some criminal behaviours may be more likely to be consistent than others (Woodhams & Toye, 2007). It is crucial to identify what these behaviours are to maximise the chances of successfully linking cases. Some behaviours are more common than others and are therefore less likely to act as reliable linking factors as there will not be enough discrimination between offenders' behaviour to accurately identify separate series. It is therefore important to establish base rates for behaviours (Woodhams, Bull, et al., 2007) to determine which behaviours are unlikely to help identify serial crime. Furthermore, it is suggested that researchers can identify unique series if they use multiple behavioural indicators (i.e. identify a unique combination of behaviours) (Hazelwood & Warren, 2003) in the form of themes or domains. Behavioural domains/themes have been identified as useful in case linkage; for example, Woodhams and Toye (2007) found that commercial robberies committed by the same offender were more behaviourally similar across four domains – target selection, planning, inter-crime distance (i.e. the distance between offence sites), and control - than offences committed by different offenders. Salfati and Bateman (2005) demonstrated that homicide offenders consistently adhere to either an expressive (i.e. emotionally driven) or instrumental (i.e. goal oriented) theme in their offending.

However, support for the usefulness of thematic categories as linking factors is not universal. For example, Bateman and Salfati (2007) tested whether it is more effective to use individual behaviours or groupings of behaviours to identify behavioural consistency. They found that only four out of 35 serial homicide behaviours consistently performed across series thus supporting the hypothesis that individual behaviours may not be effective linking factors (e.g. in this case hiding and/or moving a body is not a good indicator of linkage as both behaviours occur in a high volume of homicides). They also found that only one domain out of six was an effective indicator of whether the homicides were part of the same series. Tonkin et al. (2008) also failed to find support for the value of behavioural domains in linkage. Low levels of linkage accuracy were found for all three of their behavioural domains (target selection, target acquisition, and disposal) tested in relation to car theft. However, it is suggested that lack of data might have led to the inability to link at domain level. For example, car theft victims can only provide limited information about the offence since they are less likely to interact with the offender than victims of other offences.

Greater consistency has been observed in behaviours that are more inherent to the offender and less influenced by situational factors (Woodhams, Bull, et al., 2007). Control behaviours have been found by a number of researchers as having a higher level of consistency (e.g. Bateman & Salfati, 2007; Woodhams & Toye, 2007) and it is theorised that this is because control behaviours are internal to the offender. Planning behaviour is also considered to be less dependent on situation than other behaviours and should therefore act as more reliable linking factors. This has been supported by some research (e.g. Bateman & Salfati, 2007) but receives less support from others. For example, Woodhams and Toye (2007) found planning to be less accurate than control behaviours and target selection when linking offences. However, this could be due to data quality as it can be difficult to glean planning information without information from the offender.

Spatial relationships (e.g. the distance between the offender's home address and the crime scene) have consistently been identified as strong linking factors. For example, inter-crime distance has been found to be the most accurate predictor of linkage for both commercial and domestic burglary (Bennell & Canter, 2002; Bennell & Jones, 2005). Similarly, inter-crime and inter-dump distances (the distance between where a car was stolen and where it was recovered) were found to be the most effective linking factors in Tonkin et al.'s

(2008) research. Subsequent research has continued to find support for the value of inter-crime distance as a strong linkage factor (e.g. Davies et al., 2012; Markson et al., 2010; Tonkin, Woodhams, et al., 2012; Tonkin, Woodhams, et al., 2011; Tonkin, Woodhams, Bull, Bond, & Santtila, 2012). It has been postulated that linkage success using spatial information might be because geographical data are more likely to be recorded accurately (Woodhams, Bull, et al., 2007).

The second assumption of case linkage is behavioural distinctiveness, and some studies have provided evidence for this assumption alongside evidence for behavioural consistency (e.g. Bennell & Canter, 2002; Bennell & Jones, 2005; Bennell, Gauthier, et al., 2010; Woodhams & Toye, 2007). They successfully demonstrated that crimes committed by the same offender can be differentiated from crimes committed by different offenders. This provides support for both behavioural consistency and inter-individual variation (i.e. behavioural distinctiveness). Other studies (Grubin et al., 2001; Santtila et al., 2004; Santtila et al., 2005) scan crime records for offences that look similar to the target offence, then assess whether these offences were committed by the same offender as the target offence. Again, their success in linking serial offences supports both behavioural consistency and distinctiveness.

Supplementary evidence for the assumptions has been found in research on cross situational consistency. For example, research has shown that risky behaviour contributing or causing a traffic accident is associated with criminal behaviour; i.e. those people who display risky behaviour in traffic situations are more likely to have criminal convictions that people who drive carefully (Junger, West, & Timman, 2001). This phenomenon has been called ‘offender self-selection’ (Roach, 2007a; Roach, 2007b). Further evidence of offender self-selection is evident in research on fixed penalty tickets (Wellsmith & Guille, 2005), illegal parking in disabled parking bays (Chenery, Henshaw, & Pease, 1999), and non-payment of TV licences/parking fines (Roach, 2009). Basically, people who commit low level illegal or immoral behaviour are more likely to commit serious crime than the average person. This may seem self-evident but it is of interest that several serious serial offenders have been apprehended due to detection for minor offences. For example, Peter Sutcliffe (the Yorkshire Ripper) was arrested for using false number plates, and David Berkowitz (the Son of Sam) was caught after parking his car illegally (Roach, 2007a). Offender self-selection adds weight to the theory that offenders commit different types of offences and thus highlights the importance of considering the possibility of linking across offence type when searching for serial offenders (work that has been started by Tonkin, Woodhams, et al., 2011).

Despite the differences in methodologies used to link cases, the various published studies do report consistency in offenders’ behaviour(s) thus providing support for the offender consistency hypothesis (e.g. Bennell & Canter, 2002; Bennell & Jones, 2005; Grubin et al., 2001; Salfati & Bateman, 2005; Santtila et al., 2004; Santtila et al., 2005; Tonkin et al., 2008; Woodhams & Toye, 2007). This spans a range of offence types including sexual assault (Grubin et al., 2001), homicide (Salfati & Bateman, 2005), arson (Santtila et al., 2004; Ellingwood et al., 2012), burglary (Bennell & Canter, 2002; Bennell &

Jones, 2005; Markson et al., 2010; Tonkin, Santtila, et al., 2011), vehicle crime (Davies et al., 2012; Tonkin et al., 2008), and commercial robbery (Woodhams & Toye, 2007). Evidence has also been found in support of behavioural distinctiveness (Bennell & Canter, 2002; Bennell & Jones, 2005; Bennell, Gauthier, et al., 2010; Davies et al., 2012; Grubin et al., 2001; Santtila, et al., 2004; Santtila, et al., 2005; Tonkin, Santtila, et al., 2011; Tonkin, Woodhams, et al., 2012; Woodhams & Toye, 2007).

Conclusion

The literature reveals a growing academic interest in case linkage research. Mounting support is being found for behavioural consistency and distinctiveness and there is scope for further research in this area in a number of directions. Future case linkage studies should focus on examining a range of issues including consideration of a broader range of offences and/or geographical areas, the impact of group offending on behavioural stability, the influence of growing expertise on the evolution of the modus operandi, and identifying the most reliable linking factors that can be applied universally.

Chapter 3 : Crime analysts' views and experiences of case linkage[3]

Case linkage is commonly referred to as Comparative Case Analysis (CCA) (Bennell & Canter, 2002). In the real world, CCA is typically conducted by crime analysts (Woodhams & Toye, 2007; Woodhams, Bull et al., 2007), and so it is of value to gather the views of these professionals when seeking to improve the process. The current study involved a survey to gather the experiences and opinions of analysts about Comparative Case Analysis (CCA). Analytical staff working in Northamptonshire and in the West Midlands were approached to participate in the research. These two police forces were selected because of their involvement in the quantitative aspects of this PhD research (see chapters 4 and 5).

Ethical approval was granted by the University of Leicester on 6th May 2009 (documentation available upon request). Senior police staff were approached in each force to seek permission to disseminate the survey. Once permission was granted, the invitation to participate in the research was channelled to analysts through senior analytical staff. As it is challenging to gain access to online survey tools on police computers due to security firewalls, analysts received the

[3] The research presented in this chapter has been published. Reference: Burrell, A. & Bull, R. (2011). A preliminary examination of crime analysts' views and experiences of Comparative Case Analysis. *International Journal of Police Science and Management, 13,* 2-15. DOI:10.1350/ijps.2011.13.1.212

:

survey as a Word document via email. Once completed, the surveys were returned via email.

Methodology

Tool development

The survey questions were developed using both (i) the academic literature on case linkage (e.g. to identify key issues in case linkage such as the problems of falsely linking crimes that are not committed by the same offender and/or failing to identify links between offences) and (ii) practical experience of working alongside crime analysts (e.g. phrasing questions using language familiar to analysts). A draft of the survey was reviewed and commented upon by two academic colleagues who work in the field of case linkage, and their feedback was incorporated into the final version (which had 23 questions) (see appendix A).

It was considered essential that the survey was flexible to capture the necessary information and thus it primarily consisted of open questions. Traditionally, in surveys closed questions are preferred as these are quick to answer and easier to code for analysis (Babbie, 1990; de Vaus, 1996). However, a series of closed questions may not ask about all relevant information and this can lead to misleading results (de Vaus, 1996). The questions focused on:

- Why analysts conduct CCAs
- The process of completing a CCA (e.g. how long it takes to complete a CCA, decision making around whether cases are linked)
- The evidence used to complete a CCA
- Benefits and challenges to CCA.

Sample

The survey was disseminated to an estimated 72 analysts in two UK police forces between June and September 2009. A quarter of these analysts (n=18) completed and returned the survey. One of the analysts who completed the survey reported that they had not been in post for very long, however, they had previously worked for an organisation specialising in CCA work, and was therefore able to comment extensively on CCA. For this reason, this analyst was not excluded from the sample.

It is recognised that this response rate is rather low and the sample size relatively small. However, low response rates are not uncommon when surveying police staff. For example, Jamel, Bull, and Sheridan (2008) reported receiving just 19 responses to a survey disseminated to 300 Sexual Offences Investigative Techniques (SOIT) officers despite sending out reminders. Weir and Bangs (2007) also reported low response rates in their work surveying crime analysts across England and Wales about how they use geographical information systems (GIS). However, Jamel et al. (2008) and Weir and Bangs

(2007) commented that, although their sample was small, their research may be useful.

Qualitative analysis

The responses to the open ended questions did not lend themselves to traditional content analysis coding in that it was difficult to create discrete and meaningful categories for them. For example, the survey asked analysts how long it takes to conduct a CCA. As expected, this was reported as being dependent on a multitude of factors making it difficult for analysts to provide an estimate. Therefore a qualitative analysis of the responses was conducted.

The first phase of the qualitative analysis was to read through the survey responses from each participant in detail. This provided an overarching view of the key themes emerging from the survey. The responses for each individual question were the collated and re-read in order to organise the findings into a logical order.

Despite the difficulty coding the survey responses the qualitative analysis of the transcripts revealed common themes and experiences. Quotes are used to highlight salient points, with unique identifiers to present the findings anonymously.

Results

The small sample size precludes the possibility of comparing findings across the two forces. In fact, the responses were similar.

The analysts worked in a variety of departments primarily Basic Command Units (BCUs) (i.e. police operational districts usually headed by a Chief Superintendent), community safety units (i.e. departments that focus on tackling community issues such as anti-social behaviour and crime), and the force intelligence units (i.e. analytical units that concentrate on force-wide crime issues). A number of specialist departments were also represented, for example, a confidential unit (who work with highly sensitive intelligence), a counter terrorism unit, and an Automatic Number Plate Recognition (ANPR) department (which deals with intelligence about car registration plates). The majority of the 18 analysts were female (n=15). The majority had at least two years' experience of working in an analytical role (n=14 or 78%) and two (11%) were working at a senior analyst level.

All of the analysts routinely work on serial crime and all have experience of conducting CCA, covering a wide range of offences. The offence types were typically dictated by the department the analyst worked in. CCA for serious offences, such as rape and murder, were likely to be conducted by force level analysts and specialist departments. BCU level analysts tended work on a wider range of offence types linked to BCU priorities, which varied by BCU (although burglary, robbery and car crime were commonly mentioned). Analysts rarely considered themselves to specialise in linking a particular type of offence.

How do you conduct a CCA?

There are two different approaches to conducting CCAs: (1) identifying all the offences committed by a known offender, and (2) identifying individual series within an offence type. Analysts used both of these methodologies. For example, one analyst commented:

> *"It depends what [the] starting point is and the specific tasking. Even if I've been tasked to look at an offence type, I wouldn't ignore any links to other crime types that are jumping out"*
>
> *(Participant N-5)*

However, there were some concerns about linking by offender, for example:

> *"In my experience, the majority of CCAs are completed by matching the crime types and not the offenders. If you attempt to create a CCA by matching the offenders you are assuming they are guilty"*
>
> *(W-1)*

The concerns of this analyst are understandable as it is possible that the investigation could be impeded if focus is placed on a suspect who is subsequently found to be innocent. However, retrospective CCAs can be beneficial to assist building a case against a suspect.

It was reported that searches for information should start wide but that a clear rationale is required for each search. All but one of the analysts reported using computer software to conduct CCAs. The most commonly cited software packages were Excel and i2. An example of a typical process for conducting a CCA was to retrieve data from databases using force systems (e.g. Business Objects or Discoverer), and build and complete a matrix of linking factors in Excel. Findings are typically displayed using graphical tools within Excel, i2, and/or mapping software (such as MapInfo).

The use of a matrix provides an easy method of recording and visualising the links between different offences across themes. The literature suggests that linking across multiple categories (i.e. identifying unique combinations of behaviours) is important when linking offences (Hazelwood & Warren, 2003; Woodhams, Bull, et al., 2007). The current survey indicates that analysts share this view. For example, when asked how they reduce the chances of falsely identifying cases as linked W-4 stated:

> *"…by ensuring the identifying factors (i.e. location, description, time of day etc) are the same / similar in most cases, i.e. seven out of the ten factors match the trend".*

Analysts reported that it is important that each link is re-assessed prior to submitting the CCA report, and that clear explanations are included about why cases have or have not been included in the series. Weighted links demonstrate the strength of the relationship between offences and clarify whether links are strong or tentative. In some cases, it was reported as useful to include a list of offences that might be part of the series but that have fewer links to the rest of the series. This highlights offences that might be relevant without misleading the investigative team. However, this is not favoured by all analysts with some preferring to include all offences that might be linked rather than exclude them from the analysis.

Analysts reported that it is important to take all available information into account and analysts should liaise with the officer in command (OIC) of the investigation to ensure any new information is received promptly and fed into the CCA.

What evidence do you use in CCA?

The survey provided a list of forensic, temporal/spatial, and behavioural evidence that might be used to link offences. Figure 3-1 shows how frequently these factors were used to support CCA by the analysts surveyed.

Figure 3-1: Evidence used in CCA

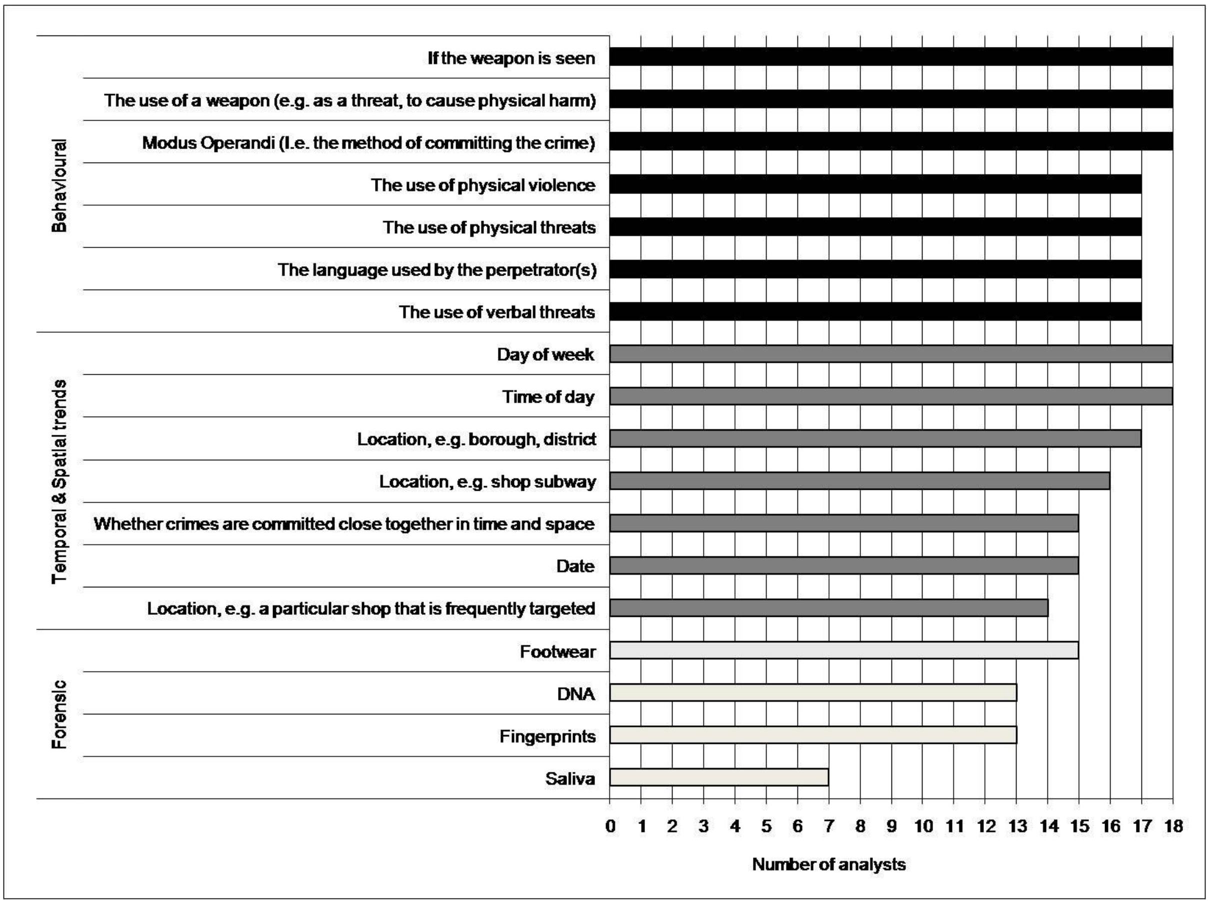


Figure 3-1 reveals that behavioural evidence is routinely used to link offences. The majority of analysts use temporal factors and/or location to link offences. Forensic evidence is used less frequently than might be expected. There are a number of reasons for this. One analyst noted that:

> *"CCA are often commissioned early in the investigative process prior to forensic evidence being gathered"*
>
> *(W-1)*

This suggests that forensic evidence is sometimes unavailable at the time the CCA is conducted. This is not surprising given the literature reports of low recovery rates for forensic evidence at crime scenes (Davies, 1992; Ewart et al., 2005; Hazelwood & Warren, 2003) and the limitations of databases (Cole, 2010).

Analyst W-1 also noted that *“serious offences are more likely to be attended by forensic specialists” (W-1)* and so analysts working on less serious offences are unlikely to be able to source forensic evidence for their CCA. Furthermore, two analysts (both from the same force) reported that *“forensic links will be highlighted by the forensic team” (N-5)* and that their force employs *“specific forensic analysts to look at DNA/ fingerprints etc. so does not really fall under my remit” (N-2)*, suggesting that, even if forensic evidence were available in the case, it may not be accessible to the analyst for the CCA.

Analysts reported using a number of other types of evidence in CCA. The most commonly cited types of information (i.e. by 13 or more analysts) were spatial and temporal trends (e.g. the distance between offence locations), and the offender description. Less commonly cited information included vehicle registration numbers, and methods of committing the offence (e.g. how the offender controlled the victim, how the offender responded to resistance from the victim), victim information (e.g. victim demographics, victim statements), and witness statements. Although information from witnesses/victims was considered useful to the CCA process, there were conflicting views about which offences were more/less likely to include such information. For example, one analyst stated:

> *"Burglaries and robberies will also often have numerous witnesses to support the case. Stranger rapes for example will occur in isolation and very often the only evidence will be that of a scared and confuse[d] victim, this often clouds statements"*
>
> *(W-1)*

However, another analyst reported:

> *"Burglary and vehicle crime are more difficult because MOs are so generic….and little information is known about the offence because the victim is usually not present"*
>
> *(N-4)*

This highlights the relevance of behavioural distinctiveness when making linkage decisions, as generic MOs can make it impossible to distinguish between offenders.

The amount of information available varied by crime type. This is either because more behaviours were observed (e.g. in offences where there is more likely to be a witness) or because more attention is paid to recording details for certain offences such as serious violent crimes or as directed by policing priorities:

“It’s simply the amount of information recorded against each crime that makes it easier to identify series. I would think murder and rapes would be easier as fewer crimes and a lot more information captured. Some burglaries simply state 'unknown MO' and have no statements, a wide time span etc, which is likely to lead to linked crimes being missed through the analytical process”

(N-5)

A lack of information and/or receiving generic crime information makes some offences more difficult to work with:

“[t]heft of vehicle is often more difficult because of a lack of MO, i.e. the car has gone and has not been recovered. More minor crimes such as breaking into vehicles are easier to link tentatively because they are often closely geographically concentrated, but the simple MOs often used (window broken, sat-nav taken) means that they are hard to link definitively”

(W-8)

Thus, it is potentially more difficult to conduct CCA with some crimes, not only because of the type of offence, but also due to a lack of information being gathered about how certain offences are committed. This emphasises the importance of robust data recording practices to ensure high quality data are collected for all offence types.

Analysts highlighted the importance of taking the reliability of data into account when making judgements about whether offences are linked. One analyst provided an example of this:

> *"I am wary of using ethnicity to link robbery offences ... particularly when the suspects are wearing balaclavas as a witness will often confuse a tanned white male, with a light skinned black male, asian male, mixed race etc if their face is partially obscured"*
>
> *(W-5)*

In the academic literature, data reliability has been consistently highlighted as a constraint on effective CCA (e.g. Tonkin et al., 2008; Woodhams, Bull, et al., 2007) and it is unsurprising that this opinion is shared by frontline analytical staff (e.g. Weir & Bangs [2007] reported that a third of their respondents stated that the quality of the data available for mapping crime was insufficient or very poor).

How long does it take to complete a CCA?

In the present survey, analysts commonly reported that estimating the time it takes to complete a CCA is difficult, it being dependent on a variety of factors. A single CCA can take anything from 20 to 30 minutes to several weeks to complete. Typically this was dependent on circumstance; for example, a quick CCA for immediate use where there is little available information can take less than an hour, whereas an exhaustive search of all information relating to a large number of crimes and the need for a detailed report could lead to the CCA taking at least a week to complete. Obviously any factor that increases the volume of information to be examined will substantially add to the time it takes to complete a CCA; for example, severe cases, more offenders, increasing the size of the geographical area, and increasing the timeframe under analysis.

Other factors reported to affect the length of time it takes to complete a CCA included:

- The need to source information from multiple systems. Often information is stored in different crime systems that all need to be searched. For example, W-8 noted that if *'many vehicles/mobiles [are] used in the commission of the offence [this] will increase the time, as they will each need to be checked under different systems'*. In addition, some systems take longer to access than others.

- The need to source information (e.g. forensic intelligence) from external units and/or other forces. In these cases, the analyst is dependent on the speed at which these units/forces can provide information.

- The complexity of the behaviours displayed by the offender as some behaviours are more difficult to interpret than others.

- Data quality – e.g. incomplete reports, poor/inaccurate recall by victims/witnesses, inexhaustive interviewing. This can force the analyst to spend more time sourcing additional information.

- Strength of similarities – if cases are very similar they are easier to link making the CCA process quicker.

- Tasking requirements - requesting high levels of information and detail in the CCA increases the time it takes to complete. Poor quality tasking requests can delay the CCA as the analyst needs to seek clarification of what is required.

- Timescales – how long analysts have to work on the CCA and how quickly the work is needed. For example, where an offender is in custody the CCA may be needed very quickly and so the analyst may spend less time on the CCA in such circumstances.

- The need to prioritise other work/workload can reduce the time the analyst has to spend on the CCA.

The proportion of an analyst's total time spent conducting a CCA varies widely and this is largely dependent on tasking. For example, an analyst might spend 80% of their time on CCA in one week but just 10% the next week. CCAs were, however, a regular task. The two senior analysts spent less time completing CCAs as their roles were managerial; in the past they had, however, spent substantial proportions of their time conducting CCA. Their CCA related work now centred on managing teams of analysts who routinely complete CCAs.

Which offences are easier to link and why?

Volume offences, such as burglary, were considered easiest to link by some analysts. For example:

> *"There maybe more Vehicle Crime, Burglary or Robbery offences, making it quicker to identify common factors"*
>
> *(W-4)*

However, the majority felt that having high volumes of offences to scan hindered the linking process. For example, W-2 stated:

> *"I would say murder/rapes easier as not so many. BDHs [burglary in a dwelling] robberies and car theft would be harder as there are more crimes to trawl through"*

For the most part, it was reported that:

> *"[a]ny crime which involves human contact is likely to be easier to link as a person's behaviour is often very individual and therefore significant"*
>
> *(W-10)*

As N-2 notes:

"with face to face crimes, i.e. personal robbery, violent and sexual offences. The offender's description/ MO [modus operandi]/ motives/ mannerisms are often key to linking offences but this is often absent in burglary and thefts".

Thus it is clear that distinctive behaviour is important when linking crimes:

"Rape and Burglary I would say are the easiest to try and link as there may be more links if offenders have certain ways of doing things"

(W-9)

However, distinctive behaviours were not always present in personal crimes:

"I found it very difficult to conduct CCA on murders - particularly where there is very little distinctive about the scene, the way the victim was left etc as there is so little known behavioural information"

(W-12)

Where distinctive behaviours are absent, it can be difficult to link offences:

"When, for example, a vehicle with the same VRM [vehicle registration mark] has committed a number of different types of offences, then they are easy to link. It is often more difficult to link,

say, burglary and vehicle crime in an area, unless the temporal patterns are unusual"

(W-8)

Overall, distinctive features were highlighted as particularly useful to the linking process, for example, if burglars eating food in the houses they are burgling is rare, finding this behaviour across crimes would suggest that these offences are linked. Such findings indicate that analysts are considering the theoretical assumption of behavioural distinctiveness in their CCA work. Thus, it is important that analysts are able to access a high level of good quality information for each offence to increase the chances of identifying distinctive behaviours with which to link offences.

What are the benefits of CCA?

The analysts were asked if they agreed with a series of statements about the benefits of CCA, the results of which are presented in table 3-1 below:

Table 3-1: Agreement with statements regarding the benefits of CCA

Statement	**N**	**%**
Do you think the identification of series assists with any of the following:		
Detection rates/ catching offenders	18	100
Prioritising suspects	17	94
Improve the efficiency of investigations	17	94
Developing our understanding of particular crime problems (e.g. burglary)	15	83

Most analysts agreed with the provided statements, however there were some exceptions. In one case, the analyst explained that they disagreed with a statement as they felt CCAs were not reviewed or debriefed for best practice. This suggests that CCAs may not be being utilised as well as they could be to boost wider knowledge of offending patterns.

Overall, analysts largely felt that CCA is valuable and they identified a number of additional benefits of CCA work. Several themes emerged including the development of crime prevention tactics (e.g. offender targeting, advice to potential victims), understanding patterns of offending (e.g. helping to understand motive, and predicting future offending), and support for the courts (e.g. building a robust evidence base, and ensuring appropriate sentences are passed). Identifying strong links between offences allows the police to charge offenders with multiple offences once they are apprehended (Bennell et al., 2009; Labuschagne, 2012, Santtila et al., 2004). CCA also supports work to encourage offenders to admit to other of their offences where there may be insufficient evidence for a formal charge (a process known as 'taken into consideration' [TIC]). CCA provides a key opportunity to alert other police forces, or BCUs within the same force, of crime series that they might not be aware of. CCA can also be used as a public awareness tool to boost public confidence in the police by highlighting where offenders have been apprehended for multiple offences.

The practical benefits of CCA were also highlighted. The CCA not only provides a concise and ordered account of a large amount of data and information, but also an easy to interpret summary of accounts for investigative teams. CCA has the additional benefit of being a living document that can be refreshed as the investigation proceeds.

What are the challenges for CCA?

Data availability, accessibility, and quality

Analysts reported that the standard of a CCA is dependent on data availability, accessibility, and quality. As discussed above, difficulties accessing information from external agencies and/or multiple computer systems, along with poor data quality, significantly impact on the time it takes to complete a CCA. These difficulties also impact on the reliability of the CCA, and therefore the usefulness of the CCA to the investigative team. It was widely agreed that the reliability of CCAs is wholly dependent on the quality and amount of information analysts have to work with. Analysts highlighted the importance of taking the reliability of data into account when making judgements about whether offences are linked. These findings are unsurprising given that the literature has repeatedly highlighted that police data can be of poor quality and that this hinders analysis (e.g. Santtila, et al., 2005; Tonkin, et al., 2008; Weir & Bangs, 2007; Woodhams, Bull et al., 2007).

Offence type

It was reported that some offences are easier to link than others. However, there were mixed – and often conflicting – opinions about which offences are easier to work on. These differences are probably linked to data quality. For example, one analyst reported that:

> *"robbery is probably most difficult as the offences tend to opportunistic"*
>
> *(N-1)*

This suggests that limited distinctive information was available about these cases, but another stated:

> *"[r]obbery gives you the most factors to analyse with analysing the IP [injured party] and Offender/weapon seen/speech used etc"*
>
> *(W-2)*

Interestingly these statements are from analysts in different forces. This could explain the discrepancy, particularly if more information is routinely collected in robbery cases in one force than the other (e.g. if robbery is a priority in one force it is possible that officers are encouraged to gather more data). Alternatively, the differences could be based on the individual analysts' differing experiences of conducting CCA with robbery; W-2 has been working in an analytical role for five to ten years compared to one to two years for N-1 which might mean W-2 has more experience of completing CCA on robbery and/or have a more developed understanding of what information to source for the CCA. Finally, the difference could be because robbery offences have different features in different areas; perhaps robberies are more organised and/or distinctive in W-2's force area and therefore there is more behavioural information to gather about these offences.

Linking across offence types

One analyst outlined the difficulties of linking across offence types: *'In my experience a CCA will only work when comparing the same crime type. It's harder to compare a crime series incorporating different types of offences'* (W-5), however another noted the importance of considering the range of offences a single offender commits: *'We look at all crime types that each individual may have committed, for example due to the fact that sex offenders generally have some history of violence, we also take into account violent offenders when investigating rapes'* (W-10). It is suggested that this discrepancy centres on the approach to CCA used, with the first analyst concentrating on identifying series from within offence groups and the second using an offender-centred approach.

Being aware of caveats

Among the biggest challenges in CCA are minimising false positives (i.e. inaccurately identifying offences as linked) and false negatives (i.e. failing to link offences that are committed by the same offender), and academic studies have explored how to maximise the number of accurate links whilst minimising false alarms (e.g. Bennell et al., 2009). Analysts are aware of this issue and proactively take steps to improve accuracy. It was emphasised by W-10 that it is important to keep an open mind and not make assumptions about people, places, and/or circumstances. The analyst must remain objective in order to ensure CCA work is not subject to bias (which can be challenging if the tasking officer has preconceptions about the case in question). Developing and testing hypotheses was considered to be useful to boost linking accuracy. It is reassuring (but not surprising) that analysts are aware of the risk of false positives and false negatives and apply caution when interpreting links to ensure the CCAs are reliably presented.

As alluded to above, analysts stressed that it is important to highlight caveats where these exist. For example, W-1 commented:

> *"Also, the receiver must also be aware of the human error factor. The CCA method is not finite and is always subject to the possibility of human error or false interpretation"*

This allows the investigative team to apply caution where appropriate when using the CCA information. W-1 suggested a potential solution to minimise human error is to have an analyst colleague review and/or dip sample the evidence. Seeking a second opinion provides some reassurance that information has been interpreted appropriately, particularly where links were tentative. Keeping an open dialogue with colleagues is therefore key to the CCA process.

Analyst recommendations for future directions in CCA

Analysts made a number of recommendations for the further development of CCA. Most of these recommendations centred on improving data collation and recording. Analysts stressed the importance of collecting as much information about offences as possible, and ensuring this information is captured accurately in the crime reports. The development, and consistent use, of a more robust data coding system for modus operandi behaviours was also recommended to support the accuracy of linkage work.

From a practical perspective it was highlighted that having dedicated time to conduct CCAs would improve the quality of the work. More timely access to data would facilitate the CCA process; in particular it was suggested that investing in more sophisticated computer software could substantially reduce the time spent searching for information. Building and maintaining effective communications between BCUs, and between police forces, would allow quicker access to information for CCA, and might also yield supplementary datasets that could be included in CCA work.

Peer review of CCAs was highlighted as a good method of minimising human error and false interpretation. Maintaining an open and honest dialogue with peers also encourages collaborative working and the cross fertilisation of learning. This will, in turn, help to enhance the quality of CCA products.

One analyst highlighted the need for more research:

> *"What would also help would be continuing research particularly around behavioural consistency (what parts are more stable and what parts aren't)"*
>
> *(W-12)*

This is an encouraging finding for academics working in the field of case linkage. The focus of applied research is to ensure findings can be of practical use, and so it is reassuring that ongoing research on behavioural consistency would be considered useful for analysts working on the frontline.

It is clear that analysts share the view of the academic community that data access and quality needs to be improved to enhance the ability to link offences accurately. However, analysts also identified more practical issues (such as the negative impact of poor tasking and the importance of being allowed adequate time to complete the CCA) that are less likely to be identified as barriers to CCA by the academic community. This demonstrates the value of surveying analytical staff, alongside the quantitative research, when developing CCA techniques.

Discussion

The CCA provides a concise account of a large amount of information and analysts believe these to be beneficial to criminal investigations. The findings of the present survey clearly indicate that CCA forms a key part of the analyst role, and that a range of information, including temporal and spatial trends, forensic evidence, MO behaviour, and offender/victim characteristics, are used to link offences committed by the same offender. Analysts emphasised the importance of linking across multiple factors and the value of using distinctive behaviours to build strong links between cases.

However, analysts highlighted a number of challenges in CCA that need to be addressed to improve the quality and value of the CCA product. Most notably, analysts expressed concerns about data availability, accessibility, and quality. This is a view shared by the academic community who have (i) reported that the quantity and quality of information varies widely from case to case (Santtila et al., 2005) and (ii) expressed concerns that selective questioning by the police officer can result in details they deem to be irrelevant being ignored or omitted from crime reports (Canter & Alison, 2003, cited in Woodhams, Bull, et al., 2007; Tonkin et al., 2008). There are a number of ways in which data quality could be improved including interviewing victims more skilfully (Milne & Bull, 1999), and developing a robust data coding system for MO behaviours. There might also be opportunities to incorporate more forensic evidence into CCAs as police forces increase the number crime types attended by forensic teams. For example, good practice published by the Association of Chief Police Officers (ACPO) recommends forensic teams attend all burglary scenes (National Police Improvement Agency, 2011) and minutes from a performance monitoring committee meeting (dated February 2010) in Northamptonshire reported that 100% of burglary dwelling scenes are now attended by the Scenes of Crime Officers (SOCO) to maximise forensic recoveries and obtain evidence to identify and prosecute the offenders responsible. The development of computer systems that allow data to be input, updated, and stored more efficiently, and strengthening communication networks with external organisations, would facilitate faster access to forensic evidence. This would boost the level and quality of information available for analysis.

This research has indicated that analyst concerns about CCA commonly mirror those of academics. For example, W-1 reported that a scared and confused victim (in rape cases) might not be able to provide much information. This supports concerns expressed by Woodhams, Bull, et al. (2007) that the trauma experienced by victims during the offence can adversely affect recall. However, analysts also outlined more practical problems (such as a lack clear tasking leaving the analysts unsure of the commissioning officers expectations and the need to be able to dedicate time to CCA) that are not highlighted in existing research literature. This demonstrates the value of gathering the views of frontline staff when researching case linkage.

Conclusion

This chapter has discussed the findings of a survey of 18 analysts, working in a range of departments across two police forces, about their views and experiences of CCA. The sample is relatively small, and so it is acknowledged that the results may not necessarily reflect the views of other analysts working within the forces surveyed, other UK forces, or indeed to police agencies in other countries. Thus, these findings are indicative rather than conclusive. However, the survey did highlight that analysts routinely conduct case linkage on a variety of offence types (ranging from car theft to murder) to support the investigative process, and that they use behaviour to identify offence series.

It is important to continue research in this area as failure to link offences accurately can waste police resources, delay the investigative process, and/ or reduce the chances of apprehending the offender (Bennell, Bloomfield, Snook, Taylor, & Barnes, 2010; Grubin et al., 2001). It is suggested that focusing on continuing to build the evidence base for behavioural consistency and distinctiveness, and identifying which behaviours are the most reliable linkage indicators will be beneficial to analysts.

The decision to use open questions proved to be prudent as the survey responses provided were very detailed. However, this level of detail might not be replicated in future survey work. Thus, expanding this research, using more in-depth data gathering techniques (such as one-to-one interviews or focus groups) to gather the views and experiences of a larger sample of analysts would be beneficial to identify opportunities to support the development of operational CCA work. Interviews with police officers who request CCA reports would also be valuable; for example, to identify examples of scenarios when an officer will request a CCA, what they hope to achieve by requesting a CCA, and feedback about how the CCA was used to provide leads for the investigation. Finally, it would be useful to review a sample of CCA reports to examine the specific types of information used and how links are formed between cases. This would be a challenging task as the content of CCA reports will be restricted due to the likelihood of containing personal information about offenders and/or victims. However, if adequate security clearance could be secured and permission granted from police forces to review this material, this would be greatly assist the improvement and further development of case linkage techniques and thus the practical value of CCAs to investigating officers.

Chapter 4 : Linking personal robbery using offence behaviour[4]

Aim

This research focuses on personal robbery; an offence previously unexplored by case linkage researchers. The central aim of the quantitative elements of the new research being presented in this thesis is to build upon the existing evidence base for the theoretical assumptions of case linkage; i.e. behavioural similarity and behavioural distinctiveness (see chapter 2 for a more in depth discussion of these concepts). This will involve comparing the behavioural similarity of linked pairs of robbery offences (i.e. two offences committed by the same offender) with the behavioural similarity of unlinked pairs of robbery offences (i.e. two offences committed by different offenders). The finding that linked pairs are more behaviourally similar than unlinked pairs would provide support for both of the assumptions.

Case linkage is a varied activity. Not only is it conducted on different offence types, but also in different police force areas, and with differing levels of information. The new research to be presented here seeks to establish how case linkage performs under different conditions with a view to providing

[4] Study 1 presented in this chapter has been published. Reference: Burrell, A., Bull, R., & Bond, J. (2012). *Linking personal robbery offences using offender behaviour. Journal of Investigative Psychology and Offender Profiling*. Advance online publication. DOI: 10.1002/jip.1365

practical advice to crime analysts working on case linkage in an operational setting. The possible effects of a number of factors will be examined:

1) *Domains:* This research explores whether some behavioural themes are more useful than others for the linking of offences.

2) *Constraints on inter-crime distance:* The research tests whether placing constraints on distance when creating unlinked pairs affects the performance of inter-crime distance as a linkage factor.

3) *Urban versus Rural:* The research tests the same behavioural variables in two police force areas – one rural and one urban – to determine whether there are any significant differences in case linkage performance between these different environments.

4) *Domain performance:* The research tests whether adding more behavioural variables to domains improves case linkage performance.

Hypotheses

A number of relevant hypotheses have been formed.

Hypothesis 1 For personal robberies linked pairs will be more behaviourally similar than unlinked pairs.

Rationale: The qualitative research (see chapter 3) revealed that crime analysts do conduct case linkage on personal robbery. However, research has hitherto not tested behavioural consistency or distinctiveness in relation to this type of offence. Assessment of this offence type will therefore broaden our knowledge and understanding. Analysts had mixed views about how easy it is to link personal robberies (see chapter 3), however, the methodological approach used in the present research has been successfully employed in a number of earlier studies (e.g. Bennell & Canter, 2002; Bennell & Jones, 2005; Markson et al., 2010; Tonkin et al., 2008; Tonkin, Santtila, et al., 2011; Woodhams & Toye, 2007) covering a range of crime types (e.g. burglary, car theft, and commercial robbery). It is therefore anticipated that the approach will provide evidence that offender behaviour can be used to distinguish between linked and unlinked pairs of personal robbery offences.

Hypothesis 2 Some behavioural domains will emerge as stronger linkage factors than others.

a. *Inter-Crime Distance* will be the most useful linkage factor.
b. *Temporal Proximity* will be a useful linkage factor.
c. *Target Selection* will be a useful linkage factor.
d. *Control* will be a useful linkage factor.
e. *Approach* will be a useful linkage factor.
f. A *Combined* domain containing all the behaviours from a specified number of domains will perform better than any of the individual domains in isolation.

g. An *Optimal* model, made up of relatively few domains, will be identified.

h. *Property* will not be a useful linkage factor.

Rationale: Previous research has determined that some domains outperform others in case linkage. Hypotheses 2a – 2g are based on such findings. It is anticipated that *Property* (hypothesis 2h) will not be useful for linkage in this case because most personal robberies involve the theft of the same kinds of property (i.e. small valuable items easily hidden about the robbers' person, most notably mobile phones and cash) and so it will not be possible to distinguish between offenders based on what is stolen.

Hypothesis 3 The power of *Inter-Crime Distance* as a linkage factor will deteriorate if geographical constraints are placed on the data.

Rationale: The case linkage literature consistently highlights *Inter-Crime Distance* as the most powerful behaviour for linking offences. However, previous research has not considered how the geographical size of the research area might impact on the strength of this effect. Previous research has tended to utilise the whole study area when generating unlinked pairs of offences, but this is problematic for several reasons. Firstly, offenders tend to operate in a relatively small geographical area (Santtila, Laukkanen, & Zappalà, 2007) and so selecting random pairs of offences from anywhere in a large study area (e.g. a police force area) to act as unlinked pairs is not reflective of known patterns of offending thus potentially biasing the results. Secondly, police analysts conduct case linkage at a local (i.e. borough/Basic Command Unit [BCU]) as well as a force-wide level (Burrell & Bull, 2011 - see chapter 3), and so considering how the distance between unlinked pairs might impact on linkage accuracy is particularly relevant to the practical application of case linkage. Finally, there is evidence that offenders learn from each other (Clarke & Eck, 2005) and so those active in the same local area might adopt similar methods of operation thus complicating the linkage. Therefore, identifying which behaviours can be used to link crimes reliably at a local level will offer practical help to analysts who work with a local remit. The issues described above could impact on the similarity of unlinked pairs, and so it is possible that the case linkage performance of some behavioural domains would deteriorate if the offences forming unlinked pairs were geographically closer together.

Hypothesis 4 Evidence for case linkage assumptions will emerge in both rural and urban areas.

Rationale: Urban involves irreversibly built-up areas comprising settlements with a population greater than 10,000 people (Office for National Statistics, 2004). Rural encompasses all other areas including small towns and fringe areas, villages, hamlets and isolated dwellings in a rural domain (*ibid*). Case linkage research has been conducted in different parts of the UK and also abroad with promising results. It is therefore anticipated that evidence for the theoretical assumptions of case linkage will be found in both urban and rural areas of the UK.

This new research utilises data from one rural and one urban police force. Northamptonshire is the rural police force (over 90% of the Northamptonshire geographical area is classified as rural), and the West Midlands conurbation with 86% of the geographical area classified as urban is the urban police force. It is possible that the different urban/rural ratio of these two police force areas affect the ability to distinguish between linked and unlinked pairs. However, it is difficult to predict whether performance will be better in the urban force or the rural force. The frequency of personal robbery is higher in urban areas (Smith, 2003). As such there will be more cases to sift through when making linkage decisions; a factor identified as a barrier to effective linkage by analysts (see chapter 3). Conversely, the greater number of personal robberies could mean that this offence type is more likely to be identified as a priority in urban areas. Therefore more emphasis might be placed by the police on accurate and detailed data recording, thus potentially providing better information upon which to base linkage decisions.

Hypothesis 5 Domain performance will be improved by adding more behavioural variables.

Rationale: More detailed robbery information were available for West Midlands than for Northamptonshire. This allowed for additional behavioural variables to be coded. It is anticipated that inputting this additional information into the analysis would yield better results.

The hypotheses were tested using a series of three studies. These studies utilised the same standard case linkage procedures (as outlined in the upcoming methodology section) to test linkage performance under different conditions. The studies are as follows:

Study 1. Linking personal robbery offences using offence behaviour in Northamptonshire (phase 1 and 2)

Study 2. Linking personal robbery offences using offence behaviour in the West Midlands (phase 1 and 2)

Study 3. Incorporation more variables into the behavioural domains.

The first two hypotheses are tested in all three studies. Also, all three studies involve a range of behavioural domains allowing hypothesis 2 to be assessed.

Each study was split into two phases. Phase 1 compared linked pairs to unlinked pairs that have been generated using data from the whole police force area under consideration. Phase 2 reduced the geographical area that unlinked pairs can be sourced from by ensuring that both offences within the unlinked pair occurred in the same borough/Basic Command Unit. Comparison of the results for phase 1 and phase 2 of each study provided the opportunity to test hypothesis 3 (concerning *Inter-Crime Distance*).

Hypothesis 4 will be assessed by comparing the findings of study 1, which used data from the rural police force (Northamptonshire), with study 2 which uses data from an urban police force (West Midlands).

The fifth hypothesis was assessed by comparing the results of study 2 with the results of study 3.

Methodology

Sample

The data were extracted from police records for solved personal robbery offences for two UK police forces; Northamptonshire (the third most rural police force) and West Midlands (the second most urban police force) (Bond, 2012).

Northamptonshire

Permission was granted by Northamptonshire Police for a dataset to be provided for this research. A Northamptonshire Police crime analyst extracted data on personal robbery from the police force systems and rendered it anonymous (e.g. replacing offender names with a unique reference number, removing victim names and addresses etc.). From this dataset, a sub sample of solved robbery offences was extracted for analysis. This comprised 166 offences (committed by 83 offenders) that were reported between 1st January 2005 and 31st December 2007. Seventy-seven offenders were male, and five were female (the gender was recorded as unknown for one offender). The offenders were aged between ten and 44 years with an average age of 18 at the time of the offence. Females were a little older than males on average (mean = 23, range = 12 to 44 compared to mean = 28, range = 10 to 41 for males). Over 70% (n=58) of the offenders were recorded as being White (including four out of five of the females), 13 were recorded as Black, and 12 (including one female) of mixed heritage.

West Midlands

Permission was granted by West Midlands Police for a dataset to be provided for this research. A West Midlands Police crime analyst extracted personal robbery data from police systems. The current author was provided with desk space in a secure office to anonymise and code these data. A sub sample of solved robbery offences was extracted for analysis. This comprised 554 offences committed by 277 offenders that were reported between 1st April 2007 and 30th September 2008. The majority of offenders were male (n=258 or 93%). The offenders were aged between 11 and 45 years with an average age of 19 at the time of the offence. Females were slightly younger than males on average (mean = 16, range = 12 to 24 years compared to mean = 19, range = 11 to 45 years for males). Almost half of the offenders (n=138) were recorded as being from a Black background (including nine females). Just under 30% are White (n=78) (of which eight were female), and 15% (n=42) were recorded as Asian. Less than 1% (n=2) were from a mixed or other minority background. Ethnicity was unknown in 17 (6%) of cases (of which two were female).

Procedure

This research compares the behavioural similarity of linked offences (i.e. offences committed by the same offender) with the behavioural similarity of unlinked offences (i.e. offences committed by different offenders). The finding that linked offences are more behaviourally similar than unlinked offences would provide support for both of the assumptions of (i) behavioural consistency, and (ii) behavioural distinctiveness.

It is standard practice to include a constant number of offences (usually two) per offender in case linkage analysis. This is primarily to remove the bias that might be presented by prolific offending (Bennell & Canter, 2002; Bennell & Jones, 2005; Woodhams & Toye, 2007). Some offenders are more prolific than others and it is possible that including all of the offences (in each series) would unduly influence the results if very prolific offenders display particularly high or low levels of behavioural similarity in their offending (Bennell & Canter, 2002). Furthermore, in this research the timeframes sourced were limited. Consequently the entire offending series for each offender was not available and so the option of including all offences in the series in the analyses was not feasible. Also, it is noteworthy that a recent publication from the Federal Bureau of Investigation (FBI) in the USA identifies serial murder as “the unlawful killing of two or more victims by the same offender(s) in separate events” (Morton, 2008; p.9). This indicates that two offences are sufficient to be considered a series.

The details of how linked and unlinked pairs were selected, how the data were coded and domains created are outlined below along with details of the statistical processes used to test behavioural similarity. The methodological procedure used to compare behavioural similarly is standard across the three studies. Each study is conducted in two phases to allow for hypothesis 3 to be tested. Phase 1 compares the similarity of linked pairs of offences with unlinked pairs of offences committed within the same police force area (which are quite large geographically). Phase 2 reduces the geographical area that unlinked pairs can be sourced from by ensuring that both offences within the unlinked pair occurred in the same borough/Basic Command Unit. This overcomes the aforementioned limitation of generating unlinked pairs using a large geographical area allowing the research to test whether behaviour can be used to distinguish between linked and unlinked pairs on a local level as well as on a force-wide basis (the latter as tested by phase 1 of each study).

Crime pairs

Selecting linked pairs

This research uses the two most recent offences for each offender to create a linked offence pair, thus mirroring the approach used by other researchers (e.g. Woodhams & Toye, 2007). However, there were some cases where the two most recent offences could not be used for fear of compromising the independence of the datasets. This is because the Home Office Counting Rules (Home Office, 2012) state that a separate crime should be recorded by the police for each victim rather than each incident and so a single incident can result in multiple offences being recorded if there is more than one victim. There were cases in both datasets where the date, time, and location of offences were identical and the modus operandi information suggested that the two most recent offences were actually part of the same incident. To include such pairs in the analysis would falsely inflate the level of similarity in linked pairs. Therefore, 19 offenders from Northamptonshire and 70 from West Midlands had to be removed from the analysis.

In a similar vein, a further 21 offenders were omitted in Northamptonshire and 91 from West Midlands where one or both of the offences associated with the offender already appeared in the respective datasets as part of the crime series of another offender (i.e. their co-offender) and so the inclusion of the pair would again compromise the independence of the linked pairs sample. A further 12 offenders were excluded from the Northamptonshire dataset due to missing data about their offences.

The two most recent offences (that were not part of the same incident) were selected for each of the remaining offenders in each area (83 in Northamptonshire and 277 in West Midlands), forming two discrete samples of linked crime pairs for analysis (as previously described in the sample section).

Selecting unlinked pairs for phase 1

The current research mirrors previous case linkage research utilising an unlinked sample with the same number of pairs as the linked sample (e.g. Markson et al., 2010, Tonkin, Woodhams, et al., 2011; Tonkin, et al., 2008). The unlinked pairs have been generated using the =RAND() function in Microsoft Excel to randomly re-order the rows within each linked sample. The unlinked pairs were created by using row 1 and row 2 as pair 1, row 3 and row 4 as pair 2 and so on. The data were then checked manually to ensure that all the unlinked pairs were indeed unlinked as the random re-ordering of rows could have resulted in a few linked offences being matched together as unlinked pairs.

A total of 83 unlinked pairs were created based on the 166 offences contained within the linked sample for Northamptonshire. This dataset is labelled **'NH - unlinked1'** throughout this thesis.

A total of 277 unlinked crime pairs were created based on the 554 offences contained within the linked sample for West Midlands. This dataset is labelled **'WMP – unlinked1'** throughout this thesis.

At no time were offences from Northamptonshire and West Midlands combined into one dataset, although the findings from studies 1 and 2 are directly compared to test hypothesis 4.

Selecting unlinked pairs for phase 2

A second unlinked sample was created for each police force (labelled '**NH - unlinked2'** and **'WMP – unlinked2'** throughout the thesis) to allow for further comparisons with the associated linked dataset. The totally random nature of allocating offences to an unlinked pair in phase 1 of the studies means that a single offence could be matched with an unrelated crime located anywhere in the police force areas. The police force areas are geographically large - West Midlands is 348 square miles and Northamptonshire is 913 square miles (Office for National Statistics, 2004), and so there is a high likelihood of unlinked pairs being located far apart. In fact, further examination of the data revealed that the two offences within linked pairs tended to occur in the same borough/BCU (82% in Northamptonshire and 77% in West Midlands) whereas the two offences within unlinked1 pairs typically occurred in different boroughs/BCUs (75% in Northamptonshire and 95% in West Midlands). This difference between the samples of linked and unlinked1 pairs could introduce bias into the analysis, potentially inflating the predictive ability of *Inter-Crime Distance*.

There are six boroughs in Northamptonshire and 21 Basic Command Units (ranging in size from three square miles to 69 square miles) in West Midlands[5]. The unlinked2 pairs were generated by randomly re-ordering the rows in the linked sample to create new pairs but this time controlling for borough/BCU to ensure the offences in each unlinked2 pair occurred in the same local area.

In Northamptonshire, the borough for each offence was identified using the crime reference number, which includes a reference to the borough. There are slightly fewer unlinked pairs in this sample (n=81) as two boroughs had an odd

[5] The West Midlands Police force area has now been restructured into 10 Local Policing Units (LPUs). The boundaries of these new LPUs are not co-terminus with the previous BCU boundaries and therefore the areas cannot be directly compared. However, this is not a concern for the current research as the aim was to consider whether case linkage is feasible at a local as well as force level. In this instance, as the research has been conducted on much smaller geographical areas than currently exist in West Midlands, if inter-crime distance is reinforced as a useful linkage factor at BCU level then it should be also be a useful linkage factor in the now larger LPU areas.

number of offences associated with them meaning that there was a single offence 'left over' after pairs had been created. In addition, one borough only had two offences associated with it – these were both committed by the same offender and could therefore not be included as an unlinked pair. The dataset is labelled **'NH – unlinked2'** throughout this thesis.

In West Midlands, the BCU is recorded within the dataset. There are slightly fewer unlinked pairs in this sample (n=272) as ten BCUs had an odd number of offences associated with them meaning that there was a single offence 'left over' after pairs had been created within each of these BCUs. The dataset is labelled **'WMP – unlinked2'** throughout this thesis.

The new unlinked samples were then combined with their respective linked sample and the statistical analyses re-run (i.e. phase 2) to determine if the same behaviours emerge as useful linking factors.

Data coding

A description of how the offence was reported as having been committed (i.e. the modus operandi) is included in the police records. Content analyses of these descriptions was conducted and a checklist of dichotomously coded behaviour variables created. Binary coding - i.e. 1 denoting the presence of a behaviour, and 0 the absence of a behaviour - was used because previous research has indicated that more complex coding methods are difficult to apply to police data in a reliable way (Canter & Heritage, 1990).

A total of 68 crime commission behaviour variables were identified from the modus operandi information across the two police force areas. However, a large proportion of these variables were not included in the current studies. Reasons for exclusion were:

1. The behaviour was deemed to be more indicative of victim or bystander behaviour than offender behaviour (e.g. victim resistance, victim compliance). Such behaviours are dependent on the victim and so are not representative of the consistency or distinctiveness of offender behaviour. The offender’s response to victim resistance or compliance would be though, hence associated behaviours could be included if they met the other inclusion criteria.

2. The behaviour occurred in less than 1% of cases (e.g. the offender urinates on the victim). Rare behaviours are often removed from the analysis by case linkage researchers (e.g. Woodhams & Toye, 2007) to avoid clusters displaying very unusual behaviours (Grubin et al., 2001).

3. The behaviour had a poor inter-coder reliability score (e.g. blitz attack). Two people independently coded the modus operandi data into the dichotomous variables (for 10% of the crimes). The level of agreement between the two coders was then assessed using kappa. A low kappa score indicates a low level of agreement between coders. This suggests that these behaviours would be difficult to code consistently in an

applied setting. They are therefore removed from the analysis at this stage.

Study 2 did not strictly conform with all aspects of the exclusion criteria as it was designed to be an exact replication of study 1 in terms of the behaviours tested.

A total of 19 modus operandi behavioural variables, each of which had a very good overall inter-coder reliability score ($\kappa = 0.95$), were selected for inclusion in study 1. These variables were combined with other variables extracted from the recorded crime data (e.g. time of day, day of week, property stolen) to form a final 'behaviour' checklist of 52 behaviours. This checklist was also used for study 2.

Study 3 added 26 behaviours into this checklist. The new behaviours included nine location variables that were not available in the Northamptonshire data, and four weapon types that occurred in more than 1% of cases in West Midlands but not Northamptonshire (and so were excluded from studies 1 and 2). Seven types of stolen property were also added; these items were stolen in more than 1% of offences in West Midlands but not recorded as stolen in large numbers in Northamptonshire. The final six behaviours were derived from the modus operandi field; four behaviours (offender snatches/grabs property, verbal threat, victim resists – met with violence, and property discarded) were added as they met both the volume and the inter-rater reliability criteria for inclusion. The final two behaviours (approach – distraction, and approach – blitz) did not meet the inter-rater reliability criteria. However, they were added due to academic interest (the reasons for this will become clear as the findings of studies 1 and 2 are discussed).

The behaviour checklist for the three studies is in appendix B, which also includes the frequency of each behaviour by police force area.

Domain formation

Individual offence behaviours can be arranged into clusters, each thought to serve a different purpose in the offence (Tonkin et al., 2008). For example, weapon use and threatening language are both examples of how to seek to control victims during an offence. Thus, the behaviours were grouped into behavioural clusters or domains for analysis. Domains were originally modelled on those used by Woodhams and Toye (2007) in their analysis of commercial robbery, namely planning, target selection, control, and property. However, adjustments were made due to data availability and the differing nature of commercial and personal robbery. For example, it was not possible to create a domain for planning due to a lack of relevant behaviours recorded in relation to the personal robbery offences. The *Target Selection* domain encompasses some behaviours used by Woodhams and Toye (2007) (i.e. day of week and time of day). However, the time of day variables were structured differently to be more representative of patterns in personal robbery and were based on the timebands used by Smith (2003) in his research on personal robbery. Commercial robbery is limited to when businesses are open. The opportunities for committing personal robbery are spread more evenly across the day (although they will cluster where there are more people). Furthermore, Woodhams and Toye (2007) used uneven timebands and there was no rationale to replicate this. Variables relating to whether the offender was known to the victim, and whether the victim was at a cashpoint at the time of the attack were also included in the *Target Selection* domain for studies 1 and 2. Study 3 added nine location variables to this domain.

The *Approach* domain contains behaviours associated with how the offender(s) first come into contact with the victim. There were four approach variables in study 1 and 2, with study 3 adding a further two behaviours to the domain.

The *Control* domain includes variables in relation to weapon use, violent actions, offender commands, and whether the victim and/or offender were alone or part of a group when the offence occurred (n=15 behaviours in total). Study 3 added four weapon types, and three violent actions to the domain.

The *Property* domain for studies 1 and 2 contained 14 types of property plus whether any property was returned to the victim by the robber(s) during or following the offence. Study 3 added seven property types and a variable for 'property discarded'.

Temporal Proximity – i.e. the number of days between offences – and *Inter-Crime Distance* (calculated using Pythagoras' theorem – see appendix C for details) were also included in the analysis in all three studies. These final two behaviours were included because they proved to be useful predictors of linkage in previous research (e.g. Tonkin, Santtila, et al., 2011). Furthermore, the analyst survey (see chapter 3) revealed that the majority of analysts (15 out of 18) use spatial and temporal behaviours to support linkage decisions. Therefore, it is important to test the validity of these variables.

Statistical procedures

The following statistical procedures were utilised during the three studies to compare the behavioural similarity of linked and unlinked pairs, and to identify the most useful factors for linkage. Step 1 translates the raw crime data (i.e. the dichotomous variables on the respective checklist) into similarity scores. These similarity scores then become the core dataset for steps 2 and 3 of the analysis.

Step 1 - Measuring similarity

The similarity of pairs across each behavioural domain was measured using Jaccard's coefficients. These do not take joint non-occurrences into account (Porter & Alison, 2004; Porter & Alison, 2006a; Real & Vargas, 1996) and so using Jaccard's means that the level of similarity does not increase if the behaviour is not reported to have occurred within an offence pair (Woodhams, Grant, et al., 2007). This is an important issue when working with police data as the absence of a behaviour does not necessarily mean that the behaviour did not occur (Porter & Alison, 2004; Porter & Alison, 2006a), but perhaps that it was not reported or was not recorded (Tonkin et al., 2008). Some research has tested other similarity measures against Jaccard's namely taxonomic similarity (Woodhams, Grant, et al., 2007) and the simple matching index (S) (Ellingwood et al., 2012) however neither measure was found to perform significantly better than Jaccard's. Therefore the decision was made to use the Jaccard's similarity measure in this thesis.

Jaccard's coefficients are expressed as a value of between 0 and 1, with 0 indicative of no similarity and 1 denoting perfect similarity. Thus, higher Jaccard's coefficients for linked pairs than unlinked pairs would provide support for behavioural consistency and distinctiveness. Jaccard's coefficients have been calculated using the Statistical Package for the Social Sciences (SPSS) version 18.0© (IBM Corporation, NY United States). SPSS calculates the similarity of pairs of offences based on the behaviours input into the analysis producing a matrix containing the Jaccard's coefficients for all possible combinations of offences. Jaccard's coefficient matrices were produced for each behavioural domain (i.e. *Target Selection, Control, Approach,* and *Property*). In line with other research (e.g. Tonkin, Santtila, et al., 2011) Jaccard's coefficients were also calculated for a '*Combined*' domain. This contains all behaviours from the *Target Selection, Control, Approach,* and *Property* domains.

The relevant Jaccard's coefficients for each domain were extracted from each matrix for each pair in the linked, unlinked1, and unlinked2 samples (i.e. the Jaccard's coefficient for *Target Selection* for linked pair 1, the Jaccard's coefficient for *Target Selection* for linked pair 2 etc.). All other Jaccard's coefficients were excluded from the analyses. The Jaccard's coefficients for each domain plus the variables *Temporal Proximity* and *Inter-Crime Distance* form the dataset for the next stage of the analysis.

Step 2 - Comparing similarity of domains

To determine which test of difference to use in the initial analysis it was necessary to assess whether the data met the assumptions for parametric testing (i.e. normally distributed data). A visual assessment of histograms indicated that the data were not normally distributed. Although histograms can indicate that distributions are different from normal, they cannot determine whether this deviation is large enough to select a non-parametric test rather than a parametric test. Therefore, Kolmogorov-Smirnov tests were conducted to confirm whether the distribution of the data were not normal. The Kolmogorov-Smirnov (D) tests of normality revealed that the distribution of Jaccard's scores, *Inter-Crime Distances*, and *Temporal Proximities* were significantly different from normal in all three studies (see appendix D for the outcomes of the Kolmogorov-Smirnov tests). This means that the median rather than the mean scores should be reported to compare similarity (Field, 2005), and that a non-parametric test of significance should be used to assess whether there is a statistically significant difference between similarity scores for linked and unlinked pairs. Previous research (e.g. Davies et al., 2012; Markson et al., 2010; Tonkin et al., 2008; Woodhams & Toye, 2007) has used Wilcoxon matched-pairs signed rank tests to test differences due to concerns about the independence of the data. However, it is contended that the current data are best considered to be independent. This is for two reasons: firstly, although the linked and unlinked samples utilise the same crime data within individual studies, individual scores (i.e. Jaccard's coefficients, *Inter-Crime Distances*, and

Temporal Proximities) are generated using data points from two separate offences. As such, no individual score impacts on the value of another. Secondly, unlike some previous research (e.g. Bennell et al., 2009), the current research only compares linked pairs with one possible combination of unlinked pairs at a time. Therefore the underlying crime data are only used twice within a single set of analyses rather than to a large extent. A Mann-Whitney U test was therefore selected to determine if there is a statistically significant difference between linked and unlinked pairs for each domain in each phase.

Reporting effect size is good practice in statistics (Field, 2005) as this provides a measure of the size of the difference between two populations (in this case linked versus unlinked pairs). Effect sizes have been calculated by converting z-scores from the Mann-Whitney U analysis into the effect size estimate r using the following equation cited in Field (2005, p.532).

$$r = \frac{z}{N}$$

where:

r is effect size

z is the z-score produced by the Mann-Whitney U analysis

N is total number of pairs.

A r =.10 represents a small effect size (explaining 1% of the variance), r =.30 represents a medium effect size (explaining 9% of the variance), and r =.50

represents a large effect size (explaining 25% of the variance) (Field, 2005). Thus, the closer the r is to 1.0, the larger the effect.

Step 3 - Identifying predictive factors of linkage

A split-half validation method was introduced at this stage by dividing the Jaccard's datasets into experimental samples (to build the predictive models) and test samples (to test the predictive models). This mirrors the approach used by other researchers (e.g. Bennell & Canter, 2002; Bennell & Jones, 2005; Ellingwood et al., 2012; Tonkin, Santtila, et al., 2011). Each dataset was randomly split in half to form the experimental and test samples.

The Jaccard's scores calculated from Northamptonshire dataset (**NH – linked**) were used for study 1 with 42 linked pairs and 42 unlinked1 pairs forming the experimental sample, and 41 linked pairs and 41 unlinked1 pairs forming the test sample for phase 1. The **NH - unlinked2** sample was also split into an experimental dataset (comprising of 41 unlinked pairs of offences) and a test sample (made up of 40 pairs). These were combined with the experimental and test datasets for the linked sample to create the dataset for phase 2 of study 1.

The West Midlands dataset was used for study 2 with 138 linked pairs and 138 unlinked1 pairs forming the experimental sample, and 139 linked pairs and 139 unlinked1 pairs forming the test sample for phase 1. The **WMP - unlinked2** sample was also split into an experimental dataset (comprising of 136 unlinked2 pairs of offences) and a test sample (made up of 132 unlinked2 pairs). These were combined with the experimental and test datasets for the linked sample to create the dataset for phase 2 of study 2.

Study 3 splits crime pairs into the same experimental and test samples as study 2 to allow for the direct comparison of the two studies. However, the Jaccard's scores forming the datasets were different because additional variables had been added into each of the domains.

Single-factor logistic regression models were conducted on the experimental datasets to explore whether any of the behavioural domains can be used as accurate predictors of linkage. Regression models consisting of multiple factors were also tested. This was achieved through standard logistic regression with multiple factors or utilising stepwise logistic regression. This determined whether the single-factors could be combined to generate optimal models with improved predictive performance.

The Constant (α) and Logit (β) values from the regression models were used to calculate the estimated probabilities for each pair in the test samples using the process outlined in Bennell and Canter (2002) (see appendix E for details). The α and β values from the experimental sample for phase 1 were used to calculate the probabilities for the test sample for phase 1, and the α and β values from the experimental sample for phase 2 were used to calculate probabilities for the test sample for phase 2 (within each study). The resulting probabilities are measured between 0 and 1 with higher values indicating a greater likelihood that the two offences in the crime pair are linked.

The probabilities were used to perform Receiver Operating Characteristic (ROC) analyses, a technique that is becoming standard practice in case linkage research. ROC analysis is a measure of predictive accuracy and uses the area under the curve (AUC) to assess the linkage accuracy of the data that give rise to the ROC curve (Bennell et al., 2009). An AUC of 0.5 indicates chance level and an AUC of 1.0 indicates perfect discrimination, meaning the larger the AUC, the higher the predictive accuracy (Woodhams, Bull, et al., 2007). AUCs of between 0.5 and 0.7 are indicative of low levels of accuracy, 0.7 to 0.9 indicate moderate levels of accuracy and 0.9 to 1.0 high levels (Bennell & Jones, 2005; Swets, 1988). The approach has many advantages and has been used to overcome concerns about statistical independence and to set decision thresholds (e.g. Bennell & Jones, 2005; Bennell et al., 2009). ROC analysis is also a useful method of calibrating the validity of linkage features identified by regression models, and this is what it is used for in the current studies.

The ROC analysis was conducted for each domain using SPSS version 18.0 using the probabilities as test variables and linkage status as the state variable. It was hypothesised that the ROC analyses would mirror the trends found in the regression analyses, thus providing validation for the regression models developed with the experimental sample.

Interpretation of the Results

This methodological approach used in the new studies presented in this thesis involve a considerable number of statistical tests. This section briefly outlines how to interpret these tests.

Kolmogorov-Smirnov Test and Median Scores

The key statistical output for the Kolmogorov-Smirnov test is the D score, the degrees of freedom (df), and significance value (p). A significant p value indicates that the data are significantly different from normal. The Kolmogorov-Smirnov tests (see appendix D) revealed that the data are not normally distributed in any of the studies. This means that the medians (the middle value in an ordered set of observations) rather than the means (arithmetic average) should be reported to compare similarity (Field, 2005). For the purposes of this research higher median scores for linked pairs than for unlinked pairs provides evidence for the theoretical assumptions.

Mann-Whitney U test

The key aspect of the Mann-Whitney U test is the significance of the U statistic and its associated z-approximation. A significant result (i.e. with a p value of less than 0.05) indicates that there is a statistically significant difference between two populations (in this case linked versus unlinked pairs); a favourable finding, providing evidence for the theoretical assumptions of case linkage.

The effect size provides a measure of the size of the difference between linked and unlinked pairs. The larger the effect size, the larger the difference is between the two populations under consideration. The desired result is therefore a large effect size (as close to 1 as possible).

Regression

The results tables for the regression models include a wealth of information. Table 4-1 (see over the page) outlines what is included and what each statistic means.

Table 4-1: How to interpret regression tables

Statistic	**Explanation**
α	The α is the constant for the regression model. The α is used in the equation to calculate the probabilities in the test sample for use in the ROC analysis.
β	The β is the co-efficient for the individual predictor. The β is used in the equation to calculate the probabilities in the test sample for use in the ROC analysis. Labelled B in the SPSS output.
Wald (df)	A non-significant Wald statistic indicates that the individual predictor should be removed from the regression model. The desired outcome is therefore a significant Wald score.
Model χ^2	The χ^2 is a measure of goodness-of-fit, i.e. how well the regression model fits the actual data. The desired result is a statistically significant χ^2 as this means the model fits the data well.
Nagelkerke R^2	The R^2 represents the amount of variance that is explained by the regression model. The SPSS output expresses R^2 as a figure of between 0 and 1 which can be converted to a percentage by multiplying by 100. The desired result is a high R^2.
Random	A percentage score representing the chances of correctly identifying a linked or unlinked pair based on chance.
Model	A percentage score representing the chances of correctly identifying a linked or unlinked pair based on the regression model.

ROC analysis

The key statistic in ROC analysis is the Area Under the Curve (AUC). This represents the predictive accuracy of the data that give rise to the ROC curve. An AUC of 0.5 indicates that the data does not perform any better than chance level whereas an AUC of 1.0 indicates perfect discrimination. The desired outcome is a high AUC. The p value indicates whether the AUC result is statistically significant.

The 95% confidence intervals were used to assess whether there were statistically significant differences between AUCs. If the confidence intervals do not overlap then the difference between the AUCs is statistically significant. In this research comparing the confidence intervals allows for analysis of whether there were statistically significant differences between the AUCs for phase 1 compared to the AUCs for phase 2.

STUDY 1: Linking personal robbery using offence behaviour in Northamptonshire (phase 1 and 2)

This study utilises the methodology outlined earlier in this chapter. The data sample used is the Northamptonshire Police sample outlined in sample section of the methodology. This comprises 166 solved personal robbery offences committed by 83 offenders reported to Northamptonshire Police between 1st January 2005 and 31st December 2007. The sample has been used to generate three sub-samples – 83 linked pairs, 83 unlinked1 pairs, and 81 unlinked2 pairs. Phase 1 of the study compares the **NH - linked** sample to the **NH - unlinked1** sample, and phase 2 compares the **NH - linked** sample to the **NH - unlinked2** sample.

Medians

Table 4-2 shows the median Jaccard's scores plus the *Inter-Crime Distances*, and *Temporal Proximities* for each sample. Linked pairs displayed higher Jaccard's scores for *Target Selection, Control*, and the *Combined* domains compared to unlinked pairs. Linked pairs also had smaller *Inter-Crime Distances* and fewer days between offences than unlinked pairs. This indicates that linked pairs are more behaviourally similar and distinctive than unlinked1 and unlinked2 pairs for these domains. However, the median Jaccard's scores for *Approach* and *Property* are the same across the three samples suggesting that these domains may not be useful for linkage.

Table 4-2: Median Scores

Behavioural domain	**Linked**	**Unlinked1**	**Unlinked2**
Inter-Crime Distance (m)	803.6	12,989.8	2,313.5
Temporal Proximity (days)	36	292	144
Target Selection	.250	.000	.000
Control	.250	.167	.125
Approach	.000	.000	.000
Property	.000	.000	.000
Combined	.214	.143	.091

These results indicate that it might be possible to distinguish between linked and unlinked pairs across all domains except *Approach* and *Property* (lending tentative support for hypothesis 1 and partial support for some aspects of hypothesis 2). However, more analyses are needed to drill down into the data to explore the effects. Firstly, tests of difference were conducted to determine if there were statistically significant differences between the median scores. Regression models have then been developed (with the experimental samples) to identify the behavioural domains that can be used as predictors of linkage. ROC analyses were then used to validate the regression models (using the test samples).

Test of difference

Table 4-3 shows the outcomes of the Mann-Whitney U tests for phase 1 (force-wide) and phase 2 (local).

The Mann-Whitney U tests indicate that the differences between linked and unlinked samples are statistically significant for *Inter-Crime Distance, Temporal Proximity, Target Selection,* and the *Combined* domain in both phases. This suggests that all of these domains can be used to link crimes at both a local level and on a force-wide basis. *Control* was close to significance (p=0.06) in phase 1 but reached significance in phase 2 indicating that this domain might be more useful at a local level. Interestingly, the effect sizes for the *Target Selection* and the *Combined* domains also increased between phase 1 and phase 2 indicating that these domains might be more useful for linking crimes within borough compared to force-wide.

Table 4-3: Mann-Whitney U test outcomes

Domain	**Mann-Whitney U (z)**		**Effect size (r)†**	
	Phase 1	**Phase 2**	**Phase 1**	**Phase 2**
Inter-Crime Distance	659.500 (8.889)*	1735.000 (5.176)*	.69	.41
Temporal Proximity	1491.500 (6.313)*	2164.000 (3.942)*	.49	.31
Target Selection	2380.000 (3.590)*	1975.000 (4.840)*	.28	.38
Control	2884.000 (1.859)	2670.500 (2.350)*	.14	.18
Approach	3361.500 (1.419)	3280.500 (1.401)	.11	.11
Property	3429.000 (.071)	3355.000 (.031)	.01	.00
Combined	2342.500 (3.565)*	1953.000 (4.644)*	.28	.36

*p<0.05 †Field (2005) indicates that r=.10 is a small effect size (explaining 1% of variance), r=.30 is a medium effect size (explaining 9% of the variance), r=.50 is a large effect size (explaining 25% of the variance).

Conversely, *Inter-Crime Distance* and *Temporal Proximity* are more useful on a force-wide basis than on a local level with lower effect sizes reported for phase 2 than for phase 1. The results for *Inter-Crime Distance* were not surprising given the methodology for creating unlinked2 pairs, which reduced the median distance between an unlinked pair from 12,990m to 2,314m. It is promising, however, that linked pairs were still demonstratively closer together on average than unlinked pairs, and that this finding was statistically significant. This indicates that *Inter-Crime Distance* remains a useful linkage tool even at a local level; in fact, its effect size suggests it remains better than the other behavioural domains examined. The reduction in the average number of days between offences and the effect size from phase 1 to phase 2 is not as easily explained for *Temporal Proximity*. However, a re-examination of the raw data (i.e. the 166 offences) revealed that offences within each borough tended to be weighted towards either the start or the end of the timeframe examined. In fact, no borough had offences from all three years represented within their sample, therefore this anomalous finding is attributed to the distribution of date of offence across the data.

There were no differences in the median Jaccard's coefficients for the *Property* and *Approach* domains. Furthermore, the effect sizes were small indicating that these domains are unhelpful for linkage purposes. Overall, these analyses provide support for the assumptions, albeit not across all behavioural domains.

Regression

The Mann-Whitney U tests were a useful starting point for determining which behavioural domains might be the most useful for differentiating between linked and unlinked samples. However, additional analysis was needed to drill down into the results and identify the predictive value of each domain. Tables 4-4 to 4-11 outline the results of the regression analyses.

Table 4-4: Inter-Crime Distance (study 1)

Statistic	Phase 1	Phase 2
α	1.831 (.431)	.720 (.328)
β	.000 (.000)	.000 (.000)
Wald (df)	12.132 (1)*	6.426 (1)*
Model χ^2	52.737*	11.313*
Nagelkerke R^2	.627	.170
Random	50.6	50.6
Model	81.9	57.8

*p<0.05

As expected from the Mann-Whitney U tests, the regression model for *Inter-Crime Distance* for phase 1 performed very well explaining 63% of the variance and improving predictive accuracy by over 30%. Furthermore, the model for phase 2, although much weaker (explaining 17% of the variance and only improving predictive accuracy by 7%) nevertheless replicated the trend highlighted by the Mann-Whitney U test.

Similarly, the trends for *Temporal Proximity* (see table 4-5) correlated with those highlighted by the Mann-Whitney U tests, suggesting a deterioration in how useful the behaviour was between phase 1 and phase 2. Although the phase 2 model for *Temporal Proximity* performed very poorly (explaining less than 1% of the variance and not improving predictive accuracy much beyond chance), this is likely to be due to the distribution of date of offence in the data (as stated above). Furthermore, *Temporal Proximity* did explain 14% of the variance and improved predictive accuracy by 27% in phase 1 indicating that it might still be useful in some circumstances (e.g. when working on a force-wide basis).

Table 4-5: Temporal Proximity (study 1)

Statistic	Phase 1	Phase 2
α	.736 (.336)	.117 (.304)
β	-.003 (.001)	-.001 (.001)
Wald (df)	8.161 (1)*	.195 (1)
Model χ^2	9.632*	.196
Nagelkerke R^2	.144	.003
Random	50.0	50.6
Model	66.7	51.8

*p<0.05

Table 4-6: Target Selection (study 1)

Statistic	Phase 1	Phase 2
α	-.0570 (.307)	-.675 (.305)
β	2.519 (.969)	3.653 (1.121)
Wald (df)	6.757 (1)*	10.097 (1)*
Model χ^2	7.929*	13.440*
Nagelkerke R^2	.120	.199
Random	50.0	50.6
Model	65.5	67.5

*p<0.05

The single-factor model for *Target Selection* performed fairly well explaining 12% of the variance and improving predictive accuracy by 16% in phase 1 (see table 4-6). The positive result was replicated in phase 2; this time explaining even more of the variance (20%) and improving predictive accuracy by 17% beyond chance. This replicates the trends highlighted by the Mann-Whitney U test and suggests that *Target Selection* might be especially useful for linking offences when working on a borough level.

Table 4-7: Control (study 1)

Statistic	Phase 1	Phase 2
α	-.387 (.298)	-.112 (.295)
β	1.832 (.974)	.553 (.799)
Wald (df)	3.535 (1)	.480 (1)
Model χ^2	3.899*	.485
Nagelkerke R^2	.060	.008
Random	50.0	50.6
Model	56.0	54.2

*p<0.05

The results for the *Control* domain (see table 4-7) were contrary to what would be expected given the Mann-Whitney U results with phase 1 outperforming phase 2 in relation to R^2 (level of variance explained) and predictive accuracy. Furthermore, the chi-square was significant for phase 1 but not phase 2 indicating that the model for phase 2 does not fit the data well. However, in this regression analysis, the predictive accuracy of the models for phase 1 and phase 2 were low compared to chance, and neither model explained much of the variance. Combined with non-significant Wald statistics (indicating the domain should be removed from the model as it is a poor predictor), this analysis suggests *Control* is of limited value to case linkage.

Table 4-8: Approach (study 1)

Statistic	Phase 1	Phase 2
α	-.024 (.220)	.000 (.221)
β	21.227 (40192.970)	21.203 (40192.970)
Wald (df)	.000 (1)	.000 (1)
Model χ^2	1.398	1.374
Nagelkerke R^2	.022	.022
Random	50.0	50.6
Model	51.2	50.6

*p<0.05

Property and *Approach* were both identified as poor predictive factors for linkage by both phases of the research (see tables 4-8 and 4-9), as non-significant chi-squares indicated that the models did not fit the data well, and the non-significant Wald statistics indicated that these individual predictors should be removed from the regression model. Furthermore, neither of the single-factor models explained very much of the variance, and predictive accuracy did not improve much beyond chance.

Table 4-9: Property (study 1)

Statistic	Phase 1	Phase 2
α	.103 (.240)	.098 (.241)
β	-.806 (.788)	-.623 (.848)
Wald (df)	1.047 (1)	.540 (1)
Model χ^2	1.097	.554
Nagelkerke R^2	.017	.009
Random	50.0	50.6
Model	56.0	55.4

*p<0.05

The results were not unexpected noting the outcomes of the Mann-Whitney U tests and added weight to the argument that the property stolen during a robbery is not useful when predicting whether two offences are linked.

Table 4-10: Combined (study 1)

Statistic	Phase 1	Phase 2
α	-1.290 (.474)	-.963 (.408)
β	7.269 (2.414)	5.553 (1.989)
Wald (df)	9.068 (1)*	7.795 (1)*
Model χ^2	12.916*	10.323*
Nagelkerke R^2	.190	.156
Random	50.0	50.6
Model	63.1	62.7

*p<0.05

The *Combined* domain performed favourably compared to the single-factor models for its component domains (i.e. *Target Selection, Control, Approach,* and *Property*) in phase 1. Although the predictive accuracy of the *Target Selection* regression model was slightly better (16% compared to 13%), the *Combined* domain explained more of the variance (19% compared to 12%). The *Combined* regression model for phase 2 performed on par with the *Combined* model for phase 1, suggesting that this domain has some value for predicting whether offences are linked at both a local and a force-wide level.

A forward stepwise logistic regression highlighted *Optimal* models consisting of *Target Selection* and *Inter-Crime Distance* for both phases of the study (see table 4-11). Although there was some deterioration in the predictive ability of the models between phase 1 and phase 2, the *Optimal* models performed the best in both phases. The *Optimal* model explained 69% of the variance and improved predictive accuracy by 33% in phase 1 and explained 31% of the variance and improved predictive accuracy by 18% in phase 2. Furthermore, the chi-square values were significant for both *Optimal* models indicating that they fit the data well.

Based on these results, it is suggested that it might be possible to limit the amount of information required to make linkage decisions about personal robbery with minimal impact on the accuracy of linkage decisions, particularly when working on a force-wide basis.

Table 4-11: The Optimal Model (study 1)

Statistic	**Phase 1**	**Phase 2**
α	1.044 (.469)	.005 (.399)
β	*Target Selection* 4.647 (2.036) *Inter-Crime Distance* .000 (.000)	*Target Selection* 3.451 (1.218) *Inter-Crime Distance* .000 (.000)
Wald (df)	*Target Selection* 5.209 (1)* *Inter-Crime Distance* 12.283 (1)*	*Target Selection* 8.032 (1)** *Inter-Crime Distance* 4.855 (1)*
Model χ^2	60.267*	22.038*
Nagelkerke R^2	.688	.311
Random	50.0	50.6
Model	83.1	68.7

*p<0.05

ROC analyses

The results of the ROC analysis (see table 4-12) were largely consistent with the logistic regression analyses, with the *Optimal* model (which combined *Target Selection* and *Inter-Crime Distance*) and the single-factor *Inter-Crime Distance* model emerging as the best predictors of linkage in phase 1, with AUCs of .904 and .918 respectively. AUCs of between 0.90 and 1.00 represent a high measure of discrimination accuracy for the linkage feature that gives rise to the curve (Swets, 1988) indicating that the *Optimal* model, and more particularly, *Inter-Crime Distance* were very useful in discriminating between linked and unlinked pairs of personal robbery. *Temporal Proximity, Target Selection,* and *Combined* are not far behind with moderate AUCs of .829, .640, and .635 respectively.

Table 4-12: ROC analysis outcomes (study 1)

Domain	**AUC (SE)**		**95% Confidence Interval**	
	Phase 1	**Phase 2**	**Phase 1**	**Phase 2**
Inter-Crime Distance	.918 (.028)*	.750 (.055)*	0.862–0.974	0.643–0.857
Temporal Proximity	.829 (.045)*	.717 (.059)*	0.740–0.917	0.601–0.832
Target Selection	.640 (.061)*	.691 (.059)*	0.520–0.760	0.575–0.806
Control	.563 (.064)	.657 (.061)*	0.437–0.689	0.538–0.776
Approach	.512 (.064)	.512 (.065)	0.387–0.638	0.386–0.639
Property	.448 (.064)	.451 (.064)	0.323–0.573	0.325–0.577
Combined	.635 (.062)*	.708 (.058)*	0.574–0.756	0.593–0.822
Optimal	.904 (.033)*	.782 (.050)*	0.840–0.969	0.684–0.881

*p<0.05

The value of *Inter-Crime Distance* is substantially less for phase 2 (.750 compared to .918 in phase 1). This difference was statistically significant as the confidence intervals did not overlap (Melnyk et al., 2011). The AUC for *Temporal Proximity* also declined in phase 2, however, this result was not statistically significant. As with the regression analysis, the value of *Target*

Selection was greater in phase 2 (the AUC was .691), however, as the confidence intervals overlap, this difference was not statistically significant. Of interest, the AUC for the *Combined* domain improved to .708 in phase 2 compared with .635 in phase 1. This was contrary to the regression findings but is in line with the Mann-Whitney U outcomes. Similarly, the AUC for *Control* was greater in phase 2 (.657) compared to phase 1 (.563), which was in line with the Mann-Whitney U test (and its associated effect size) but not the regression analyses. Comparison of the confidence intervals indicated that the difference in AUCs between phase 1 and phase 2 were not significant for either the *Combined* or *Control* domains.

As would be expected based on the Mann-Whitney U outcomes and the regression analyses, neither the *Property* nor the *Approach* domains achieved a significant AUC in either phase. In fact, with AUCs of less than 0.50, the *Property* domain was non-informative (Swets, 1988) performing at below the threshold set by chance.

Conclusion

The findings of study 1 phase 2 suggest that it is possible to link offences based upon a variety of behavioural domains, including *Inter-Crime Distance.* However, the predictive accuracy of domains can be subject to change if geographical constraints for the unlinked pairs are imposed. In some cases, predictive accuracy was improved, most notably *Target Selection*. Even where performance deteriorated (as measured by the predictive accuracy of regression models, and the AUC of ROC curves), statistical differences were still found between linked and unlinked offences for some domains, most notably *Inter-Crime Distance*, indicating that these behaviours are still useful for case linkage.

STUDY 2: Linking personal robbery using offence behaviour in the West Midlands (phase 1 and 2)

This study sought to replicate study 1 this time using data from an urban police force with a view to determining whether the same factors emerged as useful for case linkage. The data sample used is the West Midlands Police sample outlined in sample section of the methodology. This comprises 554 solved personal robbery offences committed by 277 offenders reported to West Midlands Police between 1st April 2007 and 30th September 2008. The sample has been used to generate three sub-samples – 277 linked pairs, 277 unlinked1 pairs, and 272 unlinked2 pairs. Phase 1 of the study compares the **WMP - linked** sample to the **WMP - unlinked1** sample, and phase 2 compares the **WMP - linked** sample to the **WMP - unlinked2** sample.

Medians

Table 4-13 shows the median Jaccard's scores, *Inter-Crime Distances*, and *Temporal Proximities* for each sample. As with study 1, linked pairs displayed higher Jaccard's scores than unlinked pairs for *Target Selection, Control*, and the *Combined* domains. Linked pairs also had smaller *Inter-Crime Distances* and fewer days between offences than unlinked pairs. This indicates that the two offences making up linked pairs are more behaviourally similar and distinctive than the offences making up unlinked1 and unlinked2 pairs for these domains. However, the median Jaccard's scores for *Approach* and *Property* were the same across the three samples reinforcing the finding from study 1 that these domains are not useful for linkage.

Table 4-13: Median scores (study 2)

Behavioural domain	**Linked**	**Unlinked1**	**Unlinked2**
Inter-Crime Distance (m)	608.59	10,356.45	2,208.79
Temporal Proximity (days)	1	150	137
Target Selection	.500	.000	.000
Control	.333	.143	.143
Approach	.000	.000	.000
Property	.000	.000	.000
Combined	.333	.133	.133

Inter-Crime Distances were smaller in West Midlands (table 4-13) compared to Northamptonshire (see table 4-2). The average distance between linked pairs was 195m shorter, the average distance between unlinked1 pairs was approximately 2,600m shorter, and the average distance between unlinked2 pairs was over 100m shorter. This was not surprising given that this urban force is just 348 square miles compared to 913 square miles for Northamptonshire. On average linked pairs in the West Midlands also occurred closer together in time – just one day between offences compared to 36 days in Northamptonshire. The median scores for linked pairs were also higher than in Northamptonshire for *Target Selection, Control,* and *Combined* domains (e.g.

.500 compared to .250 for *Target Selection*). This suggests that linked offences were more behaviourally similar in West Midlands than in Northamptonshire and therefore stronger evidence for these domains might be found in this study compared to study 1.

Test of difference

Table 4-14 shows the outcomes of the Mann-Whitney U tests for phases 1 and 2 of study 2.

The Mann-Whitney U tests indicated that the differences between linked and unlinked samples were statistically significant for all observations. Unlike study 1, the effect sizes were more stable between phases, except *Inter-Crime Distance,* which was different between phase 1 and phase 2. This was not unexpected given the methodology for selecting unlinked2 pairs (i.e. limiting the geographical area for selecting unlinked2 pairs). Nevertheless it is encouraging that a medium effect size was still achieved in phase 2 as this suggests that *Inter-Crime Distance* might still be useful to link crime at a local level. This was particularly encouraging in West Midlands, as not only is the whole police force area smaller than Northamptonshire, but the individual policing areas under analysis were much smaller too (there were 21 Basic Command Units [BCUs] in the 348 square miles of the West Midlandscompared to only six boroughs in the 913 square miles of Northamptonshire).

Table 4-14: Mann-Whitney U test outcomes (study 2)

Domain	Mann-Whitney U (z)		Effect size (r) †	
	Phase 1	Phase 2	Phase 1	Phase 2
Inter-Crime Distance	4846.000 (17.768)*	19289.000 (9.814)*	.76	.42
Temporal Proximity	10570.500 (14.862)*	10990.500 (14.469)*	.63	.62
Target Selection	19208.000 (10.473)*	19063.500 (10.331)*	.44	.44
Control	21764.500 (8.904)*	20349.000 (9.436)*	.38	.40
Approach	36425.000 (3.786)*	35768.000 (3.752)*	.16	.16
Property	34226.000 (2.607)*	32284.500 (3.503)*	.11	.15
Combined	15868.500 (11.949)*	14637.500 (12.404)*	.51	.53

*p<0.05 †Field (2005) indicates that r=.10 is a small effect size (explaining 1% of variance), r=.30 is a medium effect size (explaining 9% of the variance), r=.50 is a large effect size (explaining 25% of the variance).

The effect sizes achieved in this study were higher than in study 1 across all domains in both phases indicating a higher level of behavioural similarity in linked pairs in the West Midlands compared to Northamptonshire. The effect size for *Temporal Proximity* was in the range of .62 to .63 compared to just .31 to .49 in Northamptonshire (table 4-3). *Target Selection* had an effect size of .44

in both phases of this study, again higher than the .28 to .38 range reported in Northamptonshire. Even more striking in the comparison of the effect sizes for the *Control* domain, which were in the range of .38 to .40 in this study compared to just .14 to .18 in study 1. The *Combined* domain reached a large effect size in study 2 compared to a medium effect in study 1. Even *Approach* and *Property*, which performed very poorly in study 1, recorded better results in this study. However, although statistically significant, the effect sizes were small indicating that these domains are less helpful for linkage purposes.

Regression

As discussed in study 1, the Mann-Whitney U tests were a useful starting point for determining which behavioural domains might be the most useful for differentiating between linked and unlinked samples. However, additional analysis was needed to drill down into the results and identify the predictive value of each domain. Tables 4-15 to 4-22 outline the results of the regression analyses for study 2.

As expected from the Mann-Whitney U outcomes, the regression model for *Inter-Crime Distance* performed better in phase 1 than phase 2. However, performance was not as good as noted in study 1, perhaps due to the overall size of the police force and indeed the BCUs being smaller. Phase 1 of the present study only accounted for 26% of the variance compared to 63% for the model based on the Northamptonshire data (table 4-4). Furthermore, less than 1% of the variance was accounted for by *Inter-Crime Distance* in phase 2 of this study compared to 17% in study 1. Although phase 1 of this study improved the predictive ability by more than 30% above chance (similar to study 1), predictive ability was absent in phase 2. In fact, the regression model from phase 2 of this study performed worse than chance indicating that *Inter-Crime Distance* cannot be a reliable predictor at this local level.

Table 4-15: Inter-Crime Distance (study 2)

Statistic	**Phase 1**	**Phase 2**
α	.880 (.181)	-.006 (.124)
β	.000 (.000)	.000 (.000)
Wald (df)	33.806 (1)*	.249 (1)
Model χ^2	59.719*	.291
Nagelkerke R^2	.261	.001
Random	50.0	50.2
Model	82.1	35.2

*p<0.05.

The trends for *Temporal Proximity* (see table 4-16) mirrored the Mann-Whitney U outcomes with a stable performance across the two phases. Each model explained more than 30% of the variance and predictive ability was improved by almost 25% in both phases. This was expected given the fact that the two most recent offences were chosen for each offender to make the linked pair whereas the timeframe of 18 months was not ‘controlled for’ in the formation of unlinked pairs (i.e. the two offences could be located anywhere in the force area rather than within a specific policing area). However, the analysis did suggest that

Temporal Proximity might be useful if the overall timeframe under consideration is limited because this forces the unlinked pairs closer together in time. More research which controls for *Temporal Proximity* in unlinked pairs, might shed more light on the value of this domain in linking personal robbery.

Table 4-16: Temporal Proximity (study 2)

Statistic	**Phase 1**	**Phase 2**
α	1.017 (.185)	1.071 (.186)
β	-.011 (.002)	-.011 (.002)
Wald (df)	48.304 (1)*	49.659 (1)*
Model χ^2	72.567*	79.605*
Nagelkerke R^2	.308	.336
Random	50.0	50.4
Model	74.6	73.7

*p<0.05

As expected given the Mann-Whitney U test outcomes, the single-factor model for *Target Selection* performed well explaining 30% of the variance and improving predictive accuracy by 20% in phase 1 of study 2 (see table 4-17). This positive result was replicated in phase 2 although slightly less of the variance was explained (26%) and predictive accuracy was slightly less. The regression model for phase 1 had more predictive power than was achieved with the Northamptonshire data (table 4-6) but not much (20% compared to 16%). This difference evened out to a 17% improvement over chance in phase 2 for both study 1 and study 2. It is of note, however, that the regression models based on these West Midlands data explained more of the variance than the models developed using the Northamptonshire data (30% compared to 12% in phase 1, and 26% compared to 20% in phase 2).

Table 4-17: Target Selection (study 2)

Statistic	**Phase 1**	**Phase 2**
α	-.964 (.181)	-.867 (.177)
β	3.392 (.502)	2.996 (.457)
Wald (df)	45.611 (1)*	42.982 (1)*
Model χ^2	67.442*	58.921*
Nagelkerke R^2	.289	.258
Random	50.0	50.4
Model	69.6	67.9

*p<0.05

Table 4-18: Control (study 2)

Statistic	**Phase 1**	**Phase 2**
α	-.902 (.192)	-.915 (.192)
β	3.138 (.529)	3.295 (.543)
Wald (df)	35.234 (1)*	36.837 (1)*
Model χ^2	45.100*	48.147*
Nagelkerke R^2	.201	.215
Random	50.0	50.4
Model	67.4	69.3

*p<0.05

The results for the *Control* domain (see table 4-18) were what would be expected given the Mann-Whitney U test outcomes with a small difference in performance between phase 1 to phase 2. Just as the effect size for the Mann-Whitney U test changed from .38 to .40 between phases, the R^2 was slightly higher (22% compared to 20%). Furthermore, predictive accuracy was slightly better (19% compared to 17% for phase 1). The significant chi-squares indicate that the data fit the two models well. These results are in stark contrast to study 1 where non-significant Wald statistics indicated that the factor should be removed from the regression model (see table 4-7). Furthermore, *Control* failed to account for more than 1% of the variance in either phase of study 1 and predictive accuracy was not improved much beyond chance (6% for phase 1 of study 1 and 4% for phase 2 of that study). These results indicate that, although there was little evidence *Control* was a useful linking factor in the rural area, it holds more value in an urban environment. This might be because different methods of *Control* are needed. For example, urban robbers may be more motivated to exert control to speed up the offence thus minimising the risk of discovery within a more populous urban environment. Alternatively, it could simply be due to data recording (perhaps urban areas are better at recording *Control* behaviours?).

Property and *Approach* were both identified as poor predictive factors for linkage in both phases of the research (see tables 4-19 and 4-20).

Table 4-19: Approach (study 2)

Statistic	Phase 1	Phase 2
α	-.044 (.122)	-.030 (.122)
β	21.247 (16408.711)	21.233 (16408.711)
Wald (df)	.000 (1)	.000 (1)
Model χ^2	8.451*	8.363*
Nagelkerke R^2	.040	.040
Random	50.0	50.4
Model	52.2	51.8

*p<0.05

Table 4-20: Property (study 2)

Statistic	Phase 1	Phase 2
α	-.107 (.138)	-.146 (.138)
β	.584 (.376)	.981 (.408)
Wald (df)	2.415 (1)	5.788 (1)*
Model χ^2	2.465	6.155*
Nagelkerke R^2	.012	.030
Random	50.0	50.4
Model	52.5	54.0

*p<0.05

Neither of the single-factor models explained much of the variance, and predictive accuracy did not improve much beyond chance. The results were not unexpected noting the outcomes of the Mann-Whitney U tests and adds weight to the arguments that the *Approach* used and the *Property* stolen during a robbery are not particularly useful when predicting whether two offences are linked. These results were consistent with the findings of study 1 (tables 4-8 and 4-9).

Table 4-21: Combined (study 2)

Statistic	**Phase 1**	**Phase 2**
α	-1.605 (.248)	-1.654 (.251)
β	6.739 (.965)	7.178 (1.011)
Wald (df)	48.736 (1)*	50.409 (1)*
Model χ^2	83.186*	88.842*
Nagelkerke R^2	.347	.369
Random	50.0	50.4
Model	70.7	72.3

*p<0.05

The *Combined* domain (which comprises *Target Selection, Control, Approach,* and *Property*) performed favourably compared to the single-factor models in phase 1 explaining 35% of the variance and improving predictive accuracy by 21% (see table 4-21). However, *Target Selection* alone performed on par with the *Combined* model in this study explaining 29% of the variance and improving predictive accuracy by 20% (see table 4-17). Therefore, this research showed that the *Combined* model added little value above and beyond *Target Selection.* As it is less time intensive to code behaviours from one domain rather than four, it is suggested that efforts should be focused on gathering appropriate data on *Target Selection* instead of diluting the effort across coding multiple domains.

A forward stepwise logistic regression highlighted *Optimal* models for each phase of the research (see table 4-22 for the results).

Table 4-22: The Optimal Model (study 2)

Statistic	**Phase 1**	**Phase 2**
α	.073 (.334)	-.614 (.316)
β	*Target Selection* 2.326 (.667) *Control* 2.292 (.637) *Inter-crime distance* .000 (.000) *Temporal Proximity* -.007 (.002)	*Target Selection* 1.799 (.540) *Control* 2.892 (.647) *Property* 1.179 (.514) *Temporal Proximity* -.008 (.002)
Wald (df)	*Target Selection* 12.176 (1)* *Control* 12.938 (1)* *Inter-crime distance*12.567 (1)* *Temporal Proximity* 19.820 (1)*	*Target Selection* 11.113 (1)* *Control* 19.960 (1)* *Property* 5.269 (1)* *Temporal Proximity* 28.041 (1)*
Model χ^2	139.339*	126.475*
Nagelkerke R^2	.531	.494
Random	50.0	50.2
Model	83.2	79.9

*p<0.05

The chi-square values were significant to $p<0.05$ for both *Optimal* models indicating that they fit the data well. In relation to performance, although there was some difference in the predictive ability of the models between phase 1 and phase 2 (and *Property* replaced *Inter-Crime Distance* in the model), the *Optimal* models performed the best in both conditions. The *Optimal* model explained over half of the variance and improved predictive accuracy by 33% in phase 1. This was comparable to phase 1 of study 1 where predictive accuracy was also improved by 33% (table 4-11). This model (study 2 phase 2) explained 49% of the variance and improved predictive accuracy by 30%. Although a deterioration, these results were much more stable across phases in study 2 than in study 1 where variance explained fell from 69% to 31%, and predictive accuracy fell from 33% to 18% between phases (table 4-11).

Overall, although the *Optimal* model performed well, it was on par with *Inter-Crime Distance* for phase 1 in terms of predictive accuracy suggesting that it might be quicker to use *Inter-Crime Distance* to conduct the initial search for potentially linked cases. However, such an approach is unlikely to work locally as the effect of *Inter-Crime Distance* diminishes. Thus, more behaviours would need to be considered when making linkage decisions within local urban policing areas.

ROC analyses

The results of the ROC analysis (see table 4-23) were largely consistent with the logistic regression analyses, with the *Optimal* model and the single-factor

Inter-Crime Distance model emerging as the best predictors of linkage in phase 1, with AUCs of .910 and .943 respectively. AUCs of between 0.90 and 1.00 represent a high measure of discrimination accuracy for the linkage feature that gives rise to the curve (Swets, 1988) indicating that the *Optimal* model, and more particularly, *Inter-Crime Distance* were very useful to discriminate between linked and unlinked pairs of personal robbery at least when working on a force-wide basis.

Table 4-23: ROC analysis (study 2)

Domain	AUC (SE)		95% Confidence Interval	
	Phase 1	Phase 2	Phase 1	Phase 2
Inter-Crime Distance	.943 (.015)*	.228 (.029)*	0.915–0.972	0.170–0.286
Temporal Proximity	.868 (.023)*	.844 (.024)*	0.823-0.913	0.796–0.892
Target Selection	.777 (.028)*	.776 (.028)*	0.722–0.832	0.721–0.831
Control	.715 (.031)*	.731 (.030)*	0.655–0.775	0.672 0.790
Approach	.529 (.035)	.529 (.035)	0.461–0.597	0.461–0.597
Property	.581 (.034)*	.591 (0.34)*	0.514–0.648	0.524–0.658
Combined	.805 (.026)*	.819 (.025)*	0.755–0.855	0.771–0.868
Optimal	.910 (.018)*	.846 (.024)*	0.875–0.946	0.800–0.892

*p<0.05

The value of *Inter-Crime Distance* disappeared completely in phase 2 as the AUC dropped from being high (.943) to well below what would be expected by chance (.228). This difference was statistically significant as the confidence intervals did not overlap (Melnyk et al., 2011). As seen in study 1, the lower value of *Inter-Crime Distance* in phase 2 has been replicated in this West Midlands study. In fact, the difference is much more marked in this study, most likely due to the size of the policing areas under consideration (they were just 17 square miles on average). The AUC for the *Optimal* model was slightly less in phase 2 of this study (.846) compared to phase 1 (.910) but this difference was not statistically significant.

Temporal Proximity, Combined, Target Selection, and *Control* all achieved moderate AUCs in phase 1 (.868, .805, .777, and .715 respectively). Performance was stable into phase 2 (AUCs were .844, .819, .776, and .731 respectively). These results were in line with the Mann-Whitney U results and the regression models which displayed stability across both phases for these domains.

As would be expected based on the Mann-Whitney U test outcomes and the regression analyses, the *Approach* domain did not achieve a significant AUC in either phase. This was in line with the findings from study 1. However, the *Property* domain achieved better AUCs. These were .581 and .591, which is an improvement on the findings of study 1 where AUCs for both phases were below .50 indicating *Property* performed worse than would be expected by chance. Although, the predictive ability of *Property* was improved with this urban sample, the AUCs achieved were still low (Swets, 1988) indicating that the domain remains of limited value to case linkage.

Conclusion

The findings of this West Midlands study were similar to those of study 1 (Northamptonshire), e.g. *Inter-Crime Distance* performs well in phase 1, and *Approach* and *Property* were not a good predictors of linkage. However, the differences between linked and unlinked pairs were more marked in the West Midlands. Firstly, the effect sizes for the Mann-Whitney U test were all higher in the West Midlands when compared to Northamptonshire. Some domains performed better in the West Midlands, most notably *Control*, *Target Selection,* and *Temporal Proximity*. *Inter-Crime Distance* performed very well in phase 1 of both studies, but as predicted, it was less valuable in phase 2. This was evident across both studies but the effect was more marked in West Midlands where the regression model showed predictive accuracy falling from 82% to well below chance. This was reinforced by the ROC analysis where the AUC fell from .943 (high) to .228 (below chance).

STUDY 3: Incorporating more variables into the behavioural domains

There were more data available in the West Midlands dataset compared to Northamptonshire and so there was scope to test the value of additional variables to domain performance. Study 3 therefore replicates study 2 with the available additional behaviours that met the inclusion criteria (i.e. occurred in more than 1% of cases, achieved a good inter-coder reliability score and were not victim/bystander behaviour) added to the four behavioural domains *Target Selection, Control*, *Property,* and *Combined.* Two behaviours were also added to the *Approach* domain (approach – blitz and approach – distraction). These did not meet the inter-coder criteria (achieving only poor to moderate scores respectively) but were added for academic interest. See the shaded boxes appendix B for a list of new behaviours added to each domain*.* There was no need to re-test the single-factor models for *Inter-Crime Distance* or *Temporal Proximity* as these are stand-alone domains comprising only one behaviour. *Inter-Crime Distance* or *Temporal Proximity* were, however, included in the forward stepwise analysis to develop the *Optimal* models because they had proved valuable in the multiple regression analyses in studies 1 and 2.

The data sample used is the West Midlands sample outlined above in the sample section of the methodology earlier in this chapter. This is the same sample of offences as was used in study 2, but with the inclusion of additional behaviours for each offence. The samples were divided into the same experimental and test samples as study 2 to enable direct comparison.

Medians

Table 4-24 shows the median Jaccard's scores for each expanded sample. As in study 2, linked pairs displayed higher Jaccard's scores for *Target Selection, Control*, and the *Combined* domains than unlinked pairs. However, the median score for *Target Selection* for linked pairs was slightly lower than in study 2 and the median unlinked scores (they were both .000 in study 2) were higher. If the addition of extra variables into the domain had increased the similarity of the linked pairs without increasing the similarity of unlinked pairs this would suggest that adding the information is valuable. As it stands these results suggest the opposite. The median scores for *Control* and *Combined* were more comparable. That linked pairs still had higher median Jaccard's scores than unlinked pairs reinforces the overall hypothesis that linked pairs are more behaviourally similar and distinctive than unlinked1 and unlinked2 pairs for these domains.

Table 4-24: Median Scores (study 3)

Behavioural domain	**Linked**	**Unlinked1**	**Unlinked2**
Target Selection	.400	.167	.143
Control	.333	.143	.125
Approach	.000	.000	.000
Property	.000	.000	.000
Combined	.333	.143	.125

As in study 2, the median Jaccard's scores for *Approach* and *Property* were the same across the three samples reinforcing the finding that these domains are not useful for linkage, even when additional information is added (in this case two behaviours were added to *Approach* and eight were added to *Property*).

Test of difference

Table 4-25 shows the outcomes of the Mann-Whitney U tests for study 3. As in study 2, the Mann-Whitney U test outcomes indicated that the differences between linked and unlinked samples were statistically significant for all observations. The effect sizes achieved were higher than those achieved in study 2 (except *Approach* in phase 1) but not by much. For example, the effect sizes for *Target Selection* were in the range of .46 to .47 compared to .44 in both phases of study 2 (table 4-14). Similarly, *Control* and *Combined* only increased very slightly. The effect size for *Approach* is lower for phase 1 and exactly the same for phase 2 indicating that the additional information about approach added nothing to the value of the domain. The increase in effect size for *Property* was more marked (rising from a range of .11 to .15 in study 2 to .20 to .21 in the current study). However, this domain still failed to reach the threshold for even a medium effect size, indicating that property stolen is of little use when making linkage decisions.

Table 4-25: Mann-Whitney U test outcomes (study 3)

Domain	**Mann-Whitney U (z)**		**Effect size (r) †**	
	Phase 1	**Phase 2**	**Phase 1**	**Phase 2**
Target Selection	18206.000 (10.798)*	17473.000 (10.985)*	.46	.47
Control	21313.500 (9.111)*	19819.000 (9.691)*	.39	.41
Approach	33334.000 (3.143)*	31852.000 (3.730)*	.13	.16
Property	34506.500 (4.676)*	337.4.500 (4.914)**	.20	.21
Combined	14750.500 (12.538)*	13959.000 (12.764)*	.53	.54

*p<0.05 †Field (2005) indicates that r=.10 is a small effect size (explaining 1% of variance), r=.30 is a medium effect size (explaining 9% of the variance), r=.50 is a large effect size (explaining 25% of the variance).

Overall, these findings suggest that including extra information does not substantially enhance the value of domains for linkage purposes (i.e. there is no appreciable improvement in the ability to differentiate between linked and unlinked pairs based on behavioural similarity).

Regression

Although the Mann-Whitney U test outcomes suggested that there was limited value to increasing the number of behaviours in each domain, it may still be useful to complete the regression and ROC analyses to confirm these findings. Tables 4-26 to 4-31 provide the results of the regression analyses.

Table 4-26: Target Selection (study 3)

Statistic	**Phase 1**	**Phase 2**
α	-1.101 (.199)	-1.097 (.200)
β	4.013 (.619)	4.089 (.620)
Wald (df)	42.020 (1)*	43.523 (1)*
Model χ^2	65.158*	67.229*
Nagelkerke R^2	.280	.290
Random	50.0	50.4
Model	69.9	66.8

*p<0.05

As in study 2, the single-factor model for *Target Selection* performed well explaining 28% of the variance and improving predictive accuracy by 20% in phase 1 (see table 4-26). This is directly comparable to study 2 where 29% of the variance was explained and predictive accuracy improved by 20% in phase 1 (table 4-17). This study explained slightly more of the variance in phase 2 (29% compared to 26% in phase 2 of study 2) but did not improve predictive accuracy beyond what was achieved in phase 2 of study 2 (in fact it was slightly lower 16% compared to 18%). These results indicate that the addition of behaviours to *Target Selection* did not improve domain performance.

Similarly, the addition of variables into the *Control* domain did not improve performance of the domain compared with study 2 (see table 4-27).

Table 4-27: Control (study 3)

Statistic	**Phase 1**	**Phase 2**
α	-1.096 (.209)	-.993 (.200)
β	4.198 (.675)	3.910 (.645)
Wald (df)	38.709 (1)*	36.764 (1)*
Model χ^2	53.875*	51.024*
Nagelkerke R^2	.236	.227
Random	50.0	50.4
Model	67.4	68.2

*p<0.05

Similar variance was explained (23 to 24%) compared to study 2 (20 to 22% [table 4-18]) and the increase in predictive accuracy remained at the 17 to 18% level compared to chance (predictive accuracy improved by 17 to 19% above chance in study 2). Although it might appear disappointing that the model did not improve with the addition of more behaviours to the domain, it is actually useful to determine that including extra variables did not degrade the value of the domain. For example, a finding that a domain with fewer variables is comparable with a domain with more variables is easier to then implement in an applied setting with less effort required to source and code data for analysis.

As in studies 1 and 2, this study identified *Property* and *Approach* as poor predictive factors for linkage in both phases (see tables 4-28 and 4-29).

Table 4-28: Approach (study 3)

Statistic	**Phase 1**	**Phase 2**
α	-.088 (.124)	-.084 (.125)
β	2.054 (.799)	2.571 (.977)
Wald (df)	6.606 (1)*	6.925 (1)*
Model χ^2	9.880*	12.100*
Nagelkerke R^2	.047	.058
Random	50.0	50.4
Model	54.3	53.6

*p<0.05

As previously, neither of the single-factor models explained much of the variance, and predictive accuracy did not improve much beyond chance. The results were not perhaps to be expected given the outcomes of the Mann-Whitney U tests. Moreover, it adds weight to the arguments that the *Approach* used and the *Property* stolen during a robbery are not particularly useful when predicting whether two offences are linked. Furthermore, the results are comparable to the findings of study 2 (e.g. the predictive accuracy of *Property* was 3% in phase 1 of both study 2 and 3, and 4% in phase 2 of study 2 and 3). This indicates that there is no evidence that increasing the number of behaviours in the domain enhances its performance in this case.

Table 4-29: Property (study 3)

Statistic	**Phase 1**	**Phase 2**
α	-.142 (.138)	-.152 (.138)
β	.874 (.422)	1.085 (.438)
Wald (df)	4.293 (1)*	6.128 (1)*
Model χ^2	4.494*	6.604*
Nagelkerke R^2	.022	.032
Random	50.0	50.4
Model	53.3	54.4

*p<0.05

The *Combined* domain (which comprises *Target Selection, Control, Approach,* and *Property*) performed slightly better than the *Combined* domain of study 2 explaining 38 to 41% of the variance (see table 4-30) compared to 35 to 37% in study 2 (see table 4-21). In addition, predictive accuracy increased by 22 to 23% above chance compared to 21 to 22% for study 2. Although performance was slightly improved perhaps suggesting it is valuable to include more behaviours in domains, it is argued that instead this analysis lends further weight to the argument that it is not necessary to code all available behaviours.

In this research, a total of 26 additional variables were added with very little improvement to predictive accuracy overall.

Table 4-30: Combined (study 3)

Statistic	**Phase 1**	**Phase 2**
α	-1.894 (.279)	-2.009 (.290)
β	8.544 (1.207)	9.327 (1.287)
Wald (df)	50.074 (1)*	52.529 (1)*
Model χ^2	91.528*	99.465*
Nagelkerke R^2	.376	.406
Random	50.0	50.4
Model	73.2	72.6

*p<0.05

A forward stepwise logistic regression highlighted *Optimal* models for each phase of study 3 (see table 4-31). The chi-square values were significant to p<0.05 for both *Optimal* models indicating that they fit the data well. As with study 2 (see table 4-22), *Target Selection, Control, Inter-Crime Distance,* and *Temporal Proximity* form part of the model for phase 1, although *Approach* was also included. The amount of variance explained by the model is higher (57% compared to 53% for phase 1 of study 2), however, predictive accuracy was not enhanced much (34% above chance compared to 33% above chance in phase 1 of study 2).

As in study 2, *Inter-Crime Distance* was removed from the model in phase 2. In contrast to study 2 *Property* did not appear in the phase 2 model. *Approach* was included instead. The amount of variance explained by the phase 2 model was also higher than the phase 2 model of study 2 (56% compared to 49%), however, predictive accuracy did not change (both studies achieved 31% above chance in phase 2).

Table 4-31: The Optimal Model (study 3)

Statistic	**Phase 1**	**Phase 2**
α	-.052 (.366)	-.650 (.332)
β	*Target Selection* 2.838 (.829) *Control* 2.864 (.856) *Approach* 3.275 (1.150) *Inter-crime distance* .000 (.000) *Temporal Proximity* -.009 (.002)	*Target selection* 3.050 (.792) *Control* 3.129 (.778) *Approach* 5.580 (1.522) *Temporal Proximity* -.010 (.002)
Wald (df)	*Target Selection* 11.732 (1)* *Control* 11.189 (1)* *Approach* 8.114 (1)* *Inter-crime distance* 9.497 (1)* *Temporal Proximity* 23.450 (1)*	*Target selection* 14.831 (1)* *Control* 16.175 (1)* *Approach* 13.448 (1)* *Temporal Proximity* 31.546 (1)*
Model χ^2	153.126*	148.256*
Nagelkerke R^2	.571	.559
Random	50.0	50.2
Model	83.6	81.0

*p<0.05

ROC analyses

Table 4-32 presents the outcomes of the ROC analyses. The AUCs for *Target Selection* are slightly higher compared to study 2 (.783 compared to .777 in phase 1 and from .790 compared to .776 in phase 2). However, neither increase boosts the predictive accuracy above .90 which is the threshold denoting a high level of predictive accuracy. The AUC for *Control* was slightly higher in phase 1 compared to study 2 (.717 compared to .715) but slightly lower in phase 2 compared to study 2 (.729 compared to .731). The AUCs for *Approach* and *Property* were better than those from study 2. The AUCs for Approach were in the range of .557 to .565 compared to .529 in both phases of study 2. Similarly, the AUCs for *Property* improve from a range of .581 to .591 in study 2 to a range of .592 to .597 in study 3. Despite the improvement, the addition of extra behaviours into the *Approach* and *Property* domains has not impacted significantly enough to warrant their inclusion going forward. This is because the AUCs were still below the threshold for even a moderate level of predictive accuracy.

The AUCs for the *Combined* domain improved slightly (to .817 and .824 compared to .805 and .819 for study 2). This is not surprising given the increase in AUCs shown across the domains that form the *Combined* model. The results for the *Optimal* model were mixed; the AUC was slightly reduced in phase 1 compared to phase 1 of study 2 (.902 compared to .910). However, the AUC for the present phase 2 was slightly higher when compared to phase 2 of study 2 (.851 compared to .846).

Table 4-32: ROC analysis (study 3)

Domain	AUC (SE)		95% Confidence Interval	
	Phase 1	Phase 2	Phase 1	Phase 2
Target Selection	.783 (.028)*	.790 (.027)*	0.729–0.838	0.737-0.843
Control	.717 (.031)*	.729 (.030)*	0.657–0.777	0.670–0.788
Approach	.557 (.034)	.565 (.035)	0.490–0.625	0.497-0.632
Property	.592 (.034)*	.597 (.034)*	0.525–0.658	0.530–0.664
Combined	.817 (.025)*	.824 (.025)*	0.767–0.866	0.775–0.872
Optimal	.902 (.019)*	.851 (.024)*	0.865–0.940	0.805–0.897

*p<0.05

Overall, the AUCs achieved in this study were comparable with the AUCs from study 2. Thus, the ROC analysis confirms that the inclusion of the extra variables in the behavioural domains did not enhance performance.

Conclusion

This study focused on determining whether including some additional information in the behavioural domains enhanced their performance. The results indicated that performance was broadly unaffected. This is a positive finding in that it highlights that it is not necessary to include all available information in the search for linked cases. This offers potential to reduce the amount of time needed to source and code information for case linkage. Further research may be able to reduce the number of behaviours within domains without diluting performance (streamlining the behaviours included if you will). This will be particularly valuable if the behaviours identified are easy to source and code from police records (e.g. time of day).

Discussion

The preceding section outlined the results of a series of three quantitative studies developed to test five hypotheses relating to case linkage. This section will assess whether the findings provide support for each of the hypotheses. Potential implications of the findings that might be valuable in the practical application of case linkage are highlighted where appropriate.

Evidence for the hypotheses

Hypothesis 1 For personal robberies linked pairs will be more behaviourally similar than unlinked pairs.

The primary hypothesis that linked pairs of personal robbery offences are more behaviourally similar than unlinked pairs of personal robbery offences is borne out in all three studies. Linked pairs of offences were demonstrably more behaviourally similar than unlinked pairs even when geographical restraints were placed on the selection of unlinked pairs (phase 2 of each study). There were differences by domain (discussed in more detail below) but overall, the significant differences between the behavioural similarity of linked and unlinked pairs provides evidence for the theoretical assumptions of case linkage (i.e. behavioural consistency and distinctiveness). This implies that it is possible to link personal robberies using offence behaviour.

Hypothesis 2 Some behavioural domains will emerge as stronger linkage factors than others.

The three studies tested a range of behavioural domains – *Inter-Crime Distance, Temporal Proximity, Target Selection, Control, Approach,* and *Property*. A *Combined* domain (consisting of *Target Selection, Control, Approach,* and *Property*) was also tested. Finally, regression analyses were conducted to determine *Optimal* predictive models. The following predictions were made in relation to how useful these domains would be.

a. *Inter-Crime Distance* will be the most useful linkage factor
b. *Temporal Proximity* will be a useful linkage factor
c. *Target Selection* will be a useful linkage factor
d. *Control* will be a useful linkage factor
e. *Approach* will be a useful linkage factor
f. A *Combined* domain containing all the behaviours from a specified number of domains will perform better than any of the individual domains on their own
g. An *Optimal* model, made up of relatively few domains, will be identified
h. *Property* will not be a useful linkage factor.

The overarching hypothesis is accepted as performance varied across domains. There is partial evidence for hypothesis 2a with *Inter-Crime Distance* revealed as the most useful single-factor model for predicting linkage status when working at force level. Unfortunately this effect was not as strong when geographical restraints were placed on the data (discussed under hypothesis 3), particularly in the West Midlands. However, it might still be useful as a means of sifting through large volumes of data to reduce the number of cases considered in detail when conducting case linkage (i.e. when an analyst is working on a Comparative Case Analysis (CCA)).

Temporal Proximity, Target Selection, and *Control* were all identified as useful linkage factors by the studies (lending support to hypotheses 2b to 2d). There were differences in when and where these individual domains were the most useful, but evidence was found for the assumptions in relation to all three.

It is not surprising that *Temporal Proximity* emerged as a useful linkage factor given that the two most recent offences were chosen for each offender to make the linked pair whereas the timeframes were not controlled for in the formation of unlinked pairs. However, the analysis did reveal how easy it is for domain performance to be affected by the uneven distribution of data. In this case, offences were clustered by date of offence within borough in Northamptonshire which impacted on the effectiveness of the domain in phase 2 (study 1). However, the date of offence was more evenly distributed in the West Midlands data and so the performance of *Temporal Proximity* was stable across phases. More research which controls for *Temporal Proximity* would be useful to shed more light on how reliable this domain is. If evidence is found in favour of *Temporal Proximity* as a strong linking factor, this would be useful to analysts because limiting the timeframe for a search would reduce the number of cases under examination. Furthermore, even though analysts already use how close offences are in time and space to make linkage decisions (see chapter 3) it is important to determine whether the evidential base for this is sound.

The *Target Selection* domain largely consisted of variables about when offences occurred. There are several reasons why these times of day/days of week might be consistent for an offender. Firstly, from a practical perspective, there may only be particular days or times of day that the offender is available to rob people. Similarly, there are times of day that are more likely to present opportunities to commit robbery (e.g. when there are a lot of people around).

With reference to *Control*, the positive results are unsurprising. There is prior evidence available that many robbers develop a consistent method of committing their offences (Deakin et al., 2007) which will include means of controlling victims. Furthermore, people base their actions on previous experience (Harbers et al., 2012; Juliusson, Karlson, & Gärling, 2005) and so if an offender finds an effective method of controlling victim(s) it is likely that he/she will continue to use this method (and therefore display behavioural consistency) in later offences.

The *Approach* domain was identified as a poor predictor of linkage status by all three studies leading to the rejection of hypothesis 2e. Whilst it is true that there were some statistically significant differences between linked and unlinked pairs in relation to *Approach*, the associated effect sizes were small and predictive power was minimal compared to chance. There are a number of potential reasons why this domain performed so poorly. Firstly, taking the theoretical assumptions into account, it could be that there are only a finite number of approaches used by personal robbers and so the way in which the offender approaches the victim(s) is not distinctive enough. Alternatively, personal robbers might use a variety of approaches depending on circumstances and may not be consistent in their approach behaviour. It is also possible that these results could be due to the low number of behaviours included in the *Approach* domain (four in studies 1 and 2, and six in study 3). *Approach* was difficult to code due to the absence of information within the modus operandi field about how the offender(s) approached the victim(s), perhaps indicating that information about approach is not routinely collected, recorded, and/or input into crime databases. The knock-on effect of this is that approach behaviours were only recorded for some offences. Indeed, examination of the raw data revealed that information about approach could only be coded for 42% of offences (70 out of 166) in the Northamptonshire sample, and just 32% of the offences (177 out of 554) in the West Midlands. It is possible that sourcing information on the approach for all cases would boost the predictive ability of the *Approach* domain.

Finally, it should be noted that coding some of the *Approach* behaviours was more subjective than coding other behaviours. Inter-coders were more likely to disagree about how some approach behaviours were coded than they did for other behavioural variables (such as whether a weapon was seen or not [which achieved a very good kappa score in both police forces]), particularly what constituted a ‘blitz’ attack (a poor inter-coder reliability score [kappa] was recorded in both datasets for this behaviour). As there is nothing in the literature to suggest that *Approach* should be a poor predictor of linkage, it is proposed that additional research would be useful to determine the reasons why *Approach* emerged here as a poor predictor. In addition, a focus on enhancing domain performance, perhaps through more rigorous data collection, might yield more promising results.

The *Combined* domains tested performed better than any of the single-factor models for the domains that were included the *Combined* domain. It was also possible to develop *Optimal* models within each phase of each study. These comprised a combination of domains to optimise performance, and in all cases, performed better than any of the other models tested within a given phase of an individual study. These trends were demonstrated throughout all three studies lending support to accept hypotheses 2f and 2g.

With regards to practical application, it is noteworthy that the *Optimal* models in the Northamptonshire study comprised of just two domains (*Target Selection* and *Inter-Crime Distance*) in both phases. This suggests that limiting searches to information about these two domains will yield a relatively high level of predictive accuracy without the need to source all data for every offence. However, this can actually be broken down further to suggest that when working at force level it is most useful to use *Inter-Crime Distance* alone because sourcing information on *Target Selection* would only boost predictive accuracy by a further 3%. Therefore, if the analyst is working under tight time constraints, there is some justification for using *Inter-Crime Distance* on its own in the first instance. Conversely, when working at borough level, it is not advisable to use *Inter-Crime Distance* on its own as predictive accuracy is only 8% over chance. This compares to 17% for the single-factor model for *Target Selection*. Again, the *Optimal* model (comprising *Target Selection* and *Inter-Crime Distance*) performs better (predictive accuracy is 18% beyond chance) but not by much (study 1, phase 2).

The trends are more complex for the West Midlands studies with more domains coming into play in the *Optimal* models. However, as with Northamptonshire, when working at a force level, *Inter-Crime Distance* alone had almost the same level of predictive accuracy as a multi-factor *Optimal* model (improving predictive accuracy by 32% beyond chance compared to 33% for the *Optimal* model [study 2, phase 1]). However, the value of *Inter-Crime Distance* was absent when working at a local level (study 2, phase 2). In fact, this domain performed worse than chance. It is therefore argued that great caution is applied when using *Inter-Crime Distance* on a local level in urban areas. Instead it is argued that *Target Selection, Control*, and *Temporal Proximity* should be considered. Firstly, each of these single-factor models boosted predictive accuracy by at least 18% beyond chance. They were also key elements in the *Optimal* models of phase 2 in both study 2 and study 3. Whilst it is true that *Property* and *Approach* were also part of these *Optimal* models (*Property* in study 2 and *Approach* in study 3), the associated single-factor models did not explain much of the variance or increase predictive accuracy much beyond chance and so it is argued that including these domains have minimal value to linkage.

Finally, evidence from all three studies support the acceptance of hypothesis 2h as *Property* was consistently highlighted as a poor predictor of linkage status. Although there were some statistically significant differences between linked and unlinked pairs in relation to *Property,* as with *Approach*, the associated effect sizes were small and predictive power was minimal compared to chance. These results are not surprising for several reasons. Firstly, many personal robberies do not actually result in the theft of property with no property recorded as stolen in 22% of the personal robberies in the West Midlands sample (122 out of 554 offences) and 33% of the personal robberies in the Northamptonshire sample (54 out of 166 offences). Furthermore, where property is stolen these are typically limited to relatively few property types, notably cash and mobile phones (Smith, 2003). It is no coincidence that cash and mobile phones were stolen far more often than any other property type in both Northamptonshire and the West Midlands with cash stolen in 23% of offences (39 out of 166 offences) in Northamptonshire and in 27% of offences (150 out of 554 offences) in the West Midlands. Mobile phones were stolen in between 31% (Northamptonshire) and 45% (West Midlands) of cases. These studies suggest that *Property* should not be used to make linkage decisions as a general rule. There may be exceptions where something very distinctive is being targeted (e.g. a particular brand of trainers), but *Property* is unlikely to be a useful linkage factor in most cases of personal robbery.

Hypothesis 3 The power of inter-crime distance as a linkage factor will deteriorate if geographical constraints are placed on the data.

Evidence from studies 1 and 2 demonstrate that, as predicted, the power of *Inter-Crime Distance* is lower if geographical constraints are placed on the data. In Northamptonshire, the amount of variance explained by the regression model fell from 63% to 17% between phases 1 and 2, and predictive accuracy fell from 82% to just 57%. Although *Inter-Crime Distance* remained in the *Optimal* model, the predictive accuracy of this model was much lower (68% compared to 83% for phase 1). Furthermore, there was a statistically significant decrease in the AUC from .918 (classified as a high level of predictive accuracy) in phase 1 to a moderate .750 in phase 2. The differences are even more marked in West Midlands where predictive accuracy fell from over 80% to below chance, and the AUC reduced from .943 to just .288 between phases 1 and 2. These results demonstrate the importance of considering the size of the study area when making linkage decisions based on *Inter-Crime Distance*. This research does not dismiss the value of *Inter-Crime Distance* as a linkage tool but instead highlights the need for great care to be applied, particularly when working in a small geographical area.

Hypothesis 4 Evidence for case linkage assumptions will emerge in both rural and urban areas.

This research was conducted with data from one rural police force (Northamptonshire) and one urban police force (West Midlands) to test this hypothesis. The hypothesis is supported by the finding that linked pairs of offences were demonstratively more behaviourally similar than unlinked pairs in both rural (Northamptonshire) and urban (West Midlands) environments.

The overarching trends in which domains emerged as the best predictors of linkage status are comparable across the two police forces; i.e. the same single-factor models emerged as the most useful, the differences in *Inter-Crime Distance* was evident between phases, and *Approach* and *Property* were universally rejected as good linkage factors. There are, however, differences between the forces. Most notably, domains tended to perform better in West Midlands compared to Northamptonshire. The effect sizes associated with the Mann-Whitney U tests were larger for all domains in the West Midlands. Furthermore, with the exception of *Property* (both phases) and *Inter-Crime Distance* in phase 2, the West Midlands regression models (study 2) explained more of the variance and increased predictive accuracy by more than the comparable models in Northamptonshire (study 1). The performance of the *Control* domain is particularly noteworthy. This domain did not perform at all well in Northamptonshire explaining little variance and only boosting predictive accuracy by 3 to 6%. The AUCs were also low. In contrast, *Control* explained 20 to 22% of the variance in West Midlands and boosted predictive accuracy by 17 to 19% (study 2). The AUCs were also notably higher. There are several reasons why *Control* emerged as more useful to distinguish between offences in West Midlands. It is possible that offenders operating in an urban environment have less time to complete the offence due to a higher number of people in the area thus increasing their risk of being seen or apprehended. They might therefore be more likely to use controlling behaviour in order to complete the offence quickly. There was some evidence of this in the raw data as a higher proportion of offences involved the use of a weapon in West Midlands compared to Northamptonshire (41% or 228 out of 554 offences, compared to 36% or 60 out of 166 offences). Furthermore, West Midlands offences were more likely to involve a physical search of the victim (31% compared to 15% in Northamptonshire). However, similar proportions were reported for many of the other control behaviours (such as physical assault and the propensity to commit offences in groups) suggesting that this can only be a partial explanation for the differences.

Another reason could be that control behaviours were more frequently recorded in West Midlands than in Northamptonshire. It is not possible to assess whether this is true, or to measure how much impact that this might have had. Further exploration of how offences are recorded would be useful to shed some light on whether this factor is relevant.

There are a number of possible reasons why domain performance is generally better in West Midlands. Firstly, it is possible that offenders in the West Midlands commit their crimes in a more behaviourally similar way than offenders in Northamptonshire. There are more opportunities to commit personal robbery in urban areas and so offenders can perhaps be selective in who they target, when they commit offences, and how they commit offences. The lower prevalence of personal robbery in rural areas (Marshall & Johnson, 2005) suggests that these areas present fewer opportunities for personal robbery and so offenders in Northamptonshire might need to be more adaptable in how they commit offences and who they target in order to successfully complete an offence.

Alternatively, the differences could be an artefact of the differences in sample size. The West Midlands sample is considerably larger than the Northamptonshire sample (277 offenders compared to 83 offenders). Larger samples result in increased statistical power (van Voorhis & Morgan, 2007), and so the strength of the relationships could be enhanced by the use of a larger sample. Finally, the differences could be due to data recording. It is possible that West Midlands Police record more detailed modus operandi information, thus increasing the amount of data that can be coded and fed into the data analysis. With reference to the data used in these studies, it is noted that there was generally more information about modus operandi in the West Midlands data than the Northamptonshire data. However, the data accessed for the research was very limited overall and there will be much more information about offences recorded in other databases (e.g. victim statements, forensic reports, and intelligence logs). As such, it is not appropriate to compare data quality in this instance as it is likely that the analyst would be able to access more information than was available for this research.

Hypothesis 5 Domain performance will be improved by adding more behavioural variables.

Hypothesis 5 was tested through study 3 which added a number of variables to the domains for *Target Selection, Control, Approach*, and *Property* in the West

Midlands dataset. The associated *Combined* domain therefore encompassed additional variables (n=26 variables in total). The analysis was conducted again and results compared to study 2 to assess whether there were any improvements to domain performance.

There were slight improvements in performance as the effect sizes associated with the Mann-Whitney U test all increased with the exception of *Approach* in phase 1. This trend was continued through the regression and ROC analyses but the differences between study 1 and study 2 were very small. These findings suggest that it is not necessary to include all available data in case linkage analysis. As analysts have highlighted (see chapter 3) sourcing data is time consuming and can act as a barrier to case linkage. It is therefore encouraging that predictive accuracy can be improved with relatively few behavioural variables. Additional research should aim to identify the most useful individual predictors for linkage. This would re-focus data gathering towards the most useful behaviours. The overall aim should be to reduce the amount of time needed to source information with minimal impact on predictive accuracy.

Concluding comments

The research has provided support for the theoretical assumptions of case linkage, indicating that it is possible to link personal robbery offences using offence behaviour. Some behavioural domains have emerged as more useful than others and it is reassuring that the main findings have been replicated across two police forces (e.g. the same single-factor models emerge as the most useful and *Approach* and *Property* perform poorly in both areas) as this suggests that such generic findings might be applicable in other settings. Having said this, there were some differences between the two police forces in the predictive power of domains illustrating the need to consider how evidence is weighted when making linkage decisions in rural areas compared to urban areas.

The new research presented here raises a significant concern about how the geographical size of the study area can impact on the power of *Inter-Crime Distance* as a predictor of linkage status. This research indicates that less weight should be assigned to *Inter-Crime Distance* when making decisions on a local level, particularly in urban areas. Furthermore, it is suggested that the size of the study area and the method for selecting unlinked pairs should be carefully considered in future case linkage research.

On a similar note, this research highlights the dangers of taking results at face value. It could be stated that *Temporal Proximity* is worthless when working at a local level in rural areas. However, further examination of the raw data revealed that the date of offence information was skewed within each borough, thus reducing the value of this domain. The fact that domain performance was very good (and consistent across phases) in study 2 suggests that this domain should not be dismissed out of hand. Instead, a replication of study 1 with another rural dataset might yield more promising results.

Specific research on the potential impact of policing boundaries on case linkage may also be valuable, noting that criminals may not know or care where these unseen boundaries fall, or even that they might deliberately cross boundaries to commit crime to help evade detection. Crime series that span such boundaries will inevitably be harder to link if neither police force/BCU/borough has the whole dataset within the purview of a single analyst.

Finally, less is more. This research demonstrates that more data does not necessarily mean substantially better results. Whilst it is true that there were some improvements in domain performance with the addition of the extra variables, these were minimal. In practice, the time it would take to source all of the information about a particular offence and feed it into a case linkage analysis would involve far more effort than is necessary to make a valid judgement. Further work to identify the most useful individual behaviours for linkage would be useful with a view to reducing analyst workload in relation to sourcing and coding data.

Chapter 5 : Group Offending

Group crimes are offences committed by two or more offenders against one or more victims. The prevalence of group offending varies by type of offence and is more common in predatory street crimes like robbery (Alarid et al., 2009; Deakin et al., 2007; Hochstetler, 2001; Weerman, 2003). The majority of robberies are committed by groups (e.g. Kapardis, 1988; Walsh, 1986).

Group offending

Research has revealed that group offences are primarily committed by adolescents (Carrington, 2002; Conway & McCord, 2002; Lloyd & Walmsley, 1989; Porter & Alison, 2004; Porter & Alison, 2006b; Wright & West, 1981 as cited in Hauffe & Porter, 2009), including personal robbery which is typically committed by young males (Alarid et al., 2009; Porter & Alison, 2006a; Porter & Alison, 2006c; Smith, 2003). There are a number of possible reasons for this. Firstly, young people are more likely to socialise or conduct most of their activities in groups (Hauffe & Porter, 2009) potentially increasing their exposure to criminal peers. Secondly, it has been argued that adolescents are more vulnerable to peer influence than older people (Conway & McCord, 2002; Hauffe & Porter, 2009), and therefore it is not surprising that many offenders report that they were persuaded to commit robbery by their co-offenders and did so to impress them (Alarid et al., 2009), and that street robbery is associated with the desire to appear tough in front of peers (Barker et al., 1993).

Young offenders commonly have friends who engage in crime (Conway & McCord, 2002), and the attitudes and behaviours of friends has been found to be a significant determinant of whether a young person commits theft, assault, and vandalism (Hochstetler, Copes, & DeLisi, 2002). Such findings apply to both group and lone offending suggesting that it is not just the presence of the group but the indirect influences of friends' attitudes and behaviours that are relevant to the propensity to offend. This, in turn, suggests that it is not the group that encourages crime, but the deviant peers within it. Having said this, behaviour and attitudes can become more extreme in group settings (Porter & Alison, 2006c) and young offenders are more likely to commit serious crimes when in the presence of accomplices (Alarid et al., 2009).

The group context provides a comfort zone for offending, allowing individuals to feel anonymous (Alarid et al., 2009; Hauffe & Porter, 2009), to intimidate in numbers, and to experience diffused responsibility (Alarid et al., 2009; Porter & Alison, 2006b). The fact that groups are more likely to target victims they do not know (Alarid et al., 2009) may also work to depersonalise the victim. As young people become more embedded in the group, they lose their sense of individuality and may take on the collective behaviours of the group (Hauffe & Porter, 2009). Furthermore, individuals are more likely to 'show off' to their peers and/or protect their reputation in the group context (Alarid et al., 2009), leading individuals to behave somewhat differently when in a group than when they are alone.

Group offending typically declines with age (Alarid et al., 2009; Carrington, 2002; McGloin, Sullivan, Piquero & Bacon, 2008) and so it is axiomatic that the average age of lone offenders is often reported to be higher than the average age of group offenders. For example, Hauffe and Porter (2009) reported a mean age of 21 years for a sample of 203 group rapists compared to a mean age of 29 years for 60 lone rapists. It is suggested that as offenders age they are probably less susceptible to the influence of others (Hochstetler et al., 2002). Older offenders are also more likely to recognise that accomplices increase risks and reduce rewards (Alarid et al., 2009) which might shift an individual from group to lone offending later in life.

Selecting co-offenders

Male robbers have reported a preference for co-offenders who are similar in age and ethnicity with allegiance to the group understood through shared experiences and background (Alarid et al., 2009). It is not unusual for offenders to limit the number of accomplices. For example, 52% of robbers interviewed by Alarid et al. (2009) only had one co-offender, and 54% of the robbery groups examined by Porter and Alison (2006c) were made up of two offenders. This reduces the number of people to divide the proceeds with, and the risk of apprehension due to possible member disloyalty (Weerman, 2003).

Warr (1996) reported that offenders are less likely to use the same accomplices for different types of crime suggesting a form of group specialisation. Co-offenders expand criminal opportunities (Alarid et al., 2009; Porter & Alison, 2006b) through specialist knowledge (e.g. of target location or weakness), skills (e.g. breaking into a vehicle), and/or access (e.g. if they work as a security officer at a bank). Having said this, it is unlikely that any degree of specialist knowledge is needed to commit personal robbery, and so personal robbers may be more fluid in their selection of co-offenders.

Group stability

Crime groups (robbery or otherwise) are often characterised as short-lived, loosely associated, and transitory (Carrington, 2002; Weerman, 2003). The same group may not commit more than one offence together and Weerman (2003) reported that offending groups typically change after one criminal event. Furthermore, McGloin et al. (2008) report that young offenders do not tend to 're-use' co-offenders. However, while McGloin et al. (2008) argued that they found little evidence of stability in the selection of co-offenders, their results could be interpreted differently. Although more than half of offenders showed no stability, they did find that 39% of offenders showed some stability in the selection of co-offenders, and that 2% showed perfect stability. Their research used official data rather than self-reports, which means that the level of co-offender stability could have been underestimated because many offenders are not caught and thus co-offender data could be missing. The fact that the study also found frequent offenders show a greater propensity to recycle co-offenders supports this point. Finally, it does not appear that their study controlled for offence type which may have impacted on the level of co-offender stability.

Overall, although the group as a whole may not be stable, it is likely that some relationships and connections within groups will persist (McGloin et al., 2008), for example, within criminal gangs where bonds between some members are reported to be very strong and even family-like in nature (Howell, 1998). Furthermore, whilst some opportunist offenders may use a variety of co-offenders (McGloin et al., 2008), other offenders have small social networks and are likely to select the same co-offenders repeatedly, particularly when they commit multiple offences within a short timeframe (Warr, 1996).

Characteristics of group and lone offending

Research on group offending has highlighted a number of characteristics that differ between group and lone offending.

Target selection

Group offenders' victims tend to be younger than victims of lone offenders (e.g. Lloyd & Walmsley, 1989; Morgan, Brittain, & Welch, 2012). Furthermore, groups typically target lone victims. For example, Porter and Alison (2004) reported that 87% of group rapes (194 out of 223) were against a lone victim. However, groups are more likely to attack multiple victims than a lone offender (Alarid et al., 2009; Hauffe & Porter, 2009). This is not surprising as the group itself allows victims to be controlled more easily. Rape victims are less likely to resist against a group of offenders (Hauffe & Porter, 2009), and this may also apply to robbery. As mentioned above, robbers may well find the presence of co-offenders reassuring, depersonalising the victim, reducing the fear of victim resistance, and increasing confidence that they will get away with the offence

(Alarid et al., 2009). Interestingly, Alarid et al. (2009) found that group offending did not impact on victim selection and groups did not choose riskier targets. This indicates that there are other factors influencing victim selection, for example, offenders may respond to a spontaneous opportunity or the offence is targeted against a particular person (e.g. as a means of debt collecting or gang related).

Planning

Group offences are more likely than lone offences to involve some level of planning (Alarid et al., 2009). This makes sense for some crime types where individual members of the group will be assigned roles (e.g. commercial robbery). Even in more spontaneous crimes the offenders may need to discuss, however briefly, the method of approach. For example, if a group decides to rob a person they may need to plan each person's role in the crime. This is in contrast to the lone offender who only needs to consider his/her own actions to commit the crime.

Violence

The group context encourages violence (Morgan et al., 2012) and group offenders commit more violent offences than do lone offenders (Conway & McCord 1995, as cited in Conway & McCord, 2002). Furthermore, previously non-violent offenders who commit their first group offence with violent accomplices are at an increased risk of continuing to commit serious violent crime (Conway & McCord, 2002).

Group offences are more likely to involve physical violence than lone offences (Alarid et al., 2009; Conway & McCord, 1995, cited in Conway & McCord, 2002; Porter & Alison, 2006a; Porter & Alison, 2006b; Woodhams, Gillett, & Grant, 2007), and young offenders are more likely to behave violently (e.g. shooting, stabbing, punching, kicking) towards the victim(s) when committing a crime with others than when offending alone (Conway & McCord 1995, as cited in Conway & McCord, 2002). Furthermore, group offences are more likely to involve multiple acts of violence during the event. For example, Hauffe and Porter (2009) reported that 78% of group rapes (47 out of 60) included multiple acts of violence compared to 60% of lone rapes (36 out of 60). However, other research on rape has found no differences between group and lone offences in terms of injury (Wright & West, 1981 as cited in Hauffe & Porter, 2009). Similarly, Alarid et al. (2009) reported that the probability of robbery victims receiving a slight injury was comparable across group and lone offences. However, their research also found that group offences were associated with all of the serious injuries sustained by victims in that sample.

Group offenders are less likely to use weapons than lone offenders (Lloyd & Walmsley, 1989) suggesting there are different methods of controlling victims. Group offenders have strength in numbers which can be used to control the victim (Porter & Alison, 2006b), if only through intimidation rather than physical violence. The lone offender, on the other hand, is more likely to need a weapon to achieve the same level of control, and as such, the weapon could be a substitute for an accomplice (Alarid et al., 2009).

Group offending and case linkage

Group offending is a concern for case linkage researchers as it seems to differ in several ways from lone offending. For example, research has found that burglars make more conservative and cautious decisions about target selection when with a co-offender than when selecting the target alone (Cromwell, Olson, & Avery, 1991 as cited in Alarid et al., 2009) which could impact on behavioural consistency across offences. The impact of group dynamics on behavioural consistency is untested in the case linkage literature. Research from the USA has found that, although co-offending does not seem to have a significant impact on robbery victim selection, it often does increase planning (Alarid et al., 2009). This means that the robberies an offender commits with a group might differ from those they commit alone, potentially making their crimes more difficult to link.

Research in the UK on behavioural coherence (in rape) has demonstrated the existence of thematic similarities between offenders committing multiple crimes with the same co-offenders (Porter & Alison, 2004). Porter and Alison (2006a) went on to examine behavioural coherence in robbery, the results of which suggested that offenders within the same group behave in a homogenous fashion. Although these two studies focused on whether offenders in the same group behaved in a coherent way within a single offence as opposed to across different offences (i.e. that all of the offenders behaved similarly during rape A rather than across rape A and rape B), these insights are valuable for crime analysis, particularly when combined with Porter and Alison's work on leadership in robbery groups (Porter & Alison, 2006c). Porter and Alison (2006a) suggested that behavioural coherence was due to group members copying a leader. They argued that the leader not only encourages other group members to offend but that, when they do, members imitate the behaviours of the leader. Their further research (Porter & Alison, 2006c) supported this hypothesis with the finding that, in most cases, one member of the robbery group could be identified as the potential leader, i.e. they exhibited more leadership behaviour than their co-offenders (103 out of 105 groups or 98%; note that two leaders were identified in the remaining two cases). Although it was reported that other group members displayed influential behaviour during the crime, this was to a lesser degree than the leader. Thus, if groups always follow with the same leader, it would be expected that the behaviours displayed during each offence would remain consistent across a series of incidents.

Furthermore, Alarid et al. (2009) reported that if offenders commit a series of robberies in a short timeframe, they are likely to select co-offenders from the same group of associates. This suggests that co-offending might also bias towards behavioural consistency (and therefore the ability to link offences) provided that the offences are committed in relatively quick succession by the same group of offenders. Indeed, the positive results presented in chapter 4 lend further credence to the view that group offending does not impact on the ability to link cases when the offences are committed close together in time. This could be because the last two recorded offences for each offender were used to assess behavioural similarity, and so if offenders selected the same co-offenders for both offences (as would be predicted if taking Alarid et al's. [2009]

finding about selecting co-offenders into account) then behaviour would be stable across the offences.

The current study

This new study will explore the characteristics of group and lone offending. It is hypothesised that the characteristics of group offending will mirror those found in previous studies, e.g. higher levels of violence but lower incidence of weapon use. Alarid et al. (2009) found no differences in accomplice characteristics between teams of two offenders and groups of three or more. Therefore here offences are simply classified as group (two or more offenders) or lone (one offender).

The potential impact of group offending on case linkage will be examined by comparing the behavioural similarity of crime pairs. In this instance, pairs fall into three categories; (1) crime pairs where the offender committed both offences as part of a group (labelled GG), (2) crime pairs where both offences were committed by the same lone offender (labelled LL), and (3) crime pairs where the offender committed one offence as a part of a group and one alone (labelled GL). It is hypothesised that there will be no difference in the level of behavioural similarity between GG and LL because groups behave in a homogenous way across offences (Porter & Alison, 2006a) and so will not differ from lone offenders in terms of behavioural consistency. However, where one offence was committed by the offender on their own and the other as part of a group (i.e. GL pairs) there will be less behaviourally similarity, consistent with evidence offenders behave differently when they are working alone than when they offend in a group (e.g. Alarid et al., 2009; Porter & Alison, 2006b).

Sample

This new study utilises the data samples from Northamptonshire Police and West Midlands Police as described in methodology section of chapter 4. The Northamptonshire dataset comprises 166 offences committed by 83 offenders between 1^{st} January 2005 and 31^{st} December 2007. The West Midlands dataset comprises 554 offences committed by 277 offenders between 1^{st} April 2007 and 30^{th} September 2008.

Identifying group and lone offences

The data for both police forces included a variable relating to the number of defendants/ offenders involved in the crime. However, this information was found to under-represent group offending as there were cases where only one offender in a group was identified. For the purposes of the current research, group and lone offences were identified by the present researcher using the modus operandi information.

In four cases in Northamptonshire, there was insufficient information in the modus operandi to identify whether the offence was committed by a group or lone offender. The three offenders these cases were associated with were therefore removed from the dataset. As there are two crimes per offender in the raw data, a total of six crimes were excluded. The three offenders were all

White males, and removing them from the dataset did not change the age range (10 to 41 years) or average age at the time of offence (18 years). The remaining sample consisted of 160 offences by 80 offenders. Of these 160 offences, 104 (65%) were committed by groups, and 56 (35%) by lone offenders.

All of the West Midlands offences could be categorised as group or lone. The ratio of group versus lone offending was similar to Northamptonshire, with 68% of offences (377 out of 554 cases) identified as group crimes and 32% as lone offences (177 out of 554 cases).

The case linkage element of the present study uses the Jaccard's datasets generated from each of the above datasets for Studies 1 and 2 (minus the data for the three Northamptonshire offenders removed from the sample). The Jaccard's datasets were split into the three categories GG, LL, and GL as described above. Table 5-1 shows how many pairs fell into each category for the two police forces.

Table 5-1: Frequency of GG, LL, and GL pairs

Pair consists of:	**Northamptonshire**		**West Midlands**	
	N	**%**	**N**	**%**
Two group offences (GG)	38	47.5	165	59.6
Two lone offences (LL)	14	17.5	65	23.5
One group / one lone (GL)	28	35.0	47	17.0
Total	80	100	277	100

The Jaccard's scores are compared to determine if there are any significant differences in behavioural similarity, i.e. whether Jaccard's scores are higher on average for group or lone offenders.

Method

The characteristics of group and lone personal robbery were explored using descriptive statistics. It should be noted that demographic information (e.g. gender, age, and ethnicity) was only available for one defendant and one victim in each case (i.e. details on co-offenders and co-victims were not included). Comparisons are made to the literature where appropriate.

The research then explored how group offending might impact on case linkage by comparing the behavioural similarity of the three categories GG, LL, and GL. As in studies 1 to 3, the data were not normally distributed (see appendix D for Kolmogorov-Smirnov outcomes) and were considered to be independent. However, in this case the dependent variable (group/lone) had three categories instead of two (the previous studies used linkage status – linked or unlinked – as the dependent variable). Therefore, a Kruskal-Wallis test (a non-parametric version of the ANOVA) was performed to assess whether there were any statistically significant differences between the three categories. As with the one-way ANOVA, the Kruskal-Wallis test can determine if there is a difference between categories but does not identify where differences lie. Therefore, post-hoc tests are needed, in this case the Mann-Whitney U test. To allay concerns about increasing the risk of Type I errors (i.e. identifying a significant difference where there isn't one) through repeated Mann-Whitney U tests (Field, 2005), the Bonferroni correction is used to adjust the critical value for significance. This is achieved by dividing the critical value (0.05) by the number of tests conducted (in this case three). This means any p value of 0.0167 (i.e. 0.05/3) or below is considered to be significant to the $p<0.05$ level for the purposes of the Mann-Whitney U analysis in this case.

Unlike studies 1 to 3 (outlined in chapter 4), this study did not include logistic regression or ROC analyses. This is because it was not necessary to build predictive models for the dependent variable. Unlike linkage status, whether an offence is committed by a group or lone offender was known to the police in the majority of cases and so there is no value to predicting this based on behaviour. In fact, whether the offence was group or lone was known in 98% of cases (162 out of 166) in Northamptonshire and 100% of cases (544 out of 544) in the West Midlands.

Results

Characteristics of group and lone offending

The current analysis presented here revealed that the sample reflected general trends in robbery in relation to a range of issues including offender characteristics, violence and control, victim selection, resistance and injury, and property stolen.

Offenders and Victims

Robbers tended to target lone victims; 74% (117 out of 157 cases - data missing in three cases) of offences in Northamptonshire, and 67% (372 out of 554 cases) in the West Midlands were against lone victims. Where groups of victims were targeted, these crimes were typically committed by groups of offenders; for example, in Northamptonshire, just 17% (9 out of 56) of lone offenders targeted groups compared to at least 31% (31 out of 101; the status of the victim was unknown for three group offences) of group offences. Similarly, in the West Midlands, only 25% of lone offenders targeted groups (45 out of 177) compared to 36% of offences committed by groups (137 out of 377). This is not surprising as it is harder for a lone offender to control more than one victim during a robbery.

Gender

Most victims of robbery were male; 84% (135 out of 160) in Northamptonshire and 79% (439 out of 554) in the West Midlands (the gender of the victim was unknown in five cases in the West Midlands). There were some differences between group and lone offences with lone offenders targeting female victims more often than groups. However, the majority of personal robbery was male on male, particularly group offences (see table 5-2).

Table 5-2: Gender of victims versus offenders

Offender versus victim categories	Group Offences				Lone Offences			
	NH		WMP		NH		WMP	
	N	%	N	%	N	%	N	%
Male on male	92	88.5	308	81.7	38	67.9	120	67.8
Male on female	5	4.8	30	8.0	13	23.2	53	29.9
Female on female	4	3.8	25	6.6	3	5.4	2	1.1
Female on male	1	1.0	10	2.7	2	3.6	1	0.6
Unknown against male	2	1.9	0	0.0	0	0.0	0	0.0
Male against unknown	0	0.0	4	1.1	0	0.0	1	0.6
Total offences	104	100	377	100	56	100	177	100

Note: NH is Northamptonshire and WMP is West Midlands

Age

Robbery victims were commonly teenagers and young adults (see table 5-3). Victims of groups were typically rather younger (mean age = 20 years) than victims of lone offenders (mean age = 25 to 27 years).

Table 5-3: Age of victims versus offenders

Type of offence	Police Force	Victims			Offenders		
		Range	Mean	Mode	Range	Mean	Mode
Group Offences	NH	9–59	20	15	10–40	18	16
	WMP	10-85	20	16	11–45	17	17
Lone Offences	NH	11–80	25	15	12–44	20	14
	WMP	10-87	27	16	12–45	22	17
All Offences	NH	9-80	22	15	10-44	18	16
	WMP	10-87	22	16	11-45	19	17

Note: NH is Northamptonshire and WMP is West Midlands

Robbery offenders were also young with an average age of 18 in Northamptonshire and 19 in the West Midlands, with lone offenders typically being a few years older (average age 20 to 22) than group offenders (average age 17 to 18). The age ranges were similar across group and lone offences indicating that at least some very young offenders (aged 10 to 12 years) commit robberies alone and some older offenders offend in groups.

Further examination of the data revealed that 36% of offences in Northamptonshire (57 out of 160) were committed by young males against other young males (both aged under 18 at the time of the offence). This accounts for 30% (17 out of 56) lone offences and 38% (40 out of 104) group offences. A similar finding emerged in the West Midlands with 38% (213 out of 554) offences committed by young males against young males. However, here the difference between group and lone offending was more marked. Just 27% of lone offences (49 out of 177) were committed by young males against young males compared to 44% of group offences.

Ethnicity

The majority of victims in Northamptonshire were White (89% or 143 out of 160). Other victims were Black (3%, n=5), Asian (2%, n=3), and of mixed heritage (<1%, n=1). Ethnicity was unknown in 5% (n=8) of cases. Although still making up the majority of victims, White victims featured in a lower proportion of robberies in the West Midlands (69% or 380 out of 554). A higher proportion of victims were Asian (17%, n=94), Black (9%, n=50), or mixed/other (3%, n=14). Ethnicity was unknown in 3% (n=16) of cases.

The correlation is not absolute, but it is likely that these regional variations in victimisation simply reflect the differing ethnic make-up of the two areas. Figure 5-1 shows the percentage of the population in each police force by ethnic group using population estimates for mid-2009 from the Office for National Statistics[6] compared to the breakdown of victim ethnicity in each police force.

[6] The raw dataset 'Data Sheet: Estimated resident population by ethnic group and sex, mid-2009 (experimental statistics)' was downloaded from http://www.ons.gov.uk on 27 August 2012.

Figure 5-1: Ethnic breakdown by police force area

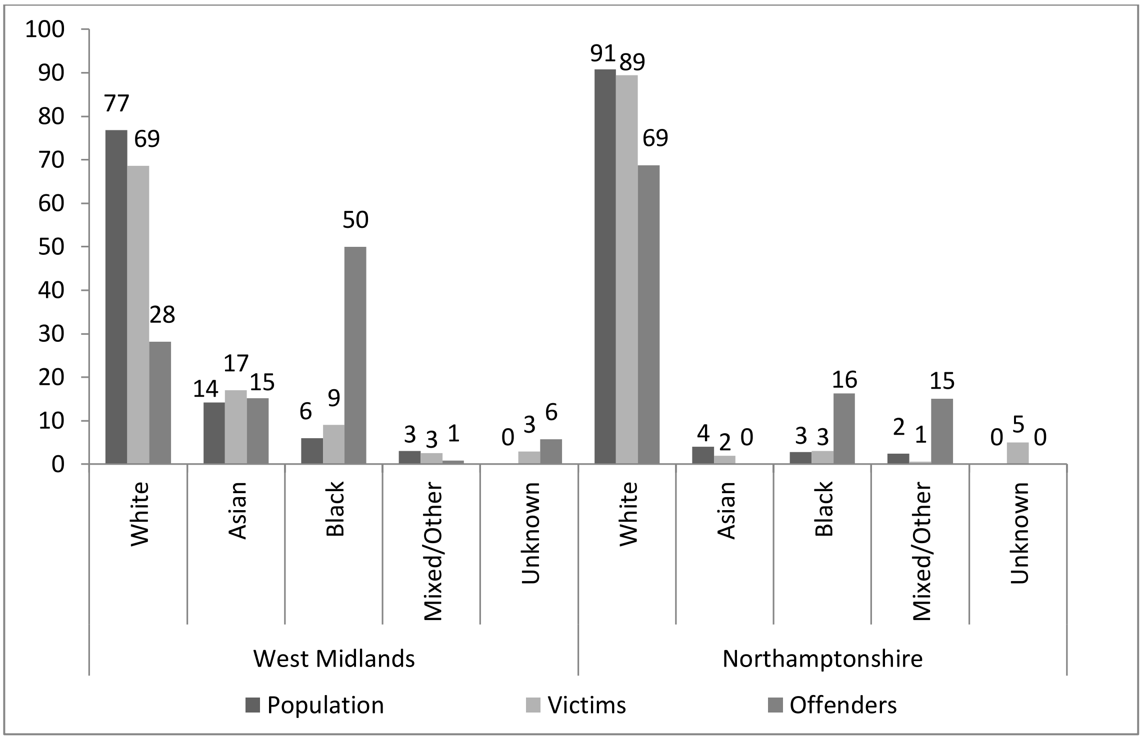


Figure 5-1 also shows the ethnic breakdown of offenders in each police force (in per cent). The findings clearly show that White offenders are underrepresented and Black offenders overrepresented in the both police forces, particularly West Midlands.

Given the marked differences between the ethnic breakdown of offenders and victims across the two police forces, the information for group and lone offending are presented by force. Table 5-4 presents the results for Northamptonshire.

Table 5-4: Ethnicity of victims and offenders in Northamptonshire

Type of offence	Role	Ethnicity N (%)					Total offences
		White	Black	Asian	Mixed/ Other	Unknown	
Group	**Victim**	93 (89.4)	4 (3.8)	2 (1.9)	0 (0.0)	5 (4.8)	104 (100.0)
	Offenders	70 (67.3)	15 (14.4)	0 (0.0)	19 (18.3)	0 (0.0)	104 (100.0)
Lone	**Victims**	50 (89.3)	1 (1.8)	1 (1.8)	1 (1.8)	3 (5.4)	56 (100.0)
	Offenders	40 (71.4)	11 (19.6)	0 (0.0)	5 (8.9)	0 (0.0)	56 (100.0)

In Northamptonshire (see table 5-4), the majority of victims of group offences were White (89%); an unsurprising finding given that Northamptonshire is predominantly White British (see figure 5-1). Four per cent of victims of group offences were from Black backgrounds, and 2% were Asian (data was missing in 5% of cases). The ethnicity of group offenders followed a slightly different pattern; although the majority were White (67%), a higher proportion of group offenders were from minority ethnic backgrounds than might be expected based on the population statistics with 14% of group offenders recorded as being from a Black background and 18% recorded as Asian.

As with group offences, the majority of victims of lone offenders were White, with relatively few people from minority ethnic backgrounds reporting being victimised by a lone robber. The majority of lone offenders were White (71%), with 20% recorded as being from a Black background, and 9% recorded as Asian.

Table 5-5: Ethnicity of victims versus offenders in West Midlands

Type of offence	Role	Ethnicity					Total offences
		White	Black	Asian	Mixed/ Other	Unknown	
Group	Victim	261 (69.2)	30 (8.0)	70 (18.6)	6 (1.6)	10 (2.7)	377 (100.0)
	Offenders	97 (25.7)	188 (49.9)	66 (17.5)	4 (1.1)	22 (5.8)	377 (100.0)
Lone	Victims	119 (67.2)	20 (11.3)	24 (13.6)	8 (4.5)	6 (3.4)	177 (100.0)
	Offenders	59 (33.3)	89 (50.3)	18 (10.2)	1 (0.6)	10 (5.6)	177 (100.0)

In the West Midlands (see table 5-5), 69% of the victims of group offences were White, however, just 26% of group offenders were White. This is surprising as 77% of the population in the West Midlands are White British (see figure 5-1). In contrast, Black individuals were underrepresented as victims, and overrepresented as offenders, in group offences. Around 18-19% of victims and offenders in group offences were Asian, and around 1-2% were of mixed heritage. Similar patterns were displayed in lone offences.

In Northamptonshire, 65% (104 out of 160) of all offenders robbed someone of the same ethnic background. This was mostly White on White offending (102 out of 143 [71%] of offences against White victims were committed by White offenders). In contrast, only 35% (192 out of 554) offences in the West Midlands involved a victim and offender of the same ethnic background. However, no data was available concerning the ethnicity of co-offenders so it is possible that the actual proportion of within-ethnicity victimisation is higher. Overall, it is unclear whether ethnicity plays any significant part in victim selection.

Violence and control

Violence and control can take many forms in a personal robbery. Table 5-6 outlines the types of controlling behaviours used by offenders which relate to stealing the property.

Table 5-6: Controlling behaviours used to steal property

Type of offence	Police Force	Offender requests property		Offender demands property		Offender(s) search the victim(s) property		Offender(s) snatch/ grab property	
		N	%	N	%	N	%	N	%
Group Offences	NH	20	19.2	33	31.7	19	18.3	8	7.7
	WMP	84	22.3	111	29.4	139	36.9	73	19.4
Lone Offences	NH	12	21.4	16	28.6	8	7.7	10	17.9
	WMP	32	18.1	61	34.5	73	19.4	39	22.0
All Offences	NH	32	20.0	49	30.6	24	15.0	18	11.3
	WMP	116	20.9	172	31.0	172	31.0	112	20.2

Note: NH is Northamptonshire and WMP is West Midlands

Offenders tended to demand that victims hand over property, although some did use more casual approaches (e.g. "Can I use your phone?" and then refusing to return the item). Groups more often physically searched the victim. In relation to snatching/grabbing property, around a fifth of offenders in the West Midlands displayed this behaviour and there was little difference between group and lone offenders. However, although occurring less often overall in Northamptonshire, where this behaviour did occur it was commonly associated with groups.

Table 5-7 lists four violent and controlling offender behaviours exhibited during personal robberies. There was a clear difference between Northamptonshire and West Midlands offenders, with the former using verbal threats more often while the latter using physical violence more often. Although the level of physical assault was similar, the level of physical contact[7] was much higher in West Midlands. This is likely to be due to the more detailed information available within the modus operandi description in the West Midlands dataset allowing this behaviour to be coded more efficiently[8].

[7] Defined as where the modus operandi information indicates that there was physical contact from the offender against the victim, e.g. grab, push, held down/restrained, physically blocked escape, struggle attempt to remove things from the victims pocket, and "physical altercation".

[8] It should be noted that the inter-raters did not agree on the definition of physical contact. The kappa score was very poor meaning it was excluded from the case linkage research. However, all data were coded by the same coder for analysis and is at least consistent, allowing it to be used here for comparison.

Table 5-7: Violent behaviours displayed during the robbery

Type of offence	Police Force	Verbal threat		Violence - physical contact		Violence - physical assault		Offender physically controls the victim	
		N	%	N	%	N	%	N	%
Group Offences	NH	39	37.5	22	21.2	41	39.4	1	1.0
	WMP	106	28.1	126	33.4	157	41.6	18	4.8
Lone Offences	NH	27	48.2	15	26.8	10	17.9	3	5.4
	WMP	47	26.6	62	35.0	39	22.0	12	6.8
All Offences	NH	66	41.3	37	23.1	51	31.9	4	2.5
	WMP	153	27.6	188	33.9	196	35.4	30	5.4

Note: NH is Northamptonshire and WMP is West Midlands

These data also demonstrate that a small number of offenders physically controlled the victim (e.g. forced them to go somewhere). This was more common with lone offenders, who, for example, might force someone to go to cashpoint at knifepoint.

Weapon use

Weapon usage is another indicator of violence. Weapons were recorded in 37% of cases in Northamptonshire (59 out of 160 offences) and 41% of cases in the West Midlands (228 out of 554 offences). This was slightly higher than rates reported in the literature (e.g. Flatley et al. [2010] reported weapon use in one third of personal robberies). Weapon use was somewhat lower in group offences (34-39% compared to 43-46% for lone offences) (see table 5-8).

Table 5-8: Weapon use during the robbery

Type of offence	Police Force	Weapon used		The weapon was a knife	
		N	%	N	%
Group Offences	NH	35 out of 104	33.7	9 out of 35	25.7
	WMP	146 out of 377	38.7	102 out of 146	69.9
Lone Offences	NH	24 out of 56	42.9	12 out of 24	50.0
	WMP	82 out of 177	46.3	58 out of 82	70.7
All Offences	NH	59 out of 160	36.9	21 out of 59	35.6
	WMP	228 out of 554	41.2	160 out of 228	70.2

Note: NH is Northamptonshire and WMP is West Midlands

Knives were overwhelmingly the weapon of choice which is unsurprising as knives are readily available and have been found to be commonly associated with personal robbery (Barker et al., 1993; Flatley et al., 2010). In Northamptonshire, of the 59 cases where a weapon was used, 21 (36%) included the use of a knife, although it is noted that the weapon type was unknown (or unrecorded) in 34% of cases (n=20) so this number could be much higher. The recorded use of knives was much higher in West Midlands with 160 out of the 228 cases where a weapon was used (70%) including a knife.

In Northamptonshire knife use was proportionally higher for lone offences (50% of cases where a weapon was used) compared to group offences (26% of cases where a weapon was used). In the West Midlands knife use was more evenly distributed with a similar proportion of lone and group offences involving the use of a knife (71% and 70% respectively).

There were 13 offences in the West Midlands where more than one weapon type was recorded. Eleven listed two weapon types and two offences listed three types (28 weapon types in total). Eight of these cases involved the use of a knife. Other weapons included knuckledusters (n=4), blunt instruments (n=3), coshes (n=3), firearms (n=2), swords (n=2), bottles/glass (n=2), dogs (n=2), and other weapons (n=2). All of these offences were committed by groups.

Victim resistance

Table 5-9 presents the victims' response to the offence where this information was available. Compliance and resistance were coded separately, so it is possible for the victim to be recorded as displaying both types of behaviour during the offence. Also note information on compliance and resistance was not available in all cases and so not coded for every victim.

Overall, victims were more likely to resist the offence than to comply in that around 30% of victims of group robbery were recorded by both police forces as resisting. In Northamptonshire, victims of lone offenders were as likely to resist the offence as victims of group offences. However, in the West Midlands victims of lone offenders were much more likely to resist. (Having said this, victims of lone offenders in the West Midlands were also more likely to comply.)

Table 5-9: Victim compliance during the robbery

Type of offence	Police Force	Victim complies		Victim resistance	
		N	%	N	%
Group Offences	NH	14	13.5	30	28.8
	WMP	67	17.8	109	28.9
Lone Offences	NH	10	17.9	15	26.8
	WMP	44	24.9	72	40.7
All Offences	NH	24	15.0	45	28.1
	WMP	111	20.0	181	32.7

Note: NH is Northamptonshire and WMP is West Midlands

Bystanders intervened in around 3% to 4% of personal robberies. Weapons were used in 27% of the cases where a bystander intervened (7 out of 26 cases [3 out of 4 cases in Northamptonshire and 4 out of 22 cases in the West Midlands]). This is lower than the overall prevalence of weapon use in these samples. Bystanders were more likely to intervene against lone offenders.

Injury

There was no information available about injuries sustained in the West Midlands data. In the Northamptonshire dataset there is a variable that describes the extent of victim injuries. This contained information for 135 out of the 160 cases. These data revealed that 39% (52 out of 135) of victims received some kind of injury (on par with the 40% reported by Smith in 2003). Most of these injuries (46 out of 52 or 88%) were described as “slight”. The remaining six (12%) were described as “serious”. The likelihood of receiving a slight injury was consistent across group and lone offences (34% of victims of group [31 out of 91 victims] and lone offences [15 out of 44 victims] received a slight injury). However, all of the serious injuries were sustained during group offences.

Journey to crime

The distance between the offence location and the offender’s home address was calculated where sufficient data were available. The median scores (see table 5-10) indicate that lone offenders offend closer to home than group offenders.

Table 5-10: Journey to crime

Type of offence	Police Force	Number of cases with grid references available		Distance between offence location and offenders home address (m)	
		N	% of total sample	Range	Median
Group Offences	NH	91	87.5	62.8–163102.5	2875.5
	WMP	317	84.0	1.4–287602.0	2214.0
Lone Offences	NH	43	76.8	34.9–43417.8	2105.6
	WMP	133	79.1	0–359824.7	1521.5
All Offences	NH	134	83.8	34.9–163102.5	2446.6
	WMP	450	81.2	0–359824.7	2045.4

Note: NH is Northamptonshire and WMP is West Midlands

Table 5-10 also reveals that distances between offence location and offender home address were generally shorter in the West Midlands; an unsurprising finding given that the geographical area is considerably smaller and more urbanised than Northamptonshire.

Stolen property

Offenders stole property in the majority of offences especially in the West Midlands (88% of offences compared 68% in Northamptonshire). This occurred in a high proportion of both lone (87%) and group offences (88%) in the West Midlands. The data were different in Northamptonshire, with groups successfully stealing property more often than lone offenders (70% compared to 64%).

Table 5-11: Theft of mobile phones and cash during robbery

Type of offence	Police Force	Mobile phone		Cash	
		N	%	N	%
Group Offences	NH	34	32.7	21	20.2
	WMP	184	48.8	100	26.5
Lone Offences	NH	15	26.8	16	28.6
	WMP	66	37.3	50	28.2
All Offences	NH	49	30.6	37	23.1
	WMP	250	45.1	150	27.1

Note: NH is Northamptonshire and WMP is West Midlands

Mobile phones and cash were the most popular items stolen during personal robberies (in fact they were the only types of property that were stolen in more than 10% of offences). Table 5-11 demonstrates that there are few differences in the proportion of lone robbers who steal cash across the two police forces. However, groups in the West Midlands stole cash more often than groups in Northamptonshire. Groups were more successful in stealing mobile phones in both police forces (albeit the overall level of theft is higher in West Midlands).

Differences in levels of theft of other types of property did not vary much across group and lone offending, although there were some slight differences between forces. For example, the West Midlands offences involved the theft of a vehicle more often, whereas Northamptonshire offences included the theft of a pedal cycle more often.

Assessing the potential impact of group offending on behavioural similarity

The results so far indicate that there are behavioural differences between group and lone offences. This could impact on the ability to link crimes based on offence behaviour. Therefore, the research moves to assess whether group dynamics impact on behavioural similarity.

Inter-Crime Distance is the distance in metres between the grid references for the two crimes in the pair (see appendix C for the method used to calculate this). *Temporal Proximity* is the number of days between the two offences in the pair. Behavioural similarity has been measured using Jaccard's scores for the remaining domains (see the methodology section of chapter 4 for more information on Jaccard's). The data are not normally distributed (see appendix D for the results of the Kolmogorov-Smirnov tests) indicating that median rather than mean scores should be used to compare the behavioural similarity of each domain. Table 5-12 shows the median scores for the three group/lone categories for each behavioural domain for Northamptonshire.

Table 5-12: Median Scores (group offending) Northamptonshire

Behavioural domain	**All pairs**	**Two group offences (GG)**	**Two lone offences (LL)**	**One group/one lone (GL)**
Inter-Crime Distance (m)	803.8	788.6	741.6	1169.7
Temporal Proximity (days)	34.5	7	16	87
Target Selection	.225	.250	.225	.200
Control	.250	.286	.429	.000
Approach	.000	.000	.000	.000
Property	.000	.000	.000	.000
Combined	.207	.222	.304	.118
Number of pairs	80	38	14	28

These data suggest that there may be some differences between categories for some domains. Most notably, GL pairs had larger *Inter-Crime Distances* and more days between offences than GG and LL pairs. There were also notable differences between median scores for the *Control* and *Combined* domains across the three categories.

Table 5-13 shows the median scores for the three group/lone categories for each behavioural domain for West Midlands.

Table 5-13: Median Scores (group offending) West Midlands

Behavioural domain	**All pairs**	**Two group offences (GG)**	**Two lone offences (LL)**	**One group/one lone (GL)**
Inter-Crime Distance (m)	608.6	475.5	852.1	893.9
Temporal Proximity (days)	1	0	2	4
Target Selection	.500	.500	.500	.333
Control	.333	.429	.429	.143
Approach	.000	.000	.000	.000
Property	.000	.000	.000	.000
Combined	.333	.375	.385	.200
Number of pairs	277	165	65	47

In the West Midlands, GG pairs displayed smaller *Inter-Crime Distances* than LL and GL pairs. There were differences between all categories for *Temporal Proximity* but it is unclear whether this difference is likely to be significant given the overall number of days between offences was low for all categories. The GL category had lower median similarity scores for *Target Selection*, *Control*, and the *Combined* domain.

The Kruskal-Wallis test was used to determine if there was a statistically significant difference between categories for each of the behavioural domains.

Post-hoc Mann-Whitney U tests were then conducted to identify where any differences lie. Table 5-14 reveals the outcomes for Northamptonshire.

Table 5-14: Kruskall-Wallis test outcomes (Northamptonshire)

Behavioural domain	**Kruskal Wallis**	**Mann-Whitney U post hoc test**					
		GG v LL		**GG v GL**		**LL v GL**	
	χ^2(df)	**U (z)**	**r**	**U (z)**	**r**	**U (z)**	**r**
Inter-Crime Distance	3.189 (2)	259.500 (.134)	.02	382.500 (1.738)	.21	147.500 (1.141)	.18
Temporal Proximity	6.304 (2)*	234.000 (.670)	.09	343.000 (2.470)*	.30	145.500 (1.350)	.21
Target Selection	2.733 (2)	264.000 (.042)	.01	417.000 (1.533)	.19	151.000 (1.237)	.19
Control	21.384 (2)*	207.500 (1.215)	.17	269.500 (3.507)*	.43	31.500 (4.500)*	.69
Approach	1.934 (2)	254.000 (.743)	.10	518.000 (.858)	.11	182.000 (.157)	.22
Property	.779 (2)	257.000 (.282)	.04	485.000 (.879)	.11	184.500 (.681)	.06
Combined	14.222 (2)*	200.500 (1.352)	.19	321.500 (2.736)*	.34	61.500 (3.596)*	.55

*p<0.05

The Kruskal-Wallis test revealed significant differences between categories in relation to *Temporal Proximity* ($\chi^2(2) = 6.304$, $p<0.05$). Post-hoc tests - Mann-

Whitney U tests (with Bonferroni correction) - showed that there was only one significant difference between categories, that is between GL and GG ($p<0.05$, $r = .30$).

The Kruskal-Wallis test revealed significant differences between categories in relation to the behavioural similarity of *Control* behaviours ($\chi^2(2) = 21.384$, $p<0.05$) and the *Combined* domain ($\chi^2(2) = 14.222$, $p<0.05$). The post hoc tests showed the significant differences to be between categories GL and GG, and GL and LL in both instances.

Table 5-15 (see over the page) reveals the Kruskal-Wallis outcomes for West Midlands. The Kruskal-Wallis test revealed significant differences between categories in relation to *Target Selection* ($\chi^2(2) = 6.342$, $p<0.05$). The only significant difference between categories was between GG and GL however the effect size was small ($p<0.05$, $r = .16$). As in Northamptonshire, the Kruskal-Wallis revealed significant differences between categories for *Control* ($\chi^2(2) = 34.043$, $p<0.05$) and the *Combined* domain ($\chi^2(2) = 21.795$, $p<0.05$), and again these differences were significant between GL and the other two categories.

Table 5-15: Kruskal-Wallis test outcomes (West Midlands)

Behavioural domain	Kruskal Wallis	Mann-Whitney U post hoc test					
		GG v LL		GG v GL		LL v GL	
	χ^2(df)	U (z)	R	U (z)	r	U (z)	r
Inter-Crime Distance	4.584 (2)	4599.000 (1.641)	.11	3220.000 (1.744)	.12	1469.000 (.346)	.03
Temporal Proximity	2.489 (2)	5010.000 (.833)	.05	3354.500 (1.507)	.10	1415.000 (.689)	.07
Target Selection	6.342 (2)*	4750.000 (1.385)	.09	3015.500 (2.383)*	.16	1354.500 (1.035)	.10
Control	34.043 (2)*	5237.000 (.277)	.02	1798.500 (5.634)*	.39	701.500 (4.912)*	.46
Approach	.473 (2)	5141.000 (.555)	.07	3799.000 (.243)	.00	1431.500 (.644)	.07
Property	1.254 (2)	5177.500 (1.057)	.04	3874.500 (.023)	.02	1472.500 (.773)	.06
Combined	21.795 (2)*	5164.000 (.437)	.03	2182.000 (4.572)*	.31	896.500 (3.722)*	.35

*p<0.05

Discussion

The new findings presented here reinforce some of the key trends of group offending identified by the literature. There are also some novel findings which have implications for case linkage work.

Trends in group offending

Alarid et al. (2009) report that maintaining control is of pre-eminent importance in robbery as victims could resist, and blind spots could lead to offender injury or capture. It is argued that co-offending significantly reduces the fear of losing control of the scene (*ibid*) hence why group offending is so prevalent. The present findings support this in that group offending accounts for a substantial proportion of crime; in this instance 65 to 68% of offences were identified as being committed by groups. Furthermore, offenders typically targeted lone victims, but where groups were victimised these were usually targeted by groups of offenders (as would be predicted based on Alarid et al. [2009] and Hauffe & Porter's [2009] work). The present research also supported Smith's (2003) finding that there is a tendency for male on male youth violence within personal robbery with 36 to 38% of offences committed by young males against other young males (both aged under 18). The ethnicity of victims mirrored the ethnic breakdown of the areas (see figure 5-1) and so ethnicity appears to exert little influence in robbery victim selection.

The previous literature indicates that group offences are more likely to be planned (e.g. Foley & Powell, 1982). Unfortunately, there was insufficient data to assess the level of planning behaviour in personal robbery in this new research. However, there was a wealth of information to explore other behaviours, such as violence and weapon use. The literature suggested that group offences were more likely to involve physical violence than lone offences (e.g. Alarid et al., 2009; Porter & Alison, 2006a). This was supported by this new study where 39 to 42% of group offences involved physical assault compared to just 18 to 20% of lone offences. In contrast, lone offenders were more likely to use a weapon and/or physically control the victim. There were no differences between group and lone offences for behaviours such as requesting or demanding property, but groups were more likely to physically search the victim(s); an unsurprising finding as groups are able to both restrain and search victims at the same time; an option not open to the lone offender.

Perhaps more interesting than the group versus lone offending comparisons, this new research revealed some differences in violent and controlling behaviour between the two police forces. Offenders in the West Midlands displayed violent behaviours more often than Northamptonshire offenders. This was true across a wide range of behaviours including searching the victim(s) (31% compared to 15% of offences), snatching/grabbing property (20% compared to 11% of cases), and physical contact (34% compared to 23% of offences). Weapon use was also more prevalent (41% of offences compared to 37% in Northamptonshire), particularly the use of knives in group offences (knives were the weapon of choice in 70% of group offences involving a weapon in the West Midlands, compared to just 26% of comparable offences in Northamptonshire). In contrast, offenders in Northamptonshire used verbal threats more often (41% of robberies compared to 28% in the West Midlands).

With regards to injury, Alarid et al. (2009) found that the probability of slight injury in robbery victims was comparable across group and lone offences but that serious injuries tended to be inflicted during group offences. This was replicated in Northamptonshire (no data were available on injury in the West Midlands sample).

Victims were more likely to resist the offence than to comply, with 28 to 33% of victims resisting at some point during the offence compared to a 15 to 20% compliance rate (note that the categories were not mutually exclusive so a victim could both resist and comply during a single offence. Furthermore, information on compliance and resistance was not available in all cases). Rape research has identified that victims are less likely to resist against a group of offenders (Hauffe & Porter, 2009), but this trend towards submission was not replicated to the same extent with robbery. Whilst it is true that a higher proportion of victims of lone offenders resisted in the West Midlands (41% compared to 29%), this was not so in Northamptonshire where 29% of victims of group offences resisted compared to 27% of victims of lone offenders. This could be because lone offenders in Northamptonshire were found to be somewhat more likely to carry a weapon (43% compared to 34%). However, given that a higher proportion of offences involved weapon use in West Midlands (39% of lone offences and 46% of group offences) this does not fully explain the trend. It is interesting that a high proportion of victims of lone offenders resisted in the West Midlands (41%) despite the prevalence of weapon use. Having said this, the level of compliance in lone offences in the

West Midlands was also higher than Northamptonshire (25% compared to 18%) so these findings could indicate that resistance breeds violence that then forces compliance. Alternatively, the level of resistance could reflect the individual differences of the victims, particularly when the urban setting is taken into account. People who live in cities are arguably more used to higher crime rates and so might have different attitudes regarding how to deal with crime than people living in quieter, low-crime, rural areas.

Bystanders only intervened in around 3 to 4% of personal robberies. This could be because robbers choose isolated places to commit their offences and so there are few people around who might intervene. On the other hand, the low level of intervention might be due to fear; robbery is a violent act and intervening risks injury. Bystanders intervened against lone offenders more often. This is perhaps not surprising as it would be expected that groups would be more intimidating, particularly when they are in the process of committing a violent act. However, weapons were being used in some of the cases where bystanders intervened perhaps indicating that some people intervene regardless of personal risk. It is not possible to draw conclusions here about the psychology of bystander intervention without more information. It is suggested that further research in the area, including qualitative interviews with people who have intervened in violent crime, would be useful to understand why, and in what circumstances, some people are sufficiently motivated to intervene to prevent or disrupt a crime.

With regard to stolen property, students of Ron Clarke will not be surprised to learn that the most commonly stolen items were cash and mobile phones. These items are 'hot products' (Clarke, 1999); small, portable, and valuable and therefore ideal targets. Furthermore, they feature prominently on the list of what people are likely to carry around with them, and therefore what is available for the thief to steal. With regards to group and lone offending, groups were unsurprisingly more successful at stealing mobile phones than lone offenders. However, there were some differences between police forces, with offenders in the West Midlands managing to steal mobile phones in 45% of robberies compared to just 31% of offences in Northamptonshire.

Lone offenders in Northamptonshire tended to commit offences closer to home than group offenders; an average of 6,311 metres (range 35 to 43,418m) compared to a mean of 13,370 metres (range 63 to 163,103m) for group offences. This is not replicated in the West Midlands where the mean distance between offender home address and offence location is smaller for group offences (5,080m compared to 5,617m for lone offences) albeit not by much. The fact that offenders in the West Midlands did not travel as far to offend is not surprising given that the police force area is 2.6 times smaller than Northamptonshire.

Furthermore, West Midlands is more urban with a higher population density (there were an estimated 7,582 people per square mile in the West Midlands compared to 749 per square mile in Northamptonshire[9]) providing more opportunities to commit robbery thus reducing the need to travel to find suitable targets. The difference in mean distance between lone and group offenders in Northamptonshire is not so easy to try to explain. It is possible that groups travel to meet up somewhere that is mutually convenient, and therefore perhaps a little further from home. Friends and associates increase awareness space (Brantingham & Brantingham, 2008), and this brings new crime opportunities, so it is possible that group offenders feel more comfortable offending further away from home if the space is familiar. Even when the area is unfamiliar, the presence of co-offenders might increase group knowledge about the location thus making it more comfortable to offend there. It is also possible that the group offences were committed closer to the home of a co-offender and additional data on the home addresses of co-offenders would influence the results. Overall, these findings perhaps raise more questions than they answer and it is suggested that focus on the relationship between offence location and offender home address is conducted. This could enhance understanding of group dynamics, the presence/absence of behavioural consistency in case linkage. It could also examine the role of anchor points and awareness space in geographical profiling (e.g. assessing whether it is useful to map the home addresses of all co-offenders as part of the profile).

[9] West Midlands is 348 square miles with an estimated population of 2,638,700 in 2009. Thus, 2,638,700/348 = 7,582. This is compared to 683,800 people in Northamptonshire which is 913 square miles. This equates to 683,800/913 = 749. Source for population statistics is the Office for National Statistics (The raw dataset 'Data Sheet: Estimated resident population by ethnic group and sex, mid-2009 (experimental statistics)' downloaded from http://www.ons.gov.uk on 27 August 2012). Source for size of police areas is the Rural and Urban Classification 2004.

Group offending and behavioural similarity

The initial rationale for conducting this group/lone study was to examine the potential impact of group offending on behavioural consistency. Clearly, should group offending adversely affect behavioural consistency, this could reduce the accuracy of case linkage decisions based on behavioural evidence.

The results of this new research are promising. Firstly, there were no statistically significant differences between the median Jaccard's scores, *Inter-Crime Distances*, and *Temporal Proximities* for GG pairs compared to LL pairs. This indicates that pairs of group offences displayed similar levels of behavioural consistency to pairs of lone offences. This is beneficial to case linkage as it means that it is feasible to link group offences based on behaviour. These results were not unexpected given the literature on behavioural coherence. Furthermore, given the prevalence of group offending in robbery, the linkage studies outlined in chapter 4 would not have been successful if group dynamics had a big impact on behavioural consistency. Although positive, further research is needed to determine if behavioural consistency in group offending can be attributed to any particular circumstances. For example, was behavioural consistency attributable to the fact the offences occurred close together in time (all pairs were selected based on the two most recent crimes that the offenders were caught for)? Alternatively it could be because the offence was committed by the same group (i.e. there is stability in the selection of co-offenders), and/or because the group followed the behaviours of a leader. This will help to ensure that any limitations are identified and parameters are developed that can be applied in operational work.

Perhaps more promising than the non-significant Kruskal-Wallis outcomes for GG compared to LL are the results that demonstrate there is some behavioural consistency across GL pairs. The previous literature suggests that people behave differently when offending in a group to when offending alone (Alarid et al., 2009; Porter & Alison, 2006b) which would lead to lower levels of behavioural consistency in GL pairs compared to GG and LL pairs. Although this was true for some behavioural domains, this new research suggests it may possible to link across group and lone offences based upon certain behaviours. Firstly, despite apparently divergent median *Inter-Crime Distances* between GG, GL, and LL pairs, the Kruskal-Wallis tests indicated that these 'differences' are not significant in either police force. This suggests that *Inter-Crime Distance* remains useful, even when linking across group and lone offences. Thus, the general rule that the smaller the distances between any two crimes, the more likely they are to be linked, still applies regardless of whether the robberies were committed by a group or a lone offender.

As the literature predicts that offences that occur close together in both time and space are more likely to be committed by the same offender (Bernasco, 2008), it would be expected that *Temporal Proximity* would be useful to link across group/lone as well as within group/lone. However, Cromwell et al. (1991, as cited in Alarid et al., 2009) reported that groups are more prolific and are more likely to commit multiple offences in the same night than lone offenders. This is hypothesised to be due to the need for higher rewards as there are more members to satisfy, and/or the excitement experienced by groups during the offences. This suggests that there might be differences between group and lone offences in terms of *Temporal Proximity*. It is not surprising therefore that this new study found that median *Temporal Proximities* were smaller for GG pairs than for LL pairs. However, these differences were not statistically significant indicating that whilst the tendency for groups to offend in quick succession exists, this is not significantly quicker than lone offenders re-offending. Having said this, it should be noted that *Temporal Proximity* was measured in days for the purposes of this study, and it is possible that significant differences would be found if the unit of measurement were reduced to hours.

Larger *Temporal Proximities* were found in GL pairs (in both police forces) than in GG and LL pairs, particularly in Northamptonshire, where the difference was statistically significant. There are a number of potential explanations for this difference. Firstly, it could be due to variations in decision making processes in the lead up to the offence, e.g. it is possible that the offender will be choosier about when they commit an offence alone. Secondly, it could be due to the sample size; there were only 80 pairs in the whole analysis compared to 277 pairs in the West Midlands dataset. Finally, the difference could be an artefact of the distribution of date within the Northamptonshire dataset (as explained in the discussion of the results for study 1 in chapter 4).

GL pairs were less behaviourally similar than GG and LL pairs in terms of *Target Selection*. This difference was very small (and not statistically significant) in Northamptonshire. There was, however, a significant difference between GG and GL pairs in West Midlands. There are several possible reasons for this.

Firstly, it is possible that offenders might choose different times of day to commit robbery if they are alone compared to when they are with a group. Secondly, as demonstrated above, they may be more likely to target a group of victims when offending in a group compared to when they are alone. Alternatively, it is possible that the divergent sample sizes – there were only 47 GL pairs compared to 65 LL pairs and 165 GG pairs in the West Midlands – could have exaggerated the differences between categories. It is of interest to note that the p value was on the threshold of significance ($p = 0.017$ which is the threshold when using the Bonferroni correction in this case). Furthermore, the effect size was small ($r = .16$) suggesting that the influence of GL on *Target Selection* is minimal.

There were no differences between GG, GL, and LL pairs for *Approach* and *Property*. Unfortunately, these domains have poor levels of behavioural consistency. In fact the median Jaccard's scores were 0.000 for all pairs across both datasets indicating that these behaviours are not useful for linkage, and thus these behaviours should be eliminated from linkage decisions regardless of whether the analyst is trying to link lone or group offences.

The only behavioural domain that emerged as a substantial problem for linking across group and lone offences was *Control.* The behavioural similarity of GL pairs was low for the *Control* domain, with median scores of just 0.143 in the West Midlands and 0.000 in Northamptonshire. This is not surprising given the differences in violent behaviour and weapon use between group and lone offences. The Kruskal-Wallis test revealed significant differences between GG and GL pairs and between LL and GL pairs in both police forces for *Control*, reinforcing the finding that control behaviours differ across group and lone offences. However, there were no significant differences in the behavioural similarity of GG when compared LL pairs. This suggests *Control* is equally useful in linking group offences to each other and lone offences together. Given the differences between group and lone offending, it is likely that a different combination of control behaviours will be useful depending on whether the analyst is linking group or lone offences. The key finding is that, although it is possible to link two group or two lone offences together using *Control*, the analyst should not look for a similarity of control behaviours when seeking to link group offences to lone offences. Instead, linkage decisions should be made using other information.

Limitations

The data were not specifically collected for a study on group offending. The structure of the case linkage studies required pairs of offences committed by known offenders. Thus, the sample was a sub sample of all robbery and comprised only solved offences. The potential impact of using solved offences rather than all offences is well documented in the literature (e.g. Bennell & Canter, 2002). In this instance, there is an added dimension as Gagnon and LeBlanc (1983, as cited in Alarid et al., 2009) found that lone robbers were less likely to be caught. This suggests that lone offenders were underrepresented in the present sample. This is further compounded by Erikson's (1971, as cited in McGloin et al., 2008) warning that researchers should beware of the 'group hazard hypothesis', which contends that group offences are more likely to be reported to the police. Combined with evidence that group offenders are more likely to be known to the police (Hindelang, 1976, as cited in McGloin et al., 2008), this suggests that group offending may have been over-estimated in the current study. As the data for this study was originally sourced for a different purpose, and was a subset of all robbery, it is possible this sample is unrepresentative of all robbery. Replicating this study with a sample of all offences reported to the police would be useful to assess the reliability of the present results.

Chapter 6 : Discussion

The aim of the research

The core aim of the new research presented in this thesis was to examine whether further evidence could be found for the behavioural assumptions of case linkage - behavioural consistency and behavioural distinctiveness. This was done by comparing the behavioural similarity of linked pairs and unlinked pairs of offences with significantly higher behavioural similarity scores being found for linked pairs providing evidence for the assumptions. The current research also explored whether there were differences in behavioural similarity across police forces by testing data in one rural force and one urban force. The research also aimed to determine whether behavioural similarity was impacted by the level at which analysts operate (i.e. borough or force). The potential impact of group offending on behavioural similarity was also examined.

Summary of key findings

Analyst survey

The first element of research presented in this thesis explored analysts' views and experiences of case linkage (known as Comparative Case Analysis in a practical setting). The key outcome of the analyst survey (see chapter 3) was that it provides a strong rationale for the subsequent quantitative case linkage work (studies one to three in chapter 4). Firstly, the survey, albeit involving a small sample, demonstrated that analysts routinely work on linking offences together and that they use a range of evidence (including behavioural information) to inform case linkage decisions. This demonstrates the importance of identifying the behaviours that are the best predictors of whether (two) offences are linked or not. Furthermore, the survey revealed that analysts work on linking many different types of offences both within borough and across their police force area (reflecting their job role). This highlights the importance of assessing the feasibility of linking different types of offences within both local areas and across borough boundaries (i.e. force-wide).

Evidence for behavioural consistency and behavioural distinctiveness

The new case linkage studies presented in this thesis have enhanced the evidence base for the theoretical assumptions. This was demonstrated through the significant differences found between behavioural similarity scores (as measured using Jaccard's co-efficient), in *Inter-Crime Distances* (measured in metres), and *Temporal Proximities* (the number of days between offences) for (i) linked pairs of offences (i.e. two crimes committed by the same offender) and (ii) unlinked pairs of offences (i.e. two crimes committed by different offenders). Evidence for the assumptions has been found previously using the same methodology (e.g. Bennell & Jones, 2005; Markson et al., 2010; Tonkin et al., 2008; Tonkin, Santtila, et al., 2011; Woodhams & Toye, 2007), but there was no published work specifically on personal robbery found within the case linkage literature.

The current research found that linked pairs had larger similarity scores for *Target Selection, Control,* and the *Combined* domain plus smaller *Inter-Crime Distances*, and fewer days between offences than unlinked pairs. This final chapter will now discuss the behavioural domains outlining the usefulness of each domain for linking personal robbery offences, and consider why some domains perform better than others.

Inter-Crime Distance

The current findings support the previous case linkage research which has consistently found *Inter-Crime Distance* to be one of the most useful single-factor models (Bennell & Canter, 2002; Bennell & Jones, 2005; Burrell et al., 2012; Markson et al., 2010; Tonkin et al., 2008; Tonkin, Santtila, et al., 2011; Woodhams & Toye, 2007). Furthermore, the AUCs this research produced (in all but phase 2 of study 2) are comparable with those found in the literature. For example, Bennell and Jones (2005) reported a range of .76 to .91 for *Inter-Crime Distance* in their research on burglary, with other researchers' AUCs for *Inter-Crime Distance* also falling within this range.

The *Inter-Crime Distance* models performed well in terms of predictive accuracy when applied at the force level (a 31% improvement over the random model in Northamptonshire and 32% in West Midlands). However, the predictive accuracy of the regression model and the AUCs for *Inter-Crime Distance* was lower in phase 2, particularly in the West Midlands where the single-factor model for *Inter-Crime Distance* performed 15% below chance. This indicates that caution must be exercised when linking local crimes using *Inter-Crime Distance* alone because its predictive power appears to diminish when working at a local level, particularly in urban areas. This is most likely because the local policing areas are geographically smaller increasing the likelihood of the offender crossing borough boundaries to commit his/her offences. Nevertheless, *Inter-Crime Distance* still achieved a moderate AUC (actually the highest AUC for a single-factor model) in phase 2 of study 1 (Northamptonshire) indicating that *Inter-Crime Distance* may still have some value when working at a local level in large rural police forces.

There are a number of reasons why *Inter-Crime Distance* might emerge as a useful linkage factor. Firstly, research consistently demonstrates that offenders tend to operate within a limited geographical area or 'comfort zone'. For example, Santtila et al. (2007) found the median distance for committing a rape was 2.44km from the offender's home; this was 0.85km for homicide. Furthermore, routine activity theory would suggest that offenders will tend to keep within the area of their day-to-day actions (Canter & Youngs, 2009), and as rational decision makers, offenders have a tendency to act on the first or closest opportunity to commit crime (the least effort principle) (Rossmo & Rombouts, 2008). As such, once the offender has found a good location to commit a robbery there is no immediate reason for them to travel very far to commit the next robbery. The least effort principle would be more pronounced in rural areas such as Northamptonshire (which is 90% rural; Office for National Statistics, 2004) where opportunities to commit crime are limited and/or clustered geographically (e.g. robberies will cluster in the more urbanised parts of rural areas, such as small market towns with surrounding villages, which are often located some distance from one another). The clustering of targets may therefore help the linkage task as the analyst may only need to search a limited geographical area to identify other crimes in the series. However, it may also have an adverse effect as numerous offenders are likely to operate within any cluster of potential targets. Thus, the frequency of offending in these areas may make it difficult to distinguish between individual offenders (Bennell & Jones, 2005) suggesting it would be valuable to also consider other behaviours alongside *Inter-Crime Distance* when making affirmative linkage decisions.

Despite the positive results from phase 1 of studies 1 and 2, the key message from this research would be that, notwithstanding the evident value of *Inter-Crime Distance* when working at force level, it should be treated with more caution when working at a local level. It is argued therefore that it should not be used in isolation to link crimes. This is particularly important as analysts may have successfully used *Inter-Crime Distance* to link other offence types locally and may assume that this could simply be extended to personal robbery. Research exploring the thresholds for deciding whether crimes are linked based on *Inter-Crime Distance* in different sized geographical areas (i.e. force-wide and borough) also needs to be conducted to assist analysts to make informed linkage decisions.

Temporal Proximity

The current research suggests that *Temporal Proximity* is a useful linkage factor, particularly in the West Midlands where predictive accuracy was improved by at least 23 to 25%, and AUCs of .844 and .868 were achieved (study 2). These results mirror the findings of previous research testing *Temporal Proximity*. For example, Tonkin, Santtila et al. (2011) reported predictive accuracy improved by 23 to 24% and AUCs of .82 in their study of burglars in Finland, and Markson et al. (2010) reported predictive accuracy improved by 26% and an AUC of .86 in their study of residential burglary in the UK. *Temporal Proximity* has been identified as a useful linkage factor in earlier research showing that offences that occur close together in time (and space) are more likely to have been committed by the same person (e.g. Bernasco, 2008).

Whilst it is true that the predictive accuracy of *Temporal Proximity* was lower when working locally in the rural police force (study 1, phase 2) this result was attributed to the uneven distribution of data (i.e. crimes were clustered by time within each borough). This demonstrates the importance of considering the characteristics of data when interpreting results. This is reinforced by Tonkin, Woodhams, et al's. (2011) research on the feasibility of linking across crime types, (i.e. linking a personal and a commercial robbery committed by the same person) and crime categories (i.e. linking a personal robbery and a residential burglary committed by the same person). Their research found that the predictive accuracy of *Temporal Proximity* was slightly lower for across crime types and crime categories (a 21 to 22% improvement beyond chance) compared to within crime type comparisons (a 26% improvement).

Overall the findings for *Temporal Proximity* are encouraging. The fewer days there are between offences, the more likely they are to be linked (i.e. committed by the same offender). However, it is important to continue to explore the value of *Temporal Proximity* especially as temporal behaviour (combined with spatial behaviour) has been highlighted as a useful method of concentrating investigative efforts in serial cases (Rossmo & Rombouts, 2008). It is crucial that temporal information continues to be recorded by the police for all offences. It is also important to establish how temporal data might be used in the most effective way. For example, is the number of days between offences the best measure of temporal proximity or should it be measured in different units (e.g. minutes, hours, weeks, months, or years)? It would also be interesting to determine whether the unit of measurement should be adjusted for different offence types to maximise success.

Target Selection

The literature indicates that the performance of the *Target Selection* domain can vary considerably, suggesting that this domain might be more useful in some offence types than others. For example, target selection behaviours have performed better with samples of commercial robbery (Woodhams & Toye, 2007) and commercial burglary (Bennell & Canter, 2002) compared to car theft (Tonkin et al., 2008). Also, its performance seems to vary by country, for example, *Target Selection* performed well in Tonkin, Santtila, et al's. (2011) study of residential burglary in Finland, however, it performed less well in Markson et al's. (2010) study of residential burglary in the UK. This could occur for a number of reasons including which behaviours are included (or not included) in the domain, the quality of data recording and coding, and/or because differing social structures may present different opportunities to commit crime. The highest levels of predictive accuracy found in the literature was Woodhams and Toye's (2007) study on commercial robbery where the regression model performed 21% above chance and an AUC of .79 was reported. The results for the current Northamptonshire research (study 1) were within the range reported within the literature (a 15 to 18% improvement in predictive accuracy and AUCs of between .640 and .691). Performance was more comparable to Woodhams and Toye's (2007) study in the West Midlands (studies 2 and 3) where AUCs were in the .776 to .790 range. Further research on this is needed to identify the optimal combination of *Target Selection* behaviours to use for linkage purposes, and whether these vary by offence type.

In Northamptonshire, the *Target Selection* domain performed slightly better at a local level than on a force-wide basis (although the difference was not statistically significant). This is perhaps unexpected because different areas present different opportunities (or targets) for robbers, so some homology of targets might be anticipated when multiple offenders are operating in the same area. Therefore, as active decision makers and risk assessors (Cornish & Clarke, 1986), it would be expected that robbers operating in the same area would identify the same or similar people to target, therefore making it more difficult to distinguish between individual offenders. However many offenders operate within a 'patch' (Deakin et al., 2007) and if these areas do not overlap, combined with the evidence that offenders do not travel far to commit their offences (Rossmo & Rombouts, 2008; Santtila et al., 2007), this may explain why an individual offender's crimes might be easier to link using *Target Selection* at the more 'local' level in the rural police force. Furthermore, it is likely that there will be fewer active robbers operating in any single local area than force-wide, thereby increasing the potential to distinguish between different series of offence using *Target Selection*.

Control

Control has not been included as a behavioural domain in many studies, possibly because this can be difficult to code or is not relevant in some crime types (e.g. burglary). However, Woodhams and Toye (2007) found *Control* to be the best predictor of linkage in commercial robbery, even performing better than *Inter-Crime Distance* thus demonstrating the potential value of exploring this behavioural domain. The current Northamptonshire study (study 1) failed to replicate this for personal robbery with predictive accuracy only improving a few per cent above chance, although there were some promising trends in phase 2 (borough) of the study (e.g. an AUC of .657). The differences were not attributed to sample size, as study 1 had a comparable number of linked and unlinked pairs to Woodhams and Toye's (2007) study (83 pairs in each sample compared to 80 per sample). The differing results may be due to the different variables included in the domain. For example, Woodhams and Toye (2007) included information about the manner in which the offence was committed (i.e. calm/confident, anxious/agitated, or loud/aggressive) whereas it was not possible to code this behaviour from the modus operandi information available for the current research.

There was more information available in the West Midlands, which may explain why the West Midlands studies (2 and 3) were more successful in relation to *Control*. Predictive accuracy was improved by 17 to 19% beyond chance and AUCs ranged between .715 and .731. The availability of more information is just one possible explanation for the better success of *Control* in linking robbery in the West Midlands. However, the findings could also suggest that offenders in the West Midlands were more behaviourally consistent in their *Control* behaviours than their counterparts in Northamptonshire. If group dynamics impact on the *Control* behaviours displayed during the offence (as suggested by the findings of the new study reported in chapter 5), and if there had been a higher prevalence of group offending in Northamptonshire, this might explain the differences in the predictive accuracy of the *Control* domain across the studies. However, the prevalence of group offending was similar across the two police forces (65% in Northamptonshire, and 68% in West Midlands) suggesting that this is not likely to be a feasible explanation for the differences between study 1, and studies 2 and 3.

As discussed in chapter 4, based on the literature it is not surprising that offenders display the same *Control* behaviours across their crimes, i.e. robbers develop a consistent method of committing their offences (Deakin et al., 2007) and base their offence behaviour on previous experience (Harbers et al., 2012; Juliusson et al., 2005). Overall, none of the studies within this thesis were able to replicate the scale of the success using *Control* as a linkage factor as achieved by Woodhams and Toye (2007). However, it was possible to extract data on control behaviours and demonstrate that these have a better than chance level of predictive accuracy. The findings of this research, and the success of Woodhams and Toye (2007), suggest that there is potential for *Control* to be a very useful predictor of robbery linkage, although more work is needed to identify which individual behaviours are the most useful to include in the domain. More in-depth information about the interaction between the victim and offender(s) would be beneficial in terms of identifying and coding *Control* behaviours in a way that could be utilised for case linkage. This could be achieved through access to original victim and witness statements as these are likely to contain more detailed information than the modus operandi data available for these new studies.

Approach

Low Jaccard's scores for the *Approach* domain indicate it is not useful for linking offences. The *Approach* domain in the current research only contained four variables in studies 1 and 2 (see chapter 4) and this probably impacted on the ability to distinguish between linked and unlinked pairs. It is noted that the original coding dictionary (of 68 behaviours) included seven approach variables but three were removed due to poor inter-rater reliability scores. Previous research identified different approaches used by personal robbers. Smith (2003) classified approach into ‘blitz’, ‘confrontation’, ‘con’, ‘snatch’, and ‘victim initiated’, and was able to allocate almost all offences (99.7%) into one of these categories. In contrast the current research was only able to identify how the offender approached the victim in 39% of cases in Northamptonshire and 29% in the West Midlands. This could be due to what data were available and/or how this information was coded. It is possible that utilising a more robust method of recording data and/or using a different approach to coding might yield more useful results.

Property

The *Property* domain performed poorly, being unable to distinguish between linked and unlinked pairs of robberies. This can perhaps be (at least partially) explained by that fact that property stolen during an offence is one of the most situation-specific criminal behaviours (Bennell & Canter, 2002) as it is dependent on what is available to steal (Wellsmith & Burrell, 2005). This could impact on the consistency of behaviour across offences: just because different property is stolen doesn’t mean the offences are not linked, it could be because victims possess different types of property. Another reason why the *Property* domain is unhelpful to link offences is likely to be that many robbers typically target the same small, high-value items such as mobile phones, cash, and jewellery (Monk et al., 2010; Smith, 2003); i.e. items that can be easily carried off. Therefore, the type of property stolen is likely to be a characteristic of personal robbery generally, and thus unlikely to help distinguish between offenders. Overall, the results for *Property* tend to confirm the findings of earlier research reporting low levels of predictive accuracy and AUCs compared to other behavioural domains (e.g. Bennell & Canter, 2002; Tonkin, Santtila, et al., 2011).

Combined

The *Combined* domain (which comprised *Target Selection, Control, Approach,* and *Property*) performed favourably compared to the single-factor models in all three studies of chapter 4, with predictive accuracy either on par with or better than the individual domains. The performance of the *Combined* domain was similar across both phases of each study, suggesting that it is equally as useful locally and on a force-wide basis.

Given the poor performance of the *Approach* and *Property* domains, the other two behavioural domains are probably driving the success of the *Combined* domain. In Northamptonshire, the central behaviour is *Target Selection*. In this case (study 1), the single-factor model for *Target Selection* actually performed better than the *Combined* domain indicating that its predictive value was somewhat diluted by adding the other three behavioural domains into the *Combined* domain. In West Midlands, *Control* emerged as a good predictor of linkage alongside *Target Selection*. The success of *Control* boosted the value of the *Combined* domain leading to this domain performing better than any of the single-factor models. In conclusion, the new research indicates that linkage accuracy would be improved by considering both *Target Selection* and *Control* in the West Midlands, but *Target Selection* alone in Northamptonshire. Further research, testing different combinations of behaviours in the *Combined* domain, would be useful to determine whether there is any further evidence for this proposition.

Optimal models

The *Optimal* models in Northamptonshire (study 1, chapter 4) comprised *Target Selection* and *Inter-Crime Distance* in both phases and these performed better than the single-factor models. The differences in phase 1 were not large compared to *Inter-Crime Distance* alone, accounting for a similar proportion of the variance and comparable improvements to predictive accuracy recorded. However, the *Optimal* model was favourable compared to the *Inter-Crime Distance* model in phase 2 accounting for 31% of the variance compared to 17%, and improving predictive accuracy by 18% compared to 7%. This suggests that, although *Inter-Crime Distance* is the most useful linking factor if working at force level, it may be useful to combine this with *Target Selection* if working locally. This is somewhat supported by the ROC analysis as *Inter-Crime Distance* recorded the highest AUC in phase 1 but the *Optimal* model performed best in phase 2, and although the difference between the AUCs did not quite reach significance, the confidence intervals did not overlap by much (0.862 - 0.974 compared to 0.684 – 0.881).

The findings were different in West Midlands. The *Optimal* models comprised of far more behavioural domains. In study 2 (which replicated study 1 with data from West Midlands) the *Optimal* model included *Target Selection* and *Inter-Crime Distance* but was also joined by *Control* and *Temporal Proximity*. *Property* replaced *Inter-Crime Distance* in the *Optimal* model for phase 2. In study 3 (where more behaviours were added into the domains) the Optimal model for phase 1 was the same as in study 2 with the addition of *Approach*. In study 3 phase 2 the *Optimal* model included *Target Selection, Control, Approach*, and *Temporal Proximity*. It is possible that more behavioural domains were included in the *Optimal* models due to the higher occurrence of recorded behaviours in West Midlands compared to Northamptonshire (see appendix B for the frequency of each behaviour). Interestingly, the *Optimal* models for phase 1 of each study improved predictive accuracy by the same amount – 33 to 34% beyond chance. Furthermore the AUCs for the *Optimal* models were comparable across the three studies (.902 to .910). This suggests that *Target Selection* and *Inter-Crime Distance* are the most useful linkage factors in the first instance with *Control* and *Temporal Proximity* added to support linkage decisions at force level. However, when working in more local, urbanised areas, there is a wealth of other behaviours that can be used to help inform linkage decisions.

In the West Midlands, as in Northamptonshire, the predictive accuracy of *Optimal* models was lower when working locally compared to force-wide. However, the accuracy of the models only fell slightly (to 30 to 31% above chance) compared to Northamptonshire (where predictive accuracy was only 18% above chance in phase 2). Furthermore, the AUCs remained moderate at .846 to .851. This lends support to the argument that behaviour can be used to link crimes in geographically small areas as well as across force. This is encouraging given that some of the local command units used for the West Midlands studies were very small (they ranged between three and 69 square miles with an average of 17 square miles).

The impact of adding additional behaviours

Study 3 (chapter 4) demonstrated that domain performance was not significantly improved by adding more behaviours to each domain. This is promising as it indicates that success can be achieved in case linkage without needing to source all the information about each offence, which would be very time consuming. Focusing on identifying the most useful behaviours and concentrating on coding these behaviours efficiently and accurately would be beneficial to support the practical implementation of case linkage.

Overall, the new findings provide some support for the theoretical assumptions of case linkage as there were statistical differences between linked and unlinked pairs across a number of behavioural domains. However, the results also suggest that the predictive ability of some behavioural domains may be sensitive to whether the unlinked pairs have meaningful constraints put on their *Inter-Crime Distance* (i.e. 'local' versus 'force-wide' pairings).

Group offending

The current research identified facts about group offending that mirrored those outlined in the literature (see chapter 5). In summary it identified that group offending is prevalent in personal robbery, and that many offences are male on male youth violence. Furthermore, group offences involved more physical violence and less weapon use than lone offences. Where serious injury occurred it was associated with group offending.

The current research provided new evidence for behavioural coherence in groups as there was no significant difference between the similarity scores for linked pairs of offences committed by groups compared to pairs of offences committed by an individual lone offender (for any behavioural domain) in either police force. There was also some evidence of behavioural consistency within linked pairs of offences where the offender committed one crime alone and the other as part of a group, as there were few significant differences between these pairs and other pairs for many of the behavioural domains. Differences were found for *Temporal Proximity* in Northamptonshire, *Target Selection* in the West Midlands, and *Control* and *Combined* in both police forces. The most noteworthy is *Control*, where Group/Lone (GL) pairs had significantly lower Jaccard's scores than Group/Group (GG) and Lone/Lone (LL) pairs in both police forces. The majority of behaviours in the *Control* domain relate to violent acts and weapon use and, as the current research demonstrated differences between group and lone offences for violence and weapon use, this result is not surprising. The new findings indicate that differences between *Control* behaviours need to be carefully considered when seeking to link group and lone offences by the same offender to avoid false negatives (i.e. failing to link cases that were committed by a common offender).

Limitations

As with all research, there were limitations to the data and with the methodological approaches used in these new studies. Efforts have been made to bear these in mind when interpreting findings; however, it is important to clearly state the limitations to inform the development of future case linkage research.

Police recorded crime data

Much of the prior case linkage research has been conducted using police recorded crime data and this new research is no exception. The limitations of working with police data are clearly outlined in the case linkage literature, including the challenges presented by possible inaccuracies (Tonkin et al., 2008), and the inability to assess the reliability of data coding within police data systems (Bennell & Canter, 2002) (though the quality of the relevant policing interviewing has rarely been mentioned in this literature). Furthermore, it is well reported in the criminology literature that crime under-reporting is a perennial problem (Felson, 2002). With reference to case linkage, under-reporting results in gaps in data (Ainsworth, 2001) potentially making it more difficult to identify series as some offences in the series might not have been reported to the police. As under-reporting is more of a problem in some offence types than others (Felson, 2002; Tarling & Mooris, 2010) – for example, rape is notoriously under-reported (Wolitzky-Taylor, Resnick, McCauley, Amstadter, Kilpatrick, & Ruggiero, 2011) – it is possible that some types of offence series will be more difficult to identify than others.

Another limitation to using police recorded crime data is that the type of data and information collected about offences is determined by police practice. The Home Office Counting Rules dictate when a crime should be recorded and the National Crime Recording Standard (NCRS) govern how the police should record crime information. This will influence what kind of information is collected about offences. This, in turn, might impact on data analysis as analysis is based on what information is available about crime rather than all aspects of the offence. It is possible that gaps in information about crime has led to a cyclical problem with data analysis of flawed datasets leading to incomplete theories, which in turn influence recording practice as the police strive to collect information highlighted as pertinent by crime theory. So, in the context of this work, how much of what we know about serial robbery is based on what the police think it is important to record about robbery? This is difficult to quantify but the potential limitations should be considered when developing theoretical frameworks based on data analysis of police recorded crime information.

However, despite these limitations, using police recorded crime data remains one of the most ecologically valid methods of conducting linkage research (Woodhams & Toye, 2007). This is because recorded crime data forms the basis of the information used to perform case linkage in an applied setting (*ibid*).

Solved offences

Concerns have also been raised about the use of solved offences as the basis for the linkage task (Bennell & Canter, 2002); not only is this unrepresentative of case linkage in an applied setting (Tonkin, Woodhams, et al., 2012), but it is also possible that one of the reasons cases were solved is because they were behaviourally similar and/or geographically and temporally proximal (Bennell & Jones, 2005). Thus, using solved offences could inflate the similarity scores or artificially reduce the geographical and temporal distances of linked offences compared to unsolved serial crimes (possible solutions to this are outlined in the Directions for Future Research section of this chapter).

Number of unlinked pairs

This research compares a linked sample to unlinked samples of a comparable size (as the research focused on controlling the size of the area in each phase). In an applied setting the analyst is looking for series of offences from within all recorded crime. Thus, limiting the sample of unlinked pairs in this way is not reflective of the linkage task and this might have inflated or depressed the value of behavioural domains for linkage. This limitation could be overcome by comparing the linked sample to all possible combinations of unlinked pairs.

Methodological Approach

The methodological approach used in the current research was complex and time consuming to administer. This could make it difficult to utilise the methodology in an applied setting. That noted, this is not important for the most part because the scope of the current research was to see if evidence could be found for the theoretical assumptions rather than to build a practical tool for case linkage. However, all practical case linkage tools would de facto involve coding behaviours based on raw data. This is a time consuming task in itself and therefore any research which can identify the most useful behaviours for linkage can reduce the number of behaviours that need to be coded. Identifying behaviours which are easy to code consistently is also beneficial; for example, *Inter-Crime Distance* can be calculated mathematically using x and y coordinates whereas items such as *Approach* need to be coded through subjective assessment of text data.

Lack of access to statistical software, such as SPSS, may also limit the scope for analysts to replicate this research in their area. There are also many statistical tests to be performed, which would need to be streamlined for operational use. Thus, it is not very practical to replicate fully the current methodological approach in an operational setting. However, provision of base rates for crime behaviours (to allow for analysts to assess the distinctiveness of behaviour), identification of the most useful behaviours for linkage, and developing an efficient tool for measuring behavioural similarity would be useful.

Directions for future research

The opportunities for future research are numerous and wide ranging. The first, and most obvious, avenue is to replicate the current work and there are a number of further options for replication.

Other crime types

Case linkage researchers have found evidence of behavioural consistency and distinctiveness for a range of crime types including burglary (Bennell & Canter, 2002), arson (Santtila et al., 2004), rape (Santtila et al., 2005), commercial robbery (Woodhams & Toye, 2007), and car theft (Tonkin et al., 2008).

However, there are many other serial crime types, including criminal damage and fraud, which remain unexplored using case linkage techniques.

Across crime types

It would be beneficial to explore the feasibility of linking across offence types, i.e. identify different types of crime committed by the same offender. After all, an individual knowingly breaking the law for, usually, personal gain is more likely to break the law in other ways too (Roach, 2009). There are a number of reasons why cross crime linkage would be useful. Firstly, identifying all of the offences in a series, regardless of offence type, would increase the amount of evidence that could be pooled in the search for an individual offender, and thus to support prosecutions. Secondly, mapping all of the offences (across a series) could help to identify how some offenders progress from minor to major crime, and so identify those offences that act as a precursor to prolific and/or more serious offending. If dangerous patterns are identified earlier in the series, this could help the police and other organisations to prevent more serious offending. Some papers have been published recently which examine behavioural similarity across crime type (Tonkin, Woodhams et al., 2011; Tonkin, Woodhams, et al., 2012), and results so far are promising, with linked across crime pairs (e.g. one personal robbery and one commercial robbery committed by the same offender) displaying comparable levels of similarity to linked within crime pairs (e.g. two personal robberies committed by the same offender). Both of these studies explored the behavioural similarity of linked across crime categories (e.g. one personal robbery and one residential burglary committed by the same offender) and found comparable levels of behavioural similarity for this condition as well. However, these publications only examined two behaviours (inter-crime distance and temporal proximity). Further research would be beneficial to explore whether these positive findings can be replicated for other offence behaviours.

However, it would be more challenging to develop a comprehensive coding dictionary for across crime linkage for other behaviours because different offences are characterised by various behaviours. The benefit of utilising inter-crime distance and temporal proximity to link offences lies in their simplicity (Tonkin, Woodhams, et al., 2012) as geographical data (x and y coordinates) and the date of offence are routinely recorded (probably correctly) in police records allowing these variables to be easily coded. Tonkin, Woodhams, et al. (2011) suggest that future research should focus on certain types of crime that share behavioural themes (e.g. robbery and rape where there are elements of offender-victim interaction, control and escape behaviours) as this is the most likely circumstance for building a tool for coding across offence type. If specific behavioural themes can be identified, this will help analysts identify behavioural consistency across different offence types within a single series.

Other areas/countries

It is important to consider whether findings can be generalised to other localities (e.g. other police force areas or countries) (Bennell & Jones, 2005; Tonkin et al., 2008). This new research found some differences between the two police forces. Findings might not be applicable to other police force areas in the UK because the different population densities, cultural factors, the level of urbanisation, and/or geographical layout might impact on crime opportunities. It is therefore necessary to replicate the work in different police forces to determine whether the current findings hold true elsewhere.

Replicating the research using data from police forces in other countries would also be valuable to determine whether the same behavioural domains emerge as strong linkage factors. Tonkin, Santtila, et al. (2011) found that inter-crime distance and temporal proximity were the most successful linkage features in a sample of burglaries in Finland; mirroring the findings of case linkage research on burglary in the United Kingdom (e.g. Bennell & Canter, 2002; Markson et al., 2010). However, this research also revealed higher levels of discrimination accuracy for target, entry, and internal behaviours for the Finnish sample compared to previous UK-based research, suggesting some behaviours may be more useful in some countries than in others.

With reference to replicating the current research, largely rural countries such as New Zealand and Norway might have police forces similar to Northamptonshire, whereas more urban centres (e.g. police forces covering capital cities) might be comparable to the West Midlands. Replicating the research in these countries with the same coding dictionary would be interesting to determine if differences are related to the rural/urban breakdown of an area rather than cultural differences across cities, regions, or countries.

Different/additional data

As with all research, more detailed data would have enabled more thorough analyses. Access to more in-depth data already held by the police (e.g. original victim and witness statements) would be beneficial to explore whether there are any additional information or behaviours that could be useful for linkage. Having said this, additional detail would increase the time it takes to conduct analyses and so might not be feasible in a practical setting. Also, caution needs to be applied to ensure that personal opinions do not skew data coding. However, if academic researchers were able to conduct analysis to identify useful linkage behaviours, this information could be fed back into operational work. In the meantime, it is beneficial to know that the standard information extracted from crime databases for analysis is sufficient to link offences in many cases.

The data gaps and limitations highlighted within this (and other) research provide a useful starting point for improving data quality and completeness. Given that this thesis strongly suggests that case linkage is feasible with police recorded crime data, then even more comprehensive and accurate data recording and better victim/witness interviewing (Milne & Bull, 1999) by the police seem warranted to improve the quality of data, and thus the potential for better analysis.

Future research needs to address concerns about the potential bias posed by using solved cases. This could be achieved by assessing the behavioural consistency and distinctiveness of unsolved series of offences that have been linked using another means (e.g. DNA or fingerprints) (Woodhams, Bull, et al., 2007). Alternatively, researchers could compare the similarity of linked pairs that were first identified through modus operandi to offences that were first linked through forensic evidence. Woodhams and Labuschagne (2011) have used this latter methodology to test case linkage principles in serial rape. They found that crime pairs that were first linked through having similar modus operandi were in fact more behaviourally similar (i.e. displayed higher Jaccard's scores) than crime pairs that had been first linked through DNA. Although the difference between the two sets of pairs was only just significant with a small effect size (Woodhams & Labuschagne, 2011), these results do confirm that the exclusive use of solved offences might be inflating the results of case linkage research. More critical analysis and research in this area is therefore warranted.

It might also be interesting to utilise different sources of data (other than police recorded crime information). For example, private companies, such as banks, collect comprehensive data to conduct internal investigations (R. Bull, personal communication, July 24, 2012).

Different methodologies

There are a number of methodologies that can be used to assess behavioural consistency and link crimes. For example, Smallest Space Analysis (SSA) (e.g. Salfati & Bateman, 2005), multi-dimensional scaling (e.g. Santtila et al., 2005), and Bayesian reasoning (e.g. Salo, Sirén, Corander, Zappalà, Bosco, Mokros, & Santtila, 2012). Even within the methodology used - i.e. comparing the behavioural similarity of linked and unlinked pairs – work is on-going to refine the statistical approach. For example, Bennell and Jones (2005) introduced

Receiver Operating Characteristic (ROC) analysis into their research to calibrate the validity of regression models and identify decision thresholds; Woodhams, Grant, et al., (2007) examined the relative value of Jaccard's and taxonomic similarity in distinguishing between linked and unlinked pairs of rapes - an approach later replicated by Melnyk et al. (2011) to assess whether the findings were applicable using other types of crime and larger datasets; Ellingwood et al. (2012) assessed the value of S as an alternative to Jaccard's; and, Tonkin, Bull, et al. (2012) compared the ability of logistic regression models and classification tree analysis in building predictive models for linkage.

Evidence for behavioural consistency and the ability to link crimes using behaviour has been found across a wide range of studies, regardless of the methodological approach used. This is reassuring for case linkage researchers, however, it would be interesting to analyse whether the same findings emerge if different methodologies were applied to a common dataset.

Setting thresholds for linkage factors

Whilst it is useful to identify which behaviours are useful for linking crimes committed by the same offender, this information is probably of minimal value without a frame of reference for base rate levels of individual behaviours, and/or decision thresholds. Firstly, as mentioned above, base rates are necessary to assess the distinctiveness of individual behaviours. Common behaviours (e.g. the theft of a mobile phone during a robbery) are not usually useful for linkage as they cannot be used to distinguish between different offenders (unless the offender does something distinctive such as target a particular type of phone not targeted by other offenders). Therefore identifying the base rates for each behaviour (bearing in mind these rates will differ by offence type and area) will be important to inform linkage decisions. Decision thresholds are necessary to maximise the number of correct linkage decisions made (Bennell & Canter, 2002). For example, Tonkin et al. (2008) used Youden's Indices to set decision threshold for car theft, reporting that theft locations that are less than 4.44km apart should be considered to be linked. Further research to expand on this work to identify decision thresholds for different types of offence in different areas would be useful. Tonkin et al.'s (2008) work was based on data from a rural police force and it is possible that the decision threshold would be much smaller in an urbanised area where car theft is more prevalent.

Behavioural consistency in group offending

The new study outlined in chapter 5 found that there were no statistically significant differences between the behavioural similarity of pairs of offences committed by groups (GG) compared to pairs of offences committed by lone offenders (LL). This supports the notion that offenders behave in a coherent manner when committing crimes together. However, there were differences between (i) the behavioural similarity of pairs of offences where one offence was committed as part of a group and one alone (GL) and (ii) the GG and LL categories. This lends weight to the argument that offenders behave differently when they are alone compared to when they offend in a group.

Whilst the results are promising, there is a lot of scope for further research. Firstly, as discussed in chapter 5, the data for the study utilised information that had been collected for a different purpose and was not, therefore, reflective of all personal robbery. Replicating the research with a sample of all offences reported to the police would be useful to assess the reliability of the current findings. Research to explore the reasons for consistency within group offending would be useful to identify any limitations to linking group offences together. For example, is it only possible to link group offences if they are committed by the same combination of co-offenders? In addition, if selection of the same co-offenders is time-limited (as reported by Alarid et al., 2009), would temporal proximity still emerge as a good linkage factor if the whole series was assessed rather than the two most recent offences only?

Overlay with other theoretical frameworks

It is useful to encompass a broad range of theoretical frameworks when conducting research. With reference to case linkage, embracing applied criminological theory may be advantageous as it may help to inform linkage decisions. There are four specific topics which have emerged as potentially useful for case linkage.

Firstly, if linked offences are committed close together in time and space (as demonstrated by the positive findings for *Inter-Crime Distance* and *Temporal Proximity* in this research), 'hotspot analysis' is an obvious complementary area of enquiry. 'Hotspot analysis' identifies geographical clusters of crime and timeframes can be specified, and so could be utilised as a starting point for case linkage analysis by highlighting where series might be occurring. Having said this, hotspots of crime should be interpreted in the context of other environmental criminological theory. For example, crime attractors and generators (Brantingham & Brantingham, 1993), and opportunity theory (Felson & Clarke, 1998) should be considered. ‘Crime attractors’ are places which are well known to be associated with crime (such as red-light districts and drugs ‘markets’), and crime generators are places where large volumes of people gather for non-criminal reasons (such as shopping centres, sports events, and festivals). In short, these localities present of opportunities to commit crime and will therefore appeal to different offenders, including robbers (Bernasco & Block, 2011). This means that hotspots of crime may not be an indication of one crime series but the result of a lot of different offenders operating independently (e.g. a cluster of muggings in a pedestrian subway does not necessarily mean they are linked, it could mean that subways offer better opportunities to commit robbery and are less risky regarding detection and apprehension). It is therefore argued that it is also important to consider other aspects of behaviour (alongside geographic and temporal proximity) when linking crimes together. Thus, the analyst could identify and prioritise clusters of offences using hotspot analysis, and then focus on identifying consistent and distinctive behaviours, in their search for independent crime series within these.

The second area for consideration is decision making. Decision making is a key area of research to consider when trying to make the links between offences committed by the same offender(s). Rational Choice Theory (Cornish & Clarke, 1986) presents offenders as rational decision makers, arguing that they weigh up the pros and cons of the offence prior to committing it. Whilst it is true that people base their actions on previous experience (Juliusson et al., 2005) (for example, serial offenders who identify their victims within the vicinity of their work often repeat this behaviour in future crimes [Harbers et al., 2012]), offenders might make different decisions in varying circumstances. The most obvious example is that offenders may behave differently when operating as part of a group compared to alone (Alarid et al., 2009; Porter & Alison, 2006b) and so decision making process might be impacted by group dynamics.

Furthermore, varying circumstances offer different opportunities to commit crime and so the offender might have to make different kinds of decisions depending on what kind of offence he/she is considering committing. It is argued that some offences are more likely to involve a rational decision making process than others (Cornish & Clarke, 1986). Also, there is some disagreement about whether certain offences are the product of rational choice or not. Take, for example, robbery. Woodhams and Toye (2007) describe personal robbery as unplanned and situation based, and Katz (1991) argues that the situational aspects of robbery mean it is not conducive with rational choice theory. Furthermore, Feeney's (1986) research found that robbery is largely opportunistic with more than half of robbers claiming to do no planning prior to the offence. However, Groff (2008) reports that the instrumental nature of robbery means it is more likely to involve a rational decision making process than other offences.

This is important for case linkage as, if spontaneous, situation-based offences are less likely to be planned, the behaviours of an individual offender might be less consistent across his/her offence series. In sum, it is possible that case linkage might be less effective with some offence types than others due to a lack of behavioural similarity across the crime series caused by differences in offender decision making.

The third area for exploration would be to overlay case linkage work with the research on repeat victimisation and 'near repeats'. Repeat victimisation is where the same target/person is victimised more than once (Clarke & Eck, 2003). The 'near repeat' phenomenon describes offending akin to an infectious disease (Haberman & Ratcliffe, 2012) predicting that people/locations close to previously victimised people or premises are at an increased risk of being targeted (i.e. predicting crime occurs close together in time and space). The evidence for repeat victimisation and near repeats is strong, with research indicating that crime is clustered in time and space more than would be expected by chance (e.g. Farrell & Pease, 1993; Johnson & Bowers, 2004; Pease, 1998; Townsley, Homel, & Chaseling, 2003).

Having demonstrated that clustering does occur, researchers have examined who commits repeat and near repeat offences. Research has shown that burglaries occurring close together in time and space are more likely to have similar modus operandi's than burglaries that are geographically and temporally more dispersed (Bowers & Johnson, 2004). Furthermore, pairs of detected burglaries that are close together in time and space are more likely to have been committed by the same offender(s) than pairs that are temporally and spatially diverse (Bernasco, 2008). Repeat victimisation has been demonstrated to occur in virtually all crime types except murder/manslaughter (Townsley et al., 2003). A lot of the near repeat research (e.g. Bernasco, 2008; Bowers & Johnson, 2004) has focused on residential burglary, however, evidence for near repeats has been found in other crimes, albeit with different spatiotemporal patterns (Youstin, Nobles, Ward, & Cook, 2011). For example, near repeat robberies tended to occur within one day and within two to four blocks from the first offence, whereas car theft usually occurred within four days and four to six blocks of the original car theft (*ibid*).

This body of research is clearly relevant to case linkage as it incorporates work on identifying behavioural similarity across offences and linking crimes to common offenders. The fact that repeat and near repeat victimisation occurs across different offences, and that these offences have different near repeat patterns, only adds to the rationale for conducting research on more than one offence type when setting thresholds for decision making in case linkage.

Finally, the feasibility of using behavioural case linkage in conjunction with offender network analysis should be considered as a possible method of identifying short lists of offenders. Offender profiling is a connected area of research and could be used to prioritise suspects on any short list.

The potential impact of cross border offending

Cross border crime is where the offender crosses a police force boundary to perpetrate crime (Porter, 1996). Research has estimated that around 10% of detected crime in the UK is attributable to offenders living outside of the police force area where the crime occurred, i.e. cross border (Porter, 1996). There is even evidence that some offenders (albeit a small minority) are aware of force boundaries and deliberately operate across them in order to reduce the likelihood of being apprehended (Kock, Kemp, & Rix, 1996; Porter 1996). Not only are there police force boundaries but the structure of police forces into smaller geographical areas to facilitate operational policing (e.g. boroughs, Operational Command Units etc.) also creates additional boundaries. The arbitrary nature of such policing unit boundaries mean that they can be very easily crossed by an offender even if (s)he does not make a deliberate effort to do so, and many offenders do therefore operate in multiple areas (Woodhams, Bull, et al., 2007).

Cross border offending presents a challenge to both investigative officers and analysts because the information on any individual offender and their crimes is split across multiple jurisdictions. This forces police staff to liaise with other areas in order to source the information they need; an often time-consuming process which can delay the progress of an investigation or analysis. With reference to case linkage specifically, the incomplete data resulting from cross border offending makes it more difficult to identify a whole crime series. Additional research on the scale of cross border offending, and how it might differ across offence types, would therefore be useful to estimate how much data is potentially missing, and in turn, how this impacts on the success of case linkage.

Additional research in personal robbery

There is a clear gap in the literature in relation to personal robbery. There have been a number of studies of commercial robbery (e.g. Gill, 2000), but not many studies that focus on personal robbery. In some cases where studies of personal robbery are identified it becomes apparent that these are focused on 'street crime', which encompasses other crimes (such as snatch thefts, low level violence, and sometimes gang activity), rather than personal robbery specifically. Furthermore, definitions of personal robbery differ (particularly in different countries) making comparisons between studies challenging. Future research on the scale and nature of personal robbery would therefore be beneficial. It would also be useful to conduct qualitative interviews with robbery offenders to explore the factors that affect their decision making (e.g. in relation to target selection, modus operandi, forensic awareness and the use of countermeasures, and the selection of co-offenders) to add context to the existing literature.

Applicability to policing

A core focus of any research should be to identify findings that can be translated for practical implementation in an applied setting. A number of suggestions can be made based on the studies presented in this thesis.

First and foremost this research offers reassurance that behaviour can be used to link offences. Analyst W-12 (see chapter 3) expressed that evidence for behavioural consistency (specifically identifying which behaviours are stable and which are not stable) would be useful to analysts. This new research did indeed provide evidence for behavioural consistency as well as behavioural distinctiveness. Furthermore, the overarching trends (i.e. *Inter-Crime Distance* tends to be useful and the *Property* stolen does not) matched the literature which is encouraging for analysts already using these behaviours to link crime. However, this new research also introduced some caveats to using behaviour to link crime, most notably the potential impact of the size of the geographical area under consideration on the effectiveness of *Inter-Crime Distance* as a linkage factor. This information would be useful for analysts to consider when they are making linkage decisions to help avoid false positives (i.e. making a link between offences where there is none).

The research found similar overarching trends in both the rural and the urban police forces indicating that analysts can utilise the same types of behaviours to link crimes in different areas. However, there were differences in the median values, the effect sizes (Mann-Whitney U), the predictive power of regression models, and AUC scores. This indicates that different thresholds should be used in rural areas compared to urban areas when making linkage decisions. More work is needed in this topic to set specific thresholds for use by analysts.

This new research highlights the need to cautiously interpret research findings when applying them in a practical setting. For example, the disparity between the performance of *Inter-Crime Distance* in phase 1 and phase 2 of studies one to three indicates that analysts should consider how their area compares to the study area reported in research publications before applying published thresholds to their area.

The success of *Inter-Crime Distance* and *Temporal Proximity* in some of the studies indicates that these behaviours might act as useful filters for analysts. If an analyst is looking at robbery in an urban police force area, for example, they might select offences that occur within 608 metres and one day of each other to start with (based on the median scores from study 2, phase 1). This would reduce the sample size, facilitating the identification of linked crimes based on other behavioural similarities.

The results of the analyst survey (chapter 3) indicate that analysts do link across multiple categories (e.g. W-4 stated that they focused on identifying factors that were the same or similar in most cases when making links between offences). Combined with the success of the *Optimal* models generated in studies one to three (see chapter 4), this new research highlights the value of linking cases using multiple behaviours. It is therefore suggested that analysts are encouraged to make links between offences across as many behavioural factors as possible if they are not doing so already.

In the short term, sharing the findings of this new research with analysts should support their work by helping to inform linkage decisions. However, more research is needed and recommendations for future research have been outlined in this chapter. In short, the key area for development for frontline analytical work would be further work to boost the reliability and quality of data.

As study three (see chapter 4) demonstrates, additional variables do not necessarily increase linkage accuracy. However, better recording and coding of fewer key variables might prove more fruitful.

Conclusion

This thesis has presented qualitative and quantitative research on case linkage. To revise, case linkage uses crime scene behaviours to identify series of crimes committed by the same offender. A survey of analysts (chapter 3) reinforced that case linkage is being conducted at an operational level (it is known as Comparative Case Analysis in this context). This provided a strong rationale for studies one to three (chapter 4) which focused on expanding the evidence base for the theoretical assumptions of case linkage.

The theoretical assumptions of case linkage - behavioural consistency and behavioural distinctiveness – were tested by comparing the behavioural similarity of linked pairs of offences (i.e. two offences committed by the same offender) with the behavioural similarity of unlinked pairs of offences (i.e. two offences committed by different offenders). The quantitative research did indeed find evidence for both assumptions as linked pairs of crimes were demonstrably more behaviourally similar than unlinked pairs.

Behavioural similarity was compared across themes, with some behavioural themes emerging as more useful for linkage than others; i.e. they were more accurate at discriminating between linked and unlinked pairs. *Inter-Crime*

Distance and *Target Selection* emerged as the most useful linkage factors with promising results also found for *Temporal Proximity* and *Control*. No evidence was found to indicate that the *Approach* used or the *Property* stolen were useful for linkage. However, phase 2 of studies one and two (chapter 4) found that the predictive accuracy of domains was different when geographical constraints were placed on the data. The predictive accuracy of some domains was better when working at a local level, most notably *Target Selection*. However, the new research also indicated that caution should be applied when using *Inter-Crime Distance* to link crimes in small geographical areas (particularly urban areas) as the predictive accuracy of this behaviour was much lower when working locally.

The addition of extra behaviours into domains improved performance in some cases but not substantially (see study 3 in chapter 4). This indicates that volume of information alone is not the key to accurate linkage. It is suggested that instead focus should be placed on acquiring more detailed information on key behaviours. This is based on the finding that predictive accuracy was generally better in the West Midlands compared to Northamptonshire, which was argued to be attributable, at least in part, to the more detailed information available in this police force as this allowed for more behaviours to be coded. Feedback from the analyst survey (see chapter 3) would support this recommendation. The analyst survey results also highlight the potential value of improving and/or facilitating quicker access to data to enhance Comparative Case Analysis work.

The new research also considered the potential impact of group offending on the theoretical assumptions of case linkage. Although there were some differences found between group and lone robberies, the research demonstrated that case linkage is feasible so long as the offences under examination are either group or lone in nature rather than a mixture of the two. This is a valuable as it demonstrates that it is possible to link group offences together opening up opportunities to expand case linkage work.

This new research offers reassurance that linking crimes using behaviour is feasible. None of the findings conflict directly with the literature, although caveats were highlighted. Most importantly, the size of the geographical area should be considered when interpreting the value of *Inter-Crime Distance* in linkage decisions. As identified by previous work, linking offences across multiple behaviours should be best practice in case linkage. In addition, offender group dynamics do not have to limit the scope of case linkage so long as appropriate analytical measures are taken (i.e. only link across group or lone offending rather than both). Further research is needed to build upon the existing evidence base for the theoretical assumptions of case linkage, and to set thresholds for making linkage decisions based on different behaviours.

Appendix A: Survey Tool

Crime linkage research

My name is Amy Burrell; I have been working in crime and community safety research for 5 years and am currently undertaking a PhD at the University of Leicester. My research focuses on establishing methods of proactively identifying serial (personal) robbery using police recorded crime data. The overarching aim of the work is to help provide tools to assist the investigative process when working with serial crime.

As part of this work, I would like to canvass the views of analysts working across the crime and community safety field about their experiences and thoughts about case linkage, or comparative case analysis as it more commonly known. I have designed a survey (attached below) and your participation, through completion and return of this survey, would be most appreciated.

I would welcome views from any analyst working in the field, even if you have not been involved in comparative case analysis work. The survey is quite short but many of the questions are free text as I am keen to gather your views rather than put words in your mouths. I would therefore be very grateful if you could expand your answers as much as possible. Please email all responses to amb58@le.ac.uk

All parts of the survey are voluntary and findings will be presented in an anonymised format in any papers resulting from the work.

If you have any questions in advance of completing, or during, the survey please contact me at amb58@le.ac.uk I will endeavor to respond to all queries as promptly as possible; this is likely to be within hours during weekdays.

Please could you read the consent to participate section below (this comprises a standard list of questions set by the University) and check the box 'I agree to participate'. Please ensure you have checked this box otherwise I will not be able to use your survey in my analysis.

Section 1: Consent to participate

1. I understand that my participation is voluntary and that I may withdraw from the research at any time, without giving any reason.

2. I am aware of what my participation will involve.

3. I understand that there are no risks involved in the participation of this study.

4. All questions that I have about the research have been satisfactorily answered.

☐ I agree to participate (Date:)

Thank you for agreeing to participate – please turn to the next page to complete the survey.

Section 2: Crime linkage survey

Please note the shaded areas denote where text can be added. Tick boxes can be checked/unchecked by clicking on the appropriate box.

1. Job title:

2. Time in post (analytical role):

   ☐ up to 12 months
   ☐ 1 to 2 years
   ☐ between 2 and 5 years
   ☐ between 5 and 10 years
   ☐ over 10 years

3. Organisation/Police Force:

Crime linkage is the process of identifying serial crime, i.e. offences which are committed by the same perpetrator(s).

Crime linkage is also known as Comparative Case Analysis.

4. Do you work on serial crime? (i.e. do you actively try to link cases together?). If so, which type(s) of crime?

5. Are there particular type(s) of offences (e.g. murder, rape, robbery) which you are more likely to be tasked to do comparative case analysis on? If so, which types?

6. Do you specialise in linking a specific crime type? If so, which crime type(s)?

7. What proportion of your time do you spend on crime linkage/comparative case analysis? (e.g. full time, a day a week, 10 per cent)

8. Why do you work on crime linkage/comparative case analysis?

9. Do you use computer software to assist you with crime linkage/comparative case analysis work? If so, what do you use?

10. If you use computer software, how is this beneficial to the linking process? (e.g. is there a particular stage of the analysis where the software is particularly useful?)

11. What evidence do you consider when judging whether crimes are linked to one another (i.e. part of a series committed by the same perpetrator(s))?

12. Do you consider any of the following in your efforts to identify series of offences (please tick all that apply):

    Forensic evidence

    - ☐ DNA
    - ☐ Saliva
    - ☐ Fingerprints
    - ☐ Footwear
    - ☐ Other (please specify below)

Temporal and spatial trends

- ☐ Time of day
- ☐ Day of the week
- ☐ Date
- ☐ Location, e.g. borough, district
- ☐ Location, e.g. shop, subway, street
- ☐ Location, e.g. a particular shop that is frequently targeted
- ☐ Comparison of spatial and temporal trends (i.e. whether crimes are committed close together in time and space)

Behavioural evidence

- ☐ Modus Operandi (i.e. the method of committing the crime)
- ☐ If a weapon was seen
- ☐ The use of a weapon (e.g. as a threat, to cause physical harm)
- ☐ The use of verbal threats
- ☐ The language used by the perpetrator(s)
- ☐ The use of physical threats
- ☐ The use of physical violence
- ☐ Other (please specify below)

Other evidence

- ☐ The type of property stolen
- ☐ Any other, please specify below

13. Could you estimate how long it takes to complete a comparative case analysis?

14. What factors affect the length of the process?

15. How do you minimise the chances identifying false positives (i.e. incorrectly linking offences together) and/or false negatives (failing to identify cases which are linked)?

16. Is it easier to identify series of cases for some crime types than others (e.g. murder, rape, burglary, car theft, robbery etc.)?

17. Do you try to identify all crime types committed by the same offender/group of offenders (e.g. all the burglary and car crime they have committed) and/or by offence type (e.g. trying to identify prolific offenders with the ultimate aim of reducing a particular crime type)?

18. Do you actively try to identify series of personal robberies? If so, how so? And if not, is there any particular reason why not?

19. Do you think it is beneficial to try to identify series of offences? If so, why? If not, why not?

20. Do you think the identification of series of offences assists with any of the following (please tick all that apply):

☐ Detection rates / catching offenders
☐ Prioritising suspects
☐ Developing our understanding of particular crime problems (e.g. burglary)
☐ To improve the efficiency of investigations (e.g. by allowing multiple cases to be subsumed into one over-arching investigation)
☐ Other benefits (please specify below)

21. What would help you to identify series of offences more effectively (i.e. more successfully) and/or efficiently (i.e. quicker/using fewer resources)?

22. Do you have any comments about the robbery, crime linkage, suspect prioritisation and/or this research in general which you would like to share with me?

23. Any additional comments?

Thank you for taking the time to complete this survey - your views are invaluable to my research and I appreciate your help.

Have you ticked the consent to participate box at the start of the survey?

Please hand completed forms back to me – thank you!

If you wish to be kept updated on the research please feel free to email me anytime at amb58@le.ac.uk

Appendix B: Behaviour Checklist

Table Appendix.B1: Behaviour Checklist for studies one to three chapter 4 in and the case linkage section of chapter 5

Domain	Offence Behaviour	Explanation	West Midlands		Northampton-shire	
			n	%	n	%
Target Selection	Monday	The offence was committed on a Monday	89	16.1	39	23.5
	Tuesday	The offence was committed on a Tuesday	90	16.2	22	13.3
	Wednesday	The offence was committed on a Wednesday	76	13.7	22	13.3
	Thursday	The offence was committed on a Thursday	76	13.7	23	13.9
	Friday	The offence was committed on a Friday	72	13.0	24	14.5
	Saturday	The offence was committed on a Saturday	75	13.5	25	15.1
	Sunday	The offence was committed on a Sunday	76	13.7	11	6.6
	22:00 to 01:59	The offence occurred between 22:00 and 01:59	91	16.4	34	20.5
	02:00 to 05:59	The offence occurred between 02:00 and 05:59	16	2.9	5	3.0
	06:00 to 09:59	The offence occurred between 06:00 and 09:59	14	2.5	5	3.0
	10:00 to	The offence occurred between 10:00 and 13:59	76	13.7	22	13.3

	13:59					
	14:00 to 17:59	The offence occurred between 14:00 and 17:59	207	37.4	46	27.7
	18:00 to 21:59	The offence occurred between 18:00 and 21:59	150	27.1	54	32.5
	Known Offender	The modus operandi described the offender as known	106	19.1	41	24.7
	Unknown Offender	The modus operandi described the offender as unknown	226	40.8	64	38.6
	Victim at cashpoint/ bank	The victim was approached at a cashpoint or had just been to a cashpoint when the offence started. This included where the victim had been to the bank earlier in the day and it looked like they had been selected due to this	8	1.4	2	1.2
	Road	The offence took place on a road – i.e. road was mentioned in location description	291	52.5	[Not applicable]	
	Private dwelling	The offence took place in or around a private dwelling – i.e. it was mentioned in location description	40	7.2		
	Shops	The offence took place in or around shops – i.e. it was mentioned in location description	13	2.3		
	Public	The offence took place in or around public buildings – i.e. it was	9	1.6		

	Buildings	mentioned in location description				
	Park / Garden	The offence took place in or around a park or garden – i.e. it was mentioned in location description	64	11.6		
	Bus / bus stop	The offence took place in or around a bus or bus stop – i.e. it was mentioned in location description	58	10.5		
	Car park	The offence took place in or around a car park – i.e. it was mentioned in location description	18	3.2		
	Public footpath/alley/underpass/towpath	The offence took place on a public footpath, alleyway, underpass or towpath – i.e. it was mentioned in location description	70	12.6		
	Miscellaneous	The location of the offence did not fit into any of the location categories	10	1.8		
Control	Weapon used	A weapon was coded by the police as present	228	41.2	60	36.1
	Knife	A knife was listed in the weapons list	160	28.9	21	12.7
	Firearm	A firearm was listed in the weapons list	16	2.9	4	2.4
	Weapon other	An other type of weapon (that did not fit into any of the existing weapons categories) was listed in the weapons list	20	3.6	11	6.6
	Knuckledust	A knuckleduster was listed in the weapons list	8	1.4	[Not	

	er				applicable]	
	Cosh/ baton/ stick	A cosh, baton or stick was listed in the weapons list. This category includes baseball bats.	10	1.8		
	Bottle or glass	A bottle or glass was listed in the weapons list	6	1.1		
	Iron bar/ blunt instrument/ hammer	A iron bar, hammer, or blunt instrument was listed in the weapons list Includes brick/stone/concrete.	11	2.0		
	Group of offenders v group of victims	The modus operandi suggested that a group of offenders assaulted a group of victims	137	24.7	31	18.7
	Group of offenders v lone victim	The modus operandi suggested that a group of offenders assaulted a lone victim	240	43.3	72	43.4
	Lone offender v group of victims	The modus operandi suggested that a lone offender assaulted a group of victims	45	8.1	9	5.4

	Lone offender v lone victim	The modus operandi suggested that a lone offender assaulted a lone victim	132	23.8	47	28.3
	Offender(s) searches victim/ victims property	The offender(s) searched the victim and/or their property. This included patting the victim down and taking things out of the victims pocket but not asking them to empty their pockets. The search had to be completed by the offender.	172	31.0	24	14.5
	Violence – physical assault	The modus operandi indicated that the robbery included a physical assault of the victim by the offender. Holding a knife to someone's throat counted as physical violence.	196	35.4	55	33.1
	Weapon threatened	The modus operandi suggested that the offender threatened to use a weapon. The weapon did not have to be seen. Includes where the victim was threatened with the future use of a weapon. Threat to stab included. This category is where a weapon might be waved around/threatened that there is one but there is no contact between the weapon and the victim – if the weapon made contact with the victim (e.g. held to throat) then it was coded as weapon threatened and weapon used. Note that seeing a weapon does not automatically count as a threat – e.g. one offender asked the victim to look after a weapon.	183	33.0	36	21.7

	Weapon shown/seen	The modus operandi indicated that a weapon was seen by the victim, includes the offender showing a weapon to the victim. Fists are not included as weapons but dogs were. Note that weapons that did not meet the criteria to be included as an individual category would be included here.	168	30.3	29	17.5
	Offender requests property	The offender(s) asked the victim for property. Includes asking if they have property. Includes phrases such as 'what have you got for me?'	116	20.9	32	19.3
	Offender demands property	The offender(s) demanded property from the victim.	172	31.0	54	32.5
	Offender(s) snatch/ grab property	The offender snatched or grabbed property from the victim (including attempts). Includes taking things forcibly – e.g. forcibly removing rings/ripping rings from the victims fingers.	112	20.2	[Not applicable]	
	Verbal threat	Includes phrases such as 'offender uses threats' mentions of verbal threats or the term "threatened IP" DOES NOT includes verbal altercation as this was coded as argument [later excluded due to low prevalence]. Includes where the offender(s) tried to scare the victim by telling them something, e.g. tells victim he has been in prison for murder	153	27.6		

	Victim resists – met with threat	The victim resisted the offender(s) and was then threatened.	47	8.5	9	5.4
	Victim resists - met with violence	The victim resisted the offender(s) and the offender(s) reacted violently.	54	9.7	[Not applicable]	
Approach	Dupe	The modus operandi suggested that dupe tactics were used to set up the robbery, e.g. a fake advert or posing as a delivery man.	12	2.2	3	1.8
	Carjacking	The offence is classified as a carjacking. Victim was targeted for the car. Includes attempts.	17	3.1	4	2.4
	Offender breaks into/ forces entry into premises	The offender(s) broke into the victim's home. Would be coded as present where there was evidence that the victim disturbed a break in. Included where the offender forced their way into the property. Does not include where the offender 'enters' (e.g. via an insecure door) or 'attends' property as this could be for legitimate reasons. Kicking the door in would be coded as present	16	2.9	6	3.6
	Approach from behind	The offender(s) approached the victim from behind.	29	5.2	7	4.2

	Approach - distraction	The modus operandi indicated that distraction was used to set up the robbery, e.g. do you have the time, do you have a light, do you have change, can you spare 20p.	73	13.2	[Not applicable]	
	Approach - blitz	The modus operandi indicated that the offence was a blitz attack, i.e. immediate violence was used.	30	5.4		
Property	Cash	Cash was listed as stolen/damaged. Includes cash box.	150	27.1	39	23.5
	Mobile phone	A mobile phone was listed as stolen/damaged. If the category description was telecom but the sub category was mobile this was coded as mobile.	250	45.1	51	30.7
	Cards	Cards were listed as stolen/damaged – this includes credit cards, debit cards	44	7.9	8	4.8
	Jewellery/ watch	Jewellery and/or a watch was listed as stolen/damaged	39	7.0	5	3.0
	Wallet/ purse	A wallet and/or purse was listed as stolen/damaged	47	8.5	11	6.6
	Keys	Keys were listed as stolen/damaged. This includes household keys, car keys	33	6.0	6	3.6
	Documents	Documents were listed as stolen/damaged. Includes passports, driving licenses, bus passes, bank books, chequebooks, national insurance cards, pension book, mobile phone top up cards, vouchers,	28	5.1	8	4.8

		photos, diaries etc.				
	Luggage	Luggage was listed as stolen/damaged. This includes bags (all types) and briefcases	36	6.5	6	3.6
	MP3 player	An MP3 player was listed as stolen/damaged.	15	2.7	7	4.2
	Clothing/ footwear	Clothing and/or footwear was listed as stolen/damaged. This includes clothing, footwear, sunglasses and spectacles.	25	4.5	7	4.2
	Food	Foodstuffs were listed as stolen/damaged. Includes alcohol.	6	1.1	3	1.8
	Cigarettes	Cigarettes were listed as stolen/damaged.	10	1.8	4	2.4
	Pedal cycle	A pedal cycle was listed as stolen/damaged.	18	3.2	14	8.4
	Telecom	Telecom listed as stolen/damaged – this does not include mobile phones.	6	1.1	[Not applicable]	
	Car	A car was listed as stolen/damaged Taxis coded as cars.	44	7.9		
	Other vehicle	An other vehicle (i.e. not a car) was listed as stolen/damaged. Includes bus/public service vehicle/moped/lorry etc but not pedal cycles	11	2.0		
	Audio and video equipment	Audio and/or video equipment listed as stolen/damaged. This includes video cameras, DVDs, CDs, videos, satellite navigation systems, radios, photographic equipment, TVs, and other audio goods. This category includes headphones but does not include MP3 players [coded separately].	25	4.5		

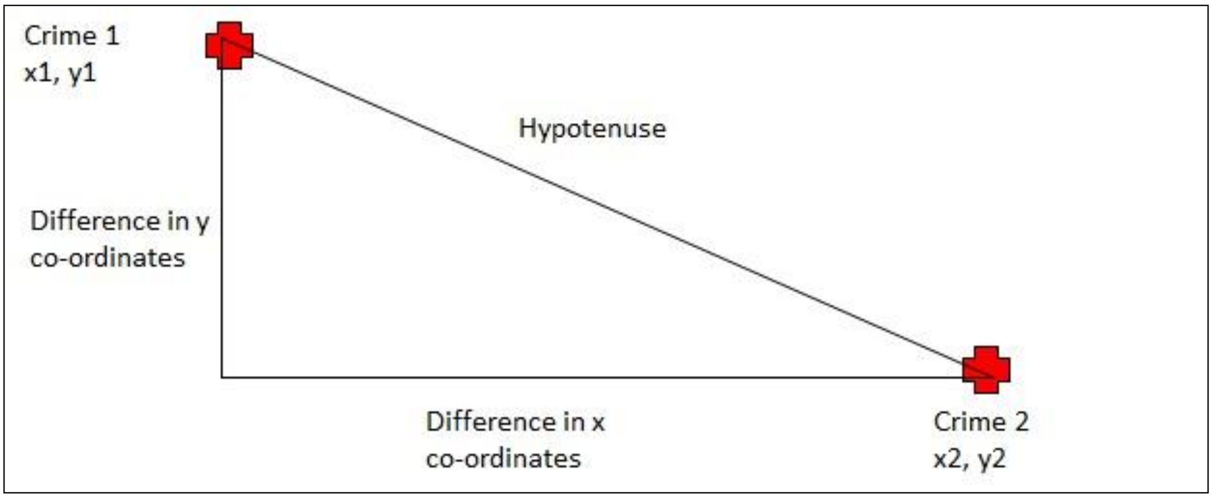
	Computing products	Computing equipment was listed as stolen/damaged. This includes computers, laptops, computer software, and computer add ons. Includes memory sticks.	13	2.3		
	Fixtures and furnishings	Fixtures or furnishings were listed as stolen/damaged. This includes doors, windows, and furniture.	7	1.3		
	Other	West Midlands Police list item(s) stolen/damaged as ‘other’	34	6.1		
	Miscellaneous	Miscellaneous items listed as stolen/damaged. Often these types of items were taken in a very low number of cases. Items include toys, cosmetics, musical equipment, tools, fancy goods, and medical equipment. Includes motorcycle helmets and SIM cards.	10	1.8	13	7.8
	Property returned	The offender(s) returned property to the victim(s). Does not include recovered property, it has to be returned to the victim by the offender.	21	3.8	3	1.8
	Property discarded	The offender(s) discarded the property.	6	1.1	[Not applicable]	
Inter-Crime Distance		The distance in metres between offence 1 and offence 2 in any given crime pair.	[Not applicable]			
Temporal Proximity		The number of days between offence 1 and offence 2 in any given crime pair.	[Not applicable]			

Please note shaded boxes highlight variables that were added into domains for study 3 (chapter 4).

Appendix C: Calculating Inter-Crime Distance

Inter-Crime Distance was calculated using Pythagoras' theorem to determine the number of metres between the grid references (x and y co-ordinates) for the two crimes in each pair (see figure Appendix.C1).

Figure Appendix.C1: Calculating distances using Pythagoras' theorem



The distance between the two offences is the hypotenuse, which is calculated using the following formula:

$$Hypotenuse = \sqrt{(x1 - x2)^2 + (y1 - y2)^2}$$

This is converted into the following for calculating the between two sets of grid references[10]:

[10] Source: http://www.ordinancesurvey.co.uk/oswebsite/aboutus/reports/misc/calculate.html

$$Distance = \sqrt{(eastings1 - eastings2)^2 + (northings1 - northings2)^2}$$

Where

- eastings1 is the Eastings grid reference (x co-ordinate) for offence 1 in the pair
- eastings2 is the Eastings grid reference (x co-ordinate) for offence 2 in the pair
- northings1 is the Northings grid reference (y co-ordinate) for offence 1 in the pair
- northings2 is the Northings grid reference (y co-ordinate) for offence 2 in the pair

It was necessary to translate this into the following Microsoft Excel function for practical application:

=SQRT((POWER(eastings1 – eastings2,2)+(POWER(northings1 – northings2,2))))

Each grid reference contained 6 digits. Therefore the resulting distances between offences is measured in metres[11].

[11] Grid references with 3 digits measure distances to the closest KM, 4 digits are measured to the closest 100m, 5 digits are distances measured to the closest 10m and, 6 digits to the closest metre (m).

Appendix D: Kolmogorov-Smirnov tests of Normality

Results of Kolmogorov- Smirnov Tests

Table Appendix.D1: Kolmogorov-Smirnov outcomes for study 1 (Northamptonshire)

Behavioural domain	**Linked**	**Unlinked1**	**Unlinked2**
Inter-crime distance	D(82)=.218*	D(82)=.127*	D(80)=.216*
Temporal proximity	D(83)=.252*	D(83)=.092	D(81)=.125*
Target Selection	D(83)=.175*	D(83)=.286*	D(81)=.353*
Control	D(83)=.158*	D(83)=.212*	D(272)=.262*
Approach	D(83)=.538*	Variable=constant	Variable=constant
Property	D(83)=.465*	D(83)=.461*	D(272)=.469*
Combined	D(83)=.119*	D(83)=.090	D(272)=.156*

*p<0.05

Table Appendix.D2 Kolmogorov-Smirnov outcomes for study 2 (West Midlands)

Behavioural domain	Linked	Unlinked1	Unlinked2
Inter-crime distance	D(276)=.442*	D(276)=.294*	D(271)=.436*
Temporal proximity	D(277)=.314*	D(277)=.089*	D(272)=.110*
Target Selection	D(277)=.200*	D(277)=.292*	D(272)=.300*
Control	D(277)=.114*	D(277)=.201*	D(272)=.217*
Approach	D(277)=.540*	Variable=constant	Variable=constant
Property	D(277)=.355*	D(277)=.407*	D(272)=.431*
Combined	D(277)=.101*	D(277)=.098*	D(272)=.120*

*p<0.05

Table Appendix.D3: Kolmogorov-Smirnov outcomes for study 3 (West Midlands)

Behavioural domain	Linked	Unlinked1	Unlinked2
Inter-crime distance	D(276)=.442*	D(276)=.294*	D(271)=.436*
Temporal proximity	D(277)=.314*	D(277)=.089*	D(272)=.110*
Target Selection	D(277)=.145*	D(277)=.209*	D(272)=.205*
Control	D(277)=.120*	D(277)=.171*	D(272)=.191*
Approach	D(277)=.520*	D(277)=.536*	D(272)=.531*
Property	D(277)=.338*	D(277)=.402*	D(272)=.421*
Combined	D(277)=.087*	D(277)=.075*	D(272)=.104*

*p<0.05

Table Appendix.D4 Kolmogorov-Smirnov outcomes for study 4 (Northamptonshire Group v Lone)

Behavioural domain	Two Group Offences	Two Lone Offences	One group/ one lone
Inter-crime distance	D(38)=.200*	D(14)=.259*	D(27)=.209*
Temporal proximity	D(38)=.263*	D(14)=.365*	D(28)=.277*
Target Selection	D(38)=.173*	D(14)=.201	D(28)=.225*
Control	D(38)=.134	D(14)=.142	D(28)=.310*
Approach	D(38)=.538*	D(14)=.534*	Variable=constant
Property	D(38)=.494*	D(14)=.473*	D(28)=.433*
Combined	D(38)=.158*	D(14)=.171*	D(28)=.116*

*p<0.05

Table Appendix.D5 Kolmogorov-Smirnov outcomes for study 4 (West Midlands Group v Lone)

Behavioural domain	Two Group Offences	Two Lone Offences	One group/ one lone
Inter-crime distance	D(164)=.437*	D(65)=.456*	D(47)=.272*
Temporal proximity	D(165)=.327*	D(65)=.349*	D(47)=.278*
Target Selection	D(165)=.250*	D(65)=.179*	D(47)=.153*
Control	D(165)=.125*	D(65)=.122*	D(47)=.273*
Approach	D(165)=.541*	D(65)=.536*	D(47)=.536*
Property	D(165)=.357*	D(65)=.338*	D(47)=.369*
Combined	D(165)=.119*	D(65)=.085*	D(47)=.139*

*p<0.05

Appendix E: Calculating Probabilities

The equation to calculate the probability that a crime pair is linked is as follows:

$$p(linked) = \frac{e^{\alpha + \beta 1X1 + \beta 2X2 + \ldots + \beta nXn}}{1 + e^{\alpha + \beta 1X1 + \beta 2X2 + \ldots + \beta nXn}}$$

This is a complex equation and has been broken down into stages. The process outlined in Bennell and Canter (2002) has been used; the first step of which is to calculate the log odds for each crime pair.

$$\log\left(\frac{p}{1-p}\right) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n$$

where p is the probability of a crime pair being linked, α is the constant for the regression model, and $\beta_1 \ldots \beta_n$ are logit coefficients (labelled B in SPSS output files) which are multiplied with the observed crime pair similarity scores (i.e. the Jaccard's similarity scores), represented as $X_1 \ldots X_n$, to generate the log odds.

The log odds are then converted into the odds of a crime pair being linked. This is a ratio of the probability that a crime pair is linked to the probability that a crime pair is unlinked. The odds are calculated by exponentiating the log odds using the following equation.

$$odds(linked) = e^{\alpha + \beta 1X1 + \beta 2X2 + \ldots + \beta nXn}$$

Exponentiation can be achieved in Microsoft Excel using the =EXP() function. Odds of 1 indicate that a crime pair is just as likely to be linked as unlinked. Odds of less than 1 indicate that the crime pair is more likely to be unlinked, and odds of more than 1 indicate that a crime pair is more likely to be linked.

The final step is to convert these odds into probabilities that can be used in the ROC analysis. This is calculated by dividing the odds by 1 plus the odds (see below).

$$p(linked) = \frac{odds}{1 + odds}$$

The resulting probabilities are measured between 0 and 1 with higher values indicating a greater chance that the two offences in the crime pair are linked. It is expected that linked crime pairs will display higher probabilities than unlinked crime pairs.

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