Thesis submitted for the Degree of Doctor of Philosophy

EXPLAINING TEMPORAL PATTERNS IN STREET ROBBERY

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Declaration

I, Lisa Tompson, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

Signed:

Daupron

Date: 12th November, 2015

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Dedicated to my father 27th April 1952 - 6 January 2013

ABSTRACT

This thesis is concerned with explaining spatio-temporal patterns in street robbery through the lens of environmental criminology. The research question 'what makes a place criminogenic for street robbery at some times and not others?' is used to frame seven hypotheses. These centre on some of the features of the natural and built environment that can be considered criminogenic (i.e. crime producing). Specifically, the hypotheses test the time-varying influence of darkness, weather conditions, and the use of land by different groups of victims.

Through a variety of statistical methods, and data analyses at various micro-units of analysis, it is shown that all of these environmental features are associated with temporal patterns in police recorded street robbery in the Strathclyde area of Scotland. The findings from this research can be summarised as follows:

- Aggregation bias is a threat to research on crime and place when micro-temporal patterns are ignored.
- 2) Seasonal patterns in robbery in the study area are (partly) driven by the condition of darkness.
- Weather features exert their influence on the robbery event differentially over different seasons, days of the week and hours of day.
- 4) Spatio-temporal patterns in street robbery are related to facility types that are *socially relevant* to particular victim occupations.
- 5) Variations in levels of robbery seem to be strongly coupled to time periods where discretionary activities are prevalent.

The micro-level approach taken in this thesis generates nuanced findings that elicit fresh insight into the characteristics of settings where street robbery concentrates. Consequently, this facilitates theorising on the mechanisms underpinning spatio-temporal concentrations in robbery. Crucially, the findings have tangible practical value in informing crime prevention activities that can be used to reduce robbery victimisation.

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Publications

The following publications were produced from the research findings generated in this thesis:

- 1. Tompson, L. and Bowers, K. (2013). A Stab in the Dark? A research note on temporal patterns in robbery. *Journal of Research into Crime and Delinquency*. Vol 50(4), pp. 616-631. [Chapter 4]
- 2. Tompson, L. & Bowers, K. (2015). Testing time-sensitive influences of weather on street robbery. *Crime Science*. 4(8). [Chapter 5]
- 3. Tompson, L. & Bowers, K. (in preparation). Robbery victimisation, routine activities and the built environment. [Chapter 6]
- 4. Coupe, T. & Tompson, L. (in preparation). In: S. D. Johnson & Bruinsma, G. (Eds.) Research example: Time and Opportunity. *Oxford Handbook of Environmental Criminology*. [Chapters 3-6]

Presentations

The following presentations are based on research contained in this thesis:

- 1. Tompson, L. & Bowers, K. (2015). The role of victim routines in explaining robbery patterns in time. Presented at the Stockholm Criminology Symposium. Stockholm, 9th June.
- Tompson, L. and Bowers, K. (2014). Robbery and weather conditions: testing the temporal cone of resolution. Poster presented at the 22nd Environmental Criminology and Crime Analysis conference. Kerkrade, Holland, 18th June.
- 3. Tompson, L. (2011). A stab in the dark? Analysing temporal aspects of street robbery. Presented at the International Crime and Intelligence Analysis Conference. Manchester, 4th November.
- 4. Tompson, L. (2011). Advanced time-series analysis. Presented at the International Crime and Intelligence Analysis Conference. Manchester, 3rd November.
- Tompson. L. (2011). A stab in the dark? Analysing temporal aspects of street robbery. Presented at the 19th Environmental Criminology and Crime Analysis conference. Durban, South Africa, 19th July.
- 6. Tompson, L. (2010). The Circadian Rhythm of Street Robbery. Poster presented at the American Society of Criminology Conference. San Francisco, 22nd November.

1. INTRODUCTION

Crime is a complex, dynamic, and oftentimes fleeting event; its occurrence is found to concentrate across many dimensions (e.g. people, places and products). Whilst considerable scholarly attention has been devoted to defining and explaining spatial patterns of crime, the temporal dimension of criminal behaviour is conspicuously absent from much empirical work (Felson & Poulsen, 2003; Ratcliffe, 2006). The aim of this thesis is to explain spatio-temporal patterns in street robbery through the lens of the routine activity approach (Cohen & Felson, 1979). Adherents to this approach, and the framework of environmental criminology more generally (Brantingham & Brantingham, 1981a), maintain that crime is the product of the convergence of victims and offenders in space-time, in the absence of capable guardians. Spatio-temporal concentrations of robbery, as revealed throughout this thesis, point to periodic convergences of victims and offenders in favourable environmental contexts.

The implicit argument made in this thesis is that to advance knowledge on why crime patterns emerge it is necessary to consider the precise environmental conditions that are present microspatially *and* micro-temporally. This is in acknowledgement of the fact that places where crime events occur are not constantly conducive to crime. Due to variation in environmental conditions, and/or the composition of people using a place, the environmental context of places changes over time. In turn this dynamic context affects whether or not offenders are present and whether they decide to commit crimes.

Numerous factors can influence an offender's behaviour, be they social, biological or situational. Under the perspective of environmental criminology, guardians are believed to have a criminocclusive (i.e. crime inhibiting) influence on offenders (Felson, 1986). Guardians are defined as "someone whose mere presence serves as a gentle reminder that someone is looking" (Felson 1995: 28). The main role of guardians, therefore, is to act as a deterrent through the innocent activity of observing and monitoring their surroundings. Theoretically, I am interested in exploring how social and situational conditions which impede effective guardianship vary over time. Of equal interest are the mechanisms that cause offenders and victims to interact in micro-temporal places. To make this exploration crime specific, as advised by Felson and Clarke (1998), I intend to focus on street robbery. The general research question **'what makes a place criminogenic for street robbery at some times and not others?'** is therefore posed. Eliciting answers to this question speaks to several criminological theories concerned with crime causation. Street robbery is of particular interest because it is highly concentrated in space (Chainey, Tompson, & Uhlig, 2008) and time (Tompson & Townsley, 2010). Since it occurs in public space, on the street, this crime type is especially influenced by conditions pertaining to the natural and built environment. Moreover, it is typically committed over short time-spans, and generally recorded with good temporal precision by the police, which lends itself to spatio-temporal research focused at the micro level (Haberman & Ratcliffe, 2015; Irvin-Erickson, Kennedy, Caplan & Piza, in press).

To answer the research question it is necessary to disaggregate the police-recorded robbery data employed in this thesis into suitable micro-times and micro-places. This is done to avoid masking important variations in robbery levels and the factors that might be driving these. Hence the unit of analysis is of central concern in this thesis and, for each of the empirical Chapters, is designed to be sensitive to rhythms of human routine activities and the environmental conditions postulated as influencing the robbery event. In doing so, the research presented advances the current literature by considering the mechanisms governing the micro-level encounters of victims and offenders (away from inhibitors such as guardianship).

The findings of this study will expand insight into the features of the social and built environment that may be amenable to prediction efforts. Better prediction of crime has important practical implications; it affords the police and crime reduction agencies enhanced awareness of where to direct their finite resources in space and time so that crime occurrence – and hence victimisation - is curtailed. Due to its communicative properties about urban safety, street robbery is fear-evoking for citizens and consequently is an enduring political concern (Smith, 2003). Therefore it is of paramount importance to diminish its occurrence.

Structure of the thesis

To set the theoretical foundation for the thesis, **Chapter 2** begins with an overview of the crime and place literature. This introduces the key theories used to explain the relationship between crime and the environment, which broadly fall into two groups: 1) theories from the social disorganisation tradition which are interested in neighbourhood-level processes on crime and its control and; 2) theories from environmental criminology which are predominantly concerned with how the immediate situational context gives rise to *opportunities* for crimes to occur. Synergies across both theoretical perspectives are elicited with respect to time-varying influences on effective guardianship.

The second section of **Chapter 2** deconstructs the research question into its constituent parts (the unit of analysis, the causal processes at work and the situational influences on the timing of routine

activities) and positions these within a theoretical framework. Informed by this literature review, Chapter 2 concludes by proposing a number of criminogenic features of places that can be reliably measured and poses hypotheses, to be tested in the ensuing empirical Chapters (4 to 6), in relation to these. Each of these empirical chapters contains a bespoke literature review to couch the individual hypotheses (or set of hypotheses) within the context of pertinent literature, and an individual methods section. The thesis was organised in this way to facilitate publishing standalone papers as the research developed; thereby eliciting valuable peer review feedback to refine the work.

As a prelude to the empirical work that follows, **Chapter 3** is devoted to describing the policerecorded street robbery data used in this thesis. The aim of this is to familiarise the reader with the strengths and limitations of these data, the study area, and the underlying spatial and temporal trends. To this end, spatial concentrations of robbery are visualised through a series of maps at progressively smaller spatial resolutions. These confirm the persistent research finding that robbery clusters in urban areas (Flatley, Kershaw, Smith, Chaplin, & Moon 2010). Temporal concentrations of robbery are exposed through descriptive analyses for several temporal dimensions. Consistent with other research, this analysis shows that robbery predominantly occurs in the night-time at weekends (LeBeau & Corcoran, 1990; Cohn & Rotton, 2000; Ceccato, 2005). This suggests that robbery has a tendency to happen in the course of people's discretionary activities, when they are not engaged in formal obligatory activities (LeBeau, 1994).

The focus of **Chapter 4** is explaining seasonal rhythms in the street robbery data. Informed by a literature review on crime seasonality, this argues that darkness can be considered a criminogenic feature of the environmental backcloth (Brantingham & Brantingham, 1993a). This is in contrast to the much-studied variable of temperature which dominates prior research on seasonal patterns of crime. Whilst darkness has been theorised as being relevant to the opportunity structure for commercial robbery (Landau & Fridman, 1993; van Koppen & Jansen, 1999) and residential burglary (Coupe & Blake, 2006), it has not been explicitly tested for street robbery before.

Time series analysis is undertaken in Chapter 4 to explore seasonal variation and underlying trends in the street robbery data. This acts as an important precursor to the testing of the hypotheses, since any trends in the data need to be controlled for in later modelling efforts. Auto-regressive, integrated, moving average (ARIMA) models are therefore produced for monthly and weekly counts of robbery for the ten-year data period, with explanatory variables of darkness and temperature introduced in subsequent models. To anticipate the key findings, seasonal components are found within the time series at both levels of aggregation, but neither of the explanatory variables is found to be associated with robbery counts. It is argued that these crude levels of resolution poorly measure temperature and darkness, since both fluctuate noticeably over the course of a day. This serves to emphasise that the unit of analysis is critical in research on temporal crime patterns and justifies the micro sub-day level temporal focus that characterises this thesis.

Negative binomial regression models comprise the second empirical contribution to Chapter 4. These are performed to test the hypothesis that the trends observed in the time series models can be explained by variation in darkness, when temperature is controlled for. By assigning theoretical importance to the time of day that a robbery occurs, a more direct test of how the key variables change over the course of the day *and* over the seasons is possible. The results show that both darkness and temperature are significantly associated with an increase in robberies, but this relationship is stronger for darkness. For these reasons it is argued that darkness may be a crucial inhibitor of effective guardianship, for it reduces the availability of guardians and impedes their monitoring capabilities.

Chapter 5 extends the analysis in Chapter 4 by incorporating a greater range of weather conditions into the empirical investigation. As human activities are the cornerstone of the routine activities approach it is important to consider the patterning of activities over time, and how they relate to weather conditions. The literature review on weather and crime in Chapter 5 exposes that while the spatial variation of the impact of weather on crime has received scholarly attention (e.g. see Sorg & Taylor, 2011), the temporal influence of weather appears to be neglected. The analyses presented in this Chapter aim to address this gap in the literature.

In this Chapter an argument is advanced that people's subjective interpretation of weather is the mechanism that influences their subsequent outdoor activity, and this in turn influences who is present in a public setting to be an offender, victim or guardian. Using the same temporal intervals as Chapter 4 for the unit of analysis, two sets of complementary analysis are performed to cross-validate the effect of weather across the day: negative binomial regression and seemingly unrelated regression.

The results indicate that when winter weather is favourably unseasonal - specifically higher temperatures with lower wind speeds – increases in robbery are observed. Weather is also found to exert a stronger influence on robbery in time periods that are characterised by discretionary activities. This suggests that weather is more influential over robbery in the periods when people can choose whether they travel and spend time in public places. Importantly, the analyses conducted in Chapter 5 suggest that taking a micro-temporal approach can reveal nuanced

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relationships between weather and robbery, and offers greater explanatory power over these relationships than has been reported in previous studies.

The final empirical contribution presented in **Chapter 6** concerns the relationship between the timing of robbery victimisation and the built environment. Crucially, it is not so much about land use as *use of land over time by different groups*. Informed by the literature on how robbers select their victims, I posit that temporal patterns of victimisation are intimately related to the routine activities of victims and offenders. The analysis examines the timing of victimisation for different occupational sub-groups – specifically workers, non-workers, unemployed, school pupils and university students - in relation to facilities associated with key obligatory or discretionary activities. These comprise pubs and bars; schools; train stations; and universities and further education facilities. Time periods that are *socially relevant* to particular victim sub-groups (in terms of their routine activities) guided the units of analysis: six four-hour intervals across weekdays and weekends (hence twelve in total).

The *criminogenic reach* of each facility type is estimated through location quotients (Brantingham & Brantingham, 1997), generated from street network buffers. These pertain to the "opportunity gradient" (Eck & Weisburd 1995: 10) of crime in micro-space. I call these the *environs* of the facilities. The results from the location quotients are then converted into categorical thresholds (i.e. *inside* or *outside* the threshold) within multinomial logistic regression models – presented at the facility level – to ascertain the *relative* risk of victimisation for different occupational sub-groups. The micro-level findings show that pubs and bars, which have a clear link to recreational activities, affect a broad spectrum of victim groups, particularly at intuitively relevant times such as closing time. In contrast, facilities which are strongly associated with specific occupations, such as school pupils and university students, are found to have distinct time-varying victim profiles. These results align with predictions derived from the routine activity approach.

A short discussion section is presented at the end of each empirical Chapter, but it is **Chapter 7** where conclusions are drawn from synthesis across the three empirical Chapters. The collective meaning of the findings is summarised and interpreted in the context of relevant criminological theory. Special consideration is then given as to how the police and other crime reduction agencies could translate the findings produced in this research into practical crime prevention activities. The Chapter finishes with a discussion of how the findings of the thesis could be advanced by future research.

2. LITERATURE REVIEW & THEORETICAL FRAMEWORK

Chapter overview

The research question at the heart of this thesis – 'what makes a place criminogenic for street robbery at some times and not others' - reflects a fascination with temporal patterns in crime. Whilst the core focus is the timing of crime events, these cannot be isolated from spatial considerations. Therefore scholars interested in explaining temporal patterns are compelled to consider the interaction between space and time as central to the research endeavour.

This Chapter provides the rationale for the thesis. First, the genealogy of ideas on the relationship between crime and the environment is presented. This synthesises the literature on how people interact with their physical and social environments; considers how this influences the decision to commit a crime; and explains how these behaviours are arrayed across space and time. The empirical evidence marshalled presents a persuasive argument for the focus on crime events, rather than criminality.

The second section situates the research question into a theoretical framework. This comprises breaking the question into its constituent parts: the unit of analysis; the causal processes at work; and situational influences on the timings of routine activities. It culminates in proposing a number of criminogenic features of places that can be realistically and reliably measured. The final section is concerned with the hypotheses that feature in subsequent empirical Chapters - that arose from reviewing this (and more topic-specific) literature.

The overall objective of this Chapter is to provide a theoretical context in which this thesis is couched. It should be noted that the literature reviewed here intentionally relates to *all* crime, rather than street robbery in particular. Later Chapters provide a more specific focus on this crime type under study (including the particular environmental settings it occurs within) and theory pertinent to each hypothesis is covered in the individual thematic Chapters.

2.1 The crime-environment nexus

Criminology – as an overarching discipline – has been preoccupied by two ideological approaches to explain the occurrence of crime; individual-level theories and ecologically-oriented theories. This has broadly divided scholarly contributions into those that emphasise individual characteristics in the study of criminality, and those that champion environmental characteristics to explain crime. The former group consider distal macro-social causes, such as social and economic status, to be

important in explaining crime. The latter group favour proximal meso- and micro- factors such as the immediate situational conditions which impact on the offender at a moment in time (Wortley & Mazerolle, 2008).

Theories focussing on individual-level propensity to commit crime have attracted strident opposition for over thirty years for failing to predict with any accuracy who will become serious offenders, and when and what criminal behaviour they will engage in (Bersani, Nieuwbeerta & Laub, 2009; Gottfredson & Gottfredson, 1992; Laub & Sampson, 2003; Sampson & Laub, 2003; 2005; Weisburd & Piquero, 2008). A prominent flaw in the logic of these theories is that they neglect to consider that crime is a behavioural act, and behaviour is shaped by the interplay between genes and the environment. For this reason, it can be argued that propensity theorists are guilty of committing the *fundamental attribution error* (Ross, 1977) - the tendency to overemphasise dispositional traits and underemphasise situational explanations for interpreting the behaviour of others.

Acts of crime are unquestionably a product of the interaction between individuals (with all their characteristics, preferences and life experiences) and the situational context in which they are located. This has largely been ignored by theorists preoccupied with explaining criminality, and for this reason such scholars have been criticised for failing to specify how a predilection to be involved in criminal behaviour actually moves a person to commit a criminal act (Wikström, 2005). Viewed in this way, propensity to commit crime is only one part of the story, and possibly a small one at that. The rest of the story involves the situational mechanisms provided by the social and physical environment which activate or stimulate propensity. It is these immediate environmental conditions which have led scholars to consider how places shape behaviour and, as a consequence, the patterning of crime events.

Two prevailing theoretical approaches are used to explain the relationship between *place* and criminal behaviour; the social disorganisation perspective (Shaw & McKay, 1942; Sampson & Groves, 1989) and the triumvirate of theories comprising environmental criminology (Cohen & Felson, 1979; Cornish & Clarke, 2008; Brantingham & Brantingham, 1981a; Brantingham & Brantingham, 1993a). Both are considered to be ecologically-oriented approaches, but are concerned with different social processes and units of analysis to explain geographical patterns in crime.

Social disorganisation theory

The Chicago School of Sociology are invariably credited with the first systematic focus on the spatial aspect of social life and crime in the mid part of the twentieth century. Marking a radical departure from the genetic and dispositional perspective prior to the time, the Chicago School of scholars were

interested in how human behaviour was determined by social structure and the physical environment. These social structures were typically viewed as a complex web of dynamic processes, likened to components of an ecosystem (Lutters & Ackerman, 1996). The impressive research programme of this epoch (1925 – 1957) spawned a great number of ideas, many of which are ascribed as being the wellspring of modern criminological theory (Finestone, 1976 as cited by Brantingham & Jeffery, 1991).

The bedrock of this branch of urban sociology was human ecology. This was seen by key exponents of the Chicago School, such as Robert E. Park and Ernest W. Burgess, as the study of the spatial and temporal relations of human beings (i.e. bonds), positioned within communities and neighbourhoods. Thus, these scholars were concentrating their attention on socio-demographic variables *within* city areas, rather than larger administrative units.

Burgess (1925) studied the development of demographics across Chicago at a time of rapid urban growth. Based on shared key social characteristics Burgess aggregated neighbourhoods within the city into several zones, subsequently proffering a zonal model of the distribution of land use, crime and other social problems. These zones radiated out from the central business district in a concentric circle configuration. Shaw (1929) then used this model to frame his empirical research on the geographical distribution of crime and criminals.

The Chicago School are perhaps most famed for their development of social disorganisation theory in the mid part of the twentieth century. In essence this is a theoretical approach which focuses on the relationship between neighbourhood structure, social control and criminal behaviour. Central to this is the principle that the place dimension is of critical importance. Places are defined by the neighbourhoods which are present, and neighbourhoods are defined by the configuration of the collection of people living in close proximity to one another. Neighbourhood mechanisms, such as the social ties of the neighbourhood residents and the degree of social control exercised by these residents, are believed to shape whether or not a resident is likely to become involved in criminal activities. Viewed through this lens, the neighbourhood subculture was believed to exert more influence over a person than their individual characteristics (such as age, gender and race). In common with later 'neighbourhood theories' the social disorganisation approach was seen to place greater emphasis on the development of criminal propensity in offenders than on the crime event itself.

The term 'social disorganisation' was first attributed to William Thomas in 1918, but was later advanced and popularised by Shaw and McKay's (1942) seminal work which mapped the residences

of juvenile delinquents. Shaw and McKay espoused that "social disorganisation exists in the first instance when the structure and culture of a community are incapable of implementing and expressing the values of its own residents" (Kornhauser, 1978: 63). The theory was not intended (in its original conception) to be a general theory of all crime, but instead it was invoked to explain variation in street crime at the neighbourhood level.

Theories stemming from the concept of social disorganisation take the position that the natural ability of people to control deviancy in their neighbourhoods is impaired by structural conditions such as residential turnover, ethnic heterogeneity and poverty (Kubrin & Weitzer, 2003). Such exogenous qualities are presumed to inhibit or erode social cohesion (by interfering with the shared norms and values of a community), which subsequently impacts on how competently a neighbourhood can regulate undesirable behaviour through informal social control (Sampson & Groves, 1989).

Social networks are postulated as being responsible for the effectiveness, or otherwise, of informal social control in neighbourhoods. Collective efficacy, commonly regarded as the theoretical successor to social disorganisation theory, has been favoured to explain spatial variation in violence across neighbourhoods (Sampson, Raudenbush & Earls, 1997). The key causal mechanism in collective efficacy is social control enacted under conditions of social trust (Sampson, 2004). Hence, according to this approach, informal social control is differentially 'activated' by neighbourhood conditions such as mutual trust and willingness to intervene for the common good. These theoretical constructs are typically measured through community surveys or large-scale victimisation surveys such as the British Crime Survey (Chaplin, Flatley & Smith, 2011).

The findings emanating from the research programme undertaken by Sampson and colleagues indicate that collective efficacy is a robust predictor of lower rates of neighbourhood violence, when differences in neighbourhood composition, prior violence and other variables which could confound the analysis are controlled for. The key elements affecting the variation of collective efficacy across neighbourhoods were found to be concentrated disadvantage, concentration of immigrants and residential instability (Morenoff, Sampson & Raudenbush, 2001; Sampson & Groves, 1989; Sampson, Morenoff & Earls, 1999; Sampson et al., 1997; Sampson, 2004).

Social disorganisation theory, and its variants, offers a lens through which to view the social arrangement of neighbourhood life as it relates to the regulation of behaviour. Through social constructs it facilitates a consideration of why some neighbourhoods have much more crime than others. As many of the variables believed related to social disorganisation and collective efficacy can

vary (albeit slowly) over time, it is postulated that they may contribute to spatio-temporal patterns of crime that change over longer time frames. For example, areas where social cohesion has fragmented or physical deterioration has happened over time may be related to gradual increases in crime (Wilson & Kelling, 1982; Schuerman & Kobrin, 1986). Assertions of this nature are only recently being expressed and tested for the first time at micro levels of geography (Weisburd, Groff, & Yang, 2012) and may, plausibly, influence the temporal patterning of crime.

Environmental criminology

The other dominant perspective used to interpret the role and influence of the environment on crime is the family of theories that personify *environmental criminology*. These theories are unified by a) their attention to the immediate situational context within which crime events occur, and b) their ardent interest in scholarship informing crime reduction. The central premise of this perspective is that 'opportunities' - that is, the situational components of the context in which crime happens - play a causal role in crime occurrence (Cornish & Clarke, 2008). In what follows I briefly outline the three tributaries of environmental criminology: the routine activity approach, the rational choice perspective and crime pattern theory.

The routine activity approach

The routine activity approach is one of the most influential perspectives of the late twentieth century for explaining crime patterns. This asserts that at the micro-level there are three essential elements of crime: a motivated offender; a suitable target; and the absence of a capable guardian (Cohen & Felson, 1979; Felson, 1987). People's everyday routine activities explain how victims' and offenders' paths intertwine to create a constellation of criminal opportunities. The convergence of these three elements is dependent on how the social life of a society is organised. Thus the routine activity approach is fundamentally a micro-level theory which makes macro-level predictions (Eck, 1995; Groff, 2008).

The apparent simplicity of the routine activity approach belies its explanatory power. The first demonstration of its utility was the elegant explanation of the precipitous rise in crime in the post-war years in the US (and other western countries) against a backdrop of decreasing poverty. Cohen and Felson (1979) posited that changes in temporal patterns of activity in this epoch, in particular activity outside of the home by women who entered the workforce for the first time, increased the availability of vulnerable homes to burgle in the daytime and the likelihood of potential offenders and victims coming into contact with each other elsewhere. Combined with the proliferation of

portable goods, this was hypothesised to manufacture a greater number of opportunities for crime than had previously been available.

The routine activity approach (RAA) has since been adopted by countless scholars who have applied it at various theoretical resolutions – from the macro (wide, societal changes such as women's involvement in the workplace) through to the micro (why specific places and times experience more crime than others). However, and salient to this thesis, Wikström et al. (2010) assert that RAA fails to specify *how* (i.e. through what causal processes) convergences in the triad of actors results in acts of crime. Furthermore Matthews (2014: 77) claims that the propositions from this theoretical approach are so general that they "have limited explanatory power and tend to involve ex post facto rationalisations". Advocates of environmental criminology counterclaim that the manifestation of spatio-temporal patterns in crime are in keeping with the predictions made by RAA (Groff, 2007). Thus RAA fits with what Cornish and Clarke (2008) call 'good enough theory' and has been powerful in influencing practical policies to reduce crime (Felson, 2008).

The routine activity approach has an explicit spatial and temporal dimension – the latter of which is often overlooked and under-researched in comparison to the former (Felson & Poulson, 2003). Fundamentally the routine activity approach clarifies the social chemistry needed to explain why crimes happen at some times and not others, at some places and not others. Although originally conceived as a macro-level theory, explaining large scale change in regional or national crime levels, in recent years the routine activity approach has been more firmly grounded in micro-scale dynamics (Taylor, 1998). Indeed, Eck (1995) stresses that the theory itself cannot be truly tested unless micro-level data (measured in minutes and seconds, and metres) are available.

Theoretical extensions to the routine activity approach abound. The first component to receive theoretical attention was the offender. Originally seen as a given in the crime causation model proposed by the routine activity approach, later conceptualisation sought to integrate Hirschi's (1969) control theory so that the relationship between the offender and informal social control was more explicit (Felson & Gottfredson, 1984; Felson, 1986). People who exerted a positive influence over offenders to minimise their propensity to offend were assigned the name of 'handlers' (Felson, 1995).

Later, when studying illegal drug markets, John Eck theorised that places too were influenced by informal social control. People whom, by virtue of their job, acted to regulate and exert control over behaviour in a particular spatial sphere were termed 'place managers' (Eck, 1994). Eck (2003) later created a graphical form of these components and controls, so that an inner triangle represented

the three components of the original routine activity approach (offenders, targets and places) and an outer triangle represented the controls (handlers, guardians and managers). This became colloquially known as the problem analysis triangle (see Figure 1) and is widely used in contemporary crime analysis.



Figure 1 - The problem analysis triangle

Recent theoretical developments of the routine activity approach have involved extensive examination of the term 'guardian' (Hollis-Peel, Reynald, van Bavel, Elffers, & Welsh, 2011; Reynald, 2009a). Guardianship is often seen as the critical ingredient in understanding why crime concentrates in space and time (Eck & Weisburd, 1995; Felson, 1995). Reynald (2009a) expounds the concept of 'capable guardian' - as originally conceived by Cohen and Felson (1979) - by identifying three vital dimensions of what she terms 'guardianship in action'. Namely, these are that a guardian has to be: 1) available; 2) capable of supervising and; 3) willing to intervene in a situation. This taxonomy is an important development. Crucially, it is not so much the actual level of guardianship available at a place, but the offender's perception of how guardians operate at a particular place at that time (Johnson & Bowers, 2013).

Theoretical overlap between guardianship and informal social control

Despite Felson's (2008) reticence to consider integrating the routine activity approach with social disorganisation theory, other scholars contend that there are good reasons to consider them complementary under certain conditions (Bottoms, 2012; Kennedy & Forde, 1990; Miethe & Meier, 1990; Rice & Smith, 2002; Sampson & Wooldredge, 1987; Smith, Frazee & Davison, 2000; Weisburd, Groff, & Yang, 2012). Yet a critical omission in most theorising to date is that social disorganisation theory assumes that informal social control is exerted by residents in their own neighbourhood. The guardianship construct in the routine activity approach is applicable in non-residential areas and is thus more far-reaching. As LeClerc and Reynald recently emphasise "what makes guardianship

dynamic and distinct from informal social control is that it can function on the individual level, independently of collective, social processes" (2015: 2).

It is possible that the willingness of guardians to intervene in a situation has similarities with the tenets of collective efficacy (Reynald, 2011). In other words, the inclination of people to exert informal social control through guardianship in an area may well be dependent on conditions of social trust, and the qualities of social networks (Gillis & Hagan, 1982). Hence, social cohesion and stability may impact on the levels of active guardianship in an area. Instantiating this point, Skogan (1986: 216) notes that "When residents form local social ties, their capacity for community social control is increased because they are better able to recognize strangers and more apt to engage in guardianship behavior against victimization". Reynald's (2010) decision-making model of guardianship revealed that the sense of responsibility potential guardians feel over their fellow citizens (and their property) impacts on their willingness to both monitor and intervene in a crime event. Thus, settings in neighbourhoods characterised by strong social cohesion and social trust may be better equipped to perform guardianship, purely because they know and like their neighbours. Guardianship becomes personal.

There are other reasons to believe that the willingness for guardians to act might be linked to social conditions. Bystander 'apathy' is a well-documented phenomenon (see, for example, van Bommel et al., 2012), particularly in crowded places where a diffusion of responsibility might occur (Latane & Darley, 1969). Serious violent crime like robbery might be more likely to invoke a response from bystanders in public space than less serious crime types, as found by Hart and Miethe (2008). In their survey of 835 adolescents Gillis and Hagan (1982) report that participants were more likely to say they would intervene in an interpersonal crime than a property crime, and that willingness to intervene increased closer to their home location. Even in residential areas, where territoriality is presumed to be high, only 16 per cent of respondents to Reynald's (2010a) large-scale survey reported that they would intervene if they saw a crime occurring. Thus, willingness to intervene is not a given and is likely socially and situationally influenced.

Recent work by Hollis, Felson and Welsh (2013) has reappraised the concept of guardianship in relation to informal social control. Prominently, they delineate the two by arguing that informal social control implies an intention on the part of the actor, whereas guardianship is not dependent on people trying to inhibit criminal behaviour. Instead, as Felson and Boba (2010: 37) state, guardianship involves "ordinary citizens going about their daily lives but providing by their presence some degree of security". Hence guardians act in a symbolic capacity that reminds others that someone might be watching. This point may be especially important in urban centres which attract

an abundance of strangers. In non-residential places such as these it may be the case that guardianship operates effectively in the absence of strong social ties, but this is largely unexplored in the literature. Whilst no empirical evidence probing such a relationship exists, Leclerc and Reynald's (2015) theoretical script of guardian decision-making in public space omits social ties, which suggests they may not be relevant in non-residential areas.

The insight gained from adopting the routine activity approach to explain crime patterns cannot be understated. For the purposes of this thesis, it provides the theoretical scaffolding upon which many layers of context and detail can be hung. The remainder of this section documents how the routine activity approach has been sharpened with rational choice perspective and crime pattern theory, which were developed around the same time.

Rational choice perspective

While the routine activity approach implies a decisional offender, it did not – in its original form - make the decision process through which offenders worked explicit (Felson, 2008: 73). This is the job of the rational choice perspective - to make sense of the crime event through a series of decisions made by the offender (Cornish & Clarke, 1986). The key premise of this theory is relatively straightforward; similar to other people, criminals are rational actors who employ reasoned thought to make utilitarian decisions. (The exception to this rule is people who are mentally ill). That is, people weigh up the costs and benefits of a given course of action and make their choice according to what they perceive will maximise their personal gain.

Further to this, there are two other principles that emanate from the rational choice perspective: 1) that a crime-specific focus is needed to make sense of the different decisions and choices that offenders make, and 2) that there is a difference between choices that relate to criminal involvement (i.e. motivation to commit crime) and choices that relate to the crime event itself. The rational choice perspective unashamedly emphasises the latter of these two, preferring to leave explanations of motivation and crime involvement to other sociologists (Cornish & Clarke, 2008).

According to the rational choice perspective crime is purposive action which is designed to meet the needs of an offender – whether these relate to (say) money, status, sex, revenge or excitement. Critics argue that the model of human behaviour that is proposed through rational choice theory is more relevant for instrumental crimes than expressive forms of crime (Trasler, 1986; Hayward, 2007). This stance is often taken in response to an objection to the use of the term 'rationality'. For example, when a crime of passion is committed, to the lay observer there seem to be no rational qualities about the behaviour. Cornish and Clarke (2008: 25) counter this by saying "presuming

rationality is not, however, the same as presuming perfect rationality". Moreover, what is rational to an offender may not be deemed as so by the researcher who is studying them.

Originally conceived to support the development of situational crime prevention (which is discussed further in Chapter 7), the rational choice perspective has made innumerable contributions to the field of criminology. Importantly, it has provided an undergirding framework for interpreting empirical patterns seen in data, such as the striking decrease in suicide in the U.K. following the detoxification of natural gas (Clarke & Mayhew, 1988). Indeed, the assumptions made by the theory about human behaviour have furnished plausible explanations for concentrations in terms of the products, places and people targeted in the commission of crime. In recent advancements, rational choice has been applied to guardian decision-making (Leclerc & Reynald, 2015), and it conceivably has relevance for victim decision-making too. However, the rational choice perspective did not, in its earliest incarnation, make explicit predictions based on space and time. Thus far we have seen how the social environment is integrated into the crime event through routine activity approach, and offender's cognitive processes through rational choice. What remains is the built environment, which is the province of crime pattern theory.

Crime pattern theory

Intended as a meta-theory, crime pattern theory (CPT) aims to explain the spatial-temporal patterning of crime (Brantingham & Brantingham, 1993a). It draws from and extends previous opportunity theories in describing the interaction between crime and the urban landscape. It takes the key ingredients for a crime opportunity from the routine activity approach (an offender, a victim, and the lack of a guardian) and integrates these with geometric principles to postulate how and why the components might come together. Underpinning the tenets of CPT is the assumption of rationality. It is hence seen as the unifying theoretical approach for environmental criminology.

Explaining spatial-temporal patterns of crime necessitates a consideration of the spatial-temporal patterns of behaviour in general, whether these are examined at an individual or aggregate level. Thus, at its heart, CPT focuses on how offenders and victims move around in space and time, and how these mobility patterns give rise to crime opportunities. It draws on the assertion that routine activities dictate where people regularly spend time. It is argued that through their dominant activities people become familiar with the physical and social environment they pass through, thus building up personal *activity spaces* which represent their most frequent travel patterns. The visual extent of the activity space is known as their *awareness space*, which can be thought of as a collection of locations familiar to an individual (Brantingham & Brantingham, 1993a). The

fundamental premise of pattern theory is that offenders identify opportunities for crime in their awareness spaces through the course of their daily activities. Crime *generators* and *attractors* are key concepts of pattern theory (Brantingham & Brantingham, 1995) that are discussed later in this Chapter.

In their earlier geometric theory of crime, Brantingham and Brantingham (1981b) proposed four elements of the built environment that shape people's awareness spaces. The first are *nodes*, which are locations of high activity. Nodes are places where people spend a large amount of time and, in a purist form, represent anchor points around which routine activities are performed. Hence nodes can be used to describe people's residences, their places of work or school, or other places in which obligatory activities are undertaken, and to a lesser degree areas where people shop, visit friends and family, and engage in recreational activities. As people spend a lot of time in and around their nodes, they can be expected to have a high degree of familiarity with these areas. Over the life-course nodes are supplanted and renewed, and therefore are not static (Bernasco & Kooistra, 2010).

Some nodes, like residences, are highly individual, whereas others such as shopping or entertainment nodes are common to many. Different types of crime are postulated to happen at these different nodes; disputes between people who are acquainted are believed most likely to occur at residential nodes, whereas violent altercations between strangers are most likely at nodes where people go to drink alcohol. Nodes exhibiting high crime are likely to be part of many people's awareness spaces (Brantingham & Brantingham, 1993a).

The routes that people pass through to get from one node to another are known as *paths* (the second geometric element [Brantingham & Brantingham 1993b]). Based on the street network, and available transportation options, paths shape people's travel patterns and, when considered at an aggregate level, the concentration and flow of people through the built environment. Within an awareness space, people may be familiar with multiple routes between nodes.

Districts and *edges* are the final elements from the geometric theory of crime. Districts can be thought of as defined areas or regions with commonalities. Edges are the boundaries that delineate one type of district from another. In residential areas these districts may take the form of neighbourhoods with different socio-demographic characteristics. In non-residential areas these edges may represent the boundaries of different types of land use. At times such edges will be obvious and part of the built environment (for instance, roads or walls). Contrarily edges can also be socially constructed by people's perceptions - e.g. the 'bad' part of town. Edges are thought to be

particularly important in the urban milieu as they are posited to contain a mix of people from different social backgrounds, with different purposes for being in that location at that time (Brantingham & Brantingham, 1993b).

Pattern theory, as a general theory that seeks to explain the enormous complexity of crime, is necessarily complex in itself. For this reason, a test of the theory in its fullest incarnation has yet to be completed – for the data required are simply not available. While CPT has not been tested as rigorously as other theoretical models (Bottoms, 2012), extant evidence tends to lend credence to its theoretical plausibility (Bernasco & Kooistra, 2010; Davies & Johnson, 2015; Haberman & Ratcliffe, 2015). Importantly, CPT provides a means of considering the complex person-situation interaction as it pertains to the spatial patterning of crime events.

A brief summary

The preceding theories expand understanding of why crime exhibits geographical patterns. Both crime pattern theory and the routine activity approach are salient to the research in this thesis and are used to guide the empirical analysis. Pattern theory integrates ideas about offender's movements with the spatial distribution of potential crime targets (Eck & Weisburd, 1995). Routine activities are a powerful means of considering the temporal rhythms which govern such movements and the places of the urban landscape which are frequented at particular times of the year, week and day.

The theories that comprise environmental criminology are kindred in the fact that they focus on the situational context of crime events. In doing so, they de-emphasise potential social processes that underpin the social context at places. In this thesis I am interested in integrating explanations of the social context into discussions on the environmental backcloth. I therefore return to the concepts of social disorganisation and collective efficacy in Chapter 7, where the theoretical implications of the findings of this thesis are expounded.

2.2 Deconstructing the research question

This section provides the theoretical justification for the research question 'what makes a place criminogenic for street robbery at some times and not others'. It outlines key literature which set the foundations for the thesis and identifies new directions in which to expand knowledge. The first part starts to unpack the research question; focussing on the historical development of geographical studies of crime and their corresponding units of analysis. The second part discusses criminogeneity – that is, conditions which promote crime, and why this is important. The final section builds the

case for time-sensitive places, recognising that criminogeneity is in constant flux. It considers three dimensions of the environment - the natural, physical and social – and how these influence the timing of routine activities and the convergence of the elements necessary for a crime event at particular places.

Places as micro-spatial units of analysis

The connection between geography and crime has roused academic curiosity for nearly two centuries. The origins of a spatial focus on crime can be traced to a handful of key European scholars in the nineteenth century, such as Guerry, Balbi and Quetelet (Andresen, Brantingham & Kinney, 2010). This founding generation of spatial criminologists used the official data of their time; large geographical units such as countries, regions and provinces. These provided the means to systematically compare crime figures against socio-demographic (and other) data collected by the government. Visually, these scholars popularised thematic mapping of areal units (see Chapter 3), however the units of analysis they employed do not appear to have been chosen with geographical sensitivity. This did not go wholly unnoticed. Using much smaller geographical areas John Glyde (1856) showed that there was significant variation across the county of Suffolk, which called into question the reliability of previous work. Moreover Henry Mayhew (1861-1862) undertook a journalistic study of the poor in Victorian London at extremely small units of geography (streets, squares and buildings). Collectively, these nascent nineteenth century studies spurred the recognition that there was considerable value in examining the relationship between place and crime at different scales.

This tradition continued throughout the twentieth century; prompting an increasing trend for scholars to use smaller, more precise units of geography than ever before (Braga, Hureau & Papachristos, 2010). Consequently, the definition of a 'place' has progressively moved down the geographic *cone of resolution* (Brantingham & Brantingham, 1981a) as both theory and data have developed in tandem to support a more precise focus on micro-places (Taylor, 1998). Presently a place is considered to be a very small geographical area, "usually a street corner, address, building or street segment" (Eck & Weisburd, 1995: 1).

An impressive range of language is used to describe a 'place' in the criminological lexicon, which hampers consistency across studies. Although all take the position that a place is a *micro* unit of geography, nested within a larger social environment (such as a community or neighbourhood), the unit of analysis used in research has ranged from US census blocks (Bernasco & Block, 2010; Roncek & Faggiani, 1985); clusters of a hundred addresses on a street (Groff et al. 2009; Weisburd et al.

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2004), street segments, also known as block faces (Groff, Weisburd & Yang, 2010; Rice & Smith, 2002; Smith et al., 2000); and buildings and addresses (Sherman, Gartin & Buerger, 1989).

There is no definitive level of geography to study the relationship between place and crime; the unit of analysis is, or at least ought to be, dependent on the theory being tested (Bernasco, 2010). That said, consensus seems to be growing amongst scholars who study the opportunity structure of crime that those units should as small as practicably possible (Oberwittler & Wikström, 2009; Rengert & Lockwood, 2009; van Wilsem, 2009; Weisburd et al., 2012). It generally holds that the smaller these initial units of analysis are, the greater the prospects for testing theory at different scales; for once data are collected at small units it is easy to aggregate them up to larger geographical units.

As the literature above attests, micro-place studies are becoming increasingly common in criminological research, yet micro-spatio-temporal units of analysis are only just beginning to receive theoretical and empirical attention (Haberman & Ratcliffe, 2015; Irvin-Erickson et al., in press). This is important, for places where crime happens are not constantly conducive to crime. Instead, certain temporal windows exist where criminogenic features interact with motivated offenders to produce favourable conditions for crime. These temporal windows might in some cases be narrow, in minutes or perhaps seconds. Alternatively they might span much longer periods. To illustrate, consider crime which occurs within the central business district of a city. Here it is apparent that different populations use the space in different ways at different times. To understand different crime problems in this area one needs to consider micro-spatio-temporal units of analysis to avoid masking important variations in crime levels and the factors that might be driving these.

That people use space differently at different times of the day, week and year dovetails with Sherman, Gartin and Buerger's (1989) proposition that places can have routine activities too. They, and successive scholars, recognised that the routine activities of a place can be viewed as "...the social organization of behaviour at a particular place" (Reynald & Elffers, 2009: 39). This has parallels with the approach taken by ecological psychologists who view *behaviour settings* as places where standing patterns of behaviour are observed within a physical milieu (Barker, 1968; Moss, 1976). Recurrent behaviour and events stemming from this behaviour are what define a behaviour setting. The definition offered by Reynald and Elffers above resonates with this view. Hence behaviour settings, or micro-temporal places, are created by the manifestation of aggregate routine activity patterns (Wikström & Sampson, 2003) and are dynamic.

The criminogeneity of places

Crime is known to concentrate in some places and not others. Considerable scholarly effort has been devoted over the past few decades to determining what characteristics of places are associated with high volume crime settings (Bernasco & Block, 2009; Block & Block, 2000; Brantingham & Brantingham, 1981; Brantingham & Brantingham, 1993a; Clarke, Belanger & Eastman, 1996; Eck, Clarke & Guerette, 2007; Groff & McCord, 2011; Johnson & Bowers, 2009; Johnson et al., 2009; Kinney et al., 2008; McCord & Ratcliffe, 2007; 2009; Roncek & Faggiani, 1985; Stucky & Ottensmann, 2009; Weisburd et al., 2012). Collectively, the findings have revealed a variety of physical and social features of places that enhance their attractiveness to offenders, but often such studies fail to explicitly state how these contribute to the places being criminogenic (i.e. crime producing) and how that subsequently translates to crime occurrence (Eck & Weisburd, 1995).

In this thesis I adopt the view that crime is an event process; it is the outcome of a sequence of decisions by the offender and, to a lesser degree, the decisions of victims and potential guardians. Crime causation is as much dependent on *who* people are (with their personal characteristics and life experiences) as *where* and *when* they are (the characteristics of the environments they are exposed to). Echoing contemporary criminological theory (Brantingham & Brantingham, 2008; Cornish & Clarke, 2008; Wikström, 2009) I take the position that an individual's crime propensity interacts with criminogenic features of places to produce crime events. Thus, on encountering environmental inducements in a setting, an individual who is (at least somewhat) motivated to commit crime will, plausibly, exploit such opportunities. Motivation is thus a contributory factor to the crime event, but needs to be *activated* by the environment (Brantingham & Brantingham, 1981a; Wikström & Trieber, 2009).

From an environmental criminology standpoint, opportunities are believed to be a key influence in criminal motivation. Readiness is activated – or triggered - by a combination of the environmental backcloth and a suitable target (Brantingham & Brantingham, 1993a). Simply put, the environmental backcloth refers to the context at a particular setting which influences the chance of a crime occurring. Brantingham and Brantingham purposely use the term to "...attach a label to the uncountable elements that surround and are part of an individual and that may be influenced by or influence his or her criminal behaviour" (2010: 280). The backcloth contains many dimensions: social, cultural, legal, spatial and temporal, and is dynamic. In many respects it is the ambiance of a place; perceptible but often tacitly acknowledged.

Brantingham and Brantingham (1993b) propose that the backcloth emits environmental *cues* and *sequences of cues* which people process and use to generate a cognitive image of their surroundings. That is, at a given point in time, people will perceptually evaluate the environment they find themselves in and use this assessment to choose whether to engage in criminal, or non-criminal, activities. Over time, offenders with existing readiness learn which cues, clusters of cues and sequences of cues are associated with suitable targets.

Spatio-temporal concentrations of crime can point to the fact that there are time-sensitive environmental cues in a place which attract many offenders, or are so compelling for one offender that they invite repeated offending behaviour. Such cues might be an obvious lack of guardianship, easy access to the site, or the presence of readily attainable valuables (Eck & Weisburd, 1995). For interpersonal crime it will depend on *who* is (and to a certain extent who is not) present in a place at a given time. For property crime such as burglary, spatio-temporal patterns may be tied to an offender's willingness to travel to search for suitable targets, which plausibly varies by time of the day (Bowers & Johnson, 2015). There might also be social or moral contexts which increase the likelihood of crime at particular micro-temporal places (Wikström, 2006).

Time signatures in areas of crime concentration can display evidence of temporal regularity or instability (Johnson, Lab & Bowers, 2008; Kurland, Johnson & Tilley, 2014). Ratcliffe's (2004) *hotspot matrix* categorises temporal concentrations of crime by time of the day, and juxtaposes these against spatial concentrations of crime within hotspot areas. In this, he proposes three classifications of time signatures: 1) diffused, whereby there are no discernible peaks or troughs in the hourly distribution of crime; 2) focused, which implies that there is a temporal interval (or intervals) in the day in which crime concentrates; and 3) acute, which refers to a distinct concentration of crime into a (perhaps narrow) time interval. Since Felson and Poulsen (2003: 595) claim that "crime varies more by time of day than by any other predictor we know", understanding diurnal patterns in crime is crucial for devising effective prevention activities.

One potent manifestation of spatio-temporal crime concentration is found in the phenomena of *repeat victimisation* (Farrell, 2015). This can be conceived as the multiple criminal victimisations of a person, target, place or product, and is a pervasive empirical finding within environmental criminology. Indeed, a substantial body of research has confirmed that the risk of victimisation is infectious, in both space and time (Pease, 1998; Ratcliffe & McCullagh, 1999; Morgan, 2000; Bowers & Johnson, 2005; Townsley, Homel & Chaseling, 2003; Johnson et al., 2007). In this tradition, scholars have generated cogent evidence that the time course of re-victimisation exhibits distinct patterns and has a short half-life (Polvi et al., 1991; Johnson et al., 2009).

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Two mechanisms have been proffered to explain these patterns in space and time; the 'flag' account relates to some enduring characteristics about a place (or target) which indicates its suitability as a victim (Sparks, 1981; Johnson, 2008). The 'boost' account refers to the activity of the same offender optimally foraging for targets (Pease, 1998). Under these conditions the risk of future victimisation is boosted by an initial crime event, with the level of risk decaying over space and time. Empirical and computer simulation findings to date have suggested that both mechanisms are required to adequately explain temporal patterns of victimisation (Johnson, 2008; Tseloni & Pease, 2003).

Repeat victimisation has been conceptually augmented to include both *virtual* and *near* repeat victims (Pease, 1998; Morgan, 2000). Both of these variants speak to how offenders estimate target suitability. *Virtual repeats* refer to targets having similar characteristics, such as a specific victim population or the same make and model of a vehicle, so that they fit a preferred profile. These need not be related in space or time. *Near repeats* on the other hand are defined as targets that are both virtually the same and spatio-temporally proximal as an antecedent crime event. These concepts have generated substantive insight into the spatio-temporal patterns seen in a variety of crime types such as burglary (Townsley, Homel & Chaseling, 2003; Johnson et al., 2007), vehicle crime (Johnson, Summers & Pease 2008) and shootings (Ratcliffe & Rengert, 2008).

In actual fact, as Summers (2010) points out, even a repeat victimisation is a near repeat, insofar that it occurs to the same person, product or place, but is *near in time*. This notion of *nearness* is the bedrock to Farrell's (2015) recently proposed crime concentration theory. In this he posits that all patterns of crime concentration can be explained by nearness (otherwise thought of as similarity) along at least one dimension – whether that is space, time, offender, product or a range of other factors. Moreover, Farrell (2015) stresses that it is likely that nearness occurs along multiple dimensions, albeit some are stronger than others. Employing this logic, temporal patterns in crime are not solely influenced by space, but by coincident offenders, victims, products and/or guardians, all of which in certain configurations produce the opportunity structure for crime.

Situational influences on the routine activities of places

As mentioned previously, the stability - or indeed instability - of the opportunity structure for crime may be causally related to the routine activities of *places*. These can be thought of as rhythms of human activity in micro-spaces and are analogous to the concept of behaviour settings in ecological psychology. Behaviour settings represent the agglomeration of many individual's routine activities. Put differently, the standing patterns of behaviour that are observed in micro-space are attributable to the collection of people using the space at a given moment and, by logical extension, the activities they are undertaking. For instance the behaviour setting of a church on Sunday mornings will contain church goers who are meeting for worship and socialisation activities. The same place on a Tuesday morning may comprise a different set of people: a children's play group or a couple of church or grounds workers. The ambience at each time frame will be self-evidently different with respect to, say, noise levels. Hence, the summative effect of individuals' routine activities dictates the behavioural norms and social rules of a setting. The people using space at a moment in time are, therefore, an important facet of the environmental backcloth since they can influence whether a crime occurs (or not). Hence the backcloth is theoretically multi-layered, with the human and non-human elements melding to create the environment.

A core assumption made throughout this thesis is that it is the cumulative effect of people's presence in a micro-temporal place that initiates opportunities for interpersonal crime. Of equal importance is the nature of the activities that people are engaged in. Clearly, a church-goer has different intentions than a commuter or a hedonistic party-seeker. The specific type of activity that brings people together in one place at a moment in time is believed to set the social climate; a point I return to later in the Chapter.

Routine activities can be affected by physical attributes such as the presence or accessibility of a high activity location; natural forces such as weather; or by social conditions (i.e. lifestyles and shared community norms). Clearly, these conditions impact on human mobility patterns, and thus determine the frequency and timing of the confluence of victims and offenders in micro-space. Moreover, these situational features may influence the efficacy of the guardianship possible at the place at certain times. To elaborate, guardians are believed to have a criminocclusive influence on offenders (Brantingham & Brantingham, 1995) and therefore are seen as the critical ingredient in the 'crime chemistry' (Felson, 2002).

Recall that Reynald (2009b) proposed that the first stage of effective guardianship was the availability of guardians. This is highly influenced by the tempo of people's routine activities. For example, different areas will have unoccupied spaces at different times of the day - residential areas might be unprotected during the day because residents are out at work; whereas urban centres might be vacant in the early hours of the morning when people are at home asleep. The intensity of the use of a place varies by time of day, day of week and time of year. At a late hour few pedestrians are on the street and guardianship might be low for street crime (but see Angel, 1968). At a different hour of the day there will be plenty of guardians present. Bus stops and train stations are a good example of how this guardianship can change rapidly during the course of a day (Newton, 2014).

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The natural environment

Taking each of these dimensions of the environment in turn (natural, built and social), the natural environment is taken to mean the atmospheric conditions at a micro-temporal place. The timing of routine activities can be influenced by forces in nature; the most obvious one being weather. Weather conditions shape the types of activities, obligatory and discretionary, that people tend to take part in (LeBeau & Corcoran, 1990; LeBeau & Langworthy, 1986). People are more likely to stay indoors in inclement weather and be outdoors when weather is pleasant. Outdoor activities usually peak in the summer months in temperate climates, whereas regions with harsh weather conditions in winter have a population used to staying at home a great deal of the time. Such seasonal influences inevitably affect the availability of guardians present in a particular setting, as well as the convergence of victims and offenders.

The other environmental condition governed by nature is the presence of sunlight (and moonlight). Lighting conditions have an obvious bearing on observation activities. Poor lighting conditions, whether they are so because of weather variables (e.g. poor visibility or heavy rain) or the absence of sunlight, could be a significant obstacle to surveillance and thus have an effect on guardianship and, consequently, crime. Further to this, Rotton and Kelly stress that darkness affords offenders the advantageous conditions of anonymity; darkness is "deindividuating" (1985: 288). Considered in this way darkness weakens guardians' ability to identify potential offenders, for they cannot distinguish them from other community members in the dark. Relatedly, darkness can afford criminals the camouflage needed to evade notice from others (Felson, 2002). Hence darkness can be thought of as a key inhibitor to capable guardianship.

The built environment

Turning now to the built environment, which is defined as the configuration of man-made structures (such as buildings and roads), the impact of the design of the built environment on crime has been an enduring topic of theorising for several decades. In her eminent book, Jacobs (1961) drew attention to the central role of the ambient population to facilitate opportunities for surveillance. She proposed a model of 'natural policing' whereby increased pedestrian traffic, produced by mixed-use neighbourhoods, encouraged 'eyes on the street' that served as a deterrence mechanism to reduce criminal behaviour. In essence Jacobs believed that the constant flow of people – many of whom would be strangers to one another – provided constant surveillance of streets.

Oscar Newman (1972), another protagonist of the crime and design movement, furthered Jacob's ideas in his book on defensible space a decade later. His thesis posited that defensible spaces are

maintained through three components, namely territoriality, natural surveillance and milieu. All three of these critical components depend upon the design of the built environment to facilitate informal social control. In contrast to Jacobs, Newman maintained that strangers were a threat to safety rather than a protective factor, and the design principles he espoused centred on limiting access to places to residents whom possessed instincts of territoriality.

Empirical studies have sought to test these theoretical propositions. The permeability of the street network in particular has been associated with a higher risk of victimisation of burglary (Davies & Johnson, 2015; Johnson & Bowers, 2009). Because of their position in the street network, accessible places will be part of many people's awareness space as they serve a higher pedestrian population. Moreover it is credible that well-connected roads will be used by residents and non-residents, whereas isolated roads (such as cul-de-sacs) will be limited to those who live on them and their visitors. From an offender's point of view places with an easy escape route, facilitated by the built environment, are preferable for opportunistic criminal offending (Monk, Heinonen & Eck, 2010).

High activity nodes influence the spatio-temporal flow of people. Some nodes in particular have a strong time signature: for example schools attract children in the daytime; entertainment facilities attract people in the evenings and weekends; and retail premises have a greater footfall at weekends and during holidays. When those nodes are associated with a higher than normal crime occurrence they are referred to as *crime generators* and *attractors*.

Crime generators are defined by Brantingham and Brantingham (1995) as places with predominantly non-criminal routine activities, but which draw large numbers of people because of the land use (e.g. retail complexes, large sporting events, music concerts). As an artefact of this high volume of human activity, some opportunities for crime will be available which those who are criminally inclined can exploit. In contrast, crime attractors are said to be places that attract offenders who are seeking out a specific crime opportunity. Often this is linked to an illicit market, but may also relate to a targetrich setting where measures of social control are absent. Bowers (2014) suggests that property crime may have a stronger affinity with areas considered to be generators while violent types of crime may be more common in attractor areas. Both of these concepts help us to interpret what features of the built environment might be driving crime patterns.

To date, a consistent understanding of what spatial scale crime generators and crime attractors operate at has not been achieved. Crime generators are often taken to be locations with a specific function, for example schools (Roncek & Faggiani, 1985), public transportation nodes (Block & Block, 2000; McCord & Ratcliffe, 2009) and other specific types of land use (Kinney et al., 2008). In

comparison, crime attractors are more loosely defined in space, primarily because they are more likely to encompass public space such as parks, or collections of streets where illicit markets are located. In sum, crime generators and attractors are powerful concepts for helping us to understand what brings victims and offenders into contact with each other, but fall short of fully exploring the impact these places have on the temporal flow of capable guardians. Each setting may very well have different types of people who act as guardians at different times.

The capability of guardians to monitor their surroundings, regardless of whether this is intentionally performed, is intrinsically linked to their surroundings being observable. The opportunities for observation are somewhat dependent on the built environment. Certain situational conditions facilitate the observation of people and places, others inhibit. For example, linear streets offer good sight lines, which is important for visibility. The defensive space literature is replete with examples of the built environment that have been found to assist or hinder natural surveillance (Newman, 1972; Perkins, Meeks & Taylor, 1992). This is an important point, as Brantingham and Brantingham (1995) note that many researchers have found that surveillability – that is, the possibility of being watched by someone who might intervene – is a more important consideration to offenders than territorial markers.

The social environment

The last dimension that conceivably influences routine activities at places is the social environment. A behaviour setting will be nested, temporally, within a place. A place in turn will be bounded by a wider neighbourhood, and that neighbourhood will have a distinct social character to it (as espoused by scholars from the Chicago School). Thinking back to the behaviour settings used by the ecological psychologists, these are purported to have "...surrounding and supporting physical milieu" (Taylor, 1998: 10). This *milieu* is defined by the personality of the neighbourhood, which is made up of the lifestyles of the people both living and passing through the area, as well as the configuration of major nodes of activity. This links back to the community-level tenets of social disorganisation theory.

The lifestyle patterns of a community are inherently rhythmic. A neighbourhood with a high proportion of elderly people is unlikely to be a thriving night-spot. A neighbourhood with a large proportion of school-age children is going to have predictable weekday cadences during term-time. Public space is shared by many different communities, each with their own lifestyle patterns, whereas as a rule residential neighbourhoods are less heterogeneous. The lifestyle patterns of a community can thus contribute to what Newman (1972) referred to in his defensible space work as

the *image* of a place. This image communicates to people through the environmental cues that exist in a setting (Brantingham & Brantingham, 1993a).

Territoriality, discussed extensively by Newman (1972), and later by scholars such as Taylor (1998) is an important component of the social environment. How people manage the locations they own or use is central to the notion of guardianship. Territoriality has long been associated with social ties and social networks (Taylor, Gottfredson & Brower, 1984). Taking a simplistic example, if a neighbourhood has a low residential population but a high transient population (i.e. people coming to the area for work or recreation) then the social ties between the population are likely to be weak. Few people on the street know each other and the space is 'owned' by no one. Under these conditions informal social control and, as a natural extension guardianship, is more challenging to uphold than in an area where long-term residents all know each other and take ownership over what happens in their neighbourhood.

The social environment of a setting is thus strongly influenced by who uses that space at a given time. The level of informal social control that a community wields over its residents - i.e. as handlers, guardians and place managers - can be seen as setting the *social climate*. For example, if a neighbourhood regularly allows unregulated behaviour on the streets (in the form of teenagers or public drinking to name two examples) then disorderly behaviour is likely to proliferate. If antisocial behaviour and criminality go unchallenged, these forms of behaviour become perceived as permissible by the offenders, and members of the community remain passive to its occurrence. Hence, inaction on the part of residents can set the tone of what behaviour is socially acceptable or, at the very least, not successfully managed by the members of a community.

This chimes with the central premise of the broken windows hypothesis (Wilson & Kelling, 1982) and the signal crime perspective (Innes, 2004), which presume that social and physical disorder act as symbolic signs to residents that the place is unsafe. This in turn leads to people avoiding such places, which reduces the capacity for informal social control. Crime is assumed to flourish under these self-perpetuating circumstances. To date, these theories have largely confined their explanations of crime to residential areas; however it is not unreasonable to suppose that they might be appropriate for explaining the decline of urban centre spaces too.

How people perceive the environments they pass through and their subsequent behaviour (such as exhibiting territoriality) is, intuitively, time-sensitive. For instance, due to the rhythms of routine activities the social climate changes perceptibly over the day, and is likely different in the evenings compared to daytime hours. Certain people may feel fearful of crime in hours of darkness and

refrain from spending time in public space (Hough, 1995). Solymosi et al. (2015) have begun to test the dynamics of fear of crime and found that perceptions of safety change according to not only personal dispositions but the (micro) places people are in at a particular moment in time. Hence the social environment is perceptively different across spatial and temporal dimensions.

Certain types of people using places may result in predictable social disorder outcomes. For instance, Wikström and Sampson (2003) assert that places where unsupervised young people are dictating the rules are more likely to have permissive moral contexts, which result in conventional rule violations. The type of young people (and their propensity to crime) present in a place may further contribute to the likelihood of rule breaking, especially when behaviour is unconstrained by informal social control. Places where there is a critical mass of young people operating in these circumstances are hypothesised to produce a greater concentration of co-offending than is typified elsewhere (Felson, 2003).

Temporal variation of the social climate is tangible in places that serve multiple functions to human mobility patterns. Some urban centres change from well-managed places in the daytime to unruly environments on evenings when the night-time economy is in full swing. Places without obvious place managers (Eck, 1994) may emit environmental cues, or an image, that social rules are absent or unenforced. Relatedly, social rules may be flagrantly ignored when the users of a place are incapable of registering the place managers; for example, because they are inebriated. The time-sensitive capacity of place managers to exert social control over the places they are in charge of, is therefore believed to have an important influence on the occurrence of crime (Felson, 1995).

Summary

The aim of this section was to set out the theoretical backdrop for the research question being addressed in this thesis. As the preceding narrative illustrates, much has been theorised about why crime clusters in time and space, but the empirical focus has - until now - been firmly rooted in the geographical dimension. This is despite the recognition that the opportunity structure for many types of crime has been found to be time-specific (Rossmo, 1995; Ratcliffe, 2001).

Examining spatial or temporal patterns in isolation only provides one dimension of crime concentration. Thus, it is necessary to define smaller, more precise, units of analysis that speak to a micro-spatio-temporal focus. In doing so in this thesis, it is hoped that the rhythms of human activity that are associated with crime occurrence will be more readily identified. Deconstructing time into periods that are meaningful to human activities permits an empirical examination of the

drivers behind those activities; in particular, those that stem from the natural, built and social environments.

2.3 The present study

Even though substantial research evidence has emerged that crime is patterned in predictable ways according to geographical and social features (see Bernasco & Block, 2009 for an overview), we are only in the beginning stages of being able to understand why this is so. Taking a crime science stance on this topic necessitates that we ask *why* some (space-time specific) places experience lots of crime, whereas others do not. Hence, the theoretic and empirical focus needs to be driven towards understanding the underlying causal processes between place and crime. This thesis aims to expand knowledge as to why crime clusters contemporaneously in space and time and, as a corollary, elicit insight into the characteristics of settings where crime concentrates. In turn, this assists theorising about the mechanisms driving crime causation at precise micro-temporal places.

A core assumption made throughout this thesis is that it is the type of people present in a place at a specific time, and the nature of the activities they are engaged in, that give rise to opportunities for street robbery. As such, I focus on integrating social and environmental explanations for why crime clusters in certain locations and hence join a contemporary criminological shift towards seeing the environment as a medley of who and what is present at a given moment (Weisburd et al., 2012).

I am primarily concerned with the flag account of risk heterogeneity in this research; those characteristics of a setting that signal to motivated offenders that the likelihood of committing a successful offence is high. This may be due to target attractiveness or vulnerability. Theorising to date has largely assumed that these characteristics are time-stable (Sparks, 1981; Tseloni & Pease, 2003; Wittebrood & Nieuwbeerta, 2000), or have offered little in the way of imagining how they might vary over time. It seems appreciable that the opportunity structure for many crime types is non-static over time; burglars are often (but not always) deterred by occupied houses (see Coupe & Blake, 2006), robbers may not be able to pinpoint a suitable target in the morning rush hour. If this is so then there are, plausibly, features of the natural, built and social environment that can provide extra explanatory weight to why crime concentrates in space and time in the way observed.

According to the routine activity approach, a special aspect of target vulnerability is the presence and efficacy of guardianship at certain times. It is possible that guardianship may be stronger in some places and times than others. In this thesis it is asserted that the situational conditions which foster effective guardianship are both environmental and social in nature. For this reason, in the course of this research I aim to unpack and explore the influence of some of the features which can be considered to be integral to a criminogenic environmental backcloth. These features are elucidated in the next section which describes the research question and hypotheses.

Street robbery is the specific crime type under study in this thesis. In contrast to other property crimes, this can be considered a predatory crime type that often occurs between strangers – thus aligned to the original formulation of the routine activities approach (Cohen & Felson, 1979). Robbery occurs in a variety of outdoor ecological settings and, since robbers prefer stealing items of value, is not constrained to economically disadvantaged neighbourhoods. Since the focus here is on *street* robbery, the natural and built environments are particularly important in the criminogenic backcloth, thus making this a natural fit with the aims of this study.

Research question and hypotheses

The foregoing provides the conceptual backdrop in which my research question – 'what makes a place criminogenic for street robbery at some times and not others?' – is couched. This section briefly focuses on breaking this overarching question down into two thematic strands, the natural and built environments, and derives specific hypotheses that can be tested through empirical enquiry. These arose through examination of literature specifically relating to each strand (see Chapters 4, 5 and 6). The thought that guided the formation of these hypotheses is: *what features of the environment can explain spatio-temporal variations in street robbery*?

Taking each in turn, the first dimension that plausibly affects the temporal patterning of robbery at places is the natural environment. In the first instance, it is conjectured that the absence of natural light from a setting (i.e. when the sun has set) will inhibit the ability of guardians to monitor their surroundings, and result in an increased likelihood of street robbery events. Hours of darkness are also associated with the routine activity patterns of certain sub-groups of the population (e.g. young people), who are known to be overrepresented in both victim and offender populations for this crime type (Smith, 2003; Tilley et al., 2004). Yet, it is also important to disentangle the influence of darkness from that of temperature, since the two variables are hypothesised to covary (see Chapter 4 and Michael & Zumpe, 1983). This has been formalised as:

H1: The presence of darkness will increase the likelihood of street robbery occurring when seasonal variations in temperature are accounted for.

The relationship between weather conditions and street robbery occurrence is less clear from prior research. On the one hand, pleasant – i.e. warm and dry - weather encourages people to spend time in outdoor settings, increasing the likelihood of offenders and victims converging, and hence

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increasing opportunities for robbery. On the other hand, wet weather interferes with people's ability to perform capable guardianship as visibility, and hence the opportunity for surveillance, is impaired. Inclement weather may also influence people's willingness to stop and intervene in a situation. Based on this we might anticipate that robbery levels will increase in wet and cool weather. Testing for the influence of weather conditions in a UK region which experiences considerable variation in temperature and precipitation will help to determine the direction of the relationship on street robbery levels.

At a general level of abstraction, the natural conditions of an environment are believed to impinge on people's willingness to be in public space, which is a prerequisite of street robbery. The following hypotheses have been generated to test this supposition:

H2: Reductions in street robbery will be associated with adverse unseasonal weather and increases in robbery will be associated with favourable unseasonal weather.

H3: Weather will have a stronger influence on robbery when travel is (in general) more likely to be optional.

The second influence examined in this thesis is the role of the built environment. A substantial body of research exists that evidences the relationship between certain aspects of the urban landscape and the likelihood of crime occurrence. In this thesis I give further consideration as to who uses man-made structures over time. Thus there is a distinct social component to the built environment, such that who is occupying the space at a particular time is theoretically important.

The location of high activity nodes impacts on peoples' geographical behaviour, whereas the function of the nodes (e.g. what service or function they provide) has a strong influence on peoples' temporal behaviour. Some nodes will have a distinct time signature and can be expected to exert influence over the types of people present there. Clearly, schools attract pupils and parents; pubs and bars attract patrons and so on. In turn, this is hypothesised to affect whether a setting is criminogenic. The effect of crime generators on street robbery levels in the proximal area – what I call the *environs* - will be explored in relation to victim sub-groups to generate new insight into the effect of land use (and use of land over time) on robbery. The following hypotheses have been created in relation to this:

H4: The environs of schools will be associated with the disproportionate relative risk of school pupils being victimised on weekdays, in the hours after schools close. (In these hours pupils will be making their way home from these facilities and socialising nearby).

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H5: The environs of universities and further education institutions will be associated with the disproportionate relative risk of students being victimised in the late evening and very early morning hours on weekends. (Students will socialise near to these facilities at these times due to their residential proximity).

H6: The environs of pubs and bars will be associated with the disproportionate relative risk of workers and students being victimised in the evening hours on weekdays and weekends. (Workers and students have the recreational time and resources to use drinking establishments in these hours).

H7: The environs of train stations will be associated with the disproportionate relative risk of workers being victimised in the daytime and early evening hours on weekdays. (Workers will be using these facilities for commuting purposes at these times).

The intention of posing these hypotheses is to address knowledge gaps identified in the literature. Hypothesis 1 is tested in Chapter 4, with hypotheses 2 and 3 receiving empirical attention in Chapter 5. Hypotheses 4 to 7 form the last piece of empirical analysis in Chapter 6. I return to discussions of the influence of the social environment in Chapter 7.

The next Chapter acts as a prologue to the empirical analysis, focusing on the street robbery data used in the remainder of this thesis and the study area from which it comes. This draws out general spatial and temporal patterns prevalent in the data and initiates a dialogue on the suitability of different units of analysis. Importantly, it establishes that street robbery in the study is clustered in space and time, sometimes into compact places and moments. The findings provide further justification for the argument that studying the criminogenic environmental backcloth necessitates a micro-level approach.

3. SPATIO-TEMPORAL PATTERNS IN STREET ROBBERY IN STRATHCLYDE

Chapter overview

The key data for this thesis were provided by Strathclyde Police and cover the geographical extent that this force was responsible for policing. This Chapter is dedicated to describing these street robbery data, highlighting their strengths and limitations and presenting general spatio-temporal trends which will be deconstructed to a micro-level in subsequent empirical Chapters. Other data sources (e.g., astronomical, weather, land use) are described elsewhere in the context of the specific hypotheses being tested. For that reason they are not included here.

Street robbery has been chosen as a crime type in this research for several reasons. First, robbery is significantly serious enough to warrant police attention and prioritisation, and this means that it is generally recorded with good temporal precision (personal communication with data provider, 6/3/2012). Thus, as a crime type it is more befitting of precise micro-level analyses of temporal patterns than traditional property crime (which might have happened over a large, unknown time period). Second, due to the usual loss of property, victims have more reason to report the crime to the Police than if they had been subject to a non-serious violent crime (Flatley et al., 2010). Third, by definition street robbery takes place outdoors, in street settings. These are areas where the natural, built and social environment is believed to be influential in the crime event, and hence susceptible to crime prevention measures levelled at those situational features. Therefore, when analysing robbery, it is important to be able to tease out those situational qualities of a setting which may predictably increase the risk of robbery occurring. With robbery an enduring political concern (Smith, 2003), it seems timely to produce in-depth research which reveals some of the situational characteristics that may be amenable to prevention efforts.

This Chapter begins by describing the crime data and providing a brief outline of the study area. Preliminary analyses are then presented. The aim of these analyses is to familiarise the reader with the temporal and geographical patterns in the data as a prelude to the empirical Chapters in the thesis.

To précis the findings, robbery is found to cluster in both time and space, the latter being particularly pronounced. Descriptive analyses of the time-series data reveal a distinct seasonal trend on a general downward trajectory over the ten-year data period. Consistent with prior research, the day of the week and hourly patterns highlight that weekend evenings are associated with an increased likelihood of street robberies. Spatial concentration is demonstrated at various scales of interest

(regional, sub-neighbourhood and micro-locational), providing justification for the imperative to conduct research on street robbery with a micro-spatio-temporal focus.

3.1 Street robbery data

This first Chapter section introduces the robbery data employed in the thesis. This highlights recording issues pertaining to robbery and describes the data; providing details of its provenance, structure and the study area from which it comes. Data cleaning – an integral component to any analytical work – is thoroughly described so that decisions made throughout the research process are transparent. This usefully underpins the following sections which are concerned with the spatio-temporal patterns within the robbery data.

Definitions of robbery and recording issues

Robbery is legally defined in Scottish common law as follows:

"Robbery is the felonious appropriation of property by means of violence or threats of violence. Violence or threats of violence are an essential element of robbery, and must have been used with theftuous intent. The appropriation of the property must be simultaneous with the violence used or threatened."

Further to this, robbery *to the person* is where the goods that are stolen belong to a person, rather than a business. For the purposes of this research, 'personal robbery' is seen as synonymous to 'street robbery', as the bulk of it occurs to people (outdoors) in the urban landscape. Throughout the remainder of this thesis all mentions of robbery pertain to street robbery.

Street robbery is also commonly known as mugging, which usually encompasses the crime of 'snatch theft' too. Snatch theft differs from street robbery in that it is the taking of property from a victim without the use or threat or intimidation. Pick-pocketing is a subset of this, whereby the victim is unaware of the property being stolen. Whilst robbery and snatch theft both refer to the theft of property from people, this research does not specifically cover snatch theft. This is because snatch theft, and more specifically pick-pocketing, depends on a different situational context from robbery – it typically requires a crowd of people for the offender to successfully commit their crime (Clarke et al., 1996). Contrastingly, robbery generally requires the absence of people – or guardians – for a successful crime (Felson, personal communication, 15 November 2014).

Following the introduction in England and Wales of the National Crime Recording Standard on 1 April 2002, the (then) Association of Chief Police Officers in Scotland (ACPOS) Crime Standing Committee

developed a new crime recording standard for Scotland. The aims were to provide a more victim orientated approach and to ensure uniformity in crime recording standards throughout Scotland¹. This was achieved and endorsed on 3 February 2003. Readers of this research should be aware that this change in counting rules means that data from February 2003 onwards are not directly comparable to those records prior to this date. Though as the bulk of the data fall after this date it is not deemed to be a serious problem for the empirical analysis.

A well-known limitation of police-recorded crime data is that it does not account for the 'dark figure' of crime (Maguire, 2007). That is, crimes recorded by the police do not capture those which are not reported, or for whatever reason not recorded. Under-reporting of particular crime types can be surmised from large scale victimisation studies; namely the Crime Survey for England and Wales (CSEW). Previous estimations from the British Crime Survey (the predecessor to CSEW) put the reporting rate in England and Wales at around 49 per cent for robbery victims in 2010 (Chaplin et al., 2011). While a comparable figure is not available from Scottish Crime and Justice Survey (SCJS), based on similar cultural incentives and disincentives to report robbery, it is plausibly around the same figure in Scotland.

Scholars have cross-referenced police data on violent crime (an allied interpersonal crime type to robbery) with data collected at Accident and Emergency departments and found similar seasonal patterns over time (Rock, Judd & Hallmayer, 2008). This suggests that police-recorded crime may not be an unrepresentative sample of all crimes to happen. However this work only speaks to temporal trends; it is currently unknown to what extent recorded crime faithfully represents spatial patterns in crime.

Robbery data provenance

The bulk of the street robbery data were received in December 2011, with a follow up sample being provided in March 2012. These data come from the crime recording system managed by Strathclyde Police, where the majority of robberies in Scotland are recorded, and cover the calendar years 2002 to 2011. The fields included in the data set are detailed in Table 1. As the data fields include demographic information for the victim and offender, part of the data sharing agreement included a clause stipulating that no point-level geographical patterns would be generated in the course of the research, so as to protect the anonymity of the victims. This is a fundamental obligation of the Data Protection Act 1998 which states that information on victims falls under the category of sensitive

¹ See <u>http://www.acpos.police.uk/Documents/Policies/CRIME%20-</u>

personal data. Under this legislation, personal data that is "either by itself or in combination with other information held or likely to come into the possession of the holder, however recorded, can identify a living individual"² is protected, so that damage and/or distress are not inflicted on the victim. Depersonalising the data through aggregation – so that no victim was identifiable – was a crucial step of the ethics procedure for the analysis in this thesis.

Data field label	Description
CR number	Crime report reference number
Date from	Start date of offence
Date to	End date of offence
Time from	Start time of offence
Time to	End time of offence
Crime text	Crime category
Easting	The X coordinate of the offence location
Northing	The Y coordinate of the offence location
Organisati2	Location description (for example: road, footpath, park)
Organisati	Second qualifier of location description (for example: waste ground)
Victims number	How many victims there were for this offence overall
Victim gender	The gender of the victim for this crime report
Victim occupation	The occupation of the victim for this crime report
Victim age	The age of the victim for this crime report
Victim SCRO	If the victim has a criminal conviction
Detected	Whether the offence has been detected
Number offenders	How many offenders there were for this offence overall
Offender gender	The gender of the offender for this crime report
Offender age	The age of the offender for this crime report

Table 1 - Description of data fields

The Strathclyde Police study area

Since the data were acquired the eight Scottish Police Forces have been merged into a central Police Service of Scotland. This has consequently changed the personnel arrangements, but not the geographical boundaries. The overview of the study area is provided to describe the Policing arrangements as they stood during the data period, prior to the creation of Police Scotland.

The Strathclyde Police area was the largest of the eight Scottish police forces by personnel and the second largest by area (just under 14,000 km² - see Figure 2). It covered the Inner Hebrides all the way down to the major metropolis of Glasgow, with some 2.3 million people living within its

² http://www.legislation.gov.uk/ukpga/1998/29/part/I

boundaries. There were approximately 8,000 police officers and 2,400 police staff in Strathclyde Police during the data period.

Figure 3 displays the Basic Command Units (BCUs) within Strathclyde Police. The rugged rural scenery in the northern part of the study area covers many miles of coastline and islands, as well as Loch Lomond. This part of the Force is known as the Argyll, Bute and West Dunbartonshire division and attracts hill walkers and mountaineers. It has an established Force Mountain Rescue team to deal with visitors to the area.

Glasgow Airport is in the Renfrewshire and Inverclyde division and accommodates around eight million passengers each year. The Ayrshire division also receives many tourists, who visit the area for the golf courses and numerous sites of historical heritage. A range of large public events are held throughout the year in Strathclyde Country Park, which falls in South Lanarkshire division. North Lanarkshire division sees fewer seasonal visitors, although there are rapid social and economic changes going on in this division which are changing the employment opportunities and regenerating several towns.

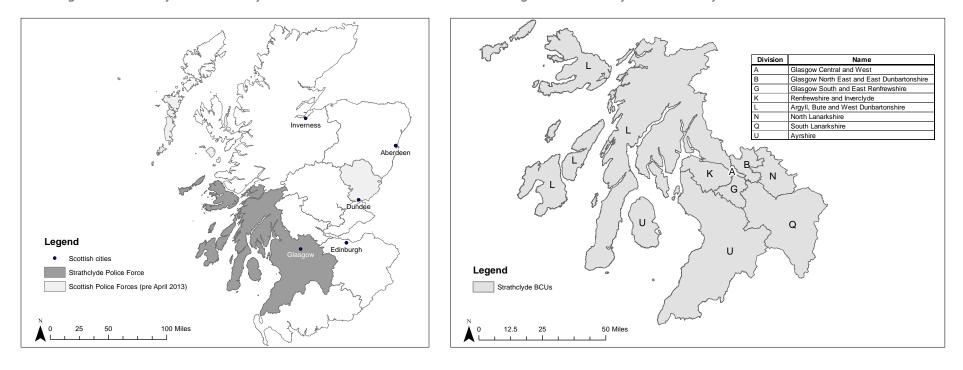
The metropolis of Glasgow is divided into three divisions: Central and West, East and East Dunbartonshire and South and East Renfrewshire. The resident population is estimated to be around 769,960 for the whole area, and around 400,000 people visit the city centre every day to work, shop and visit. Many commercial and leisure facilities draw people into the city, as well as the cultural sites. Together, these divisions encompass a range of densely populated areas in the city centre, moving to semi/rural villages on the outer edges. There are stark socio/economic differences across the Glasgow divisions; from relative affluence to pockets of severe social deprivation.

One of the main limitations of the Strathclyde Police data is that they are unlikely to include robberies that occur on public transport. These are customarily recorded by British Transport Police and the tram and bus companies that operate in the Strathclyde area. This is an important omission, for previous research has found a substantial minority of offences occur on public transport (Smith, 2003; Smith et al., 1986). Whilst it is possible that these other agencies can pass on information regarding robberies on public transport to Strathclyde Police, analysis of the location type for the robberies (see section 3.2) suggests this happened for only four robberies that occurred on buses. However, as police crime recording systems seldom have a flag for transport locations (Newton, 2014), the possibility remains that some robberies were not accurately coded to indicate whether they occurred on public transport.

51

Figure 2 - Strathclyde Police study area within Scotland

Figure 3 – Strathclyde Police study area Basic Command Units



Data recording issues

A number of factors may affect the accurate recording of a robbery event in a crime report. Bank robbery victims often have a less-than-perfect memory of the details of the crime they were subjected to (Christanson & Hubinette, 1993). This may also be the case for victims of street robbery, for the offence involves the threat or use of violence which may inhibit a person's ability to rationally absorb key details of the event. As victims of robbery are typically those who are more vulnerable – through their demographic profile or a temporary incapacitation (like intoxication, Brookman et al., 2007) – this is known to compromise the level of accurate detail that is able to be recorded about the location and time a robbery occurred. Further to this, there is often a delay between when the offence happened and when the victim decided to report the incident (Smith, 2003). Memories of the incident may therefore have started to decay by the time the victim reports the crime, thus undermining the precision of the information reported.

Accurately recording the spatial location where robbery takes place presents a number of challenges. Principally, most robbery takes place outdoors, and may involve the offence occurring over a stretch of space. Thus, robbery often happens at 'non-addressable' locations (i.e. not related to a postal address), which are difficult to geocode in police systems. It was not possible to estimate the geocoding precision in the robbery data due to the absence of address details (see Table 1), though the data provider was confident that the Strathclyde Police gazetteer was up-to-date. However, due to the reasons outlined above regarding victim memory, it seems reasonable to assume that there will be some discrepancies in the data between the locations recorded and the precise locations where robbery events occurred. This is somewhat unavoidable, and one of the chief limitations of doing micro-level spatial analysis.

Related to this, most people do not look at their watches immediately before becoming a victim of a robbery. Hence, when they report the crime, it is often only an estimation of when the crime took place, rather than an exact time. This is reflected in the amount of start and end times in the data which are on the hour, half hour, or quarter to or past the hour. Almost two thirds (65%) of the crime reports had a start time that was on one of these quarter-hour markers; the breakdown was 23% for on the hour, 22% on the half hour, with 9% and 10% for quarter past and quarter to the hour respectively.

Data cleaning

The data were cleaned prior to analysis using the Statistical Package R with the code editor RStudio. This involved editing the data fields so that they were in an appropriate format for each variable. This was particularly important for the date and time fields. Two new date-time variables were created - taking the POSIXIt format in R. POSIX is the name of a set of standards that refer to the UNIX operating system. POSIXIt refers to a date stored as a list of vectors for the year, month, day, hours and minutes. This is the most sophisticated way of storing temporal information in the base package of R and enables the data to be used in time calculations.

The 'from date-time' variable (starttd) was examined to ascertain if there were any data entry errors. One record was found to have no start time recorded, and was subsequently excluded. This was because there was no way of determining at what point in the day of the start date the event occurred. Two further records were found to have invalid from date-times. These events were recorded to have happened at the UK daylight saving time 'clock change' – a date-time which simply does not exist. As it could not be discerned whether the data entry error was referring to an hour earlier or later, these two records were excluded.

The 'to date-time' variable (endtd) was inspected next. In 80.6% of records this field was blank, which was indicative of only one date-time being recorded (the 'from date-time') for the robbery event. As robbery is typically committed over small temporal windows (sometimes referred to as *moments* in temporal data nomenclature) this is to be expected. When both the date to and time to fields were blank they were assumed to be the same as the start date-time time-stamp, and therefore the date to and time to values were pasted into these fields for each record. Once this was complete 82 per cent of the data (n = 12,309) had identical start and end date-times.

date from	time from	date to	time to	Treatment of missing data	n
03-Feb-02	21:30	-	-	Substituted values from date and time from variables into date and time to variables	11,969
03-Feb-02	21:30	03-Feb-02	-	Substituted values from time from variable into time to variable	128
03-Feb-02	21:30	-	21:35	Substituted values from date from variable into date to variable	12
03-Feb-02	23:50	03-Feb-02	00:00	One day added to date to variable	10

128 records had no time to information, but did have the date to field completed. In this scenario the robbery was assumed to have the time to information identical (or near to) the time from information (when the date from and date to were identical), thus this information was substituted into the time to field. 12 records had no date to information, but did have the time to field filled in. In this instance, it was assumed that the date the robbery was committed was the same as the date to, with the timespan of the offence denoted by the time from to time to. After these substitutions one record that spanned the daylight saving time clock change remained with missing data. This record was consequently excluded. Table 2 summarises these various data replacement choices.

Once the missing data were dealt with, the next stage of the process was checking for data recording errors in the temporal information. This involved generating a time-span variable which represented the temporal window in which the robbery event was recorded to occur. 10 records had a negative time-span, or in other words, with the start time of the offence being later than the end time. On closer inspection these 10 records had a **time to** value as midnight, with the **date to** field identical to the **date from** field. These were assumed to have the **date to** field inaccurate (insofar that midnight denotes the start of a new day), and this date was thus increased by one day (see Table 2). This assumption was made based on prior knowledge of the common types of data entry errors that creep into crime data.

Time-spans of robbery events

Temporal bin	Ν	Per cent	Cumulative per cent
0 mins	12,305	82.0	82.0
1-5 mins	249	1.7	83.7
6-10 mins	380	2.5	86.2
11-20 mins	677	4.5	90.7
21-30 mins	636	4.2	94.9
31-60 mins	414	2.8	97.7
61-120 mins	124	0.8	98.5
121-240 mins	72	0.5	99.0
Over 240 mins	83	0.6	99.6
Total	14,940	99.6	-

Table 3 – Frequency and proportion of the time-spans for the robbery eventsN.B. events spanning over 240 minutes were excluded from analysis

The time-span of each robbery event was calculated from the difference between the time from and time to fields. Table 3 illustrates the frequency of the different time-span bins created, along with

the proportion and cumulative proportion of records in each bin. As this shows, 82 per cent of records had a time-span of zero minutes (but see aforementioned section for the assumptions behind a large share of these), and 94.9 per cent of all records were recorded as occurring within a 30 minute period.

Large time-spans (however defined) denote an imprecise record of when the robbery occurred and hence are unsuitable for the micro-level trends analysed in this thesis. For this reason robberies that had been recorded as occurring over a four-hour window were excluded from the analysis. This threshold was chosen somewhat arbitrarily, but in the absence of guidance on this topic in the academic literature, four hours was considered a sufficient period over which the temporal precision was compromised. Once these 83 records that did not conform to this were excluded (see Table 4), the mean time-span for the remaining robberies was 5.4 minutes.

Much of the analysis in this thesis employs a temporal interval – i.e. the span between two times - as the unit of analysis (see Chapters 4 and 6 for how these units were defined). This represents a compromise between sufficient levels of aggregation so that statistical modelling can detect relationships with the robbery levels, and the micro-level focus of enquiry that characterises this research. Robberies that fell in intervals not completely covered by the data period (the overnight period on 31 December 2001 and 2011) were removed from the data (n=4).

The time-span data are remarkable because much of the analysis in this thesis is dependent on using one time-stamp for each robbery event. In other property crime data (e.g. vehicle crime, burglary, theft from the person) we customarily see large time-spans which are a consequence of the victim having an imprecise understanding of when the offence took place. In these latter crime types, it is difficult to ascribe certainty to when the event occurred, meaning that micro-level temporal analysis can be unreliable. Robbery event data are recorded with a greater temporal precision, and the small time-spans in this dataset justified the decision to take the start time-date as the time-stamp in the empirical analysis in subsequent Chapters.

Excluded records

In total 157 robbery events were excluded from the analysis, which equated to a loss of one per cent of the data. Table 4 summarises the reasons for these exclusions alongside the number of records falling under each criteria. 14,857 records remained once the data cleaning was complete.

Reason	n excluded
Robberies targeted to a non-human victim ³	66
Data entry errors for start or end time/dates	4
Robberies with a time-span over four hours	83
Robberies falling in an incomplete temporal interval	4
Total	157

Table 4 - Reasons and frequencies of the data records excluded from the analysis

3.2 Robbery patterns in space

That crime clusters geographically is now an unquestioned precept in Criminology (Weisburd 2015). Substantial empirical work has been devoted to defining and explaining the spatial distribution of crime over the last 150 years (see Johnson, 2010 for a good overview). Importantly, crime has been found to cluster at various spatial scales (Sherman et al., 1989; Weisburd, Bushway, Lum & Yang, 2004). This section presents a series of analyses that expose spatial heterogeneity across different levels of geography - a finding that echoes the crime and place literature (Weisburd et al., 2012). The processes underpinning each method are discussed with their associated strengths and limitations.

Concentration by areal geography

A classic way of presenting spatial distributions of crime is geographic boundary thematic mapping, also known as choropleth mapping (Chainey and Ratcliffe, 2005). The heritage of this method stems from data being collected at the level of administrative units such as police districts, census blocks or areas, wards and other polygonal geographies. Such areal units can be shaded in accordance with the aggregated numbers of crime. The resulting maps are easily interpreted by a lay audience, and census areas in particular can be linked with other data collected at the same geographical resolution. Thematic maps are popular in many fields for producing patterns at a level of geography (i.e. counties, administrative areas) that the map user can relate to, and can be used to unify focus across several agencies that are responsible for servicing a common geography.

The critical issue with these units of analysis is that the boundaries have not been created with crime analysis in mind; they are artificially constructed for political or administrative purposes. For example, census areas competently group similar socio-demographic groups into units for the

³ These related to robberies to a Post Office mailbox (personal communication with data provider, 6/3/2012).

explicit purpose of studying the country's population. However, they often fail to reflect the sociospatial distribution of land use, people and crime events that are of interest to crime researchers (Schmid, 1960).

Moreover, the use of boundaries in geographical analysis is encumbered by issues of scale. Brantingham, Dyreson and Brantingham (1976) introduced the concept of the *cone of resolution* to criminologists from their original field of geography. In doing so they illustrated that viewing murder and burglary rates at different levels of geography can result in changeable patterns. This message – "that crime can form very different patterns at different scales of analyses" echoes through their later work (Brantingham, Brantingham, Vajihollahi & Wuschke, 2009: 88) and has been corroborated by other scholars doing similar studies (Ouimet, 2000; Wooldredge, 2002).

The differential patterns seen at different scales of interest are a long-standing geographic phenomenon. Debated at length for decades (Bailey and Gattrell, 1995), this is commonly referred to as the *Modifiable Areal Unit Problem* or MAUP (Openshaw, 1984). The MAUP occurs when point-based data (for example, crime or other spatial phenomena) are aggregated into areal units and the resulting summary values are influenced by the choice of unit and its (modifiable) boundaries. Thus, it refers to aggregation bias; where statistical results change depending on the choice of the unit of analysis. Put simply, when point data are aggregated to areal units the patterns that manifest may be an artefact of the underlying boundaries, rather than the spatial distribution of the data. Hence the MAUP can undermine the reliability of thematic maps.

The MAUP is closely related to *zonation effects* – the difficulty of drawing meaningful boundaries around a geographic area which reflects a variable of interest (Openshaw, 1984; Oberwittler & Wikström, 2009). Administrative geographies often use major roads as their boundaries, which delineate between different socio-demographic groups. However crime (and other behavioural phenomena) concentrates along major routes and at other large facilities such as shopping or leisure centres. Thus any natural concentrations of crime might be effectively cut in half and thus concealed when using such units of analysis.

More subtly the MAUP also refers to the problem of scale; or rather, how large the units of analysis should be. Patterns displayed at large geographic units mask important lower geographic variability, and local area effects are obscured. This is another source of aggregation bias, known as the *ecological fallacy* (Robinson, 1950, Jonassen, 1949). This fallacy occurs when an inference is made about an individual (or collection of individual data points) based on the aggregate data for an area. For example, when visualising crime concentration through thematic (choropleth) maps, an area

falling within the mid-range of aggregate values may be disguising one high crime area and a number of low crime areas. Hence it should not be assumed that all possible targets in this area have a medium level of risk. To do so would incur Simpson's paradox. The dangers of this fallacy are the greatest at higher levels of geography (Brantingham et al., 1976). As crime has been shown to be distinctly localised in nature (Groff, 2013b; Sherman et al., 1989; Weisburd et al., 2012), these issues are non-trivial in crime analysis and research.

With these limitations in mind, a series of thematic maps are presented which begin to explore the different levels of spatial concentration of robbery in the study area. Figure 4 visualises the distribution of robbery over the different basic command units (BCUs) within the Strathclyde Police area. (BCUs are a police administrative geography, also known as divisions). From this we see that robbery is heavily concentrated in BCUs 'A', 'B' and 'G', which represent the urban area of greater Glasgow. In the northern part of the study area, BCU area 'L', which contains Loch Lomond and other areas of natural beauty, robberies are relatively uncommon.

In the region south of Glasgow robbery levels are more modest, BCUs 'U' and 'G' experienced 1,000 - 1,500 robberies apiece over the ten years. Lastly BCU 'K' has a slightly elevated distribution of robbery, containing between 1,500 - 2,000 robberies. It would seem from Figure 4 and 5 that, at a very general level, robbery clusters relative to the more urban sectors of the study area, a finding that resonates with prior research that UK robbery is overwhelmingly concentrated in metropolitan areas (Flatley et al., 2010).

However, as noted above, such a coarse geographical resolution will mask more fine-grained patterns. Progressing to smaller units of analysis we can also view the patterns of robbery by census output area (OA) in Figure 5. Doing so for the whole study region however disguises the patterns at this smaller level of geography, as there are 19,888 OAs to interpret, most of which have no crime. Thus, Figure 5 does not reveal much other than the significant heterogeneity of concentration within BCUs, which confirms the ubiquitous finding from prior research.

Figure 6 visualises robberies at the OA area for the Glasgow region. Heterogeneity is obvious across this area, with many OAs displaying a small to medium amount of robbery. The greatest concentration appears to be at the centre, located in Glasgow city centre. Figure 7 zooms in further to the city area and is the most expressive in terms of visualising the distribution of robberies. Here it is apparent that there is intense clustering in the city centre area; however the second highest thematic classification (51 – 200 robberies) is dispersed across four BCUs. This reinforces the point made previously about areal units being insensitive to distributions of crime.

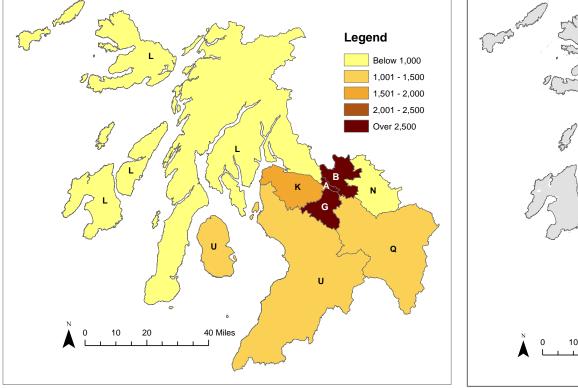
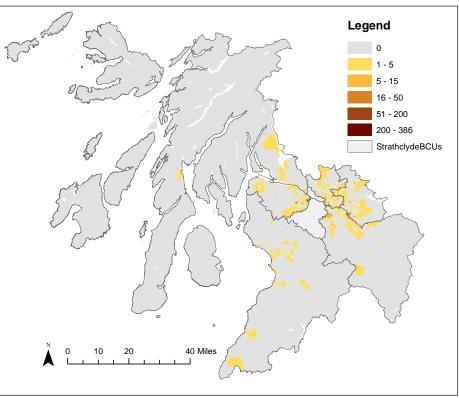


Figure 4 – Thematic map of robberies by Strathclyde Police Basic Command Unit

Figure 5 - Strathclyde thematic map of robberies by census Output Area



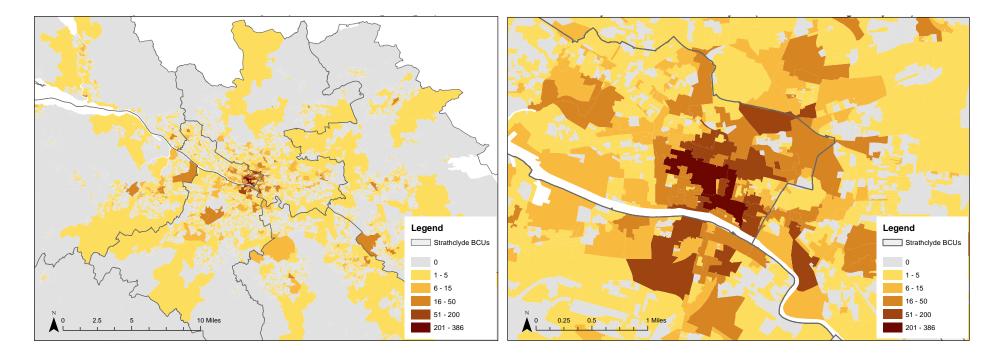


Figure 6 - Glasgow region thematic map of robberies by census Output Area

Figure 7 - Glasgow city thematic map of robberies by census Output Area

KDE hotspot maps

Kernel density estimation (KDE) offers several advantages over thematic mapping of areal units. This method involves aggregating point-level crime data to (usually small) grid cells. Together these generate a continuous surface that represents the density of events per spatial unit, which is calculated using a user-specified search radius (or bandwidth). A smooth surface map, unconstrained by geometric boundaries, is generated from this process. The resulting map is aesthetic and able to represent the morphology of the spatial distribution of crime. Due to this, KDE is widely regarded as a suitable analysis technique for visualising distributions of crime (McGuire & Williamson, 1999; Williamson et al., 1999; 2001; Eck et al., 2005). Other, more statistically robust, techniques such as GI* (Getis & Ord, 1992) can also be used to detect crime concentration. Nonetheless, KDE is sufficient for the purposes of this section - to describe and visualise the spatial patterns in the robbery data.

The KDE method is not without its limitations. The arbitrary manner of defining the cell size and bandwidth used in the calculations of the density surface can result in wildly different maps. Whilst guidance exists (see Ratcliffe & McCullagh, 1999; Chainey & Ratcliffe, 2005) there are no canonical rules for parameter-setting. Further, Eck et al. (2005) draw attention to the subjectivity in selecting an appropriate thematic classification system with which to display the density surface. (This is also true of choropleth maps, but its impact is greater on density values which are less intuitively interpreted). Nevertheless, KDE remains a popular technique amongst practitioners and researchers alike, for it outperforms other methods in predicting future spatial patterns of crime (Chainey et al., 2008).

Figure 8 displays the KDE map for the Strathclyde area. Congruous with the previous maps, this demonstrates that the robberies cluster over the BCUs proximal to Glasgow city centre. Robberies falling in the four divisions with the highest concentration of crime in Figure 4 (A, B, G, K) were extracted and a separate KDE map was generated for these events (Figure 9, n=10,827). At this closer resolution we again see the distribution of robbery concentration situated on Glasgow, with density diffusing in a nondescript way the further one gets from the city centre.

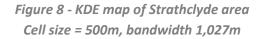
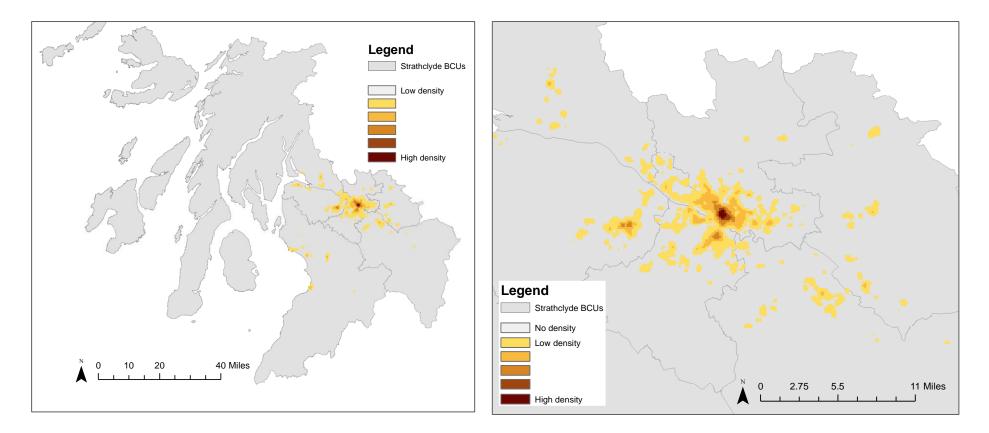


Figure 9 - KDE map of Glasgow region Cell size = 200m, bandwidth = 500m



Street-level concentration

Turning now to street level, over 162,000 street segments transect the Strathclyde area (each of which has the unique identifier 'Toid' in the Integrated Transport Network dataset). Despite most robberies being recorded as happening in a *street setting* (see more below), not all were geocoded to an actual street by the Strathclyde Police gazetteer. This foments the question of how far the street network reasonably exerts an influence on crime. For example, a robbery occurring in the centre of a large park cannot sensibly be attributed to any of the circumscribing street segments. The relationship between land use and streets will be investigated more fully in Chapter 6. Here it is important to establish the distance between each robbery and the street segment it falls closest to, for large distances would undermine assumptions that robberies were related to street segments that are proximal to particular facilities.

To explore this further within the Strathclyde data the 'near' command in ArcGIS was used to compute a distribution of the distances between all robbery events and the nearest corresponding street segment. Descriptive statistics are provided in Table 5 to summarise this distribution for the whole Strathclyde region and the Glasgow city centre area. These show that the maximum distance to the nearest street segment for the Strathclyde area is much greater than the city centre area, although as the other summary statistics are similar this seems to be influenced by outliers.

	All Strathclyde	Glasgow city centre	Location description
Min	0.13	0.57	Alley
Q1	15.41	14.93	Car park
Median	18.92	18.77	Footpath
Mean	22.71	21.01	Open space
Q3	24.49	25.22	Park
Max	6205.00	76.85	Playing field
			Street
			Waste ground
			Total

Table 5 - Summary statistics for robbery distance (m)
from the street

Table 6 - Location description forrobberies over 100m from street network

Count

Outliers in Table 5 (for the whole Strathclyde area) were investigated by profiling those robberies that fell more than 100 metres from the street network by their recorded location description (n=42). Table 6 shows that most of these locations could be defined as being in open spaces, although just under a fifth of this subset is classified as a 'street'. It may be the case that these streets are new and, as yet, unrepresented by the street network data. It is also possible that these

offences have been misclassified through data entry errors, which would weaken any analysis that relied upon their relation to the street network. This point accentuates the previous discussion about data recording issues.

To assess street-level concentration the robbery events needed to be associated with a proximal street segment, which had to be done computationally in the absence of any offence details. The ArcGIS 'near' command was once again used to generate a distance for each robbery event to the nearest street segment. The robbery data was subsequently joined to the street network file through the unique identifier for each Toid. (This was considered superior to the 'spatial join' function which was found to double-count events that fell equidistant to multiple street segments.) This process produced a street segment field for each robbery event which was subsequently used to generate a measure of concentration by street segment.

Table 7 shows the extent of clustering of robberies by street segment. Some 36.5 per cent of robberies (n = 5,417) occurred on segments with only one event recorded over the ten year study period. At the other extreme, segments with over ten robberies each comprise 10.8 per cent of all robberies (n = 1,610) despite only encompassing 1.1 per cent (n = 90) of all segments with robbery. This reflects the well-established empirical finding that robbery clusters at a small percentage of places (Van Patten, Mckeldin-Coner & Cox, 2009). The mean number of robberies per segment per year (for street segments that had any robberies) was 0.18 (s.d. = 0.23).

n robberies	count	% of segments	sum of robberies	% of robberies
1	5,417	67.2	5,417	36.5
2	1,379	17.1	2,758	18.6
3	526	6.5	1,578	10.6
4	267	3.3	1,068	7.2
5	144	1.8	720	4.8
6	94	1.2	564	3.8
7	52	0.6	364	2.5
8	38	0.5	304	2.0
9	26	0.3	234	1.6
10	24	0.3	240	1.6
11-15	50	0.6	621	4.2
16-20	18	0.2	324	2.2
21-30	14	0.2	351	2.4
31-40	4	0.0	138	0.9
41-50	3	0.0	125	0.8
51-60	1	0.0	51	0.3
Total	8,057	100.0	14,857	100

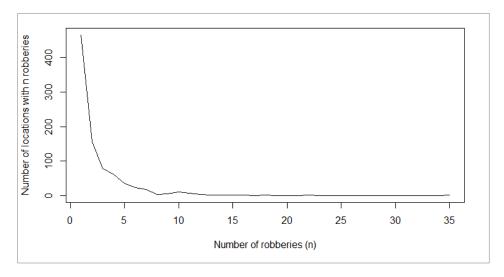
Table 7 - Concen	tration of	robbery	by street	segment
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Locations

Drilling down into the data permits an inspection of the features of the precise point locations within the street segments. As stated on page 49, these will not be geographically displayed to protect victim identities. Due to the expected data reporting and recording inconsistencies the patterns reported here should be interpreted as indicative.

Unique and repeat locations

Extending the descriptive analyses on street segments above, repeat victimisation can be examined at the location level (defined as a point with the same recorded easting and northing coordinates). The concentration of street robbery at locations is represented as a J-curve chart (Clarke & Weisburd, 1990) in Figure 10. This shows that, in keeping with the so-called *iron law of troublesome places* (Wilcox & Eck, 2011), a small number of locations (places) account for a large proportion of robbery. Inversely, a large number of locations only experience one robbery. Figure 10 suggests that the distribution is a reverse exponential, although given the number of street segments with no crime (see above) this may in actual fact more appropriately resemble a zero-inflated Poisson distribution.





Visual inspection of the attendant Table 8 reveals that over half of robberies happen at locations that only have one event recorded over the study period (n = 8,571). Conversely, just under half (43.3 per cent) of robberies occur at repeat locations. Comparing this with Table 7 it is evident that the level of clustering is relative to the scale at which repeats are measured; at the larger unit of analysis of the street 60.5 per cent have multiple robberies.

n robberies	count	% of locations	sum of robberies	% of robberies
1	8,571	80.9	8,571	57.7
2	1,234	11.6	2,468	16.6
3	364	3.4	1,092	7.4
4	173	1.6	692	4.7
5	95	0.9	475	3.2
6	45	0.4	270	1.8
7	32	0.3	224	1.5
8	18	0.2	144	1.0
9	11	0.1	99	0.7
10	14	0.1	140	0.9
11-15	24	0.2	307	2.1
16-20	9	0.1	151	1.0
21-30	5	0.0	124	0.8
31-35	3	0.0	100	0.7
Total	10,598	99.8	14,857	100

Table 8 - Concentration of robbery by location

Location characteristics

A description of the location where robberies occurred is provided in two fields (see Table 1). The first data field was filled in fully, with the second used as a qualifier in a subset of events (n = 459). Hence, only the first field is investigated here. It should be noted that the data entered into these have been subjectively chosen by the data recorder, and again just provide an impression of the location type rather than a definitive profile. Whilst the first field had standardised descriptors, several categories were similar enough to warrant merging for this description (for example, garden and gardens; street, road and close; open ground and open space). 64 categories remained.

We can see from Table 9 that footpaths and streets comprise the settings of 84 per cent of offences. Parks, car parks, bus stops and open spaces make up a further ten per cent of offences. A small number of categories imply that robberies occurred indoors (for example; art gallery, basement, first floor, police), however on examination these fields were almost always accompanied by a 'street', 'footpath' or 'car park' qualifier in the second field (analyses not shown).

Table 9 -	Frequency	and	percentage	of	location	description
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Location description	Frequency	%			
FOOTPATH	8,661	58.30	BUS	4	0.03
STREET	3,839	25.84	PLAYGROUND	4	0.03
PARK	649	4.37	LAYBY	3	0.02
CAR PARK	460	3.10	LIFT	3	0.02
BUS STOP	258	1.74	MARKET	3	0.02
OPEN SPACE	175	1.18	MOTORWAY	3	0.02
ALLEY	108	0.73	NEWSAGENT	3	0.02
BRIDGE	108	0.73	EMBANKMENT	2	0.01
WASTE GROUND	89	0.60	LICENSED GROCER	2	0.01
MULTI STOREY	60	0.40	POST OFFICE	2	0.01
CURTILAGE	51	0.34	PUBLIC HOUSE	2	0.01
PEDESTRIAN SUBWAY	40	0.27	SHELTER	2	0.01
CEMETERY	34	0.23	SHOPS	2	0.01
PLAYING FIELD	30	0.20	ALLOTMENTS	1	0.01
HOUSE/FLAT	28	0.19	AREA	1	0.01
TOW PATH	25	0.17	ART GALLERY	1	0.01
WOOD	24	0.16	BASEMENT	1	0.01
POLICE	23	0.15	BUILDING SITE	1	0.01
TELEPHONE BOX	22	0.15	CHEMIST	1	0.01
THOROUGHFARE	22	0.15	COLLEGE	1	0.01
CANAL	15	0.10	COMMERCIAL	1	0.01
GROUND	15	0.10	DOCKS	1	0.01
CASH DISPENSER	13	0.09	DRIVEWAY	1	0.01
RECREATIONAL	8	0.05	FARM	1	0.01
GARDEN	7	0.05	FIRST FLOOR	1	0.01
AGRICULTURAL	6	0.04	GENERAL STORE	1	0.01
BANK	6	0.04	HAIRDRESSER	1	0.01
BEACH	6	0.04	NATURE RESERVE	1	0.01
CHURCHYARD	6	0.04	OFFICE	1	0.01
FIELD	5	0.03	PIER	1	0.01
INDUSTRIAL ESTATE	5	0.03	PROMENADE	1	0.01
RIVER	5	0.03	STAIRWAY	1	0.01
			Total	14,857	100

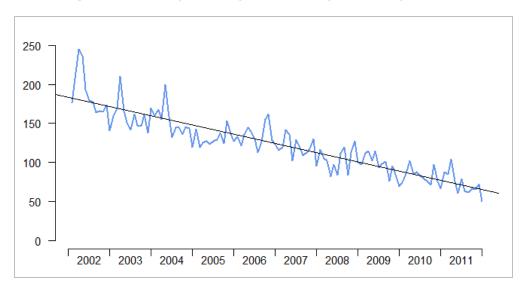
3.3 Robbery patterns in time

Due to the numerous ways in which humans define time, data can be sliced in various ways to elicit temporal patterns. The dimensions that traditionally frame crime research are daily, weekly and seasonal patterns (Ceccato, 2005; Cohn & Rotton, 1997; Farrell & Pease, 1994; Gorr & Durso, 2003; Tompson & Townsley, 2010). Further to this, practitioners often care deeply about changes over time, typically measured at an annual level to reflect business processes and government reporting

practices. The focus of this section is the temporal patterns exhibited by the robbery data. These are explored one-dimensionally and then through analyses that cross-tabulate multiple temporal dimensions.

Annual and monthly trends

The long term trends of robbery in the Strathclyde Police area are noteworthy. In parallel with the trends seen in England, Wales and the wider Scotland area, there has been a steady drop in police-recorded offence levels in the data period. This downward trend can be seen in Figure 11 which shows the monthly fluctuation of street robbery volumes over the ten years of data. The oscillation between high and low points is more extreme in the early years, and is tempered in the later years.





This trend is mirrored in victimisation data collected by the Scottish Crime and Justice Survey (SCJS). The estimates derived from the SCJS for robbery are illustrated in Table 10 (Scottish Government Social Research, 2011) alongside personal theft and all crime, which provide a contextual background. This shows that volumes of robbery have been on a steady downward trajectory for the last three years in the data period, with sizeable percentage decreases from 2008-9. This is accordant with the documented crime drop in industrialised countries since the 1990s (Tseloni, Mailley, Farrell & Tilley, 2010; Farrell, Tseloni, Mailley & Tilley, 2011).

Even though the SCJS is executed with a rigorous research design and uses a large sample it is not immune from sample bias. That is, the sample of participants providing the survey data is not representative of the wider population. Coupled with the fact that crime is a relatively rare event the estimates generated from survey data rely on low incidence rates, and therefore are subject to error. The SCJS applies weighting to the estimates they generate to account for such biases (Scottish Government Social Research, 2011) however they cannot wholly eliminate over- or under-estimation.

					% change
	2008/09	2009/10	2010/11	09/10-10/11	08/09-10/11
All SCJS crime	1,044,809	945,419	874,142	-8%	-16%
Personal theft	109,793	130,113	123,551	-5%	13%
Robbery	19,697	18,875	12,027	-36%	-39%

Table 10 - Estimates of crime and crime change from the Scottish Crime and Justice Survey

Random noise in the time-series data shown in Figure 11 makes it challenging to discern any cyclical or seasonal trends. To decompose the time-series into its three basic parts: the trend component; the seasonal component; and the random component, requires a technique such as seasonal decomposition. This was applied to the monthly counts of street robbery over the ten year period, with the results illustrated in Figure 12. The top box illustrates the overall monthly time-series data, the next one down extracts just the seasonal component, the second to bottom reveals the overall trendline and the bottom box shows the random error terms (also known as residuals). Visual inspection of this plot confirms that there is a strong seasonal component to the data, which is operating in conjunction with the notable downward trend.

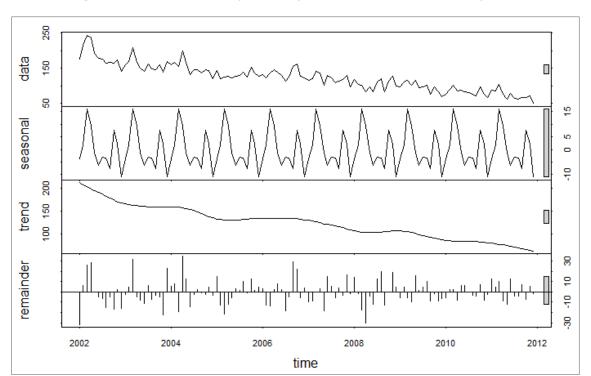


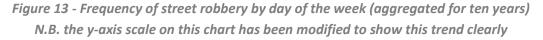
Figure 12 - Seasonal decomposition of the time-series street robbery data

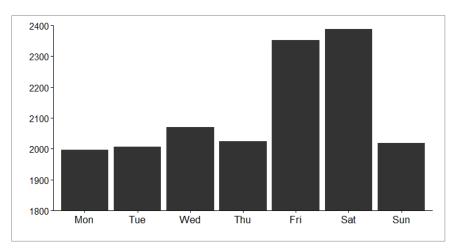
	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	Total
Jan	176	159	160	143	133	116	117	97	76	88	1,265
Feb	215	170	168	120	122	120	105	112	89	85	1,306
Mar	245	210	155	125	136	142	102	115	102	104	1,436
Apr	236	166	200	127	145	136	82	102	85	76	1,355
May	193	151	166	123	140	102	97	115	88	61	1,236
Jun	179	142	132	127	130	129	84	94	83	79	1,179
Jul	177	162	145	129	113	122	112	98	80	64	1,202
Aug	164	148	146	138	126	109	120	101	76	62	1,190
Sep	166	147	136	124	155	113	84	76	71	67	1,139
Oct	165	161	146	153	162	118	113	96	97	66	1,277
Nov	174	138	144	137	128	130	127	82	76	72	1,208
Dec	141	170	120	127	123	96	100	70	67	50	1,064
Total	2,231	1,924	1,818	1,573	1,613	1,433	1,243	1,158	990	874	14,857

Table 11 - Annual frequencies of street robbery by month

Viewing the data frequencies by months and years in Table 11 illustrates the seasonal trend in more detail. Here we see that frequencies generally tend to be highest in the months between January and March, with the earlier years in the data seeing this peak persist through the spring months. In all years but 2011 we see a noticeable increase in offences in October, which is most pronounced for the earlier years when there were more offences overall.

Weekly and daily trends





Another way of examining temporal trends in the data is to consider the day of the week when robberies occur. Figure 13 exhibits the aggregate patterning of this over the ten years. We see from this chart that street robberies happen more frequently on Fridays and Saturdays, with a slight

midweek peak on Wednesdays. This is consistent with previous research (LeBeau & Langworthy, 1986).

When the data are disaggregated into calendar years (see Table 12) we see that the Friday-Saturday peak is common throughout the years, but the Wednesday peak only appears for some years. The results of a Pearson's chi-square test on the distribution in Table 12 indicate that the day of the week distribution was independent of the year ($X^2 = 64.95$, d.f. = 54, p-value = 0.15).

	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Total
2002	323	291	321	335	343	326	292	2,231
2003	250	274	274	272	296	307	251	1,924
2004	238	260	248	247	306	280	239	1,818
2005	188	217	222	202	253	259	232	1,573
2006	200	237	219	220	275	235	227	1,613
2007	188	189	195	198	229	269	165	1,433
2008	160	160	193	162	183	215	170	1,243
2009	180	145	151	157	187	175	163	1,158
2010	146	121	122	136	149	169	147	990
2011	124	112	125	96	131	153	133	874
Total	1,997	2,006	2,070	2,025	2,352	2,388	2,019	14,857

Table 12 - Annual frequencies of street robbery by day of week

The day of week regularities in the data reflect other research on robbery. Many scholars have observed that patterns in robbery data – whether they are from calls for service incidents or offence data – appear to concentrate notably on Friday and Saturday evenings (Ceccato, 2005; Cohn & Rotton, 2000; LeBeau & Corcoran, 1990). Explanations for these patterns have been derived from a refinement of routine activity theory that maintains that time dictates whether activities are obligatory or discretionary (LeBeau & Coulson, 1996). Due to the universal finding from victimisation surveys that the frequency of socialising outside the home is correlated with victimisation risk (Sampson & Wooldredge, 1987), discretionary activities are postulated as playing an important role in robbery occurrence. Given this, weekend evenings plausibly bring suitable victims into contact with motivated offenders, when capable guardians are absent.

Hourly trends

Examining the hourly distribution of robbery start times in Figure 14 reveals that from a nadir at 6-7am there is a steady increase of robbery throughout the daytime hours. High frequencies become pronounced in the late evening hours and start to fall after midnight. As Table 3 showed, 18 per cent of robberies were recorded with a time *span*, some of which were greater than an hour. The

data in Figure 14 were hence partitioned by time-span to ascertain whether imprecisely recorded robbery times concentrated in time. This indicates that recorded robbery times are reasonably precise in the early morning to afternoon hours, but thereafter some uncertainty on when the offence happened is introduced in the data.

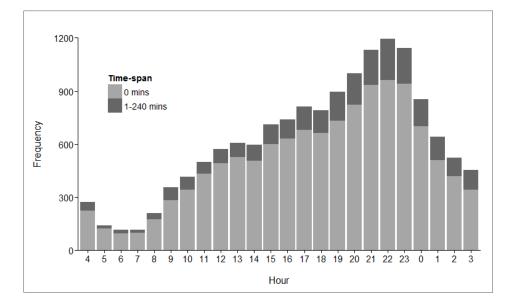
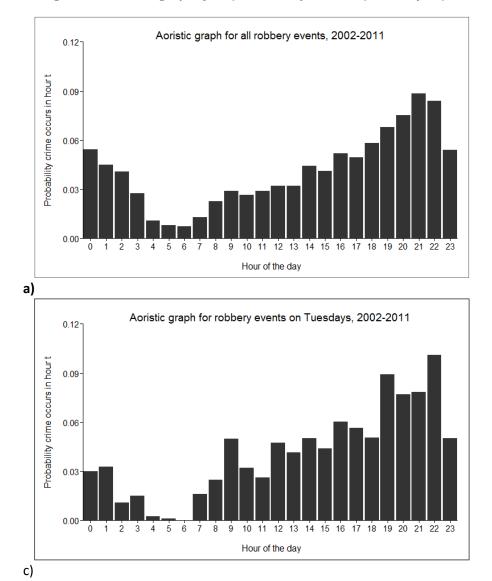


Figure 14 - Hourly distribution of all robberies, split by time-span

To ameliorate these concerns, a complementary analysis technique was employed. Aoristic analysis is a method which computes the *probability* of a crime happening in a given hour window, calculated by both start and end times of the offence (Ratcliffe, 2000). Figure 15 displays the results of this analysis for all robbery events and each day of the week. This daily disaggregation was considered to be important due to the literature on temporal patterns of crime denoting a strong correlation with day of the week patterns (Ceccato, 2005; LeBeau & Corcoran, 1990; LeBeau & Coulson, 1996; Rotton & Cohn, 2000). The first point to note is that there are some subtle differences between Figure 14 and Figure 15a (aoristic analysis of the entire data set). The most stark contrast is the plataeu of probability values at 11pm and midnight in the aoristic analysis when compared to the analysis of the first time-stamp. This is likely due to this period having the highest concentration of robberies with an imprecise time-span, which potentially relates to impaired victim recall (due to intoxication).

Viewing the aoristic distributions by day of the week exposes some heterogeneity within Figure 15a (note that these scales have been standardised for ease of comparison). Each day has a distinct time-signature profile, although when viewed dichotomously as weekday and weekend day some consistencies are observed. For example, robberies are infrequent after midnight on weekdays (and Sunday) whereas they are more common in the early hours on Friday, Saturday and Sunday





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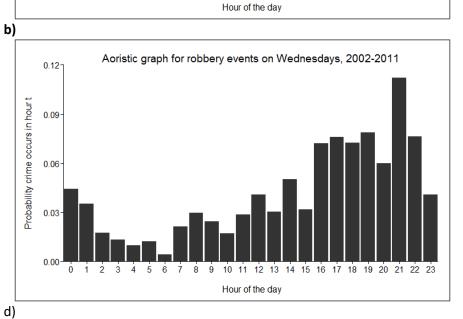
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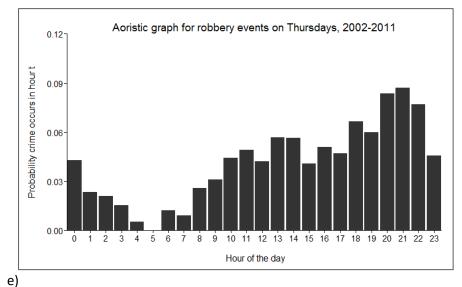
Probability crime occurs in hour t

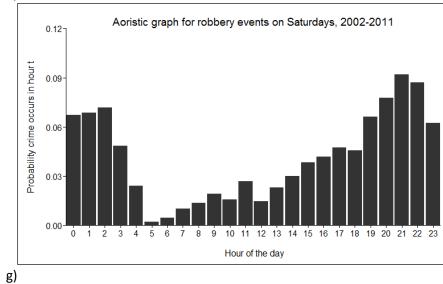


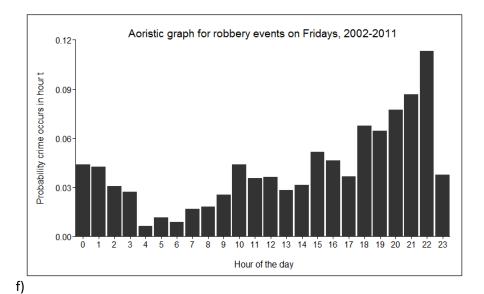
Aoristic graph for robbery events on Mondays, 2002-2011

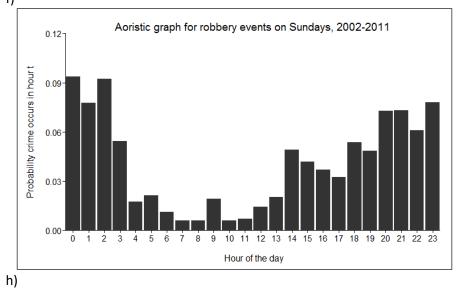
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23

74









(although it should be noted that the hours after midnight in each of the figures can sensibly be considered to be a continuation of the previous night's trends).

In a similar vein, robberies are comparatively uncommon in the morning hours of weekend days. The modest spike in offending at 8AM on Mondays and 9AM on Tuesdays is interesting, and speculatively relates to the commuting activities (to work or school) that victims are engaged in. It may also relate to drug-offenders' need to obtain goods to exchange for drugs upon waking (Deakin, Smithson, Spencer, & Medina-Ariza, 2007).

Space-time concentrations of robbery

In Chapter 2 an overview was provided on the theoretical processes believed to underlie repeat victimisation patterns. To recapitulate, the 'flag' account (or *risk heterogeneity*) refers to time-stable characteristics of victims or places, such as their enduring attractiveness or accessibility to all offenders (Tseloni & Pease, 2003). *Event dependency* pertains to the 'boost account' whereby an initial victimisation renders the victim more vulnerable or attractive than before. Both repeat victims and near-repeat victims – i.e. virtual repeat victims that share spatio-temporal propinquity with past victims – are said to contribute to concentrations of crime in space.

Identifying repeat and near-repeat victimisation patterns in crime data reveals how stable (or not) offending is at the micro-level, which can be illuminating in terms of devising crime prevention strategies and tactics. This was particularly important to establish for the Glasgow area where the greatest geographical concentrations of street robbery were found. The following analysis employed the 'Near Repeat Calculator' (Ratcliffe, 2008) to detect spatio-temporal patterns in the robberies that were located in the top three BCU areas^{4,5}. In brief, this used the following procedure:

The geographical and temporal distances between each possible pair of robberies were calculated (in metres and days, respectively). The number of pairs was 9,111*9,110/2 = 41,500,605. Ten spatial bandwidths of 50 metres (measured using Euclidean distance) and ten temporal bandwidths of seven days were used.

⁴ The Near Repeat calculator crashed when using all robberies (n = 14,861) and robberies that fell within the settlement areas (n = 11,487). Despite extensive investigation, and in the absence of an error message, I could not discern why this happened. The subset of robberies that occurred within the top three BCUs (n = 9,111) was the largest sample that I was able to successfully use in the analysis.

⁵ 7.8 per cent of all robberies were recorded as having multiple victims. An inspection of these records revealed that only one crime report was recorded for each incident, and hence do not inflate the repeat victimisation calculations.

- A contingency table was then populated with pairs of robberies according to the geographical and temporal distances that separated them.
- Next, the expected frequencies for each cell in the contingency table were calculated based on a randomly distributed data set (in terms of space and time). In this analysis one thousand expected frequency distributions were generated using a Monte Carlo simulation.
- The ratios between the observed and the average expected frequency for each cell were calculated. A one-tailed hypothesis test was used to determine the statistical significance of the ratios.

The results of this analysis are displayed in Table 13. Ratios of one indicate that observations exactly matched what would be expected by chance; a value greater than one indicates that more pairs were observed than would have been expected by chance and vice versa for values less than one. The most striking finding to emerge from Table 13 is that repeat victimisation (i.e. at the same location) is pervasive across almost all of the temporal bandwidths. The most intense repeat victimisation clustering is seen within a week of an antecedent robbery. The value in this cell is 3.91 which can be interpreted as 291 per cent more robberies at repeat locations within one week of each other than would be expected by chance. Other temporal bandwidths for the same location range from 51-100 per cent more burglary pairs than expected.

Additional analyses, not reported here, confirmed that this pattern at repeat locations extended to at least 175 days (approximately 6 months), which indicates that a number of locations in the greater Glasgow area experience chronic re-victimisation. This speaks to the flag account outlined above - that certain settings have enduring characteristics which facilitate robbery.

The other noteworthy pattern in Table 13 is that near-repeat victimisation is principally contained within small spatial and temporal boundaries; specifically within a week and 50 or 100 metres of an original robbery. For this space-time range the chance of another robbery occurring is elevated by 46 and 26 per cent respectively (cell values 1.46 and 1.26). These modest values lend weight to the argument that the flag account might be more influential than the boost account for these data. A handful of other cells (for instance, 251m to 300m and 8 to 14 days) exhibit statistically significant values, but these are not clustered in space or time in a way that is intuitively interpreted. Due to there being over 100 cells it may be the case that one of more of these values is a statistical fluke (Bonferroni, 1936).

	0 to 7	8 to 14	15 to 21	22 to 28	29 to 35	36 to 42	43 to 49	50 to 56	57 to 63	64 to 70	More
	days	days	days	days	days	days	days	days	days	days	than 70
Same location	3.91	1.91	2.00	1.55	1.51	1.53	1.57	1.96	1.69	1.78	0.96
1m to 50m	1.46	1.18	0.91	1.06	1.00	0.91	0.95	0.89	0.99	0.79	1.00
51m to 100m	1.26	1.01	1.00	1.06	1.06	1.16	1.08	1.10	1.06	0.94	1.00
101m to 150m	1.08	1.07	1.15	1.12	0.97	1.02	1.06	1.10	1.03	0.89	1.00
151m to 200m	1.19	1.12	1.12	1.04	1.05	1.00	1.14	1.05	1.05	1.07	1.00
201m to 250m	1.07	1.01	1.13	1.06	1.11	1.07	1.02	1.03	1.04	1.14	1.00
251m to 300m	1.02	1.14	1.05	1.03	0.95	1.02	0.98	1.03	1.03	0.94	1.00
301m to 350m	1.13	1.16	1.07	1.01	1.02	1.05	1.02	1.07	1.09	1.12	1.00
351m to 400m	1.10	0.98	1.00	1.00	1.04	1.09	1.03	1.01	0.99	1.01	1.00
401m to 450m	1.13	1.07	1.09	0.99	1.09	1.06	1.04	1.05	1.03	1.04	1.00
451m to 500m	1.11	1.09	1.04	1.06	1.07	0.99	1.01	1.09	1.04	1.00	1.00
More than 500m	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

 Table 13 - Results from near-repeat calculator for greater Glasgow area (n = 9,111)

NOTES: **p-value < 0.001**; **p-value < 0.05**.

Given the size of the greater Glasgow area (202.6 square miles), such localised space-time clusters of robberies seem important. They point towards compact geographical and temporal windows in which robberies concentrate. The implications this has for crime prevention are drawn out in Chapter 7.

Conclusion

The aim of this Chapter was to familiarise the reader with the characteristics and underlying trends in the robbery data being used in this research. To reiterate, robbery is particularly suited to the analysis of temporal patterns, given that it typically has a short time-span. The reporting rate and accuracy with which victims report and the police subsequently record robbery are acknowledged as limitations of the data, and will be taken into consideration when interpreting the results of the empirical analyses that follow.

It is inescapable that crime clusters, and this was established at a number of spatial scales for the robbery data in this Chapter. Consistent with prior research, spatial heterogeneity was readily identifiable when progressing down the geographical cone of resolution. One notable finding from the spatial analyses was that robbery clusters in the greater Glasgow area, with the city centre experiencing the greatest concentration.

Repeat victimisation, at both street segment and location level, was observed in the data, corroborating that robbery is highly spatially concentrated in the study area. When the locations were analysed through their description field it emerged that the majority were described as occurring on the street, with the remainder occurring in other types of public outdoor space.

In Chapter 2 I argued that to advance knowledge on why crime patterns emerge it is necessary to consider the precise environmental conditions that are present micro-spatially *and* micro-temporally. To that end, the last section of this Chapter was concerned with eliciting descriptive temporal patterns in the robbery data. Analyses revealed that a downward trend was operating in conjunction with a distinctive seasonal trend over the ten year study period. This will be explored in greater statistical depth in Chapter 4.

Robberies were found to concentrate on weekend days, a finding that mirrors previous research (LeBeau & Corcoran, 1990; Cohn & Rotton, 2000; Ceccato, 2005). Drilling down into the data revealed that the hourly distribution of robbery is markedly different for weekdays and weekends. This speaks to the obligatory/discretionary activities distinction made above (LeBeau & Coulson, 1996). Robbery has long been associated with discretionary activities, due to its spatial relationship with areas which host leisure pursuits (Felson, Savolainen, Berg & Ellonen, 2013; Harper, 2006;

Smith, 2003). These findings also indicate that aggregation bias is possible from a temporal perspective (as well as a geographical perspective, as outlined in section 3.2). This strengthens the justification for a micro-temporal focus.

Collectively, these findings have practical implications, since being able to anticipate patterns in space and time provides a fruitful means of predicting crime. When crime events are unevenly distributed through time it means that traditional police responses such as high visibility patrolling need to be carefully tailored to the geographical and temporal regularities in the crime data. Other crime control tactics may prove more successful in terms of addressing those enduring characteristics of certain settings that give rise to chronic offending. For these reasons, it is necessary to generate a more nuanced understanding of the factors influencing the spatio-temporal dynamics at settings, so that knowledge in turn can be translated into effective prevention strategies.

In sum, the analyses presented in this Chapter have revealed spatial and temporal trends in the data, which help to set the scene for the in-depth empirical contribution that forms Chapters 4 to 6. The specific situational conditions which give rise to opportunities for robbery will be explored through hypothesis testing in the coming Chapters.

4. DARKNESS AND ROBBERY

Chapter overview

The relationship between behaviour and the seasons has been contemplated since records began (Wolfgang, 1958; Harries, Stadler, Zdorkowski & Variation, 1984). Some scholars have traced this back to Aristotle's musings on the relationship between thermic seasons and suicide. Others have credited Hippocrates with writing about criminal seasonality (Brearley, 1932 as cited by Block, 1984). As such, the seasonality of criminal behaviour has been well chronicled throughout criminological history (see Baumer & Wright, 1996 for an extensive coverage). Despite an impressive corpus of research over the past two centuries, no universal trends have yet emerged regarding the seasonality of crime, either in general or for specific types of crime (Block, 1984; Mcdowall, Loftin, & Pate, 2011; Yan, 2004).

This Chapter extends the knowledge base on seasonal rhythms for the crime of robbery by considering the influence of darkness on the crime event. While this meteorological variable has been theorised as being relevant to the opportunity structure for commercial robbery (Landau & Fridman, 1993; van Koppen & Jansen, 1999) and residential burglary (Coupe & Blake, 2006), it has not been explicitly tested for street robbery (which is different from commercial robbery in several respects). This study aims to address this gap and ultimately argues that darkness is an important driving factor that may explain seasonal variation in street robbery.

A number of environmental conditions that vary over the seasons exist that may influence the opportunity for crime. Chapter 5 explores the contribution temperature, and weather conditions more generally, have to explaining robbery patterns. In this Chapter, the objective is to examine the extent to which darkness predicts the frequency of street robbery over the course of the year. The specific hypothesis to be tested is that the presence of darkness will increase the likelihood of street robbery occurring, when seasonal variations in temperature are accounted for. Thus, temperature is used as a control in this study, rather than an explanatory variable. Supplementing the focus on darkness, an ancillary objective is to examine the influence of twilight on the robbery event. This part of the analysis is exploratory since there is no theorising to date which might be applied to suggest a directional relationship.

This Chapter begins with a review of the theoretical background to the research, and outlines empirical evidence pertaining to the seasonality of robbery. Empirical analyses are then presented to: 1) explore seasonal variation and underlying trends in the data discussed in Chapter 3 using a formal time series approach, and; 2) to test the hypothesis that the trends observed can be

explained by variation in darkness. In the discussion the implications of the findings are expounded. This Chapter is based in part on the findings reported in the following paper⁶, published as a result of research undertaken for this thesis:

Tompson, L. and Bowers, K. (2013). A Stab in the Dark? A research note on temporal patterns in robbery. *Journal of Research into Crime and Delinquency*. Vol 50(4), pp. 616-631.

4.1 Theoretical background

A quintessential question is why seasonal variations in crime exist, or exhibit the particular nuances that they do. The tradition to date has been to adopt theories relating to weather – either the physiological effect of temperature (see Anderson, Anderson, Dorr, DeNeve & Flanagan, 2000 for a good summary) or the social effect of weather on the routine activities of people (Felson, 1987). Typically, the temperature-aggression hypothesis has been adopted by those wishing to explain violent crime levels, whereas the routine activity approach has been employed to understand trends in both property and violent crime (Rotton & Cohn, 2000). While both perspectives suggest that temperature and other weather variables are related to crime rates, they propose different causal mechanisms for these relationships (Hipp, Bauer, Curran & Bollen, 2004).

The criminogenic quality of darkness

Whichever theoretical standpoint is taken, it is clear that much emphasis has been given to the relationship between crime and temperature. Yet, it is plausible that another meteorological variable – darkness – is so intimately associated with temperature that it, rather than variation in temperature, might explain the patterns reported in prior research. To elaborate, seasonality is a socially-constructed category defined by a combination of hours of daylight and temperature. Temperatures peak and drop throughout the course of the day – often, but not always, corresponding with sunrise and sunset.

Humans are primarily diurnal creatures (that is, active in the daytime), with the biological need to sleep placing temporal constraints on mobility patterns (Ratcliffe, 2006). Much social behaviour, and the environment built to support it, is borne out of this activity-rest configuration. Generally speaking, for most people formal obligatory activities are undertaken in the daytime, leaving the evening and weekend periods free for discretionary activities. As a result, for many months of the

⁶ The paper published on this topic used a two-year period over which data for Strathclyde and Camden and Islington in London were available. The analysis in this Chapter therefore extends these analyses with a longer time-frame and uses more precise temperature data and the variable of twilight.

year, discretionary activities in public space are pursued in the evening during hours of darkness. These recreational subsets of routine activities comprise lifestyle choices and hence may attract specific sub-groups of the population – namely young people, males and unmarried people (Hindelang et al., 1978; Cohen & Felson, 1979). Thus, time periods characterised by conditions of darkness influence the types of routine activities people are engaged in and in turn the likelihood that suitable targets and motivated offenders will converge at particular locations in the absence of capable guardianship.

Contemporary theorising has begun to consider the influence darkness exerts on effective guardianship with respect to burglary. As Bowers and Johnson (2015: 18) write "levels of guardianship – the volume of potential guardians and their ability to detect and challenge criminal behaviour - will differ by daylight and darkness". Substantiating this assertion, Coupe and Blake's (2006) work demonstrated that some residential dwellings are excellent day-time targets for burglars whilst simultaneously being poor targets at night-time. Burglars who operated in the daylight were more likely to select unoccupied residences with better front cover (i.e. obstruction of sightlines from the front), and also employed different modus operandi from those operating in darkness. At night-time the availability of guardians in occupied dwellings did not deter some burglars, as the cover of darkness reduced the former's ability to effectively monitor their surroundings. Coupe and Blake's research demonstrates that offenders behave differently in darkness than they do in daylight, adapting and optimising their tactics to suit their surroundings to minimise the risk of being disturbed.

The configuration of the built environment – in particular the street network – plausibly affects guardianship dynamics over the day. The rhythms of activities (and behaviour) across diverse street segments can be seen as a product of usage – that is, the through movement of residents and non-residents as they perform their routine activities. On this basis, Johnson and Bowers (2013) theorise that the ecology of street segments is time-varying, which impacts on guardianship potential over the course of the day. In this work they show that the risk of burglary varies across different types of streets depending on the time of day. Specifically, major roads, which would be expected to have the greatest usage, had a significantly lower risk of burglary at night-time compared to the day-time. Contrastingly, local roads had a significantly higher risk of burglary during night-time hours compared to the day-time. This finding was explained in relation to the on-street dynamics of guardianship, in that fewer potential guardians would be largely inconspicuous (due to local roads being used by residents and non-residents).

Extending this work Bowers and Johnson (2015) reason that offenders are more likely to seek opportunities for burglary proximal to their homes during night-time hours, while in the day-time their activities and hence offending is more likely to be geographically dispersed from their residences. From this they posit that night-time burglary is more likely to be committed by *insiders* (i.e. residents) and day-time burglary by *outsiders* (non-residents). Their findings, that the distance travelled by a sample of burglars (the so called journey-to-crime) was typically shorter at night-time compared to during the day, support these hypotheses. Based on this, Bowers and Johnson (2015) reason that offender activity spaces (in the context of crime pattern theory) are likely to be time-sensitive.

Extending this logic, it is also possible that guardians' and potential victims' awareness spaces are time-sensitive too. Places that are familiar during the day-time may become unfamiliar territory at night, insofar that the people who use them vary over the course of the day. Hence, conditions of darkness may produce 'unawareness spaces', where people are more likely to be victimised (Hodgkinson & Tilley, 2007). One of the reasons for this heightened risk of victimisation may be the effectiveness of guardians at these dark places. Darkness impairs people's ability to monitor their surroundings and hence could be an important obstacle to effective surveillance, or the perception of surveillance, which may impact on guardianship and, as a corollary, crime (Bowers & Johnson, 2015).

The empirical challenge to date has been disentangling the effect of temperature from that of darkness (Michael & Zumpe, 1983). Whilst a handful of scholars have included measures of photoperiod (day length) in their analysis, this has usually been at a coarse temporal resolution so that the effect of temperature is not clearly distinguished from that of darkness. For example, Heller and Markland (1970) included hours of sunlight in a regression analysis of daily calls for service incidents but found it to be less influential than the daily average temperature. Lab and Hirschel (1988) attempted to control for lighting conditions in their research on crime and weather by constructing four sets of 6-hour periods, approximating shifts in daylight and darkness hours. In this study the relationship between temperature and assaults was consistent during the day and at night. Through multiple linear regression Cohn (1993) found that darkness was highly related to rape and domestic violence. Given that different manifestations of criminal behaviour are attributed to different opportunity structures (with dissimilar temporal rhythms) these inconsistent results are not surprising. Instead they indicate that a crime-specific approach (Felson & Clarke, 1998) is needed to elicit whether darkness is indeed criminogenic.

Whilst temperature and darkness are hypothesised to covary (Michael & Zumpe, 1983), this may not be a straightforward linear association. For some crime types the opportunity structure may favour warmer light conditions; for others warmer dark conditions may be optimal. The latter is particularly salient for street robbery which depends on the availability of victims in public space, which may plausibly be influenced by weather conditions (this is explored in greater detail in Chapter 5). It may also be the case that fluctuations in temperature explain when people use public space and that darkness is irrelevant to the criminogeneity of the robbery setting.

The seasonality of robbery

Street robbery is a unique crime type in that it does not fit neatly into either property crime or violent crime categories. Simply put it can be either, or both. Although some scholars have noted cultural, or dispositional motivations for robbery (Wright, Brookman & Bennett, 2006) it is largely assumed to be rationally committed with both instrumental and expressive motivations (Van Patten, Mckeldin-Coner & Cox, 2009), albeit often in desperate circumstances (Wright & Decker, 1997). A robber might be motivated by violent impulses, or instead, by the perceived economic reward. They might never resort to violence to procure the victim's valuables, or they might always resort to violence. Despite different motivations, what all street robberies have in common is that they are a form of violence that occurs outside of the home (and often in the absence of capable guardianship), and thus are harmonious with the theoretical framework.

Previous research on the seasonality of robbery has tended to find that both street and commercial robbery peak in frequency during the winter months (DeFronzo, 1984; Field, 1992; Deutch, 1978; Michael & Zumpe, 1983). This trend, however, is not consistent across different contexts and different measures of criminal behaviour (for contrasting trends see Block, 1984; Rotton & Cohn, 2000; Sorg & Taylor, 2011). Several explanations have been advanced for this seasonal increase in robberies. In most cultures in the northern hemisphere winter is more economically demanding; it is a time when the cost of living is higher and unemployment rates may be greater (Sutherland, 1947; Cohn, 1990b; Landau & Fridman, 1993). Both of these conditions may produce a greater supply of motivated offenders. Contemporaneously, the Christmas holiday period in western cultures produces a heightened availability of cash and desirable goods in society (in buildings and on people), and thus is theorised to create more suitable targets (Field, 1992).

An alternative explanation for the winter peak is that environmental conditions in winter – such as darkness – might facilitate robbery (Landau & Fridman, 1993). When analysing *commercial robberies* van Koppen and Jansen (1999) found there was a near symmetrical monthly pattern of

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commercial robberies either side of the winter solstice that could not be explained in relation to the period preceding Sinterklass and Christmas. Using the premise that darkness is important to the opportunity structure, this sharp peak in winter offending was attributable to an increase in robberies committed in the evening hours (between 4.26pm and 10.02pm - the sunset times in midwinter and midsummer). Stepwise regression analysis was undertaken to test whether these differences in the monthly variation of robbery remained when the effects of weekdays; national holidays; hours of daylight; school holidays and weather variables were controlled for. The results led van Koppen and Jansen to conclude that "the winter peak in robberies can better be explained by the dark hours during the evening than by other possible factors" (1999: 25). These findings lend credence to the view that darkness is a facilitating environmental condition for commercial robbery.

Commercial robbery has the constraint that it can only occur whilst the target establishment is open. This is not the case for street robbery which can happen at any point in the day that targets are available. Whether the influence of darkness is a predictor of levels of street robbery has been unexplored by the research community until now.

4.2 Hypothesis, data processing and analytic strategy

The purpose of the analyses in this Chapter is two-fold. First, as a precursor to the analysis which follows in this and subsequent Chapters, time series analysis in the form of auto-regressive, integrated, moving-average (ARIMA and ARIMAX) models are used to detect underlying trends in the street robbery data. Based on the descriptive analysis in Chapter 3, it is anticipated that a seasonal component will be found to be important in these data. The second stage makes use of a different modelling strategy - negative binomial regression models – which are employed to explain the patterns found in in preceding time series analysis.

The objective of this study is to examine the extent to which darkness predicts the frequency of street robbery over the course of the year. I previously conjectured that temperature and darkness may be strongly related. It is thus important to assess the degree of association between these two variables, and the consequent relationship this has with levels of street robbery. The specific hypothesis tested in this Chapter is:

H1: The presence of darkness will increase the likelihood of street robbery occurring when seasonal variations in temperature are accounted for.

This research thus aims to contribute to the knowledge base on seasonality in street robbery. The time of day robbery occurs is central to this study, which permits a more direct test of the effect of darkness alongside the control variable of temperature. Consequently, this research advances prior

studies considering the influence of darkness by sharpening the unit of measurement so that it more faithfully represents the covariates being studied.

In the tradition of crime science the use of only one crime type speaks to crime *specificity* (Felson & Clarke, 1998), and protects against crime-type heterogeneity which is commonly seen in studies on seasonality and crime. Whilst this limits the generalizability of the findings (for other offence types), it enriches the knowledge base for street robbery which, despite having very different characteristics to other types of crime, is often studied simultaneously with commercial robbery and/or violence.

This section describes the analytic approach to testing the hypothesis. In doing so I describe the data employed, the statistical models, and related diagnostic tests which determine the calibration of the models. In this analysis I also examine the influence of twilight, since this has not been investigated in the extant research literature.

Data

This research employed the robbery data discussed in Chapter 3. Supplementary data sources used to test the key hypothesis for this Chapter are described in what follows.

Astronomical data

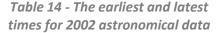
Astronomical data for Glasgow – the largest city in the study area - were downloaded from <u>www.timeanddate.com</u> for the ten-year study period (2002 to 2011). This included sunrise and sunset times, and start and end times for three different subcategories of twilight; astronomical, nautical and civil. Each of these categories of twilight is defined by the solar elevation angle – the position of the sun relative to the horizon. The further the sun is below the horizon the dimmer the twilight.

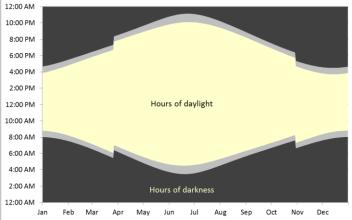
Astronomical twilight begins, in the case of morning twilight, and ends, in the case of evening twilight, when the sun is geometrically 18 degrees below the horizon. Time outside this period demarcates intervals when the sky is dark enough for the observation of all planets and stars. Nautical twilight starts later in the morning and ends earlier in the day, when the sun is 12 degrees below the horizon. During nautical twilight sailors are able to reliably identify stars for navigation using the horizon for reference. When nautical twilight segues into astronomical twilight the horizon is no longer visible.

Civil twilight occurs when the geometric position of the sun is six degrees below the horizon. During civil twilight objects on earth are perceptible and the horizon is clearly distinguishable. Civil twilight

is often used by lighting engineers to determine when street lighting should commence and conclude. For this research, civil twilight was considered to be the most suitable representation of the transition between complete darkness and complete lightness. All subsequent references to twilight hence refer to civil twilight. Table 14 displays the earliest and latest times for the astronomical data and Figure 16 depicts these values across the entirety of the calendar year (for 2002), with the grey area representing civil twilight time.

	Earliest	Latest	1
	time	time	1
Twilight start	03:29	08:01	•
Sunrise	04:31	08:48	
Sunset	15:43	22:07	
Twilight end	16:30	23:09	. 1







Temperature data

Two types of temperature data in centigrade were sourced from <u>www.wunderground.com</u> for Glasgow Airport (EGPF); daily summary values and sub-hourly weather readings. For the former, these contained the daily maximum (high) temperature, the daily minimum (low) temperature and a daily average temperature for all 3,652 days in the study period. For the latter, a total of 164,270 weather readings were available over the ten year period for which the data were analysed. These readings were typically taken every 30 minutes, although just over three per cent of the time spans were greater than this because of missing data and the daylight saving clock time changes in March.

Summary statistics for these ten years of temperature data are displayed in Table 15. This shows that there was variation in the range of temperatures recorded across the study period, from a minimum of -15 to a maximum of 28 degrees centigrade. On the coldest days, the highest temperature was below freezing, but on the warmest days the lowest temperature (presumably at night-time) can be considered quite warm. Hence, this study area experiences a considerable range of temperatures across the year, with the variance for each of the metrics being similar.

	Minimum	Mean	Maximum	s.d.
Daily high temperature °C	-8	12.9	28	5.3
Daily average temperature °C	-15	5.6	18	5.3
Daily low temperature °C	-11	9.0	22	5.0

 Table 15 - Summary statistics for temperature data for Glasgow (2002-2011)

To ameliorate concerns that readings at the weather station were unrepresentative of the wider Strathclyde study area the differences between Glasgow Airport and nearby weather stations in other parts of the study area were explored. The daily minimum, maximum and average temperature for the weather station closest to the majority of robberies (Drumalbin) exhibited good agreement with the Glasgow Airport readings (respective correlations: 0.93, 0.96 and 0.96; all pvalues were less than 0.001). Other weather stations (Islay, Oban and Glen Ogle) exhibited similar levels of agreement and thus the differences were negligible. The weather readings from Glasgow Airport were therefore considered appropriate to use as a sole data source.

Detecting seasonality with ARIMAX models

Measuring change in any phenomena over time requires the use of appropriate analytical techniques due to the intrinsic temporal ordering of – or structure to - the data. This temporal ordering typically produces *autocorrelation*, that is, the residual errors are correlated across consecutive time periods. Autocorrelation violates a key assumption in Ordinary Least Squares (OLS) regression, namely that the residuals are independent. A systematic pattern in the residuals suggests an important variable is (or variables are) omitted from the model. In this scenario, OLS regression is likely to return downwardly biased standard errors, and hence may lead to Type I errors.

Time series analysis addresses these weaknesses in OLS and is used when observations are repeatedly made over a number of time periods (usually 50 or more). Time series analysis can be used for several purposes; to detect trends in the data, to forecast, and to test the relationship between dependent and independent variables over time. In the ensuing analysis I focus on the first of these to determine if there are statistically discernible seasonal patterns present in the robbery data. This is a necessary precursor to the empirical analysis later in the Chapter, since it is prudent to correct for such trends in statistical models if they exist. Thus the aim of the analyses presented in the next section is to inform the model specification used in the regression analysis that follows.

Time series analysis of the Box-Jenkins type (Box & Jenkins, 1976) is primarily concerned with the empirical identification of a model which best fits the data, and commonly takes the form of an autoregressive (AR), integrated (I), moving average (MA) model. To correct for fluctuations in data points new variables are introduced which comprise lags of the dependent variable (AR), lags of the errors (MA), or both (ARMA). The 'I' in ARIMA refers to the integration of a dependent variable that has been made stationary (which often involves subtracting sequential observations from each other), so that the underlying trends are removed through transforming the data.

When independent variables are included in ARIMA models they are known as ARIMAX models. These capture the association between variables over time when both independent and dependent variables are observed at the same unit of analysis. One of the limitations of ARIMAX models is that the coefficients relating to the independent variables can be unintuitive to interpret. The presence of lagged values of the dependent variable means that beta coefficients for the independent variables can only be interpreted relative to the original values of the dependent variable. For this reason, ARIMAX models are employed in this study to determine whether the inclusion of the independent variables of temperature and darkness in the models is associated with an improved model fit, and hence, whether they are associated with any identified trends.

Data processing for ARIMAX models

To my knowledge there is no consensus on the most appropriate unit of analysis to use in time series analysis on temperature and crime (Rotton & Cohn, 2000), so these were chosen to reflect established units of time: months and weeks⁷. The street robberies were thus aggregated to lunar month and week intervals over the data period. For this time series 120 data points relating to months were available with a minimum of 50 and a maximum of 245 robberies per month.

Whilst lunar months are intuitive, as a unit of analysis they have some notable shortcomings. Prominently, the number of days varies across months and, furthermore, the number of *weekend* days varies across months. Since weekend days are known for driving a lot of criminal activity (LeBeau & Langworthy, 1986) more robberies may occur in months with more weekend days. Weeks were hence selected as a form of sensitivity analysis since this unit of analysis standardises the number of weekend days. The weekly aggregated robbery data resulted in 521⁸ data points with a minimum of 3 and a maximum of 64 robberies. The greater number of data points available at this

⁷ Using two intervals also makes it possible to see if the conclusions drawn are sensitive to the time periods studied.

⁸ The first week was excluded from the analysis because it only contained a partial week of data.

level of resolution increased the statistical power to detect evidence of underlying trends in the data (should they be present).

To assess the relationship between lighting conditions and frequency of robbery, a variable was created to characterise observed variation of light at each level of aggregation (months and weeks). The mean number of hours of darkness (per day) was generated at the month and week level using the astronomical data. This required transforming the time difference between the sunrise and sunset variables to numeric form, before subtracting from the equivalent of 24 hours.

From the weather data the mean daily average temperature was calculated for each month and week in the study period. The summarised weather data and astronomical data were subsequently joined to the robbery data, using the month or week number as the unifier. Once this data processing was complete, for each month and week in the data period, the data set included the count of robberies, the mean hours of darkness per day and the mean temperature.

ARIMA modelling procedure

ARIMA analysis is powerful and flexible, but requires some expertise to select an appropriate model specification. Such models have three parameters, (p, d, q), which represent the autoregressive function, the number of differencing passes (to make the data stationary) and the moving average function. A preliminary analysis is required to determine the three parameters for the existing time series before any models can be fit. Subsequently, an optimal model is chosen from candidate models through a goodness of fit test. In what follows this process is summarised first for the monthly aggregated data and then for the weekly aggregated data.

It was shown in Chapter 3 that the robbery data exhibited a downward trend over the ten years of data. Moreover, seasonal decomposition indicated that there was a seasonal trend component to the time series (see Figure 12). For ARIMA models, if serial dependency is found in the time series then the data need to be transformed to have a constant mean and variance (i.e. made stationary). For this reason, to remove the general trend the monthly counts of robbery were differenced, which relates to values being created that represent the directional size of the difference between consecutive lags. A log transformation was also taken of the differenced values to establish if this stabilised the variance, but no improvement was apparent. These three time series are illustrated in Figure 17 for the monthly counts of robbery, with the first-differenced data in the middle box and the logged first-differenced data in the bottom box.

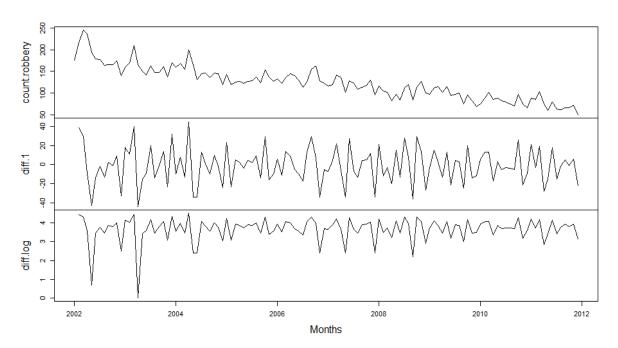


Figure 17 - Time series of robbery counts per month, with transformed values

The number of times the series needs to be differenced until it becomes stationary is reflected in the *d* parameter in the ARIMA model. The forecast::ndiffs command was used in R to employ a unit root test to verify that *d* should be 1 in the monthly time series models (thus the first-differenced data, where the difference in consecutive observations, were used). This is known as the *identification* phase of the analysis. The same ndiffs command was used on both of the independent variables, but this time the unit root tests indicated that these time series were already stationary.

The next step of the process is *estimation* whereby the *p* and *q* parameters are estimated. The autoregressive component of the time series represents the dependency among successive observations, and is denoted by the parameter *p*. Thus, auto-regression signifies that it is a regression of the variable against (lagged values of) itself. The *q* parameter refers to the order of the moving average component of the time series - the "lingering effects of preceding random shocks" (Tabachnick & Fidell, 2006: 18–1). Random shocks are otherwise known as white noise error terms. Thus, a model with three moving average terms (*q* = 3) is one in which an observation depends on the three preceding random shocks.

There are a number of ways in which the p, d and q parameters can be estimated. The prevailing approach is to visually judge the patterns exhibited by the autocorrelation (ACF) and partial-autocorrelation (PACF) functions in correlograms. Put simply, the former estimates autocorrelation between values of consecutive lags, whereas the latter estimates the autocorrelation between

values at specific lags after partialling out intervening autocorrelations (at say lag 1). Naturally, there are no intervening observations at lag 1 in the PACF so the autocorrelation for this is equivalent across both correlograms. Generating autocorrelation functions for the *pure* robbery counts results in Figure 18 and Figure 19. Both of these figures have confidence intervals - calculated from the standard error - to indicate which observed autocorrelation values are statistically significant (those values that exceed the blue dotted lines).

The autocorrelation between sequential lags is obvious in Figures 18 and 19, suggesting that something is contributing to the data generating process and that applying OLS regression would be inappropriate. Thus making these data stationary eliminates a threat to internal validity.

Figure 18 - Correlogram for non-differenced monthly time series (ACF)

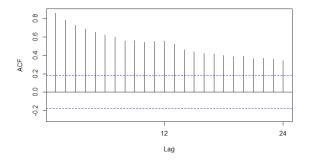


Figure 19 - Partial correlogram for nondifferenced monthly time series (PACF)

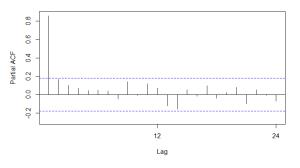


Figure 20 - Correlogram for differenced monthly time series (ACF)

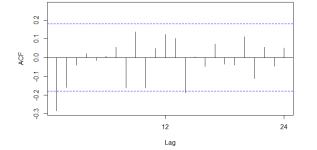
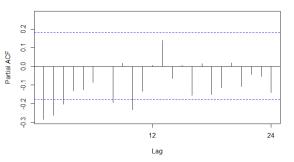


Figure 21 - Partial correlogram for differenced monthly time series (PACF)



We see from the ACF for the *differenced* data in Figure 20 that the autocorrelation at lag 1 (-0.287) exceeds the significance bounds. A negative autocorrelation such as this implies that if a particular observation is above average the next observation (or previous observation) is more likely to be below average, and vice versa. Lag 14 also displays autocorrelation in the ACF, but as this is only marginally outside the confidence interval (-0.188), and is not in the first few lags, it can be safely ignored (Hyndman & Athanasopolos, 2013). All other autocorrelation values do not exceed the significance bounds.

The PACF in Figure 21 shows that the partial autocorrelation at lags 1 to 3 negatively exceed the significance bound, and slowly decrease in magnitude (lag 1: -0.287, lag 2: -0.263, lag 3: -0.205). However, lags 8 and 10 also exhibit statistically significant autocorrelation, and whilst we could expect lag 8 to be significant through chance (as it is only marginally over the confidence interval) it is unlikely that this also applies to lag 10 which more noticeably exceeds the lower confidence interval. Hence, lag 10 may be statistically noteworthy. Since the PACF in Figure 21 is exponentially decaying, and the spike in Figure 20 is significant at lag 1, this *suggests* a first-ordered moving average model (using first-differenced data) without an autoregressive component – thus ARIMA (0, 1, 1). However due to lag 10 being autocorrelated in the PACF this is not clear-cut. If the roles were reversed and the ACF was exponentially decreasing and the PACF was only significant at the first lag this would conversely suggest a first-order auto-regressive model.

Convention dictates that a number of models should be run and the best fit assessed through a goodness of fit test. A suitable model should produce statistically independent residuals that contain no systematic components (i.e. there should be no serial dependency remaining in the residuals). For this reason the model residuals are inspected through correlograms and a portmanteau test is conducted to determine if the residuals are autocorrelated.

The forecast::auto.arima command in R can be used to estimate candidate models. To determine the number of differencing passes -d - this function uses a KPSS unit root test (closely allied to the widely-used Augmented Dickey-Fuller test) to test the null hypothesis that a time series is stationary around a deterministic trend. The test returns a value that represents the least number of differences required to pass the test at a given statistical significance level. Thereafter, the p and q parameters are selected by using the smallest corrected Akaike's Information Criterion (AICc) for a range of model specifications. In essence, the AIC is a measure of fit that introduces a penalty for adding more variables (unlike R²). The aim of auto.arima is to suggest an optimal model that best explains the temporal trends in the data (although it is worth noting that this is not always a parsimonious model).

If present in the time series data, the auto.arima command can additionally suggest models that account for seasonal patterns. This is achieved by including additional *seasonal* terms in the model. Uppercase notation is used for the seasonal terms (*P*, *D*, *Q*), whereas lowercase notation (*p*, *d*, *q*) is used for the non-seasonal parts of the model. Both terms are multiplied in the ARIMA analysis – resulting in a model written as (*p*, *d*, *q*) (*P*, *D*, *Q*)_{*m*} where m relates to the number of periods per season, *P* = number of seasonal autoregressive (SAR) terms, *D* = number of seasonal differences and *Q* = number of seasonal moving average (SMA) terms. The auto.arima command was used to estimate a series of ARIMA models for the differenced count of robberies per month. This revealed that a seasonal *and* non-seasonal first-order autoregressive component was needed to model the monthly time series, in conjunction with a non-seasonal first-order moving average component. This ARIMA(1,1,1)(1,0,0)₁₂ model produced the coefficients shown in Table 16. The portmanteau test suggested that the residuals in this model were behaving as white noise ($X^2 = 9.16$, d.f. = 8, p-value = 0.33). This is indicative of a monthly seasonal trend in the data (m = 12).

	AR1	MA1	SAR1	drift						
Coefficients	0.375	-1.000	0.162	-0.997						
s.e.	0.086	0.026	0.102	0.071						
N.B. AICc = 989.7, log-likelihood= -489.6										

Table $16 - Seasonal ARIMA(1, 1, 1)(1, 0, 0)_{12}$ model results for robberies per month (no IVs)

Including the *non-differenced* independent variables into the model specification in Table 16 produced the ARIMAX results in Table 17^9 . This shows that the inclusion of darkness and temperature into the model does not improve the model fit (the AICc increases to 1003.11), and that due to large standard errors neither of the independent variables is associated with monthly counts of robbery. The portmanteau test suggested that the residuals in this model were behaving as white noise ($X^2 = 10.74$, d.f. = 9, p-value = 0.29).

Table 17 - Seasonal ARIMAX $(1, 1, 1)(1, 0, 0)_{12}$ model results for robberies per month (with IVs)

	AR1	MA1	SAR1	Darkness	Temperature					
Coefficients	0.208	-0.754	0.230	-0.099	-0.083					
s.e.	0.152	0.097	0.103	1.015	0.834					
N.B. AICc = 1003.11, log-likelihood= -495.2										

Yet, as suggested by Greenberg (2001), theoretically we would expect the difference in robbery rates across consecutive time lags to be predicted by the difference in the independent variable values. Hence, to protect against 'spurious regression'¹⁰, further models were run with first-differenced dependent *and* independent variables. As before, the auto.arima command was used to estimate a

⁹ Running the same model specification with the covariates entered individually resulted in no appreciable difference in AICc and although the coefficients and attendant standard errors were smaller for the (singly included) independent variables they remained non-significant.

¹⁰ <u>http://robjhyndman.com/hyndsight/arimax/</u> clarifies this in his statistical forecasting blog.

series of ARIMAX models for the differenced dependent variable (count of robberies per month) and the differenced independent variables (mean darkness per day and mean daily temperature). This suggested that the best fit model was ARIMA (0, 1, 1). However this model did not satisfy the removal of autocorrelation in the residuals. After the testing of several similar model specifications an optimal model was ARIMA (0, 1, 2) which represents a second-order moving average component when modelled with differenced mean hours of darkness and mean temperature.

The results for this optimal model are displayed in Table 18. These show that the standard errors for both darkness and temperature are larger than the coefficients and hence, even when the independent variables are differenced they are not significantly associated with (differenced) counts of robbery⁹. The Box-Ljung portmanteau test returned a non-significant p-value ($X^2 = 10.20$, d.f. = 11, p = 0.51), suggesting that no autocorrelation remains in the residuals for this model. Interestingly, the AICc is on par with that of the model in Table 17, despite there being no seasonal parameters. Since the optimal model in Table 18 has fewer components it can be considered the more parsimonious model.

Table 18 – ARIMAX (0,1, 2) model results for robberies per month (with IVs)

	Intercept	MA1	MA2	Darkness	Temperature					
Coefficients	-0.989	-0.652	-0.348	-0.376	-0.382					
s.e.	0.054	0.087	0.081	0.866	0.716					
N.B. AICc = 1003.7, log-likelihood= -495.5										

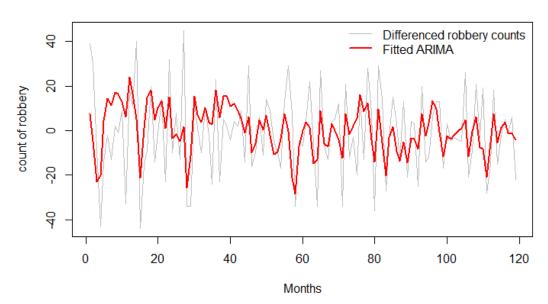


Figure 22 - Fitted ARIMA model and time series of (differenced) robberies per month

The fit between the ARIMA model in Table 18 and the differenced time series of robbery counts per month is visualised in Figure 22. Whilst obviously smoothing the trendline, the ARIMA model mimics the variance in the data. However, since this is a complex time series it is not an exact fit.

Having established that a moving average error term is important when modelling the robbery counts with the independent variables at a *month* level, it is instructive to conduct a sensitivity analysis to ascertain if this holds at a finer grain of resolution. Due to the considerable variation in both darkness and temperature in the span of a lunar month, the week level might be more appropriate as a unit of analysis. The following analyses repeat those presented above, with an abridged discussion.

Once again the first-differenced variables were used in the ensuing analysis, as log transformation of the differenced data did not noticeably improve the variance of the time series. The same unit root tests were used to verify that p was equal to 1. The ACF and PACF correlograms of the first-differenced weekly time series disclose that a moving average component is likely important to the ARIMA modelling, as the autocorrelation in the PACF decays exponentially and the ACF only exhibits autocorrelation at lag 1 (Figure 23).

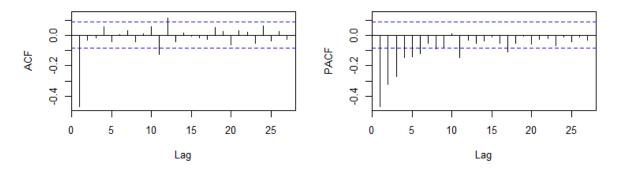


Figure 23 – ACF and PACF correlograms for (differenced) robbery counts per week

Using auto.arima an optimal ARIMA model for the weekly time series of robbery counts was determined to be ARIMA(0, 1, 1)(1, 0, 1)₅₂. Hence, this had a seasonal *and* non-seasonal first-order moving average component and a seasonal autoregressive component when first-differenced data was used. The residuals represented white noise and the AICc for this model is 3,468.9. The model coefficients are not shown, but suggest that a complex seasonal trend at the week level is present in the time series data. Running the same model specification with *non-differenced* independent variables resulted in an ARIMAX model with a larger AICc (of 3,474) and non-statistically significant independent variables (results not shown)⁹.

For the same reasons as outlined above, the final ARIMAX model had *all* the variables differenced. The optimal model generated from the preliminary analyses was ARIMA (1, 1, 2). Hence, this had a first-order autoregressive component and a second-order moving average component. The ACF and PACF plots for this model suggested no autocorrelation in the residuals remained and a Box-Ljung portmanteau test returned a non-significant p-value ($X^2 = 9.07$, d.f.= 9, p = 0.43). The model results for this are displayed in Table 19⁹. This shows that the standard errors are larger than the coefficients, and consequently neither darkness nor temperature is associated with the counts of robbery per week. The AICc for this model is slightly larger than the previous one using non-differenced data, which suggests that, although it is more parsimonious, it does not result in an improvement in model fit.

	Intercept	AR1	MA1	MA2	Darkness	Temperature								
Coefficients	-0.054	0.887	-1.767	0.767	0.038	0.026								
s.e.	0.004	0.058 0.08		0.080	0.178	0.124								
-		ALC: 2.40												

Table 19 – ARIMA (1, 1, 2) model results for robberies per week (using differenced data)

N.B. AICc = 3,483.5, log-likelihood= -1734.7

Figure 24 illustrates the fit between the ARIMAX model in Table 19 and the differenced time series of robbery counts per week. This figure is unclear as the fluctuations of the differenced time series are pronounced and numerous (over 520 weeks in the data period) making the underlying trendline difficult to visualise. However, whilst smoothing for the shocks that are obvious in this fine-grained data the ARIMAX model appears to approximate the trendline.

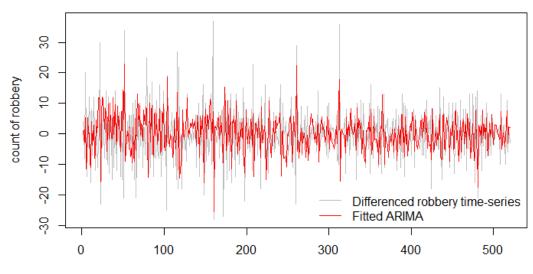


Figure 24 - Fitted ARIMA model for (differenced) count of robberies per week



Conclusions from ARIMAX modelling

Whilst ARIMAX modelling is protracted, it is the most appropriate technique for establishing whether autocorrelation exist in data (Tabachnick & Fidell, 2006). The preceding analyses reveal that at both levels of aggregation (monthly and weekly robberies) a second-order moving average parameter is required to appropriately model the time series when independent variables are included, with the week level also calling for an auto-regressive parameter.

Seasonal components were not present in the differenced time series models. However, when the untransformed dependent variable was included in separate ARIMA models an auto-regressive seasonal component parameter was required to appropriately model the seasonality. This is likely attributable to the darkness variable which exhibits a stable oscillating pattern throughout the year.

Collectively these results imply that complex trends are present in the robbery data, and modelling these necessitates a sophisticated consideration of the different influences on the shocks in the time series (which can be viewed as analogous to error terms in other statistical modelling techniques). The independent variables of darkness and temperature are unrelated to the overall count of robbery in the models at week and month level and their inclusion does not result in an improvement in model fit, and therefore they cannot be considered to be explanatory variables for the observed trends.

Considering the crude level of resolution at which temperature and darkness are being measured in these models, this is perhaps an unsurprising finding. Temperature fluctuates over the course of a day, and therefore the mean value for the week, or month, is not necessarily representative of what is occurring at micro units of time. This emphasises that the unit of analysis is crucial in research on temporal crime patterns, for the variation in explanatory variables may be masked when employing coarse levels of resolution. In addition, some scholars believe that time series models do not directly test causal relationships, and consequently should only be used for detecting trends and for forecasting (O'Brien, 2001; Shmueli, 2010).

The spatial cone of resolution discussed in Chapters 2 and 3 can be usefully adapted to account for units of analysis in temporal crime patterns. Figure 25 visualises how this might be conceived with a selection of units of time that are meaningful to human activities. At macro levels of resolution we might study crime patterns at the year or month level. Progressing down the cone to more 'meso' resolutions we might employ weeks or days as the unit of analysis. The micro level would require the measurement of crime, and any explanatory variables, at minutes or seconds. Clearly the resolution at which we study crime is dependent on the resolution at which the crime data (and potential covariates) are available. This thesis aims to advance the analytic focus further down the

cone of resolution to more precise units of time than have been used in research to date (which tend to be at the month and week level). Put differently, the preceding analysis is instructive but, by being subject to the ecological fallacy, may not provide a fair test of the hypothesis tested in this Chapter.





Negative binomial regression

To test the central hypothesis for this Chapter (that the presence of darkness will increase the likelihood of street robbery when temperature is controlled for), a different modelling approach using micro-level units of analysis that are sensitive to variation in darkness and temperature is warranted. Counts of crime - however measured, but particularly at low levels of spatial and/or temporal resolution - often display a skewed distribution, leading to a widespread assumption in the literature that crime is distributed according to a theoretical Poisson process (Piquero, Farrington & Blumstein, 2003). Poisson regression techniques have emerged in the last decade as a means of modelling such distributions.

In the current study a number of diagnostic tests were run to establish which type of Poisson regression model would best suit the distribution of the dependent variable (see more below), and negative binomial regression emerged as the forerunner. If the conditional distribution of the outcome variable has a variance greater than the mean it is said to be over-dispersed. When this is the case, the standard errors in a Poisson model are likely to be underestimated. Negative binomial regression can be considered as a generalisation of Poisson regression since it has the same mean structure, but includes an extra parameter to model 'over-dispersion'. This results in better

estimates of the standard errors and therefore produces more reliable estimates of the beta coefficients.

Whilst time series models of negative binomial distributions have been developed in recent years, Brandt and Williams (1998) report that they cannot distinguish between the underlying processes causing the negative binomial distribution: namely, temporal heterogeneity or 'contagion' across time periods. Failing to account for the over-dispersion in count data in time series models can result in errors of inference (however ARIMA models do not suffer from this problem). In what follows in this section is a summary of the process to calibrate negative binomial models for the robbery data, whilst controlling for the trends identified in the ARIMA analysis. I first consider the most appropriate unit of analysis. Next, the data processing is outlined, before a commentary on the diagnostic tests that were run. These naturally lead in to the empirical findings which are to be found in the following section.

Operationalising the units of analysis

Seasonal crime volumes might well be affected to the greatest degree at certain times of the day; however, this is often an under-exploited area in seasonality research (notable exceptions are Cohn, 1993; LeBeau, 1994; van Koppen & Jansen, 1999). Testing whether darkness is correlated with street robbery necessitates consideration of the ways in which dark conditions vary over the days in a year. Even in midwinter there is a minimum of just fewer than 7 hours of daylight per day in the study area, and this extends to over 17.5 hours in midsummer (see Table 14). The variation in darkness thus only affects a portion of the day, and at other times in the day there is no variation.

Time of day – measured by hour - is therefore critical to the present analyses because it prescribes the absence or presence of daylight, and is intrinsically linked to different types of routine activities. One approach would be to segment the data into 24 hours in the day, but this would be analytically unwise as many cells would be generated and, due to the skewed nature of crime distribution, would inflate the number of zeros across those cells. To more clearly test the hypothesis it was necessary to aggregate crime data into temporal intervals.

Diverse examples of applying temporal bins exist within the criminological literature. Felson and Poulson (2003) propose simply splitting the day into two periods; 5AM to 5PM and 5PM to 5AM. Their reasoning is that 5AM demarcates the start of a new day; sunlight materialises to prompt working people to wake and the bars and night-time establishments are closed. Likewise, 5PM signifies another transitory time when evening activities begin. Whilst useful for summarising crime

data – Felson and Poulson (2003) refer to the 5-to-5 share of offences – this approach masks the many routine activities that can be taken within the two proposed periods.

Mindful of general temporal constraints on human behaviour, Irvin-Erickson et al. (in press) chose to analyse robbery data across three different time intervals, further split by weekend or weekday. 'Business hours' represented the working day between 6AM and 6PM, 'happy hours' represented recreational hours between 6PM and 2AM and 'bedtime hours' denoted time when most people are asleep – 2AM to 6AM. These temporal intervals were constructed to be sensitive to transportation and leisure patterns in the study setting.

Employing an empirical method to construct temporal intervals, Haberman and Ratcliffe (2015) used change point regression models to analyse American Time Use Study data to identify periods of routine activities. Four time intervals emerged from this analysis which the authors inferred related to the morning commute (6:45AM - 9:59AM); the school/work day (10:00AM - 4:29PM); the evening commute and leisure hours (4:30PM - 9:14PM) and the period when most Americans were at home (9:15PM - 6:44AM).

For the purposes of this study it was necessary to link the unit of analysis specifically to the particular window when darkness variation is the most pronounced. The greatest contrast between summer and winter months in the UK in terms of lighting, and quite possibly temperature, is between 4PM and 10PM. This period is distinguishable as it is when most people are primarily engaging in discretionary routine activities, as opposed to obligatory ones (LeBeau & Corcoran, 1990; LeBeau, 1994), and this is true for all days of the week. This 6-hour temporal interval therefore contains unique qualities that relate to temperature, darkness and behaviour and formed the first temporal interval, which I labelled 'late-hours'.

The second interval that contained variation in daylight (and possibly covarying temperatures) was the 4AM to 10AM period and was named 'early-hours'. This period is not so likely to have variable routine activities however, since in the week people typically have obligatory commitments and at the weekend mornings are often spent in the home. In contrast, the period 10AM to 4PM represents the time when conditions of daylight are constant throughout the year, and the 10PM to 4AM period is characterised by constant darkness. Routine activities are more stable in these intervals (respectively named 'mid-hours' and 'early-hours'), yet temperature is prone to variation sensitive to the seasons. These four 6-hour intervals are visualised in relation to the variation in light levels over the course of the year in Figure 26.

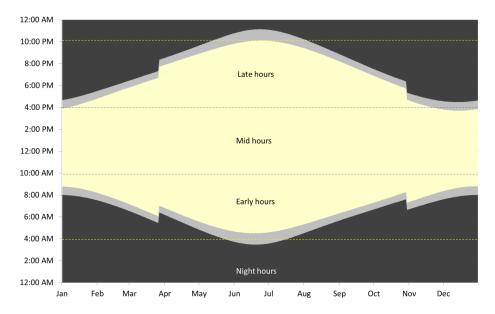


Figure 26 - Variation in light levels over the four 6-hour intervals

I thus chose the constructs of the independent variables to be as precise as the data would permit. This affords a more direct test of the influence of darkness than in prior research. Hence, I am aiming to predict the number of robberies in a particular interval that has a certain amount of darkness, and not purely trying to predict the number of robberies across the entire day. This helps to protect the analysis from the effects of potential temporal aggregation bias or the modifiable temporal unit problem (Dorling & Openshaw, 1992).

Data processing for negative binomial regression models

Robbery events were assigned to one of the four 6-hour intervals based on their start-time (this is justified by analysis in Chapter 3). Table 20 presents the distribution of robberies over these intervals and clearly shows that they are concentrated in the late- and night-hours.

Intervals	n	%
Early-hours (4AM - 9:59AM)	1,219	8.2
Mid-hours (10AM - 3.59PM)	3,416	23.0
Late-hours (4PM - 9.59PM)	5,389	36.3
Night-hours (10PM - 3:59AM)	4,833	32.5
Total	14,857	

Table 20 - Tempora	l concentration a	of street rohheries i	nto intervals
TUDIE 20 - Temporu	, concentration c	j street topperies h	nto mileivuis

Proportions of twilight and darkness were subsequently generated at the 6-hour interval level using the astronomical data. This required manipulating the date-time variables so that time calculations were possible in R. A value of 0 represented no darkness in the interval, a value of 1 represented 6 hours of darkness. Decimal values represented the proportional time when a transition from daylight to darkness (or vice versa) occurred. A separate variable was created for twilight. The maximum proportion of twilight in any interval in decimal form was 0.261 which represents just over 62 minutes of civil twilight.

The sub-hourly temperature data were then aggregated to the four 6-hour intervals and the mean temperature was calculated. Following the aggregation process 18 intervals had no temperature readings. These were assigned the mean values of temperature readings from the nearest two corresponding intervals (i.e. one day before and after). This was considered to be superior to assigning the mean values from intervals on the same day due to the notable variation in temperature over the course of a day. To explore the relationship between the two independent variables an interaction variable was subsequently created by multiplying each temperature value by the decimalised proportion of darkness in an interval.

Two control variables were created. The first was a dummy variable to control for the downward trend in robbery over the data period. This was constructed sequentially, so that all intervals on the first day of the data period were given a value of 1, the second a value of 2 and so on. The second variable was to control for the trends in the time series data, which is rarely accounted for in prior research on temperature and crime. Since the units of analysis were different in the time series analysis this was not straightforward. Following a similar approach to Steinbach et al. (2015), the daytime count of robbery – i.e. that which occurred in the 'mid-hours' interval – was used as a control variable in the models that follow. This was chosen as there was no variation in light levels (and minimal variation in twilight levels) and weekday routine activities would be stable during this period. This controlled for unusual events such as public holidays and seasonal variation in robbery frequency and helped to account for any serial correlation between the consecutive intervals. In doing so, this protected against generating downwardly biased standard errors (Brandt & Williams, 1998).

Once this processing was complete, the resulting data set contained the dependent variable (counts of street robbery in the early, late and night hour intervals for each day); the sequential control variable; the mid-hours control variable; the mean temperature in centigrade for each interval; the decimalised proportion of darkness in the intervals; the decimalised proportion of twilight in the intervals; and the interaction term. This resulted in 14,607 data points for the ten-year period (four intervals a day for 3,652 consecutive days minus one incomplete interval).

Diagnostic tests for negative binomial regression models

As is commonly seen with crime data, the dependent variable of robbery counts per interval best resembled a Poisson distribution (Osgood, 2000). These event counts were overdispersed with the variance greater than the mean ($\mu = 1.08$, $\delta = 1.49$). Vuong (1989) introduced a likelihood-ratio based test to select appropriate models with count data. Using the Kullback-Leibler information criterion, this test compares the predicted probabilities of two models. The null hypothesis is that two models fit equally well, and a null effect produces a test statistic of zero. A large positive test statistic evidences that model 1 has a superior fit to model 2; whereas a large negative test statistic evidences that model 2 is a more appropriate fit.

The pscl::vuong command was used in R to compute test statistics for each type of distribution against the count of robbery data; the results are illustrated in Table 21¹¹. This shows that extensions of the Poisson model are superior to the regular Poisson model. Zero-inflated models are used for modelling count variables with excessive zeros, when the zeros are theorised to be generated from a separate process from the count variables. Table 21 indicates that zero-inflated negative binomial is preferable to zero-inflated Poisson, but negative binomial is statistically indistinguishable from both of the zero inflated models. The most parsimonious model for these data was thus considered to be the negative binomial.

Model comparison	Vuong statistic	p-value
Poisson vs. negative binomial	-8.23	<0.001
Poisson vs. zero-inflated Poisson	-8.09	<0.001
Poisson vs. zero-inflated negative binomial	-8.09	<0.001
Negative binomial vs. zero-inflated Poisson	0.63	0.26
Negative binomial vs. zero-inflated negative binomial	0.63	0.26
Zero-inflated Poisson vs. zero-inflated negative binomial	-6.18	<0.001

Table 21 - Vuong statistics comparing different models

¹¹ Other diagnostic tests were run in R to ascertain the underlying distribution to use in the Poisson regression analyses (analyses not shown). These included Pearson Chi-squared tests, Ord plots (Ord 1967), and inspecting the results of the vcd::goodfit command, and produced convergent results. However, the Vuong statistic is considered stable and sufficient for these purposes and thus is the only one reported.

As previously argued, temperature and darkness have a strong affiliation. Therefore research which uses temperature as an explanatory variable may inadvertently estimate the effect of darkness. Scholars using both temperature and darkness in models are well advised to adequately account for any issues of multicollinearity (Cohn, 1990a), as it is difficult to imagine there is not some common variance between these variables. Heeding this, collinearity between the independent variables was assessed using variance inflation factors (VIF) scores prior to modelling. The maximum VIF score was 1.58 and the mean VIF was 1.29. As a general rule of thumb, VIFs over 10 are considered to be severe (Kutner, Nachtsheim & Neter, 2004, however see O'Brien, 2007) and are taken as an indication that multicollinearity may be improperly influencing the least square estimates (Neter, Wasserman & Kutner, 1989). As the VIFs calculated for this study were all below two the multicollinearity between the independent variables is considered acceptable.

4.3 Empirical findings from negative binomial regression

Five models were run: the first was a baseline model which included only the control variables (and hence controlled for some of the time series trends in the data). The subsequent models added in the independent variables incrementally in the following order: temperature, darkness, twilight and the interaction term. ANOVA tests were used to ascertain if each successive model improved the model fit.

To enable more straightforward interpretation, the coefficients presented have been exponentiated into incidence rate ratios (IRR). IRRs are a relative difference measure, thus facilitating an estimation of the change in the rate at which robbery events occur from each independent variable, when the other variables are held constant in the model. An IRR of one indicates parity between the dependent and independent variables, an IRR above one suggests that the independent variable is associated with an increase in robbery and an IRR below one suggests associations with a decrease in robbery. Standardised coefficients are presented alongside the IRRs to allow for a more direct comparison of the importance of the coefficients.

The results in Table 22 begin with the baseline model (model 1). As expected, the sequential variable in this model is negatively associated with a (marginal) decrease in robbery, and as this relationship exhibits little variation it is consequently highly significant. The mid-hours control variable is non-significant in this model.

Adding in the variable of temperature in model 2 results in an improved model fit (log likelihood = - 30,266.4 which is statistically significant when compared to model 1) and increases in temperature is seen to be significantly associated with (marginal) increases in robbery, with an IRR of 1.0143.

		Model 1			Model 2			Model 3			Model 4	Ļ		Model 5	
	IRR	s.b.	z-score	IRR	s.b.	z-score	IRR	s.b.	z-score	IRR	s.b.	z-score	IRR	s.b.	z-score
Intercept	0.4205***		15.46	1.3521***		8.85	0.5437***		-12.20	0.5797***		-9.56	0.1830***		-18.18
Sequential	0.9997***	-0.193	-19.94	0.9998***	-0.192	-19.81	0.9998***	-0.190	-20.12	0.9998***	-0.190	-20.14	0.9998***	-0.192	-20.54
Mid-hours robbery	0.0143	0.012	0.18	1.0146	0.013	1.37	1.0188.	0.016	1.81	1.0184.	0.016	1.77	1.0251*	0.022	2.43
Temperature °C				1.0124***	0.053	5.79	1.0443***	0.186	17.64	1.0449***	0.189	17.80	1.1295***	0.524	22.28
Proportion of darkness							2.4593***	0.252	24.46	2.3618***	0.241	21.13	9.5909***	0.633	23.04
Proportion of twilight										0.6217*	-0.023	-2.37	1.0924	0.004	0.44
Darkness*temperature													0.8967***	-0.363	-15.99
Theta			2.247			2.278			2.839			2.843			3.126
2 x log-likelihood			30,299.90			- 30,266.40		-	29,682.60			- 29,677.00		-	29,431.30
Likelihood ratio tests (df=1)					2 vs. 1	33.5***		3 vs. 2	583.8***		4 vs. 3	5.5*		5 vs. 4 2	245.7***

Table 22 - Negative binomial regression results

NOTES: ***p-value < 0.001; **p-value < 0.01; *p-value < 0.05; .p-value < 0.1; IRR = Incident Rate Ratio; s.b. = standardised beta coefficient

Model 3 includes the proportion of darkness and shows that this is also statistically significant at the 0.001 level. The mid-hours control variable also attains significance, albeit at the 0.1 level. In model 3 the IRR for temperature increases to 1.0443 but the IRR for darkness is much greater at 2.4593. The standardised coefficients for both variables support the result that darkness is more influential on variation in robbery counts than temperature. The relatively large likelihood ratio statistic for model 3 signifies that the inclusion of darkness in the model is important for explaining the variation in robbery counts.

The addition of the twilight variable in model 4 yields a marginal improvement in model fit and the proportion of twilight in an interval is significantly associated with a *reduction* in robbery, since the IRR of 0.6217 is below one. However this relationship is possibly spurious as it disappears in model 5 when the interaction variable is included. The interaction variable is significantly associated with reductions in robbery. This shows that while a higher volume of robbery is predicted in warmer periods and higher volumes are predicted in darker periods, it is not necessarily the case that the periods that are both warmer and darker experience a higher predicted level of robbery over and above this.

The other notable consequence of including the interaction variable into the model is that the magnitude of the IRRs and attendant standardised coefficients increase for darkness and robbery in this model. Here, an increase of one degree centigrade in temperature would be expected to increase the rate of robberies by a factor of 1.1295 - almost 13 per cent in volume. An increase of one unit of darkness on the other hand would be expected to increase the rate of robberies by a factor of 9.5909. In other words, traversing from full daylight to full darkness in an interval increases the predicted volume of robbery by 859 per cent when other factors are accounted for. In summation, the results indicate that the presence of darkness is a key factor in explaining robbery levels at the interval level.

4.4 Discussion

In this Chapter, for the reasons discussed above, I posited that darkness is an important environmental condition that facilitates robbery by altering the opportunity structure. This study provides the first direct test, of which I am aware, of this meteorological variable on temporal patterns of street robbery, alongside the more omnipresent variable of temperature. The research thus attempts to disentangle the effects of temperature and darkness – which is important, as prior research on crime seasonality has tended to focus purely on temperature (and other weather conditions).

The ARIMA modelling in this Chapter exposed the seasonality prevalent in the time series of the robbery data. This complex method suggested that this trend was not straightforward. For the monthly aggregated data, an auto-regressive component is present in the data (at lag 12); for the weekly aggregated data, a moving average parameter is also required to model the seasonality (at lag 52). Collectively, these results confirm that seasonality exists in the street robbery data, and that explaining such variation is important in crime analysis. The ARIMAX models included the differenced independent variables, and showed that neither darkness nor temperature was related to counts of robbery at the week or month level.

To address the ecological fallacy issue identified in the ARIMAX models, the second set of analyses was concerned with explaining these trends in the data. The negative binomial regression models tested to what extent temperature and darkness were associated with street robbery events (which followed an overdispersed Poisson distribution). By assigning theoretical importance to the time of day that a robbery occurs, a more direct test of how the key variables change over the course of the day *and* over the seasons was possible. This is a novel approach. The underlying trends in the (time series) data were controlled for by using the 'mid hours' interval as a control variable. The results showed that the environmental condition of darkness was significantly associated with an increase in the expected number of street robberies. The incident rate ratio (IRR) for darkness indicated that it was a strong predictor in the models. This finding was consistent for that found in London (reported in Tompson & Bowers, 2013) which, due to its different latitude had a different variation of darkness throughout the year.

Through the standardised coefficients produced in the negative binomial models it was determined that temperature played a less prominent role than darkness in explaining variation in robbery. In model 4 twilight was seen to have a negative relationship with robbery, however this did not hold when the interaction variable representing temperature *and* darkness was included in model 5. Interestingly, while increases in temperature and darkness are individually associated with increases in robbery, intervals which are warmer and darker do not further increase the robbery levels predicted.

In section 4.1 I argued that darkness might be a crucial inhibitor of guardianship, as defined within the tenets of the routine activity approach. The lack of sunlight may plausibly influence the three dimensions of guardianship that Reynald (2009b) defines; the availability, the capability and the willingness of guardians to intervene. Considering these in turn, people may be less likely to spend time outdoors in public space when it is dark, thus resulting in fewer guardians of others. Lastly, any

motivation to *intervene* in a crime event (by available, capable guardians), may be related to feelings of safety – which has long been assumed to be different in hours of darkness compared to daylight (Clarke, Ekblom, Hough & Mayhew, 1985).

Further, earlier sunset times in winter in the study area overlap with potential victim's routine activities. For example, robberies involving victims of school age (<18 years in the UK) are known to happen after school closing hours (4PM onwards – Tilley et al., 2004). When these hours are characterised by darkness, the opportunities for peers to rob each other may be increased. It may also be the case that recreational routine activities, which typically occur at night-time, give rise to optimal conditions for robbery; that is, they bring motivated offenders into contact with suitable victims (Roncek & Maier, 1991). That these coincide with hours of darkness fosters a greater likelihood that offenders and victims will interact in space and time without the crucial inhibitor of guardians.

The implications of these findings are first, that it is important to disaggregate data into temporal categories that are sensitive to the phenomena being modelling, to disclose the relationships between the variables under scrutiny. If this had not been done, and analysis was performed solely on whole days (with their respective daily average temperature and daylight hours) then the true relationships might have been masked. This pertains to the ecological fallacy and modifiable temporal unit problem discussed in earlier Chapters.

Second, if the relationship between darkness and robbery holds across different latitudes and data periods, then this is useful information for police resource planning. For example detection and disruption activities can be sensibly aligned to times of darkness, which differ throughout the year. Other long-term crime prevention strategies (such as improving street lighting) can be considered as a way of inhibiting street robbery at night-time.

Limitations

This study suffers from some notable methodological limitations; chiefly due to measurement issues with the variables used in the analysis. Using police-recorded violent crime or calls for service data is likely to be only one portion of all violence that actually occurred (Shepherd, 2001) and this may accentuate or temper any empirical findings. Relatedly, we cannot be certain that the fluctuations seen in the counts of robberies (at the weekly and monthly aggregations) were not influenced by police activity. In a similar vein, the study area is acknowledged as relatively large, and as such, does not account for locally geographic variations in volumes of robbery or police activity. Seasonal

patterns of crime are likely to vary at the neighbourhood level, (Cohen et al., 2003) and the space dimension was absent from this study.

This research followed in the long history of researchers having to aggregate imprecise weather data in order to derive meaningful empirical results (Cohn, 1993; Heller & Markland, 1970; Lab & Hirschel, 1988; van Koppen & Jansen, 1999). The temperature data used in the ARIMA models were derived from averaged daily observations (the daily mean temperature). These values will therefore be an imperfect approximation of the precise temperature at the time of offence and this compromises the robustness of the results. Furthermore, temperature varies a great deal over the course of a day, and especially so over a week. In recognition of this, for the ARIMAX modelling two heterogeneity variables were created which reflected the range of temperature over the week¹², but these did not improve the models or produce interesting results (analyses not shown).

In addition, this research approximated the effect of darkness by calculating the proportion of hours of darkness, or mean daily hours of darkness, as determined by the trajectory of the sun. This does not account for any residual light, whether that was natural (e.g. the luminosity of the moon) or artificial (street lighting). Due to the size of the study region, it was not possible to provide a systematic measure of street lighting for the purposes of this study.

Further work

I argue in this Chapter that darkness is a crucial inhibitor of guardianship, as defined within the tenets of the routine activity approach. Alternative mechanisms driving the correlation between darkness and street robbery may be due to the offender's motivation (i.e. lifestyle or biological processes) or the suitability of targets (i.e. the offender feeds off people with cash on their person or inebriated in hours of darkness, or interaction with illegal drugs markets). Further temporally sensitive independent variables could therefore assist in producing more powerful models of variation in crime by time of the day and across the seasons, and could fruitfully be the subject of future research. Studies which investigate the offender's viewpoint on conditions that facilitate robbery would yield explanatory findings that could feed back into empirical enquiry.

The finding that twilight has a negative relationship with robbery is interesting, but one that is not easily explained through current theory, and is potentially spurious. Twilight connotes a transitory

¹² For the first heterogeneity variable this involved taking the mean *high* weekly temperature from the maximum weekly temperature to derive a value that reflected the variance. For the second heterogeneity variable the mean *average* weekly temperature was taken from the maximum weekly temperature to produce a value that measured variance in a slightly different way.

phase in the day, where it is either changing from dark to light or vice versa. Speculatively, this period may act as a 'cue' to people that time is shifting, and either prompt a retreat to primary territories (Rotton & Cohn, 2000) in the afternoon-evening time, or signify the beginning of the day in morning when obligatory activities are beginning. As this is the first known investigation of twilight in crime research it is hoped that future studies will conjecture why this period might exert a negative influence on crime opportunities. Replicating the research presented here with a study region with either differing or time-stable twilight hours over the course of the year would be useful in clarifying whether this finding is genuine.

One of the notable limitations of this study is that variations in artificial light (that is, produced by street lighting columns and the city-scape) were unaccounted for. A recent study examining the *reduction* of street lighting across 62 local authorities in England and Wales found no evidence of an association between aggregate counts of crime and switched off lights and weak evidence for a *reduction* in aggregate counts of crime when street lights were dimmed or supplanted with white lights (Steinbach et al., 2015). However, when examining individual crime types there was suggestive evidence that lights switched off in core night-time hours may be associated with *increases* in robbery. Future work on the relationship between street lighting and crime would be instructive for revealing if this relationship is observed elsewhere.

Conclusion

The findings presented in this Chapter offer nascent evidence in support of the central hypothesis; that the presence of darkness increases the likelihood of street robbery occurring, when differences in temperature and underlying trends in the data are accounted for. The latter in particular is seldom done in count models (Brandt & Williams, 1998), which means that previous research may have made errors of inference regarding the relationship between temperature and crime. I contend that darkness has previously been overshadowed in the academic imagination by other meteorological variables such as temperature, yet it appears to be important in explaining the opportunity structure for street robbery.

Temperature was seen as a weaker predictor of the seasonal patterns in robbery in this Chapter. It is though acknowledged that temperature can fluctuate considerably over the course of the day, and is related to other weather variables (such as humidity and precipitation). An intricate examination of weather over different times of the day has the potential to clarify the influence of temperature on robbery events. To that end, the next Chapter extends the analyses presented here, employing a range of weather data to empirically investigate if it differentially impacts on the time intervals created in this Chapter.

To conclude, the findings presented in this Chapter offer the first empirical evidence that darkness is an important environmental condition in street robbery events. This relationship advances understanding of some of the criminogenic features of settings that drive seasonal patterns of street robbery, at least in a Scottish context. What is now called for is repetition across different sites to assess the generalizability of this finding.

5. WEATHER AND ROBBERY

Chapter overview

The relationship between weather and crime holds an enduring fascination to criminology scholars (see Baumer & Wright, 1996 and Cohn, 1990 for an overview of studies. Also, Anderson, Bushman & Groom, 1997; Ceccato, 2005; Cohn & Rotton, 1997; Hipp, Bauer, Curran & Bollen, 2004; LeBeau, 1994; Sorg & Taylor, 2011; van Koppen & Jansen, 1999). Collectively, empirical findings suggest that climatological and meteorological variations are associated with patterns of crime, some of which are seasonal. However the relationships are far from clear cut; to date there is little consensus on the directions of the relationships observed and the mechanisms through which weather might exert its influence (Block, 1984; Peng, Xueming, Hongyong & Dengsheng, 2011; Yan, 2004). Ostensibly, the impact of weather across different regions and microclimates is not constant; a premise which underpins the current study.

This Chapter contributes to this literature by integrating research findings from other disciplines concerned with weather and behaviour to extant criminology evidence. In doing so, an account of the likely causal mechanisms for weather on crime patterns is elicited. Using this as a theoretic bedrock, I advance an argument that people's individual interpretation of weather, and subsequent activities based on that interpretation, lead to spatio-temporal variations in criminal opportunities and hence crime. In short, weather conditions influence human mobility patterns and, as a corollary, this impacts on the timing of when offenders and victims converge at criminogenic settings. I begin to test these hypothesised effects by presenting initiatory analysis that adopts a finer temporal resolution than usually seen in weather and crime research.

The objective of this Chapter is to test two hypotheses:

- The adverse-favourable weather hypothesis: reductions in street robbery will be associated with adverse unseasonal weather and increases in robbery will be associated with favourable unseasonal weather.
- 2) The discretionary activities hypothesis: weather will have a stronger influence on robbery when travel is (in general) more likely to be optional.

The Chapter proceeds as follows: first, the argument that weather exerts its influence differentially at different times is developed. Next, the data and analytic strategy are described, which encompasses two complementary regression techniques. The empirical results are then presented and discussed in relation to the space-time convergence of victims and offenders. In the discussion I consider how these findings might be integrated into a new theoretical framework and outline a research agenda for testing this. This Chapter has been based in part on the findings reported in the following paper, published as a result of research undertaken for this thesis:

Tompson, L. & Bowers, K. (2015). Testing time-sensitive influences of weather on street robbery. Crime Science. 4(8).

5.1 Theoretical background

The allure with the weather and crime relationship has its roots in Quetelet's 'thermic law' (1842), which claims that crimes against people happen most often in summer (when it is warmer), and crimes against property happen most often in winter. This simplistic thermic law has since been contested by a number of scholars. Pre-eminently, Sutherland and Cressey (1978: 113) underscore that weather conditions "provide the habitat for human life and consequently may facilitate or impede contacts among human beings and perhaps in that sense be related to opportunities for criminal behaviour". This *social contact hypothesis* is presumably an antecedent to the routine activity approach (RAA), which has been one of the principal theoretical explanations for the effect of weather on crime (Cohn, 1990a; Lab & Hirschel, 1988; Landau & Fridman, 1993).

As human activities are the cornerstone of the routine activities approach, it is important to consider their patterning over time, and how they relate to weather conditions. Research to date has neglected to consider this in detail, as stressed by Rotton and Cohn (2000: 654): "...those who favour social contact and RA theory have been derelict in finding out what people actually do at different temperatures". Further to this, temperature and other weather conditions can vary considerably over the course of the day, as well as over the seasons. Prior research has typically examined weather variables alongside concurrent crime patterns at the day level and coarser temporal resolutions, which fails to account for the (often very significant) intra-day variation (Cohn & Rotton, 1997).

Explaining the influence weather has on human activities in public space permits hypotheses as to how this affects the constellation of motivated offenders, suitable targets and capable guardians in the context of the routine activity approach. Outdoor crimes with human victims require the presence of both offender and target but, vitally, guardianship needs to be absent for a crime event to be more likely. Weather can therefore be considered a situational influence on crime (Cohn, 1993) as it can alter the opportunity structure for crime to occur.

The adverse-favourable weather hypothesis

Weather conditions shape the types of activities that people take part in (Ceccato, 2005; LeBeau & Corcoran, 1990; LeBeau & Langworthy, 1986). Numerous scholars have postulated that people are more likely to stay indoors in adverse weather and be outdoors when weather is pleasant (Brunsdon, Corcoran, Higgs & Ware, 2009; Hipp et al., 2004; Lab & Hirschel, 1988; LeBeau & Corcoran, 1990a; Rotton & Cohn, 2000), and this is borne out by empirical findings in transport studies and public health (Böcker, Dijst & Prillwitz, 2013; Horanont et al., 2013; Tucker & Gilliland, 2007). Outdoor activities usually peak in the summer months in temperate climates when the days are longer, whereas regions with harsh weather can also be more severe at certain times of the day, such as early morning fog. Social contact between people in public settings is thus likely to be reduced when weather is perceived to be unpleasant. This inevitably affects the availability of guardians present in a particular setting, as well as the likelihood of victims and offenders converging.

The hypothesis that inclement weather leads to reduced social contact, and thus reduced opportunities for crime to occur, was first advanced by Rotton and Cohn (2000). They aimed to extend the negative affect escape (NAE) model proposed by psychologists to explain the relationship between temperature and aggression (Baron, 1972). Succinctly put, the NAE purports that up to a certain limit increases in heat will covary with increases in the likelihood of aggressive behaviour. However, once a 'critical' threshold of temperature is reached the individual is more likely to feel lethargic or want to escape that situation, which reduces the likelihood of aggression. Hence, temperature is posited as having a curvilinear relationship with aggression. Rotton and Cohn (2000) approximated social contact by including disorderly conduct calls for service in their time-series analysis, testing the relationship between weather variables and assault over different intervals in the day. Their results were consistent with a model of mediated moderation; that is, the inverted Ushaped relationship between temperature and assault purported by proponents of the NAE model was reduced when social contact was controlled for. This led the authors to postulate that inclement weather (especially extremes in temperature) could be considered a factor that decreased social contact and kept people in their 'primary territories' (homes). Later work by these scholars suggested that the shape of the relationship between temperature and aggression varied according to time of the day (Cohn & Rotton, 2005).

Wider support for this inverted NAE model can be found in research on how weather affects peoples' legitimate activities (Zacharias, Stathopoulos & Wu, 2001). Systematic review findings

reveal that an increase in temperature in many countries, particularly when accompanied by calm conditions, is positively associated with increased use of public space, up to certain heat-thresholds (Böcker et al., 2013). Thermal comfort is though influenced by many factors in addition to the temperature measured in the NAE model. Other weather conditions (including precipitation, humidity and wind speed), exposure times, cultural clothing, urban design, socio-demographic characteristics and individual traits work in concert to determine how people perceive their outdoor environment (Stathopoulos, Wu & Zacharias, 2004; Yahia & Johansson, 2013). Crucially, consistent discrepancies between objectively measured weather and people's subjective interpretation of their outdoor comfort arise from research, with the latter providing greater explanatory value for behavioural decisions made in relation to that comfort (Böcker et al., 2013).

What might explain these discrepancies between weather and perceived outdoor comfort? The literature on people's physiological and psychological reactions to weather provides some candidate explanations. Perceptions of weather are subjective; relative to the overall climate for that region, relative to the expected weather for the season, relative to recent trends and also to expectations of future weather. In what follows I elucidate these points.

Seasonal expectations of weather

Robert A. Heinlein once famously said "Climate is what you expect, weather is what you get". Climate refers to the abiding characteristics of the weather (atmospheric conditions), rather than the momentary condition of weather, and thus forms a more long-term and stable expectation of what weather can be anticipated in an area. However, climate itself is too indelicate a term to fully represent the range of conditions one might expect to find in a region, and hence microclimate – a localised atmospheric zone - is a more fitting descriptor to use when discussing geographical variation of weather.

Microclimates across the globe vary tremendously and these have shaped the cultural development and urban design of the societies which fall within them (Yahia & Johansson, 2013). Different extremes in weather variable ranges, different lengths of summer and winter periods and different cultural attitudes to weather all impact on how people perceive their current localised weather. Cross-cultural comparisons of people's thermal comfort levels in urban climatology and biometeorology reveal that the upper limits of thermal comfort vary across different populations (Chen & Ng, 2012; Yahia & Johansson, 2013). Corroborative evidence for this has been found in Kruger et al.'s (2012) cross-cultural study on outdoor thermal sensation in Curitiba, Brazil (subtropical climate in elevation) and in Glasgow, UK (maritime temperate climate). This study found at the same air temperatures respondents in Glasgow wore much less insulated clothing than their counterparts in Curitiba. These differences are colloquially infused in stereotypes of different regional cultures; in the UK for example Scottish people are considered 'hardy' and those who live in warmer southern England as 'soft'.

Further to this, Böcker et al. (2013) argue that climatological differences might become culturally embedded so that they affect attitudes to certain weather – temperature in particular. Thus, microclimates with short summers (like Scotland) may place a greater value on sunny days than equatorial microclimates. Given the health benefits vitamin D is known to have on the body it seems intuitive that cultures with less access to sunlight would prize it higher than cultures where it is plentiful.

Seasons can be thought of as the medium-term manifestation of weather trends. Anecdotally, we all become accustomed to seasonal norms in weather (depending of course on the regional microclimate), and these shape our expectations and behaviour in relation to our travel patterns, activities and clothing. Empirical findings support this proposition: Datla and Sharma (2010) demonstrated that snow has a stronger negative influence on car traffic volumes in Alberta, Canada in autumn and early spring compared with the same conditions in winter. Perhaps Albertans are better prepared for the presence of snow in winter, when it is more probable. From a more recreational viewpoint, Dwyer (1988) found that the relationship between urban forest attendance in Chicago and warm sunny weather was much stronger in spring compared with the same weather conditions in summer.

In light of this, I argue that Rotton and Cohn's hypothesis needs to be extended to truly capture people's responses to adverse and favourable weather, which encompasses a wider set of meteorological variables than temperature. What is considered to be adverse weather is likely to be interpreted differently by people in different places, and this in itself can vary over time. Leaving aside demographic and individual traits for the purposes of this exposition¹³, it is reasoned that interpretation of weather conditions is grounded in a person's *expectations* of that weather at a point in space-time. Such expectations are, plausibly, the mechanism through which weather influences outdoor activities. Expectations are hence likely to be relative to the expected weather for the season (which is intimately related to the microclimate).

¹³ I do this firstly because it is outside my area of expertise, and secondly to construct a more parsimonious theoretical model. Demographic characteristics and individual traits will certainly impact on a person's subjective interpretation of weather conditions. However it is doubtful that variation at this level of abstraction can be adequately tested by the analysis of crime data.

For the purposes of this Chapter this is called the *adverse-favourable weather hypothesis* (hypothesis 1). Adverse-favourable represents the range of weather conditions that might be tested. In keeping with the rationalisation above, I posit that reductions in robbery will be associated with adverse *unseasonal* weather and increases in robbery will be associated with favourable *unseasonal* weather.

The discretionary activities hypothesis

When considering influences on people's routine activities it is useful to differentiate between obligatory activities and discretionary activities (LeBeau, 1994). Discretionary activities are pursued by choice, whereas obligatory activities have to be performed in all but extreme weather conditions. For this reason weather exerts a stronger influence on discretionary trips for leisure reasons, compared to obligatory trips such as commuting (Cools et al., 2010; LeBeau & Corcoran, 1990; Böcker et al., 2013). As Field (1992) states, people may be willing to postpone discretionary activities until the weather is more pleasant (also see Cools et al., 2010). We should though note that obligatory and discretionary activities lie on a continuum, rather than being dichotomous. For example, certain discretionary activities, such as shopping, are more utilitarian than leisure pursuits, and therefore these might not be put-off indefinitely in sustained adverse weather. Instead it might be the case that they are pursued in a constrained way.

People, then, can plan their discretionary activities according to their expectations of future weather as well as the current conditions. It is plausible to assume that weather forecasts influence activities planned in advance, or with a long duration (Böcker et al., 2013), however to my knowledge this has not been empirically tested to date. Spontaneous discretionary activities such as those in pursuit of recreation or entertainment may be more influenced by what weather is expected over the scale of hours, rather than days, and thus decision-making is done at different temporal scales.

It is also the case that there will be temporal, spatial and social trends in people's discretionary activities. During the working week, for much of the daytime period, the employed will be conducting obligatory activities. This will (predominantly) tie them to a particular place and commute pattern¹⁴. More choice may be available later on back in their residential neighbourhood where they can choose whether to leave the house or not. Unemployed people will have more discretion for when and for how long they leave their residence. Bowers and Johnson (2013)

¹⁴ It is acknowledged that at the individual level this is an over-simplification. The contemporary increase in people working from multiple locations (i.e. different offices and from home), coupled with the fact that some business activities take place in sites other than the 'office' mean that this precept is likely to be violated. However this statement describes the majority of people and thus is sufficient when explaining aggregate patterns, as in this study.

demonstrate that offenders make shorter trips to commit residential burglary at night-time than during the day, presumably because they choose not to venture as far later on. Such travel patterns affect the availability of guardians, targets and offenders and I hypothesise that weather will have a stronger influence on robbery when travel is (in general) more likely to be optional (hypothesis 2).

5.2 Data processing and analytic strategy

Recent developments in weather data availability and advances in statistical modelling mean that we can now begin to test the conditional factors for weather interpretation outlined above. The objective of this Chapter is to test the two stated hypotheses – the influence of unseasonal weather and the influence of weather's effect on discretionary and obligatory activities, on robbery.

People's weekly and daily patterns of obligatory and discretionary activities are highly individualised. However the biological need for sleep can be considered a universal temporal constraint on people's activity patterns (Ratcliffe, 2006). At a societal level (in a UK context), we can reasonably assume that the majority of people will have their obligatory activities in daytime hours in the working week (that is, Monday to Friday). This does not, of course, include people without any formal educational or professional obligations, or people with working patterns outside of these hours. For the purposes of this study of aggregate patterns, in the absence of direct observational data on locations, this seems a reasonable position to take.

Data

Investigating patterns at a fine-grain temporal resolution has been uncommon in weather and crime research to date (see Tompson & Bowers, 2013), however it mirrors a wider trend in criminological research to investigate robbery at a micro-level (Haberman & Ratcliffe, 2015; Irvin-Erickson et al., in press). The present study employs a *6-hour interval* as the unit of analysis, effectively segmenting each day in the data period into four. As described in greater detail in Chapter 4, this aimed to produce the greatest homogeneity of weather conditions in each interval (namely temperature, which is influenced by sunrise and sunset times). The temporal boundaries for these were hence defined as 4AM - 9.59AM; 10AM - 3.59PM; 4PM - 9.59PM; and 10PM - 3.59AM. The robbery data discussed in Chapter 3 were aggregated to each complete temporal interval for every day in the tenyear data period. This equated to 14,607 intervals; 4 intervals per day multiplied by 3,652 days, minus one incomplete interval. The temporal concentration of these can be viewed in Table 20 (in Chapter 4) and this clearly shows that they are concentrated in the late- and night-hours, when most people are free from their obligatory activities.

It is worth briefly describing the distinctive microclimate of the study area, which is just less than 14,000km² and falls in a temperate oceanic climate zone. Glasgow is warmer than other areas on similar latitudes due to the Gulf Stream coming in from the Atlantic Ocean. The weather tends to be very unsettled, although Glasgow experiences milder temperatures than elsewhere in Scotland, and snowfall is infrequent. The weather in summer months can be changeable and varies from cool and wet to warm, with occasional hot days. Autumn months can sometimes bring more settled and pleasant weather. Generally speaking, Glasgow sees many overcast days with high humidity. Table 23 provides information on the mean weather values for the period 1981-2010 to give an indication of the climate. (This includes weather variables such as hours of sunshine per month which were not available in the weather data obtained for the analysis in Chapters 4 and 5.)

Month	Max. temp (°C)	Min. temp (°C)	Days of air frost	Sunshine (hours)	Rainfall (mm)	Days of rainfall
January	6.0	1.0	11.0	37.8	112.8	17.0
February	6.6	1.1	10.2	62.9	88.5	13.5
March	8.8	2.3	6.5	86.2	96.9	15.7
April	11.7	4.0	2.1	127.6	62.9	12.5
May	15.1	6.5	0.2	173.3	61.4	12.0
June	17.5	9.4	0.0	148.9	65.1	11.7
July	19.2	11.1	0.0	149.0	83.5	12.7
August	18.5	11.0	0.0	142.2	101.1	14.1
September	15.8	8.8	0.1	111.2	112.7	13.8
October	12.1	6.0	1.3	80.0	129.4	16.6
November	8.7	3.3	5.7	51.1	105.5	15.9
December	6.1	1.0	10.8	32.9	104.4	14.7
Annual	12.2	5.5	47.9	1203.1	1124.3	170.3

Table 23 - Mean weather values for the Met Office station Springburn(nearest station to Glasgow) for period 1981-2010 (www.metoffice.gov.uk)

The temperature data described in Chapter 4 were accompanied by additional weather readings. The 36 occasions when the weather readings produced null values for temperature and humidity were excluded. The weather data were then aggregated to the interval unit of analysis. Mean values were calculated for temperature, humidity and wind speed. Frequencies of observations of fog, snow and rain (per interval) were transformed into proportions using the count of weather readings per interval. Missing values were treated in the same way as described in Chapter 4.

The aggregated robbery data were appended to the aggregated weather data. A sequential variable was then created to represent the days over the study period (n = 3,652) to control for the

underlying trend of decreasing robbery. Since the hypotheses in this Chapter relate to variation in robbery over the seasons and weekends, binary variables representing these temporal periods were generated based on the interval date and time. Hence, as seasons and weekend days became important explanatory variables in these analyses, it was not necessary to control for trends relating to these, as was done in Chapter 4. The weekend was defined as Friday 4PM to Monday 4AM. Public holidays and notable celebratory events (such as Burns Night and St Andrews Day) were also represented by a composite binary variable. The dependent variable was the count of street robbery in each temporal interval for each day in the ten-year data period.

Methods

Prior research has often used variants of time-series models and OLS regression to model the relationship between weather and robbery (Anderson et al., 1997; Cohn & Rotton, 1997; 2000; Cohn, 1993; Field, 1992; Gorr, Olligschlaeger & Thompson, 2003; Heller & Markland, 1970; Landau & Fridman, 1993; Rotton & Frey, 1985). Problems are associated with both of these statistical approaches; time-series models are nowadays considered too indirect a test of causal relationships (see Chapter 4 and O'Brien, 2001; Shmueli, 2010). The diagnostic tests described in Chapter 4 also apply to the data used here. To recapitulate, the counts of robbery per interval were highly clustered in time, with the variance greater than the mean ($\mu = 1.08$, $\delta = 1.49$). Thus, negative binomial regression was the most suitable method to test the hypotheses.

Negative binomial regression

Two negative binomial regression models with interaction terms were generated; hereafter they are referred to as the negative binomial interaction models. The first tested the adverse-favourable weather hypothesis – where the effect of unseasonal weather could be estimated for the count of robbery in each interval. This model included all weather variables, spring, summer and autumn (*winter* was held as the reference category), and interactions between these. The reference categories were selected to contain a large proportion of the robberies to protect against inflated variance inflation factors (VIF) scores (Allison, 1999). The interaction between summer and snow was excluded as the zeros in this variable produced perfectly collinear coefficients. The sequential variable described above was included as a control for the downward temporal trend in the robberies, with the seasons and the public holiday variable acting as explanatory variables.

The second model tested the effect of weather on times when discretionary activities were dominant. This model included the weather variables, the interval variables (*night-hours* was held as the reference category⁷), and the variables representing weekends and public holidays. Interactions

between the weather and all temporal variables were included, as was the sequential variable. Since both models compare a number of independent variables, the problem of multiplicity – that is, testing multiple hypotheses - might undermine the analysis by increasing the likelihood of Type I error (Benjamini & Yekutieli, 2001). I used the false discovery rate to correct for this¹⁵.

Collinearity between the independent variables was assessed using VIF scores prior to the modelling (see Table 24 and 25). The maximum and mean VIF scores were 3.2 and 1.7 respectively for the seasonal model (model 1) and 1.9 and 1.3 respectively for the discretionary activities model (model 2). Since these were lower than thresholds commonly used to detect unreasonable multicollinearity (Neter, Wasserman & Kutner, 1989) the common variance between the independent variables can be considered low and should not affect the veracity of the results that follow.

Table 24 - VIF scores for seasonal model Table 25 - VIF scores for discretionary activities model

Independent variable	VIF	Independent variable	VIF
Sequential	1.01	Sequential	1.00
Spring	1.86	Early	1.17
Summer	3.24	Mid	1.48
Autumn	2.06	Late	1.84
Mean interval temperature	2.58	Weekend	1.01
Mean interval humidity	1.69	Public holiday	1.00
Mean interval wind speed	1.45	Mean interval temperature	1.29
Proportion of time in interval foggy	1.15	Mean interval humidity	1.90
Proportion of time in interval raining	1.47	Mean interval wind speed	1.35
Proportion of time in interval snowing	1.02	Proportion of time in interval foggy	1.15
		Proportion of time in interval raining	1.47
		Proportion of time in interval snowing	1.02

The relationship between humidity and temperature was investigated through bivariate coefficient correlations (analyses not shown). LeBeau (1988) contends that the association between many weather variables is nonlinear, and therefore multicollinearity concerns between the variables cannot be ascertained through simple linear relationships explored in the VIF statistic. For example, the relationship between vapour pressure and temperature is logarithmic (Lowry, 1969: 68). Thus, humidity relies heavily on temperature, and is not meaningfully interpreted on its own. The results

¹⁵ This was achieved using the 'fdr' parameter in the p.adjust command in R. I thank one of the anonymous reviewers for the paper based on this Chapter for bringing this to my attention.

of the investigation revealed no clear relationship, logarithmic or otherwise, which may be due to the consistently high humidity in the study area.

Seemingly unrelated regression

Comparing regression coefficients for different temporal slices (seasons and time-of-day intervals) in the models can be considered a form of sub-group analysis. In the negative binomial interaction models described above, comparisons of the coefficients of interactions between seasons and weather variables are made. An alternative way of modelling the coefficients across the sub-groups can be achieved through a method known as *seemingly unrelated regression*. This is used to corroborate the results of the first set of analyses.

Seemingly unrelated regression (SUR) originates from Econometrics. Proposed by Zellner (1962) SUR can be viewed as a special case of a generalised linear regression model that encompasses several regression equations. Each of these equations is presumed to have its own dependent variable and (potentially different) explanatory variables, and can be estimated as a valid linear regression on its own. The equations are related through correlation in the error terms.

SUR is deemed appropriate for this study because it allows the sub-groups (i.e. seasons and time-ofday intervals) to be estimated jointly while controlling for the correlated errors. Performing SUR on negative binomial models was not possible in R at the time of the analysis, so the models were run in Stata using the 'nbreg' command, with the 'suest' command used to provide parameter estimates of the models for each of the temporally defined outcome subgroups using a combined covariance matrix.

The 'test' command was subsequently used in Stata to compute Wald tests which compared the equality of coefficients across the models. In brief, this computes a global Wald test to determine if differences between the coefficients for each independent variable are statistically distinguishable over the different sub-groups (e.g. seasons). For model 1 this involved comparing the coefficients for the weather variables across all four *season* models. For model 2 the same comparison process was followed for all independent variables (i.e. for weather, weekend days and public holidays) across all four *time-of-day interval* models. Any variance between the coefficients for the different models would provide support to the two hypotheses articulated above.

5.3 Empirical findings

The negative binomial regression coefficients, along with their associated confidence interval values, were exponentiated to produce incidence rate ratios (IRR) – a ratio based on the incidence of counts

(as described in Chapter 4). These provide a simple means of assessing the influence of each independent variable on the rate of change in robbery events when the other variables are held constant in the model.

Seasonal model (model 1) – adverse-favourable weather hypothesis

The results of the negative binomial interaction model (model 1) can be seen in Table 26. This shows the IRR and accompanying confidence intervals, along with the p-values and adjusted p-values. Note that these should be interpreted relative to the reference category – *winter*. We see from Table 26 that temperature, humidity and wind speed are the only weather variables that influence the (general) occurrence of robbery; with increases in temperature associated with an increase in robberies, and the opposite trend for humidity and wind speed. Interestingly, however, when the interactions with season are considered, differential effects are seen for these three weather conditions. Hence, higher temperatures in winter (the reference category) increase robbery, whereas for the other seasons a (relative) decrease is seen with rises in temperature. Similarly, a higher wind speed in winter decreases robbery, whereas the reverse is seen for the other seasons. The same overall trend is apparent in humidity, but the coefficients (and therefore IRRs) do not reach the 0.05 significance threshold. The adjusted p-values were in some cases larger, but did not change the significant results.

A confirmatory set of results emerged from the seemingly unrelated regression model 1 displayed in Table 27, albeit with some interesting variations. Temperature, humidity and wind speed are the only weather variables to be significantly related to the count of robbery, and the values for winter for these three weather conditions are strikingly similar to the general variables in Table 26. When the models are simultaneously estimated however, an increase in temperature is associated with an increase in robberies in spring, autumn and winter, albeit the effect is strongest for winter and weakest for spring. Humidity is negatively associated with increases in robbery across all seasons, unlike in Table 26. Wind speed is only statistically significant for winter.

Consulting the Wald tests for the equality of coefficients (derived from Table 27) sheds some light on the relationships; these are displayed in Table 28. The only explanatory variables to reach statistical significance in the omnibus tests were temperature and wind speed, meaning that the coefficients for humidity are not statistically different from each other. In brief, for both temperature and wind speed, statistically significantly different effects are only observed when other seasons are compared to the winter model. This finding is consistent with the negative binomial interaction model results in Table 26.

	IRR	C	I	p-value	Adjusted p
(Intercept)	4.3593***	2.7622	6.8622	<0.001	0.000
Sequential	0.9997***	0.9997	0.9998	<0.001	0.000
Mean temperature (°C)	1.0381***	1.0247	1.0516	<0.001	0.000
Mean humidity	0.9876***	0.9825	0.9927	<0.001	0.000
Mean wind speed (km per hour)	0.9889***	0.9837	0.9942	<0.001	0.000
Proportion of fog	1.0018	0.9991	1.0044	0.196	0.305
Proportion of rain	1.0013	0.9997	1.0029	0.104	0.171
Proportion of snow	0.9958	0.9867	1.0042	0.345	0.508
Spring	0.5915.	0.3361	1.0422	0.069	0.138
Summer	0.5328.	0.2712	1.0471	0.067	0.138
Autumn	0.8198	0.4281	1.5705	0.549	0.673
Int: mean temperature and spring	0.9734**	0.9571	0.9899	0.002	0.008
Int: mean temperature and summer	0.9669**	0.9483	0.9859	0.001	0.005
Int: mean temperature and autumn	0.9754**	0.9596	0.9916	0.003	0.011
Int: mean humidity and spring	1.0057.	0.9994	1.0121	0.076	0.142
Int: mean humidity and summer	1.0064.	0.9996	1.0132	0.063	0.138
Int: mean humidity and autumn	1.0014	0.9943	1.0086	0.695	0.759
Int: mean wind speed and spring	1.0106**	1.0034	1.0179	0.004	0.012
Int: mean wind speed and summer	1.0102*	1.0019	1.0186	0.017	0.043
Int: mean wind speed and autumn	1.0096*	1.0021	1.0173	0.013	0.036
Int: proportion of fog and spring	0.9943.	0.9878	1.0006	0.084	0.147
Int: proportion of fog and summer	0.9987	0.9890	1.0080	0.790	0.808
Int: proportion of fog and autumn	1.0005	0.9962	1.0049	0.808	0.808
Int: proportion of rain and spring	0.9992	0.9970	1.0015	0.504	0.673
Int: proportion of rain and summer	0.9996	0.9972	1.0019	0.705	0.759
Int: proportion of rain and autumn	0.9994	0.9971	1.0016	0.577	0.673
Int: proportion of snow and spring	1.0046	0.9882	1.0201	0.562	0.673
Int: proportion of snow and autumn	1.0076	0.9807	1.0305	0.540	0.673

 Table 26 - Negative binomial interaction model for seasonal influences on robbery (model 1)

NOTES: IRR = Incident Rate Ratio; ***p-value <0.001; **p-value <0.01; *p-value <0.05; .p-value <0.1 (calculated from original p-values). Cragg and Uhler pseudo $R^2 = 0.068$, 2x log likelihood = -39,421.2.

	SPRING			SUMMER			AUTUMN			WINTER		
Variable	IRR	C										
Constant	2.7061***	1.9422	3.7704	2.2476**	1.3751	3.6738	3.5154***	2.2069	5.5995	4.3178***	2.8416	6.5608
Sequential	0.9997***	0.9997	0.9997	0.9998***	0.9997	0.9998	0.9998***	0.9997	0.9998	0.9998***	0.9997	0.9998
Mean temperature (°C)	1.0102.	0.9993	1.0213	1.0043	0.9899	1.0189	1.0126**	1.0024	1.0229	1.0386***	1.0250	1.0525
Mean humidity	0.9932***	0.9896	0.9967	0.9940**	0.9898	0.9982	0.9890***	0.9840	0.9940	0.9875***	0.9828	0.9922
Mean wind speed (km per hour)	0.9998	0.9950	1.0045	0.9990	0.9929	1.0051	0.9982	0.9927	1.0036	0.9888***	0.9837	0.9940
Proportion of fog	0.9963	0.9885	1.0041	1.0004	0.9899	1.0109	1.0023	0.9985	1.0061	1.0018	0.9989	1.0046
Proportion of rain	1.0005	0.9989	1.0021	1.0008	0.9992	1.0025	1.0007	0.9990	1.0024	1.0013	0.9997	1.0029
Proportion of snow	1.0007	0.9882	1.0133	-	-	-	1.0030	0.9901	1.0161	0.9957	0.9878	1.0037

 Table 27 - Seemingly unrelated regression results for seasonal model (model 1)

NOTES: ***p-value < 0.001; **p-value < 0.01; *p-value < 0.05; .p-value < 0.1. IRR = Incident Rate Ratio.

Explanatory Variables	Omnibus test	Spring vs. summer	Spring vs. autumn	Spring vs. winter	Summer vs. autumn	Summer vs. winter	Autumn vs. winter
Mean temperature (°C)	14.56***	n.s.	n.s.	10.05***	n.s.	11.32***	8.87**
Mean wind speed (km per hour)	11.28*	n.s.	n.s.	9.32**	n.s.	6.21*	5.97*

NOTES: ***p-value < 0.001; **p-value < 0.01; *p-value < 0.05. All tests are derived from models in Table 27. All omnibus tests have three degrees of freedom; all pairwise tests are based on one degree of freedom. Pairwise tests were estimated only for those explanatory variables with statistically significant omnibus tests.

Taken together, the results from both analyses can be interpreted as partial support for the adversefavourable weather hypothesis. The seemingly unrelated regression models indicate that increases in temperature in spring, autumn and winter increase the likelihood of robbery; ostensibly because warmer weather is less expected in these seasons. The results from both methods indicate that this effect is strongest in winter; plausibly explained by the typical low temperatures in the study area during this period. Thus, even small increases in temperature in winter can result in more robbery.

Seemingly, this supports the predictions made by Cohn and Rotton (2000) that extremely low temperatures lead to people using public space less, and thus provides fewer opportunities for robbery to occur. Further, when wind speeds are higher in winter (presumably twinned with low temperatures), decreases in robbery are observed. A cold winter wind appears to discourage outside activity. Indeed, wind has been found to be an important condition in perceptions of thermal comfort (Walton, Dravitzki & Donn, 2007), and high wind speeds lead to people staying indoors more (Horanont et al., 2013). It is interesting that other weather variables do not show noteworthy associations, but this can be explained by the microclimate of the study area (i.e. regular precipitation and seldom snowfall). The null effect of rain goes against conventional wisdom but mirrors findings by other UK research (Brunsdon et al., 2009; Field, 1992).

Whilst the magnitudes of the effects of temperature and wind speed in model 1 in both sets of analyses appear small, it should be noted that these conditions have a considerable range – for example an increase of one km per hour in wind speed overall decreases robbery by 1.1 per cent. Hence (assuming a linear relationship) if the wind speed increased by 20 km per hour this would translate to a 22 per cent decrease in robbery. It is worth stating that the negative binomial interaction model 1 (Table 26) overall only explains 6.8 per cent of the variance in the count of robbery per interval over the data period (based on the pseudo R^2 value) – a rather limited amount, but in keeping with prior research (Cohn & Rotton, 2000).

Discretionary activities model (model 2)

The negative binomial interaction model results for the time periods most likely to be used for discretionary activities (model 2) are presented in Table 29. Again, these should be interpreted in relation to the reference unit – *night-hours on a weekday in winter that is not a public holiday*. A similar trend is evident in this model, whereby temperature, humidity and wind speed are seen as influential on robberies overall, with the IRRs for each weather condition in the same direction as Table 26. Robbery is less likely in the early- and mid-hours compared to the night-hours (see Table 20 in Chapter 4) and less likely at the weekend, according to this model.

	IRR	c		p-value	Adjusted p
(Intercept)	3.4382***	2.0482	5.7506	< 0.001	0.000
Sequential	0.9997***	0.9997	0.9997	<0.001	0.000
Mean temperature (°C)	1.0126**	1.0048	1.0204	0.001	0.006
Mean humidity	0.9934*	0.9878	0.9991	0.023	0.076
Mean wind speed (km per hour)	0.9925**	0.9874	0.9975	0.003	0.016
Proportion of fog	0.9999	0.9967	1.0030	0.954	0.954
Proportion of rain	0.9997	0.9983	1.0012	0.699	0.884
Proportion of snow	1.0006	0.9859	1.0139	0.938	0.954
Early-hours (4AM-10PM)	0.2403**	0.0895	0.6376	0.004	0.019
Mid-hours (10AM-4PM)	0.5372*	0.2895	0.9979	0.049	0.124
Late-hours (4PM-10PM)	1.1747	0.6777	2.0421	0.567	0.811
Weekend	0.4669***	0.3282	0.6637	<0.001	0.000
Public holidays	0.9510	0.3942	2.2687	0.910	0.954
Int: mean temperature and early-hours	0.9740***	0.9606	0.9875	<0.001	0.000
Int: mean temperature and mid-hours	0.9866*	0.9766	0.9968	0.010	0.043
Int: mean temperature and late-hours	0.9769***	0.9679	0.9860	<0.001	0.000
Int: mean temperature and weekend	1.0002	0.9928	1.0079	0.942	0.954
Int: mean temperature and public holidays	1.0208.	0.9990	1.0431	0.063	0.151
Int: mean humidity and early-hours	1.0014	0.9906	1.0123	0.804	0.943
Int: mean humidity and mid-hours	1.0036	0.9967	1.0105	0.309	0.531
Int: mean humidity and late-hours	1.0007	0.9945	1.0068	0.833	0.943
Int: mean humidity and weekend	1.0107***	1.0069	1.0145	<0.001	0.000
Int: mean humidity and public holidays	0.9961	0.9869	1.0055	0.412	0.681
Int: mean wind speed and early-hours	1.0110*	1.0016	1.0204	0.021	0.076
Int: mean wind speed and mid-hours	1.0051	0.9982	1.0120	0.144	0.283
Int: mean wind speed and late-hours	1.0060*	1.0002	1.0118	0.042	0.120
Int: mean wind speed and weekend	1.0010	0.9964	1.0057	0.662	0.863
Int: mean wind speed and public holidays	1.0038	0.9920	1.0155	0.523	0.803
Int: proportion of fog and early-hours	0.9958	0.9901	1.0013	0.141	0.283
Int: proportion of fog and mid-hours	0.9969	0.9915	1.0021	0.247	0.462
Int: proportion of fog and late-hours	1.0011	0.9962	1.0058	0.662	0.863
Int: proportion of fog and weekend	1.0002	0.9967	1.0038	0.877	0.954
Int: proportion of fog and public holidays	1.0074*	1.0004	1.0140	0.032	0.098
Int: proportion of rain and early-hours	1.0010	0.9983	1.0037	0.462	0.736
Int: proportion of rain and mid-hours	1.0020*	1.0000	1.0041	0.048	0.124
Int: proportion of rain and late-hours	1.0015	0.9996	1.0033	0.120	0.272
Int: proportion of rain and weekend	0.9983*	0.9967	0.9998	0.023	0.076
Int: proportion of rain and public holidays	1.0020	0.9982	1.0058	0.300	0.531
Int: proportion of snow and early-hours	0.9973	0.9773	1.0159	0.780	0.943
Int: proportion of snow and mid-hours	0.9824	0.9566	1.0043	0.145	0.283
Int: proportion of snow and late-hours	0.9952	0.9793	1.0114	0.554	0.811
Int: proportion of snow and weekend	0.9985	0.9849	1.0123	0.828	0.943
					-

 Table 29 - Negative binomial interaction model for discretionary activities model (model 2)

NOTES: IRR = Incident Rate Ratio. Cragg and Uhler pseudo $R^2 = 0.23$, 2x log likelihood = -36,774.6.

The latter appears counter-intuitive as 41.7 per cent of robbery in the study period happens on weekend days (data not shown). However this can be explained by 80 per cent of weekend robbery being concentrated into the night- and early-hours, which are accounted for by the other variables. In other words, it is because lots of robbery happens at night-time that weekends have high levels of robbery – not just because they happen to be weekend days. Public holidays¹⁶ do not appear to exert an influence over robberies in general.

Examining the interaction variables in model 2 shows some subtle distinctions that provide evidence in support of hypothesis 2. For temperature, the IRR direction for the early-, mid- and late-hours contrasts with the overall temperature variable, indicating that higher temperatures in the nighthours correspond with increased robberies. Thus low temperatures at night-time dissuade people from being outdoors (because they don't have to be) – which in turn provides fewer opportunities for robbery to occur. The interaction of public holidays and temperature shows an increase in robberies for higher temperatures, but this is only significant at the 0.1 level. Conceivably this reinforces that temperature affects people's choices to be outdoors when they have more discretion over what activities they pursue.

The interaction between mean humidity and weekends is statistically significant, meaning that higher humidity is associated with increased robberies during this period. This should however be interpreted with caution; the study area is known to have consistently high humidity and this is not necessarily related to high temperatures as in other microclimates.

In a similar way to temperature, wind speed also exhibits a different influence on the night-hours than for the other times of the day. In particular, higher wind in the early- and late-hours increases robberies, relative to the night-hours. This seems to indicate that during the night-time, where the number of discretionary activities is likely to be higher, increased wind will discourage people from using public outdoor space. At other times of the day heightened wind-speed will have less of an effect in reducing robbery volumes.

One intriguing result seen in Table 29 is that increased proportions of fog (in terms of duration in the interval) on public holidays increase the likelihood of robbery. This runs counter to the hypothesised effect, but could potentially be explained by the fog affording offenders an environment with decreased visibility, which would reduce the ability of capable guardians to monitor their

¹⁶ These included: New Year's Day, 2nd January, Burns Night, Good Friday, Easter Monday, Royal events, the two May bank holidays, the Glasgow Fair, Glasgow September weekend, Halloween, Bonfire night, St Andrews Day, Christmas and Boxing Day. Additional models – not reported here - used public holidays as individual independent variables but did not show any significant effects.

surroundings. Darker conditions, which plausibly decrease visibility, have been shown to increase the likelihood of robbery (see Chapter 4).

Viewing rain at the interaction level with temporal variables also reveals an interesting pattern. Whilst not significant at the general level, rain shows a significant relationship with the mid-hours (10AM – 4PM) and weekend. For the mid-hours increased rain is associated with small increases in robbery (compared to the reference category of night-hours); for weekends this effect is reversed. As previously mentioned, robberies predominantly occur in the late- and night-hours at weekends, so it would seem that the effect of rain on the mid-hours is more likely related to weekdays. One possible reason for this is that the profile of victims is different in the week (i.e. could comprise of school-children and workers) than at the weekend. So whereas rain might not deter offenders from operating in the middle of the day, people involved in obligatory activities are also in public space as potential victims. In contrast rain at the weekend can discourage the use of public space.

It is apparent from the adjusted p-values in Table 29 that several of the variables discussed fall below the conventional 0.05 significance level when this correction method is applied. Namely these are the overall humidity; the mid-hours; and the interactions involving wind speed, fog and rain. Hence the more reliable results are those that remain significant after correcting for the multiplicity in the regression model. Clearly, more studies are needed to corroborate the other relationships found by this study.

The negative binomial interaction model results (model 2) has a greater explanatory power for the variation in robbery at the interval level (pseudo $R^2 = 0.23$) than model 1 (pseudo $R^2 = 0.068$). The inclusion of temporal variables that represent periods when people are free to pursue discretionary activities thus appears to offer greater prospects for predicting robbery.

The seemingly unrelated regression results for model 2 can be viewed in Table 30. Due to the nighthours interval being modelled separately in these, rather than behaving as a reference category as in the negative binomial interaction model (Table 29), the results can be seen from a different perspective. Temperature and wind speed exhibit relationships in the same direction for the intervals (as observed previously). Rain attains significance in the night-hours, albeit at the 0.1 significance level, with increases in rain associated with decreases in robbery. This explains why the mid-hours in the previous model saw a negative relationship with rain, as it was relative to the reference category (night-hours). In the mid-hours SUR model an increased proportion of snow predicts small decreases in robberies. As this result is only significant at the 0.1 level, it may explain why this relationship was not detected in the negative binomial interaction model.

	EARLY (4AM – 10AM)		MID (10AM – 4PM)			LATE (4PM – 10PM)			NIGHT (10PM – 4AM)			
	IRR	C		IRR	C		IRR	C		IRR	C	
Constant	0.4882**	0.2111	1.1289	2.0520***	1.4316	2.9412	2.9323***	2.2908	3.7536	1.6989*	1.0286	2.8061
Sequential	0.9998***	0.9997	0.9998	0.9996***	0.9996	0.9997	0.9997***	0.9997	0.9998	0.9998***	0.9998	0.9998
Mean temperature (°C)	0.9874**	0.9757	0.9992	0.9985	0.9913	1.0058	0.9898***	0.9842	0.9954	1.0142***	1.0072	1.0213
Mean humidity	0.9992	0.9900	1.0085	0.9999	0.9958	1.0040	0.9983	0.9955	1.0011	0.9985	0.9930	1.0039
Mean wind speed (km per hour)	1.0037	0.9958	1.0116	0.9982	0.9935	1.0030	0.9990	0.9957	1.0024	0.9934**	0.9887	0.9981
Proportion of fog	0.9962	0.9912	1.0013	0.9979	0.9928	1.0029	1.0013	0.9977	1.0049	1.0000	0.9974	1.0026
Proportion of rain	1.0001	0.9976	1.0026	1.0011	0.9996	1.0026	1.0005	0.9992	1.0018	0.9989.	0.9976	1.0002
Proportion of snow	0.9966	0.9822	1.0112	0.9833.	0.9660	1.0010	0.9945	0.9854	1.0036	0.9973	0.9873	1.0074
Weekend	1.2965***	1.1527	1.4582	0.5787***	0.5289	0.6331	1.0483.	0.9912	1.1085	1.5411***	1.4467	1.6416
Public holiday	1.1185	0.8572	1.4594	0.6156***	0.5019	0.7550	1.0182	0.8805	1.1775	0.9549	0.8137	1.1204

 Table 30 - Seemingly unrelated regression results for discretionary activities model (model 2)

NOTES: ***p-value < 0.001; **p-value < 0.01; *p-value < 0.05; .p-value < 0.1. IRR = Incident Rate Ratio.

 Table 31 - Equality of coefficients Wald test chi-square values for discretionary activities model (model 2)

Explanatory Variables	Omnibus test	Early vs. mid	Early vs. late	Early vs. night	Mid vs. late	Mid vs. night	Late vs. night
Mean temperature (°C)	31.81***	n.s.	n.s.	14.49***	3.45*	9.26**	28.29***
Weekend	315.57***	114.12***	10.25**	6.44*	120.87***	304.95***	80.13***
Public holidays	19.01***	12.18***	n.s.	n.s.	15.49***	11.00***	n.s.

NOTES: ***p-value < 0.001; **p-value < 0.01; *p-value < 0.05. All tests are derived from models in Table 30. All omnibus tests have three degrees of freedom; all pairwise tests are based on one degree of freedom. Pairwise tests were estimated only for those explanatory variables with statistically significant omnibus tests.

The SUR model also considers the *interaction* between weekends and public holidays by interval, which is not covered in the previous analyses of model 2. Table 30 reveals that robbery is much less likely to happen in the mid-hours at weekends, and is much more likely during the night- and early-hours. Similarly, robbery is less frequent in the mid-hours on public holidays. These findings are intuitive in the framework of routine activities; the temporal patterning of discretionary routine activities mean that motivated offenders and suitable targets are simply not converging during the mid-hours on these more discretionary-activity based days. This may be due to offenders not being active at this time, or perhaps there are simply too many capable guardians present in public space in the daytime – meaning that conditions are not optimal for offending. It might also be the case that in the daytime, and on weekends and public holidays, peoples' routines produce a more dispersed geographical pattern of activity, meaning that opportunities for robbery are less concentrated in space.

Only three explanatory variables achieved significance in the global Wald tests shown in Table 31: temperature; weekend; and public holidays. Mean temperature coefficients were statistically distinguishable for the mid- and night-hours comparisons. The coefficients for weekend were statistically different across all four intervals, although the magnitude of the difference was greatest for comparisons with the mid-hours. The mid-hours were again noteworthy when the chi-square values for public holidays were compared with other intervals.

The two sets of analyses present subtly different pictures. Cumulatively, these findings suggest that weather is most impactive in the night-hours, when favourable weather increases the likelihood of robbery and adverse weather decreases it. The mid-hours interval appears to be significantly associated with reductions in robbery when it intersects with days delineated for discretionary activities.

5.4 Discussion

Whilst weather and crime has been extensively studied over the past century by criminologists, the relationship between the two has eluded universal theorising. This Chapter contributes to this scientific debate by advancing an argument that it is people's subjective interpretation of weather that is the mechanism that influences their subsequent outdoor activity. Not accounting for the fact that different people use space differently at various times could be an explanation for why prior research has failed to establish a clear relationship between weather and crime. For crimes like street robbery, which require both victim and offender to interact, weather can determine whether people are present in an outdoor environment to provide the opportunity for robbery to occur. This speaks to the central thrust of this thesis; the criminogeneity of micro-temporal places.

Two hypotheses are tested in this study; the first relates to people's seasonal expectations of weather. This adverse-favourable weather hypothesis posits that when weather is markedly different than the seasonal norms people are either less or more willing to venture outdoors, depending on whether it makes conditions less or more favourable than expected. Thus, extremes in weather - excess heat in summer and extreme cold in winter – might limit people's (illegal or otherwise) contact with others in public space. Likewise, unexpectedly mild or favourable conditions might encourage increased use of public space.

The results in Tables 26 and 27 appear to support this hypothesis. Both wind speed and temperature had statistically significant effects, both at the general level on robbery counts per interval, and when they interacted with seasonal variables. The winter period exhibited the most notable results in support of the adverse-favourable weather hypothesis; showing that an increase in temperature in these months resulted in greater robbery frequencies, but an increase in wind speed in these months resulted in a decrease in robberies. These two sets of results are interrelated; they both contribute to a person's sense of thermal comfort. Wind speed accompanied by cold temperatures considerably increases the 'wind chill factor'. Therefore adverse weather in winter is more influential in this particular study area. In other microclimates it is likely to be the case that excessive temperature, humidity or stormy weather has a similar effect – a finding echoed throughout the weather and crime research (Cohn & Rotton, 1997). Importantly, the findings support Rotton and Cohn's (2000) social contact/avoidance hypothesis, which postulates that extremes in temperature (both hot and cold) reduces social contact through people retreating to their primary territories (such as homes). However, the analysis presented here extends their model by considering wider meteorological conditions than temperature and considers what might influence a person's interpretation of 'bad' or 'good' weather.

The second hypothesis tested in this study relates to discretionary activities. Here, it was postulated that variation in weather would have a stronger effect on robbery in time periods that were demarcated for discretionary (or recreational) activities. The results presented in Tables 29 and 30 provide evidence in support of this hypothesis, but show that weather conditions exert differential effects on different periods of discretionary time. In these results wind speed, temperature and humidity were again seen to be significant to robbery levels – particularly in periods when people are free from obligatory activities (night-hours and weekends).

Slightly different results were observed for rain and snow across the different analytical approaches. Notably, rain was shown to have a negative relationship with robbery at the weekends in the negative binomial interaction model, which suggests that people are less likely to venture outdoors when it is raining when travel behaviour is optional. This analysis also produced a statistically significant positive relationship between rain and the mid-hours, which can be interpreted *relative* to the negative relationship between rain and the night-hours evidenced in the SUR analysis (see Table 30). A small negative relationship was also observed in the mid-hours for snow in the SUR analysis, but this was only significant at the 0.1 level and was not present in the negative binomial regression coefficients in Table 29.

Using two methods to cross-validate the findings was analytically expedient; the negative binomial interaction models were able to assess the relationship between weather and days widely demarcated for discretionary activities (weekends and public holidays). An interesting finding to emerge from this was that fog was the only variable to significantly interact with public holidays and did so in the opposite direction to the other variables - with more fog at weekends increasing robbery levels. This exception could be related to guardianship levels; fog in particular considerably reduces the people's ability to see and hence monitor their surroundings.

Contrastingly, the SUR analysis permitted comparisons of cross-sections of time - specifically the weekends and public holidays by interval - meaning that distinctive patterns could be exposed. This analysis revealed that robbery is highly patterned into particular times of the day when people are predominantly engaged in discretionary activities. Simply put, robbery occurs less frequently in the daytime (mid-hours) on days when most people are not in obligatory activities. It was speculated that this might relate to the conditions for robbery being sub-optimal during this time of the day (due to fewer offenders, fewer targets or more guardians).

Collectively these results produced greater explanatory power for the variation in robbery at the interval level than has been seen in prior research, which potentially relates to the important influence of discretionary activity time on a crime type such as robbery, and the fine-grain unit of analysis chosen to study weather and robbery (the 6-hour interval). Such a micro-temporal level approach is critical to observing the variation of weather over the course of the day, and over other temporal scales.

Limitations

Naturally this study has some limitations. Using data from one weather station only approximates the weather across the study area, and as weather is known to vary considerably at the localised level (see Brunsdon et al., 2009) it is certainly the case that there is some error in the measurements of weather in these analyses. However, the readings from the weather station used in the analysis (Glasgow Airport) saw good agreement with other stations across the study area (see Chapter 4).

Alternative ways of capturing data on the precipitation variables (for example rain or snow in millimetres) may yield different results from those seen here. Alternative methods of estimating unseasonal effects are also acknowledged, such as statistical variation of weather across seasons.

How weather and discretionary activities vary over spatial location (i.e. inter-neighbourhood, see Harries et al., 1984; Sorg & Taylor, 2011) and different populations (i.e. stratifying victim populations by their routine activities) were also outside of the scope of this study. In the absence of spatiotemporally accurate population data, we can only indirectly estimate the influence of weather on levels of usage of public space (see e.g. Malleson & Andresen, 2015), and, as a consequence, opportunities for robbery. The change in population over time can be seen as a (currently assumed) intermediate variable in the hypothesised chain of events between certain weather conditions and changes in robbery levels. However, the general agreement of the results produced in this study suggests that there is substantial support for the proposed hypotheses.

Further work

The strength of the hypotheses presented in this paper is that, unlike other theoretical approaches, they do not limit their explanations to certain types of crime (e.g. violence). Instead, they postulate what weather conditions will encourage people to leave their homes and interact in public space. For a different crime such as burglary, it might be the case that those same conditions create opportunities for vacant houses to be burgled. To test the generalisability of these findings they should be replicated in different microclimates, with different seasonal norms and routine activities shaped by different discretionary activities (such as public holidays).

Some of the factors that might influence normalised expectations of weather were absent in the theorising in section 5.1. These might plausibly include retrospective or prospective trends. It could be argued that recent trends will affect people's expectations; a period of below average temperature following a period of above average temperature feels more of a contrast. Stormy weather will be normalised if it is prolonged, rather than episodic. Weather fronts – defined as a marked change in weather conditions over time in a particular place – have been the subject of criminological enquiry. LeBeau and Corcoran (1990) found that the rhythms of one- and two- day weather fronts correlated with volumes of calls for service. In their study swift changes in mean temperature (termed 1-day fronts) were associated with significantly lower and higher numbers of calls for services when cold fronts and warm fronts respectively arrived in Chicago. From this they posited that the cold fronts required an abrupt adjustment period for humans and their activities.

Further, it is possible that such short-term transitory adverse weather may temporally displace routine activities (Field, 1992). It may well be the case that there is a lagged effect for some weather conditions such as rain or excess heat, where people delay their discretionary activities until a time when the weather is more pleasant. Other research conducted by LeBeau (1994) on domestic disputes and temperature bolsters this hypothesis. Here, LeBeau found that most disputes occur in the late evening hours – which had no direct link to high temperatures, since temperatures are usually lower in the evening than they are in the day. He tested the hypothesis that there is a lagged relationship between weather and violent behaviour and found that across all the seasons, the 6-hour lag for the temperature humidity index had the highest positive correlation with domestic disputes.

It is also plausible to assume that weather forecasts influence activities planned in advance, or with a long duration (Böcker et al., 2013), however a detailed exploration of the role of expectations and weather forecasts for outdoor travel and behaviour has yet to be empirically undertaken. Spontaneous discretionary activities, such as those in pursuit of recreation or entertainment, may be more influenced by what weather is expected over the scale of hours, rather than days. Hence, short-term recent trends (both retrospective and prospective) can potentially impact on people's perceptions of the weather and mediate their behavioural response to it.

These theoretical propositions and how they relate to generalised human behaviour are summarised in Figure 27. This shows that for weather to be perceived as pleasant, it can either be so at a given moment, be anticipated in the short-term future, or be relatively better than expectations based on microclimate, season or recent trends. Perceptions of pleasant weather result in both discretionary and obligatory activities being pursued. Inverse propositions are given for the perception of adverse weather; that is, weather is either adverse at a given moment, is anticipated to be so in the shortterm future or is worse than expectations derived from microclimate, seasonal or recent norms.

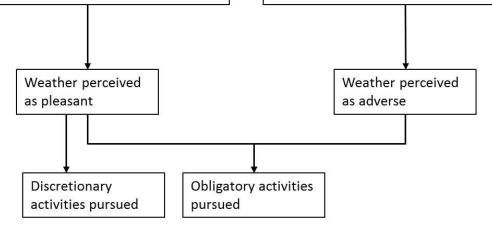
The hypothesised model in Figure 27 attempts to elucidate the causal mechanisms through which weather is interpreted. This extends the central premise for this study; that interpretations of weather give rise to behavioural decisions on whether to travel and spend time outdoors. If the propositions in Figure 27 are well-founded, a greater level of prediction accuracy is possible in future research on the relationship between weather and crime patterns. It is worth bearing in mind though that this is presented as a simple macro theory; it does not account for individual differences in perception (that might relate to socio-demographic characteristics or individual traits). Future research may prosper by integrating this extra level of complexity into the investigation of weather on crime patterns.

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Figure 27 - Hypothesised influences of weather perceptions on pursuit of obligatory and discretionary activities

- Pleasant weather at given moment
- Weather better than microclimatic expectations
- Weather better than seasonal expectations
- Recent weather pleasant
- Future weather anticipated as pleasant

- Adverse weather at given moment
- Weather worse than microclimatic expectations
- Weather worse than seasonal expectations
- Recent weather adverse
- Future weather anticipated as adverse



Conclusion

Scholars have suggested that the relationship between crime and weather is so complex that multiple theories are needed (Rotton & Cohn, 1999). The analyses presented in this Chapter find affirmative evidence that relationships between weather and time exist, and that these manifest at different scales of interest. Importantly, the findings from this study reveal that weather impacts differentially depending on season and what activities people are likely to be engaged in (i.e. obligatory or discretionary).

Police crime prevention activity is already heavily shaped by known patterns of crime in space (in terms of well-established hotspot mapping). Temporal patterns in crime are less obvious, and require a greater infiltration of theory into standard crime analysis practices, complemented by advanced statistical modelling. The influence of weather on crime will always prove somewhat intangible due to the differential effects it has in different contexts. But by considering seasonal norms, discretionary time, and the cultural expectations of people in given conditions it may be possible to appreciably understand how it might affect the interaction of victims and offenders in time and space. In turn this wisdom can help crime reduction agencies to advantageously position their resources to inhibit crime from occurring. In conclusion, weather should be considered

alongside other situational variables, particularly during times of discretionary activity or noticeably favourable weather conditions, in planning allocation of crime reduction resources.

The topic of discretionary and obligatory activities occupies a central position in the following Chapter. This is dedicated to unpacking the relationship between land use *over time* and robbery. This topic therefore changes from the natural environment to the built environment, but maintains the theme of assessing human mobility patterns. In this I focus on stratifying the victim population so that the relationship between victimisation risk and facilities, at the times at which they are most socially relevant, is revealed.

Chapter overview

Acute discrepancies in victimisation risk amongst particular groups of people are a long-standing observation in criminology (Hindelang, Gottfredson & Garofalo, 1978; Block, Felson & Block, 1985). The fact that crime concentrates in this way has important theoretical and practical implications. Explaining why certain sub-groups of the population have a heightened risk of victimisation has generally been the province of routine activity theorists. The routines of victims are held as being an important causal factor in the commission of both property and interpersonal crime (Kennedy & Forde, 1990; Miethe & Meier, 1990; Miethe, Stafford & Sloane, 1990; Sampson & Wooldredge, 1987; Skubak Tillyer, Tillyer, Miller & Pangrac, 2011). To date however, scant attention has been paid to *the time of the day* that different sub-groups are victimised; despite time governing the types of routine activities people undertake. Further, very little has been done to undertake empirical analysis looking at prominent victim groups and their changing risks as a consequence of their routines at anything other than the macro-level (e.g. Cohen & Felson, 1979).

This Chapter advances existing work concerned with the relationship between robbery location, criminogenic land uses and time by centralising the type of victim into the focus of inquiry. The objective of the study is to determine whether different sub-groups of victims, disaggregated through their occupation, are victimised proximal to facilities at times that are socially relevant to their demographic. Hence the focus is not solely land use but *use of land over time by different groups*.

Initially location quotients are produced for four facility types using street network buffers to generate an empirical distance threshold that can be used to define the criminogenic reach – the *environs* - of each facility. This threshold is subsequently incorporated into multinomial regression models, presented at the facility level. Hence, the dependent variable in the regression models is victim occupation, which is used as a proxy for routine activities (see more below). The comparison of time dependent victimisation risks of different occupational sub-groups produces estimates of *relative risk*.

Had ambient population data been available it would have been possible to calculate whether the absolute risk of victimisation at a particular time and place was heightened for different occupational groups (e.g. school pupils at an acute risk of robbery at 3pm on weekdays). Such rate data can be employed to test theories of offender targeting behaviour. However, and as elaborated upon in Chapter 7, ambient population data has yet to be collected at a resolution suitable for

granular spatio-temporal analysis, and tells us nothing about demographic groups. Hence, in the absence of these population-at-risk data, it is instructive to ask whether different occupational groups are more likely to be victims at certain times and places compared to other groups and other times and places. Patterns of conditional (i.e. relative) risk across sub-groups can be informative for crime prevention strategy formation and useful for advancing theory. In particular, explaining how victimisation risk varies across space and time as a result of how they spend the majority of their obligatory time, can elicit insight into making those routines safer.

This Chapter proceeds as follows: first, derived from ethnographic research and victimisation surveys, the literature on victimisation proneness and robbery victim selection processes is reviewed. Next the hypotheses regarding the timing of robbery victimisation of different sub-groups in relation to facilities associated with key formal or recreational activities are formulated. The data and methods employed in this study are then described, before the findings are presented. In the discussion I consider the limitations of the current study and elucidate the implications of the findings for criminological theory and crime prevention.

6.1 Theoretical background

A number of theories have been proffered to explain variations in (absolute) victimisation risk. Of these, the most influential have emanated from the opportunity perspective; encompassing the routine activity approach (Cohen & Felson, 1979), the lifestyle-exposure perspective (Hindelang et al., 1978) and crime pattern theory (Brantingham & Brantingham, 1993a). As stated in Chapter 2 this overarching theoretical perspective maintains that crime opportunities are the product of victims and offenders converging in optimal conditions. Such confluences are intrinsically spatio-temporal, in that they are distributed according to the temporal rhythms inherent in human activity (such as working and socialisation patterns). It follows that the risk of victimisation varies across time and space; which is borne out by an abundance of empirical studies (Clarke et al., 1985; Eck et al., 2007; Groff et al., 2010; Johnson & Bowers, 2004; Kennedy & Forde, 1990; Lemieux & Felson, 2012; Sagovsky & Johnson, 2007).

The routine activities approach has considerable conceptual overlap with the lifestyle-exposure perspective (Hindelang et al., 1978). These scholars found markedly similar demographic profiles of victims across eight US cities, leading them to argue that the 'lifestyles' of individuals were of central importance in explaining patterns of criminal victimisation. Certain lifestyles that increase time spent in public places, where strangers or those who are criminally inclined are likely to be, elevate an individual's exposure to risk of victimisation. In short, particular lifestyles increase the likelihood of potential offenders and likely victims interacting (see also Wittebrood & Nieuwbeerta, 2000).

Many scholars treat the routine activity approach and the lifestyle-exposure perspective as analogous (McNeeley, 2014; Miethe et al., 1990; Skubak Tillyer et al., 2011). Both theoretical stances maintain that crime is a function of victim attributes, activities and lifestyles, and that time spent away from home is associated with a heightened risk of victimisation. Latterly attempts have been made to discriminate between the two theoretical approaches, underscoring that the lifestyle perspective focuses more acutely on 'risky' activities such as socialising in public settings (Lemieux & Felson, 2012). Accordingly, Allen and Felson (2012) argue that discretionary activities arising through lifestyle choices are avoidable, and therefore are distinct from the original conceptualisation of routine activities which speaks more to those unavoidable obligatory activities, such as formal responsibilities relating to employment and education, which nevertheless can influence exposure to victimisation risks.

A focus on different types of activities resonates with Lynch's (1987) advocacy for *domain-specific* models of victimisation. In his prominent study on work-related victimisation he asserted that it was improbable that one single (routine) activity theory could explain the highly heterogeneous phenomena of crime. Instead, Lynch proposed deconstructing activities and victimisations into domains such as work, school, home and leisure and defining precise classes of victimisation to create more internally homogenous categories of crime. This, he argued, provided a fruitful means of building quantitative models with greater explanatory power, each of which could be subsequently synthesised to build a more general activity theory.

That said, the assertion that routine activities can be used to explain individual variation in victimisation is underpinned by an impressive empirical evidence base (Groff, 2007; Wilcox, 2010). Principally, studies have been concerned with identifying the influence of 'risky' routine activities on victimisation risk. In particular, the advent of large-scale victimisation surveys afforded analysis on the correlates of victimisation risk and lifestyle factors (see, for example, Miethe et al., 1990). Research utilising victimisation surveys has revealed, for example, that people who engage in leisure activities outside the home in the evenings have a higher risk of victimisation than those who stay at home (Gottfredson, 1984; Sampson & Wooldredge, 1987). This relationship manifests for property crime and inter-personal crime (Kennedy & Forde, 1990; Sampson & Wooldredge, 1987). To add in much needed individual-level spatial and temporal variation, using computer simulation Groff (2007) verifies that increasing the time victims spend away from home is associated with increases in robbery rates, lending empirical credibility to these constructs of lifestyle employed by the victimisation surveys.

Lemieux and Felson (2012) draw attention to the fact that frequency measures on evening activities outside of the home are silent on the precise settings – risky or otherwise – that people go to and for how long. Plainly, spending the evening at a friend's house carries a different risk of victimisation than socialising in public. Further, socialising in a family-oriented bar is unlikely to convey the same level of risk as one that is associated with competitive sport (Scott & Dedel, 2006). Hence, precise information on *where* people are going and for how long is required to directly test the contribution lifestyle activities have to victimisation risk.

The level of detail that is needed to accurately study these time-sensitive exposure constructs has not been available in victimisation surveys to date. These large-scale surveys were designed to provide an incidence rate of victimisation that served as an alternative to officially collated statistics. Hence, because participants can be victims *or* non-victims, *absolute* risk can be derived from such surveys. What is typically absent from large-scale surveys (presumably due to the time and cost of administering the survey across large samples) is information on specifically *where* and *when* victimisation occurred. Thus, information on the activities undertaken by victims at the time of victimisation is not available from these data. Neither is comparative information about nonvictims.

Space-time budget methods, which record hourly activities and locations of participants, have been employed in longitudinal studies on the situational causes offending (see Bernasco et al., 2013; Wikström et al., 2010). Since these data also collect information on victimisation they are a promising means of studying the situational causes of victimisation. In addition, these data offer prospects for calculating estimates of absolute risk by participant characteristics and micro-space time features. Access to these data is though understandably restricted to scholars collaborating with the Peterborough Adolescent and Young Adult Development Study (PADS+, see www.pads.ac.uk).

Another important finding to emerge from studies using victimisation survey data is that in many cases demographic characteristics of victims, such as age, gender and marital status, hold greater explanatory power than lifestyle variables (Kennedy & Forde, 1990; Sampson & Wooldredge, 1987). Credibly, there is an interactive component to demographic and lifestyle variables; for example, as people grow older and/or get married they are more likely to be involved in home-centred activities and socialise less frequently in public settings (Clarke et al., 1985; Cohen & Felson, 1979; Cohen, Kluegel & Land, 1981). Similarly the nature of one's employment can influence the type of income and lifestyle available (Lynch, 1987). Thus, certain demographic characteristics could be thought of

as an (admittedly imperfect) proxy for risky, or otherwise, lifestyle activities and can be used to model different sub-groups of the population.

Target suitability and attractiveness for street robbery

I turn now to the evidence on victim selection processes for robbery. Victim attractiveness is a highly individualised concept (Jacobs, 2010; Monk et al., 2010; St. Jean, 2007) and relates to the circumstances of the robbery offence and the motivation of the offender. Thus, "target suitability is tied to both the characteristics of the target and to the characteristics of the target's surroundings" (Brantingham & Brantingham, 1993a: 272). The characteristics of the target's surroundings are palpably the environmental backcloth, and vary over time.

Several emergent themes from the literature speak to some common victim attributes. In particular, the victim should present a low-risk in terms of acquiescing to the offender's demands (Feeney, 1986) or be perceived unlikely to report the offence to the police (Deakin et al., 2007; Tilley et al., 2004). In many cases this manifests in targeting a victim who is conspicuously physically weaker, but can also relate to exploiting vulnerability caused by inebriation, naivety, poor health, or while the victim is pursuing illegal activities (Brookman et al., 2007; Deakin et al., 2007; Marek, Widacki & Hanausek, 1974; Skubak Tillyer et al., 2011; St. Jean, 2007). Other preferable attributes are that the victim is carrying items of value to the offender (Feeney, 1986), is distracted or unaware of the offender's intentions (Smith, 2003) and/or is situated so the offender can swiftly escape from the crime scene (Monk et al., 2010).

Information elicited from offenders reveals that robbery is sometimes enacted due to a pre-existing dispute (Brookman et al., 2007) or used as a means to assert dominance over others to enhance one's reputation or 'street cred' (St. Jean, 2007). At other times robbery is a by-product of an altercation in which the taking of property is an afterthought (Wright et al., 2006), or a perceived extension of 'bullying' behaviour (Barker, Geraghty, Webb & Key, 1993; Tilley et al., 2004). Contrariwise, at times robbery is employed with purely instrumental ends to obtain goods that are desired either for personal consumption or adornment, or to exchange for drugs (Gill, 2000).

These examples serve to emphasise the high variety of robbery circumstances and victim types. Thus, as Lynch (1987) notes, even individual crime types are internally heterogeneous. But how and where do offenders encounter their victims? St Jean's ethnographic fieldwork in Chicago with offenders provides some answers: "mostly it be somewhere where you find *the right kind of people*" and "generally, you rob *where you be at* for whatever reason if you have the chance" (2007: 115, italics added). These quotes illustrate that first, offenders generally seek people that fit a preferred victim profile (such as carrying cash or other desirable possessions) and, second, victims are generally (albeit not always) pursued as part of an offender's routine activities – where they happen to be at a given time. It may also be the case that places which attract the 'right kind of people' lie outside an offender's routine activities, but are known to be good hunting grounds; thus there is a distinction between predatory and opportunistic offending. Research on UK robbery has suggested that both types of offending occur (Barker et al., 1993; Deakin et al., 2007).

It is clear from offender's accounts that many robbery offences are opportunistic in the sense that the robber did not specifically set out to rob someone (Feeney & Weir, 1975; St. Jean, 2007). In these cases the offender simply encountered an opportunity that, with their prior knowledge of what makes a target suitable, they were able to capitalise on. Yet, is worth acknowledging that some offenders will be more tuned into identifying these spontaneous opportunities than others (Jacobs, 2010) - what Brantingham and Brantingham (1993a) call the state of *readiness*. When they occur, such opportunities are highly specific and concentrate across time and space (Smith, 2003). They may also be tied to the characteristics of the victim and/or offender. Crucially opportunities hinge on the timing and frequency of a *suitable* victim's routine activities, and their overlap with the presence of capable guardians.

Routine activities and activity nodes

Routine activities are dictated by human mobility patterns in space and time, as elucidated by crime pattern theory (Brantingham & Brantingham, 1993a). Both compulsory and recreational activities are anchored to specific *nodes* - or *facilities* - on the environmental backcloth. Facilities are defined by Eck et al. (2007) as a homogenous set of places which serve a specific function. Facilities that draw a large number of people to them for legitimate activities act as *crime generators* (Brantingham & Brantingham, 1995), as they provide numerous opportunities for crime to opportunistic offenders.

For predatory crimes, minimising the time it takes to identify a suitable target is likely an important factor in offender decision-making. Target-rich environments are places where it can be assumed with a high degree of certainty that many victims that fit a particular profile will be present. Such environments are known as *crime attractors* in environmental criminology; places where offenders are attracted to for predictable crime opportunities (Brantingham & Brantingham, 1995). Jacobs (2010) conceptualises this as 'manufacturing serendipity', insofar that purposive searching for robbery opportunities in places where they are likely to be gives rise to fortuitous circumstances for the offender.

The relationship between crime and criminogenic facilities has been extensively examined in recent decades, with associations found between robbery and schools (Roman, 2002; Roncek & Faggiani, 1985), parks (Groff & McCord, 2011), stations (Block & Block, 2000; McCord & Ratcliffe, 2009), bus stops (Newton, 1999), bars (Groff, 2013b; Snowden & Freiburger, 2015), public housing (Haberman, Groff & Taylor, 2011) and ATMs (Holt, 2000), to name a few. Within each facility type nuanced patterns emerge, for example some subway stations have a stronger relationship with robbery than others (McCord & Ratcliffe, 2009). This, Wilcox and Eck (2011) argue, can be ascribed to the *iron law of troublesome places* which, simply put, relates to the pervasive empirical finding that crime concentration is not uniform across space, or micro-space. This is otherwise known as the phenomenon of *risky facilities* (Eck et al., 2007).

Crime concentration is similarly not uniform across micro-space-time. Contemporary research is beginning to unpick the dynamic spatio-temporal relationship between criminogenic facilities and street robbery. For example, a recent study by Haberman and Ratcliffe (2015) tested 12 different facility types, along with spatially lagged variables for these facilities, control variables and measures of illicit markets. Their findings indicate that only a handful of facility types have a statistically distinguishable effect across different time periods in the day. Salient to the present study, Haberman and Ratcliffe (2015) found that subway stations were found to exert a stronger influence on street robbery in the daytime and evening periods, in comparison to the overnight period.

Irvin-Erickson and colleagues (in press) conducted a temporally sensitive study, finding that bus stops and grocery stores were the only facilities to have a 24-hour criminogenic effect on robbery. These (and other) facilities exhibited different spatial spheres of influence at different times of the day. Further land uses were observed to be criminogenic at discernibly specific time periods in the week. Irvin-Erickson et al. (in press) attribute these findings to the 'social relevancy' of facilities at particular times. For example, according to their analysis, light rail stations, schools and banks had a criminogenic effect on robbery during weekday business hours at times when the facilities were open, but this relationship disappeared at other times on weekdays and at the weekend. Intuitively, bars and take-out restaurants became criminogenic after business hours, supposedly when they attract the greatest number of customers. Bowers (2014) similarly found that theft from person within bars tended to occur earlier in the evening than theft outside on the street in entertainment districts, demonstrating that the risk follows the activity of potential victims at different times.

Disentangling the singular influence of a specific facility is problematic, however, since they cannot be studied in isolation from one another. As Bernasco and Block (2010) note, many facilities are colocated in space: urban centres contain an assortment of civic buildings, public transportation options and facilities for entertainment; shops and banks cluster in land demarcated for commercial use; residential areas contain facilities suited to local use. Therefore it is important to take into consideration the conjunction of different facility types (see Hart & Miethe, 2015 for an innovative qualitative approach to this) as they coalesce to produce different opportunity structures for crime.

Taken collectively, the evidence base for the spatial relationship between crime and facilities is substantive. However, less attention has been devoted to the spatio-temporal relationship and, to date, this has not been theoretically informed by the routine activities of victims for interpersonal crimes such as robbery. The question of the spatial (and temporal) criminogenic reach of influence of facilities similarly remains unresolved, and the present research aims to contribute to the nascent set of studies exploring this.

The role of victim occupation

It has long been known that different occupations are associated with varying levels of (absolute) risk of victimisation (Block et al. 1985; Farrell, 2015). Employment in a general sense provides the scaffolding on which all obligatory and discretionary activities depend. It constrains people to particular working hours and, typically, provides a controlled and private workplace which reduces the risk of victimisation to robbery. Prior work has established that workers predominantly get robbed during night-time hours (Smith, 2003), which can be explained by this period characterising leisure time activities, or people working in occupations which service the night-time economy (such as taxi drivers).

Perhaps because they are the least likely to be victimised (Clarke et al., 1985; Cohen & Cantor, 1980), non-workers seldom feature in the academic literature on victimisation risk. These are persons not in, nor looking for, employment. Sometimes called 'economically inactive', this group comprises retirees, the long-term sick, unpaid carers and homemakers. Due to their autonomy non-workers are assumed to spend the majority of time at home, which protects them from coming into contact with strangers (Miethe et al., 1990). The research literature suggests that retired people are most commonly victimised during the daytime hours (Klaus, 2005; Tilley et al., 2004), however little is known about the times at which other non-workers get victimised.

Unemployed offenders are a recurrent theme throughout the literature on robbery (Barker et al., 1993). Due to the principle of homogamy; that is, the likeness between victims and offenders, unemployment can be considered a risk characteristic for victims (Hindlelang et al., 1978; Cohen et al., 1981). Unemployed people have more leisure time than people in structured obligatory activities, which may involve drinking or drug use and hence increase vulnerability to crime (Cohen &

Cantor, 1980). UK estimates of the proportion of robbery victims who are unemployed range between 11.8 and 15 per cent (Barker et al., 1993; Smith, 2003). Smith's (2003) descriptive analysis found that unemployed people were slightly more likely to be victimised between 6PM and 6AM.

Offender interviews in UK research have shown that university students are an "archetypal easy victim" for robbery due to their perceived naivety, visible desirable goods and the fact that offenders believe them to be easy to intimidate (Deakin et al., 2007: 57). That students are seen by offenders as being from a privileged background makes them more 'deserving' in their eyes; thus increasing their attractiveness as targets of robbery (Barker et al., 1993; Jacobs & Wright, 1999). Analysis of university student robbery victim data has revealed that they are most frequently targeted late at night as they return home from bars and night-clubs, often when inebriated (Tilley et al., 2004; Smith, 2003).

The principle of homogamy can also be invoked to explain the notable sub-group of school-aged victims. Robbery offenders have, overwhelmingly, been found to be young in both the UK and US, with older robbers comprised almost exclusively of drug-addicts (Tilley et al., 2004; Smith, 2003; St. Jean, 2007). Presumably, young offenders and young victims inhabit similar activity spaces (Brantingham & Brantingham, 1984) and thus cross paths, whether deliberately or coincidently. Research evidence suggests that school-aged robbery victims are most likely to be targeted in the hours following school, whilst they travel home from school or socialise with friends (Smith, 2003; Tilley et al., 2004). This is consistent with Garafolo et al.'s (1987) work on school-related crime which found that teenagers are most at risk of victimisation from their peers.

6.2 Hypotheses, data processing and analytic strategy

The objective of the present study is to determine whether different sub-groups of victims, disaggregated through their occupation, are disproportionately victimised proximal to facilities at times that are socially relevant to their demographic. In doing so the intention was to be sensitive to the specific *domains* in which peoples' lives are organised (Lynch, 1987). This advances previous work by focusing on locations judged to influence obligatory and discretionary activities for particular population sub-groups. Whilst victim occupation is a crude proxy for routine activities, in the absence of detailed data on victims and their mobility patterns, it provides a means of categorising victims so that their dominant activities, and hence some of their space-time tendencies to be in public space, can be inferred.

Accurately determining domains of activities is not a straightforward task, for most people have a large range of habitual activities. Hence a subset of facilities that could be considered to feature in a

large proportion of peoples' activity spaces (Brantingham & Brantingham, 1984) and were associated with clear domain-specific activities such as education, employment or leisure were selected. These comprised 1) public houses and bars, 2) schools, 3) train stations, and 4) universities and further education institutions. Undoubtedly, these do not account for all the facilities that influence peoples' mobility patterns (for example, retail complexes and offices) but these were ones for which reliable data could be obtained.

To facilitate conjectures on what activities victims were undertaking at the time of the offence it was necessary to fuse these facilities with time periods deemed relevant to activity patterns. In what follows I outline the hypotheses in relation to each individual facility type, whilst acknowledging that the spatial association between them is non-trivial.

Hypotheses

On the basis of the above exposition, and considering likely activity patterns, the following spaceand time-sensitive hypotheses are posed in relation to the four facilities being investigated:

H4: The environs of schools will be associated with the disproportionate relative risk of school pupils being victimised on weekdays, in the hours after schools close. (In these hours pupils will be making their way home from these facilities and socialising nearby).

H5: The environs of universities and further education institutions will be associated with the disproportionate relative risk of students being victimised in the late evening and very early morning hours on weekends. (Students will socialise near to these facilities at these times due to their residential proximity).

H6: The environs of pubs and bars will be associated with the disproportionate relative risk of workers and students being victimised in the evening hours on weekdays and weekends. (Workers and students have the recreational time and resources to use drinking establishments in these hours).

H7: The environs of train stations will be associated with the disproportionate relative risk of workers being victimised in the daytime and early evening hours on weekdays. (Workers will be using these facilities for commuting purposes at these times).

To test these hypotheses it is necessary to use crime data that has victim details as well as locational information and timing of the crimes they were subjected to. Being granted access to such sensitive data is a fairly rare situation. This could be to do with potential disclosure risks of such data or the

difficulties of manipulating multiple data sets to match victim details with locations. I was fortunate in being able to acquire such data and thus have an opportunity to provide a unique contribution to the criminological literature on the relative spatio-temporal risks of victimisation for different subgroups.

Data

Operationalising the facilities which attract key routine activities necessitated the selection of land use data that could be obtained within the scope of this research. 1,368 point-level pubs and bars were obtained from the Ordnance Survey (OS) 'points of interest' data. Train stations, schools and higher and further education buildings were extracted from the OS 'open map local' data. Both mainline and subway stations are represented in the point-level train stations data (n=212). 926 schools and 42 universities and further education institutions were available in polygonal form.

The OS Integrated Transport Network (ITN) was also used in the analysis. This is a network data set with a link-and-node structure, and contains information and unique identifiers for all motorways, main roads, minor and local roads, private roads and urban footpaths. Each link corresponds to the street segment that falls between two or more junctions (i.e. nodes). In the Strathclyde study area there were 162,498 street segments.

The robbery data described in Chapter 3 contained fields on the location and time of the offence and basic demographic information on the victim and suspect/offender. Address details were not available for victims or offenders, which precluded an investigation of the extent to which victims are targeted near to their homes or if non-residents are targeted in robbery events in the study area (see Klaus, 2005; Hodgkinson & Tilley, 2007). The lack of a unique identifier for victims meant that repeat victims could not be reliably identified.

Dependent variable

Victim sub-groups pertaining to occupation were created as the dependent variable. Victim occupation was recorded in a free text field with 1,982 different categories. 181 records had no occupation recorded, with a further 101 records with an occupation deemed unclassifiable for the purposes of this analysis (these included: 'not stated'; 'refused'; 'to be updated'; 'no crime'; 'tourist'; 'police'; and 'repeat victim').

Victim occupation groups were created according to the following rules:

- School pupils were defined as those with the name of a school in the occupation field, those who were of compulsory school age (under 16 years) or those who were under 18 years with the occupation 'student' (n=1,632).
- Students were defined as 18 years or above with the occupation 'student' (n=1,104). These
 refer to students in higher education (universities) and further education (vocational
 courses).
- Non-workers were defined through their occupation being recorded as 'housewife' (n=101), 'disabled' (n=37), 'incapacity' (n=3), or 'retired' (n=899).
- Unemployed people were defined through their occupation being recorded as 'unemployed' (n=4,892) or 'big issue' (n=2).
- The remaining occupations were defined as workers (n=5,923).

Other demographic variables, such as age and gender could have been used instead to categorise the victim data. However it is assumed that there is greater variation of lifestyles across male and female adult groups, and thus the categories would be less homogenous than broad occupation categories. Certain occupation groups have an obvious relationship with age; in particular school pupils and students.

With respect to gender, some occupation groups are more commonly held by one or the other gender. It is informative at this point to compare the victim demographics with the demographics of the wider population. Table 32 presents these population figures for the occupational groups, by gender, for the Glasgow city area of Strathclyde. The school pupil data come from Scottish Government¹⁷, and the remaining occupational data are derived from the 2011 Census¹⁸. From Table 32 it is evident that the gender split for school pupils, students and workers is reasonably even in the Glasgow city population, whereas there appears to be a greater proportion of unemployed males than females. In contrast, females comprise a greater share of the population for non-workers.

¹⁷ <u>http://www.gov.scot/Topics/Statistics/Browse/School-Education/HistoricDatasets/Rolls-2006</u>

¹⁸ <u>http://www.scotlandscensus.gov.uk/</u>

Occupation group	Males		Fem	Total	
School pupil	35,157	(5.9%)	33,555	(5.7%)	64,671
Student	19,904	(3.4%)	19,940	(3.4%)	39,844
Not-working	64,773	(10.9%)	97,009	(16.4%)	161,782
Unemployed	21,909	(3.7%)	13,623	(2.3%)	35,532
Working	149,277	(25.2%)	136,718	(23.1%)	285,995
Total	291,020	(49.1%)	300,845	(50.9%)	591,865

Table 32 – Frequencies and percentages of the Glasgow city populationby occupation and gender

Table 33 – Frequencies and percentages of victims by occupation and gender

Occupation group	Males		Ferr	Total	
School pupil	1,393	(9.6%)	239	(1.6%)	1,632
Student	868	(5.9%)	236	(1.6%)	1,104
Not-working	346	(2.4%)	692	(4.7%)	1,038
Unemployed	3,648	(25.0%)	1,246	(8.6%)	4,894
Working	4,463	(30.6%)	1,453	(10.0%)	5,916
Total	10,718		3,866		14,584

Whilst it is not possible to estimate absolute victimisation risk for the occupational groups from the population data, Table 32 can be compared against Table 33 (the same breakdown of occupation and gender for the victims) to imply whether particular groups are more at risk of victimisation, based on their demographic profile. For example, male victims appear to be overrepresented within the school pupil, student and working groups, and particularly so for the unemployed category. In contrast females are *underrepresented* in all groups when compared to their prevalence in the population, with the exception of the unemployed category. That unemployed people, across both genders, seem to be especially at risk of robbery victimisation is a pervasive finding in the literature, although the proportion of unemployed victims in *this* study setting (33.6 per cent of all victims) is over twice that observed in previous research (Barker et al., 1993; Smith, 2003). This can be explained by the persistently high unemployment figures for the Glasgow region¹⁹.

¹⁹ <u>http://www.gov.scot/Topics/Statistics/Browse/Labour-Market/TrendData</u>

Naturally, sample selection bias is inherent within these victim data. School children who fall prey to robbery victimisation may be manifestly different, in terms of physical or social characteristics, from those who do not. People who spend time in 'risky' settings will be more prone to victimisation than those who do not. Hence, victims may self-select themselves into the situations where crime is likely, and their routine activities provide a means of understanding why they were targeted.

Independent variables

In keeping with the study rationale it was necessary to aggregate the robbery data into temporal bins. In doing so, the primary motivation was to preserve some of the key obligatory activity periods; namely commuting patterns and the school/work day. Discretionary activities are, by their nature, more diffused and varied throughout the populace and thus more difficult to account for. I attempted to demarcate periods of discretionary time by considering the interplay between time of the day and day of the week.

Similar to other UK scholars (e.g. Smith, 2003; Tilley et al., 2004) days were disaggregated into six four-hour temporal periods, but this was extended by introducing a dichotomous weekend/weekday dimension. For daytime, 6AM-10AM marked the morning commute period; 10AM-2PM represented the core hours most school children and workers engage in their formal obligations; and 2PM-6PM signified the after-school period when school pupils socialise with friends or make their way home from school, some workers begin their commute home, and shops are still open. Moving into the evening period, 6PM-10PM denoted the commencement of discretionary time for workers and the time period in which bars, restaurants and leisure complexes are patronised; 10PM-2AM characterised the late evening hours when only revellers and late-night workers are out of the home; and 2AM-6AM typified the quietest time in terms of people on the streets. Weekend periods were defined as Friday 6PM to Monday 6AM.

Descriptive statistics are provided in Table 34 for the frequencies and proportions of victim subgroups across each of the temporal periods, along with all robberies. This shows some interesting variation in the time of victimisation for different groups. However these values do not indicate *where* victims are victimised at particular times, and hence can lead to aggregation bias. Thus it is important to drill down further into the data so that spatial behaviour is accounted for.

	Weekday				Weekend								
	2AM-	6AM-	10AM-	2PM-	6PM-	10PM-	2AM-	6AM-	10AM-	2PM-	6PM-	10PM-	TOTAL
	6AM	10AM	2PM	6PM	10PM	2AM	6AM	10AM	2PM	6PM	10PM	2AM	
All robberies ^a	502	630	1,758	2,179	2,102	1,873	889	174	343	696	1,727	1,988	14,861
Airrobberies	3.3%	4.2%	11.8%	14.7%	14.1%	12.6%	6.0%	1.2%	2.3%	4.7%	11.6%	13.4%	99.9%
Workers	251	225	464	659	782	841	580	94	124	211	677	1,015	5,923
Workers	4.2%	3.8%	7.8%	11.1%	13.2%	14.2%	9.8%	1.6%	2.1%	3.6%	11.4%	17.1%	99.9%
Non-workers	7	55	188	217	129	82	13	22	80	74	90	81	1,038
NOII-WOIKEIS	0.6%	5.3%	18.1%	20.9%	12.4%	7.9%	1.2%	2.1%	7.7%	7.1%	8.7%	7.8%	99.8%
Unemployed people	133	273	903	810	689	619	173	37	84	185	458	530	4,894
onemployed people	2.7%	5.6%	18.5%	16.6%	14.1%	12.6%	3.5%	0.8%	1.7%	3.7%	9.4%	10.8%	100%
Students	96	16	49	88	184	215	100	7	9	39	123	178	1,104
Students	8.7%	1.4%	4.4%	8.0%	16.7%	19.5%	9.1%	0.6%	0.8%	3.5%	11.1%	16.1%	99.9%
School pupils	5	42	114	357	278	87	12	10	40	181	350	150	1,626
	0.3%	2.6%	7.0%	22.0%	17.1%	5.3%	0.7%	0.6%	2.5%	11.1%	21.5%	9.2%	99.9%

Table 34 - Street robbery victim frequencies by sub-group and temporal period

^a this includes street robberies without a recorded victim occupation

Methods

Since the hypotheses posed for these facilities were concerned with how 'near' robberies happen in relation to particular facilities (the *environs*), it was important that the concept of proximity be carefully considered. Preliminary analyses were therefore undertaken to determine the criminogenic reach of each facility type on robbery. The empirically derived distance threshold value was subsequently incorporated into multinomial regression models. This section describes these two analytic procedures.

Determining the spatial influence of facilities with location quotients

Location quotients have been extensively employed in prior research to measure spatial association between crime and places. Introduced to criminology by Brantingham and Brantingham (1997), location quotients (LQs) are a ratio between the local and regional clustering of crime. For the purposes of this study LQ values were computed for street network distance buffers, using a sequence of incremental distances. Euclidean - 'as the crow flies' buffers were also used to compute location quotients (see Appendix A). But, mirroring Groff's (2011) results, Euclidean buffers were found to produce lower LQs than the street network distance buffers due to their larger geographical size.

The location quotient can be expressed as:

$LQ = \frac{\text{total crime in buffer / buffer area}}{\text{total crime in region / region area}}$

The denominator in LQs is typically the crime density in the city or region extent. As Strathclyde is a large study area (approximately 14,000km²), with many rural and farmland areas, the extent of the area was a poor denominator as it encompassed many areas where robbery was unlikely to occur (at the top of mountains, for example). Hence, the denominator used in the LQ was the density of robbery over settlement areas (1.99e-5 crimes per square metre), which contained 99.2 per cent of robbery events and covered 739.2km².

In line with Groff's (2011) recommendation the mean street segment length was used as a guide for determining buffer distances. Considerable variation in street segment length was seen when the settlement areas were compared to Glasgow city centre area (see Table 35). Since it was established in Chapter 3 that most robbery occurred within urban areas, and in particular in the greater Glasgow area, the city area statistics seemed the more appropriate of the two to use. As Table 35 shows, the mean distance of street segments in the city centre area was 57.9 metres. This was rounded down to 50 metres for convenience to provide the increments of the buffers in the following analysis.

(1)

Similar to Ratcliffe (2012) a buffer of 0 - 5 metres was also used to represent events occurring in the immediate vicinity of a facility, which ameliorates (small) geocoding errors.

	Strathclyde Settlement areas	Glasgow city centre area
n street segments	126,797	1,224
Minimum length (meters)	1	2.06
Mean length (meters)	82.1	57.9
Maximum length (meters)	5,039	401.4

Table 35 - Descriptive statistics for street segment lengths

Street network buffers were computed using the ITN data and ArcGIS's network analyst service area function. Due to the irregular street network, the *lines* parameter was found to be more suitable than the polygonal service areas (see Appendix A for more details). In brief, this consisted of generating network buffers along the street network from the point of the network closest to the centroid of the facility, in increments of 50 metres up to 1,000 metres and for 0-5 metres to capture the immediate environment. For universities the spatial association between robbery and the street network buffers was prominent beyond 1,000 metres and thus the distances were increased (in increments of 50 metres) up to 2,000 metres. A spatial join was then performed to count the number of robberies falling within each buffer distance bin, and the LQ was computed from these counts.

Whilst interesting in their own right, the LQs were generated to determine a distance threshold of criminogenic reach for each facility type which could be used as a cut-off point in the subsequent multinomial regression models. As LQs are ratios there is no statistically determinable threshold for significance. Consistent with other research, a LQ threshold of two was used to determine the distance at which robbery was no longer strongly spatially associated with each facility type (Rengert, Ratcliffe & Chakravorty, 2005; Groff, 2011). Hence, the buffer distance at which the LQ fell below the cut-off point of two was used to define the criminogenic reach – what I call the *environs* - of the different facilities.

Once these thresholds had been established, an Origin-Destination Matrix was run for each facility type in ArcGIS to ascertain the network distance from each street robbery to the nearest facility. Street robberies that fell inside the threshold for each facility type were coded as one, with the remainder coded as zero. The analytic advantage of this process is that it created a categorical

variable which could be incorporated into the ensuing models. Therefore it introduced a spatial measure into the aspatial multinomial logistic regression modelling process.

Multinomial logistic regression

This study focuses on the *relative risks* to different population groups. Hence, victim sub-group was the dependent variable, and the independent variable was a categorical variable which represented the combination of the proximity thresholds to a particular facility type and the time period. With 12 time periods and two constructs for the distance thresholds - i.e. *inside* the threshold and *outside* the threshold - the independent variable for each facility type consequently had 24 categories. Because the dependent variable contained five nominal (occupation) sub-groups multinomial logistic regression was deemed a suitable analytic approach to assess the relative spatio-temporal influence of each facility type on each sub-group.

As an extension of binary logistic regression, multinomial logistic regression models the probability of membership of each victim sub-group compared to a baseline, for each of the spatio-temporal categories. Moreover, it isolates precise contrasts between the victim sub-groups whilst simultaneously accounting for different sample sizes amongst the groups (Britt & Weisburd, 2011). Since each of the temporal periods is mutually exclusive the independence of irrelevant alternatives (IIA) assumption of multinomial regression is satisfied. Maximum likelihood estimation enables these comparisons to the baseline to be calculated simultaneously. To test the effect of each individual coefficient in comparison to the reference category p-values were derived from Wald tests (z-tests).

Multinomial models were run for each of the four facility types. Because there was no natural reference category which represented the 'control condition' the reference category for each model was defined as the victim sub-group which had the (perceived) weakest relationship with each facility type. So, for example, school pupils were the reference category for the pubs and bars model, as this sub-group is not legally permitted to enter these facilities. The coefficient values for the reference category are set as zero in a multinomial model, so as to avoid redundancy (Britt & Weisburd, 2011). Accordingly, the coefficients for each of the other dependent variable categories represent the comparison of the relative likelihood against the reference category.

Within each model a further reference category was selected for the *independent variable*. Two considerations informed this choice: 1) that the time period was a contrast to the hypothesised effects (inside the threshold distance), and 2) that there were sufficient frequencies of victimisations so as not to make the standard errors, and thus the confidence intervals, overly large. To ascertain

the most appropriate reference category for interpreting the results, a number of models were run for each of the facility types, each employing a different reference category. Whilst modestly different results were produced in each model, the general findings were in agreement with those reported in section 6.3. Whilst all the reference category choices were somewhat arbitrary, the aim was to be theoretically informed and to facilitate the greatest relative difference across the subgroups.

6.3 Empirical findings

Location quotients

The location quotients for all four facility types are shown in Table 36; a LQ of (say) three indicates a robbery rate per area three times as high as the regional average. From this table it can be seen that pubs and bars and train stations follow a broadly similar pattern insofar that the concentration of robbery is the greatest in the shortest distance buffer areas, with the LQs decreasing steadily over progressive larger distances. (Recall from Chapter 3 however that data for robberies *at* train stations is most likely missing from these data). Using the largest buffer distance that has a LQ over two we can discern the distance threshold of robbery concentration for pubs and bars as 300 metres and for stations as 800 metres. The robbery concentration at bars in the immediate vicinity (0 - 5 metres) is particularly acute at 64.69 – almost 65 times as high as the regional robbery rate.

Schools and universities display a different distribution of LQs. For these facility types the highest LQ values are seen at modest distances away from the facilities themselves – suggesting that robbers may prefer to offend in locations that are a street or two away from the actual facilities. An alternative explanation might relate to the topological relationship between these facilities and the street network. For example, schools often fell a small distance from the street network, presumably because they have private entrances and footpaths that might not feature in the ITN data. (The ITN layer captures 'urban paths' but does not claim to include non-urban footpaths.)

Using the same criteria (the largest buffer distance with a LQ over two) we can determine the distance threshold of robbery concentration for schools as 400 metres and universities as 1.85 kilometres. In sum, each facility type was found to have a different network distance threshold at which the LQ fell below two, thus justifying this facility-specific approach.

Multinomial logistic regression results

The four facility-specific models are discussed in turn. All coefficients were exponentiated to produce relative risk ratios (RRR) relative to the reference category. The effect of the victim sub-

Table 36 - Location quotients for all facility types (u	<i>inderlined values denote the distance threshold)</i>
---	---

Street network buffer	Public houses	Schools	Train	Universities and further
distance (metres)	and bars		stations	education facilities
0-5	64.69	1.78	11.70	2.63
5 – 50	16.54	1.36	5.67	3.58
50 - 100	9.70	1.70	8.15	5.24
100 - 150	5.94	1.81	8.33	6.97
150 - 200	4.47	2.07	8.28	8.85
200 - 250	3.16	2.14	7.36	8.34
250 - 300	<u>2.46</u>	2.07	6.34	8.55
300 - 350	1.91	2.09	6.13	8.62
350 - 400	1.74	<u>2.05</u>	5.62	9.59
400 - 450	1.63	1.87	6.14	7.15
450 - 500	1.26	1.75	5.47	8.94
500 - 550	1.15	1.70	3.71	8.20
550 - 600	1.18	1.45	3.52	8.22
600 - 650	1.07	1.67	2.77	8.07
650 - 700	1.03	1.57	2.52	8.45
700 - 750	0.84	1.60	1.98	8.03
750 - 800	0.77	1.36	<u>2.01</u>	7.99
800 - 850	0.78	1.17	1.99	6.44
850 - 900	0.71	1.18	1.85	7.01
900 - 950	0.66	1.14	1.74	4.87
950 – 1,000	0.64	0.83	1.54	5.83
1,000 - 1,050				7.35
1,050 - 1,100				6.03
1,100 - 1,150				4.18
1,150 - 1,200				4.48
1,200 - 1,250				4.32
1,250 - 1,300				3.81
1,300 - 1,350				3.36
1,350 - 1,400				3.30
1,400 - 1,450				2.96
1,450 - 1,500				3.97
1,500 - 1,550				3.07
1,550 - 1,600				2.14
1,600 - 1,650				2.43
1,650 - 1,700				2.86
1,700 - 1,750				1.94
1,750 - 1,800				2.11
1,800 - 1,850				2.53
1,850 - 1,900				1.69
1,900 - 1,950				1.30
1,950 - 2,000				1.49

group reference category is incorporated into the intercept value. RRRs can be interpreted as the multiplicative change in the odds of being in one victim sub-group, versus the reference category, when all other variables are held constant in the model. Hence, an RRR of 1.50 equates to a relative risk of one and a half times greater than the reference group.

I am interested, for example, in whether school pupils are disproportionately victimised on weekday afternoons relative to other subgroups and other times and places – this is evident from the individual RRRs. I am also particularly interested in, when the victim group (say school pupils) and time are held constant, whether *place matters*. Therefore, I am concerned here with the change in relative risk that school pupils during the weekday afternoons experience if they happen to be proximal to a school. Here we need to look at the *ratio* of the RRRs for that group when they are within range of the spatial influence of a school compared to when they are not in range. Hence the tables report both raw RRRs, and RRR-ratios. For presentational clarity, RRR-ratios were computed exclusively for the RRRs that were statistically significant and over one for the inside the threshold categories (e.g. within 400 metres of a school), to illuminate the *relative importance* of the presence of a nearby facility type. RRR-ratios over 1.2 are defined as noteworthy (demonstrating at least a 20 per cent difference in relative risk due to spatial proximity), and only these are discussed in what follows.

Schools

The reference category for the schools model was unemployed people, within 400 metres of a school, between 10PM and 2AM on weekdays. Table 37 presents the results from this model. This shows that, for example, school pupils on weekdays between 2PM and 6PM have a statistically significant relative risk of 3.83 when they are within the distance threshold (the environs) to a school. This can be interpreted as a risk over three and a half times greater than for the reference category. In contrast, students are observed to have a relative risk of 0.25 at this time on weekdays in the environs of schools, meaning that their risk level is a quarter of that of unemployed people in similar locations between 10PM and 2AM.

School pupils are also observed in Table 37 to have a disproportionate relative risk on (say) weekdays between 2PM and 6PM *outside* of the environs of schools, compared to the reference group. This signifies that pupils are at a greater disproportionate risk of victimisation in multiple places. However, whether this risk is greater near to schools is only discernible from the RRR-ratios.

We see from the RRR-ratio results in Table 37 that only two occupational groups are associated with increased relative risk of victimisation near schools: non-workers and school pupils. Both of these

groups are at an increased risk of victimisation in the environs of schools between 2PM and 6PM on weekdays and 6AM to 10AM on weekend days. Non-workers also have a heightened risk between 10AM and 2PM on weekend days and school pupils between 10PM and 2AM on weekend days, albeit the RRR-ratios are smaller. The other groups are significantly under-represented as victims during the day on weekdays.

Since schools are (generally) closed on weekends the association between the weekend period and increased relative victimisation risk for these sub-groups speculatively relates to spatial association with other land uses. To elaborate, schools are often located in residential areas, with the pupils who attend the schools living in close proximity. Thus, in effect the schools can be seen as a proxy for school pupils' neighbourhood areas. This may help to explain why Haberman and Ratcliffe (2015) found high schools were associated with street robbery across multiple temporal periods.

In a related vein, whilst there are no UK examples to draw on, the literature suggests that elderly people in the US are most frequently victimised in their local neighbourhoods whilst shopping (Feeney & Weir, 1975; Klaus, 2005). This may explain why this group are found to have a spatio-temporal association with schools in the daytime. It is also worth noting that the pattern for non-workers could be driven by the availability of homemakers and carers within the vicinity of schools at school pick-up times.

Again, it is important to note that the RRR-ratios demonstrate an increase in risk to pupils and nonworkers for those within 400 metres of a school compared to people elsewhere during school pickup times and weekend mornings. In sum, as hypothesised in H4, there is a significant and noteworthy relationship between school pupil robbery victims and schools in the ensuing hours after schools close. This substantiates prior research on schools as crime generators in the after-school period (Roman, 2002). Importantly, schools distillate targets and offenders into the same places at the same times (Jacob & Lefgren, 2003), thereby creating favourable conditions for robbery to occur.

This same relationship is not evident in the hours prior to and during school, suggesting that the after school period has an important bearing on the victimisation risk for school pupils. Plausibly this relates to the fact that temporal constraints imposed by obligatory activities (i.e. arriving at school for the start of the school day) act as a stronger inhibitor on offending than the after school transition into discretionary time (Ratcliffe, 2006). That is, there is simply more time to commit opportunistic robbery when young people are dispersed into public space without a specific purpose after the school day.

	Non-workers	Pupils	Students	Workers
(Intercept)	0.17***	0.16***	0.37***	1.50***
Inside 400m threshold to a school				
Weekday 6AM-10AM	0.83	1.41	0.18***	0.53**
Weekday 10AM-2PM	1.06	0.86	0.08***	0.35***
Weekday 2PM-6PM	1.79*	3.83***	0.25***	0.49***
Weekday 6PM-10PM	1.32	2.49**	0.78	0.76
Weekday 2AM-6AM	0.00	0.62	1.67	1.27
Weekend 6AM-10AM	2.24	1.48	0.00	0.87
Weekend 10AM-2PM	6.97***	5.56***	0.18	1.60
Weekend 2PM-6PM	3.43***	6.41***	0.96	0.88
Weekend 6PM-10PM	1.23	5.39***	0.97	1.25
Weekend 10PM-2AM	1.19	2.19**	1.21	1.24
Weekend 2AM-6AM	0.71	0.00	1.66	2.10***
Outside 400m threshold to a school				
Weekday 6AM-10AM	1.31	0.82	0.15***	0.56***
Weekday 10AM-2PM	1.26	0.79	0.17***	0.34***
Weekday 2PM-6PM	1.49	2.53***	0.31***	0.56***
Weekday 6PM-10PM	1.02	2.61***	0.71	0.75*
Weekday 10PM-2AM	0.71	0.88	0.93	0.88
Weekday 2AM-6AM	0.40*	0.13**	2.06**	1.25
Weekend 6AM-10AM	4.12***	1.87	0.79	2.14**
Weekend 10AM-2PM	5.23***	2.50**	0.32**	0.85
Weekend 2PM-6PM	2.04*	6.23***	0.49**	0.73
Weekend 6PM-10PM	1.12	4.76***	0.67	0.91
Weekend 10PM-2AM	0.80	1.70*	0.83	1.28
Weekend 2AM-6AM	0.35*	0.58	1.55	2.27***
RRR-ratios (inside/outside)				
Weekday 6AM-10AM				
Weekday 10AM-2PM				
Weekday 2PM-6PM	1.20	1.52		
Weekday 6PM-10PM		0.96		
Weekday 2AM-6AM				
Weekend 6AM-10AM				
Weekend 10AM-2PM	1.33	2.22		
Weekend 2PM-6PM	1.68	1.03		
Weekend 6PM-10PM		1.13		
Weekend 10PM-2AM		1.28		
Weekend 2AM-6AM				0.92

Table 37 - Multinomial model results for schools, presented as risk rate ratios

NOTES: Reference category: unemployed people, within 400 metres of a school, 10PM to 2AM on weekdays; ***p < 0.001; **p < 0.01; *p < 0.05; -2 Log-likelihood = 37,660.4; AIC = 37,852.4.

Universities and further education institutions

The second model relates to universities and further education institutions (Table 38). The reference category for this was unemployed people, within 1.85 kilometres of a university or further education institution, between 2PM and 6PM on weekdays. The RRR for non-workers within the environs of universities between 10AM and 2PM on weekend days is 3.55, indicating that this group have a relative risk of victimisation around three and a half times greater than unemployed people between 2PM and 6PM on weekdays. The RRR for the same group at the same time but *outside* the environs of universities is 5.24, meaning that the RRR-ratio is below one. Hence non-workers have a greater relative risk of victimisation in places that are outside (elsewhere than) the environs of universities.

Two general trends are apparent from the RRR-ratios in Table 38. First, and consistent with prior research, students in the environs of universities have an increased relative risk of victimisation between 6PM and 6AM on both weekdays and weekend days. That is, the RRR-ratios show a striking increased relative risk to students of victimisation within 1.85 kilometres of a university at these times, compared with locations elsewhere.

Considering that universities in the UK customarily have subsidised bars and active social programs on their campuses, it is likely that this explains the patterns seen for students; these are the locations where socialising with peers occurs. That the RRR-ratios are larger on weekdays may reflect the campus-based social activities that are on offer during the week (weekends are often quieter). No evidence is found of an association between students and these facilities in the daytime. In sum, support is found for H5, but the findings show that overnight periods on weekdays are also associated with an increased relative risk of victimisation.

A secondary trend, albeit much smaller in terms of the RRR-ratios (with values of just over 1.2), is that workers are associated with these facilities in the late night weekend periods (10PM to 6AM), which is unexpected. This may be due to workers in the night-time economy (such as bar staff, fast food workers and cab drivers) being victimised in these places. It is also possible that this finding is an artefact of the larger size of the buffer distances for universities and further education institutions, especially where these types of facilities are located in urban areas where there are many other types of land uses that attract workers. What is clear from Table 38 is that there is a specific time pattern to the victimisation of students in the environs of universities that is not seen as strongly for other population groups, and does not manifest as clearly for students victimised elsewhere.

	Non workers	Pupils	Students	Workers
(Intercept)	0.22***	0.40***	0.14***	0.77***
Inside 1.85km threshold to a university				
Weekday 6AM-10AM	1.01	0.42***	0.61	1.27
Weekday 10AM-2PM	0.80	0.37***	0.56**	0.75**
Weekday 6PM-10PM	0.78	0.87	2.69***	1.42***
Weekday 10PM-2AM	0.53**	0.31***	3.31***	1.86***
Weekday 2AM-6AM	0.15**	0.08***	7.07***	2.59***
Weekend 6AM-10AM	1.87	0.73	1.67	3.07***
Weekend 10AM-2PM	3.55***	1.08	1.08	1.81**
Weekend 2PM-6PM	1.28	2.18***	1.63	1.41*
Weekend 6PM-10PM	0.80	1.71***	2.61***	1.81***
Weekend 10PM-2AM	0.63*	0.66**	3.01***	2.73***
Weekend 2AM-6AM	0.29**	0.07***	5.29***	4.69***
Outside 1.85km threshold to a university				
Weekday 6AM-10AM	0.85	0.35***	0.27**	0.93
Weekday 10AM-2PM	1.08	0.26***	0.23***	0.60***
Weekday 2PM-6PM	1.51**	1.22	0.45**	1.14
Weekday 6PM-10PM	0.94	1.17	0.85	1.56***
Weekday 10PM-2AM	0.71	0.42***	1.16	1.64***
Weekday 2AM-6AM	0.41	0.11	1.13	2.19***
Weekend 6AM-10AM	3.40***	0.62	1.06	3.52***
Weekend 10AM-2PM	5.24***	1.31	0.37	2.06***
Weekend 2PM-6PM	2.58***	2.83***	1.28	1.61
Weekend 6PM-10PM	1.01	2.14***	0.97	2.07***
Weekend 10PM-2AM	0.77	0.75	1.57*	2.19***
Weekend 2AM-6AM	0.44	0.36***	1.94*	3.79***
RRR-ratios (inside/outside)				
Weekday 6AM-10AM				
Weekday 10AM-2PM				
Weekday 6PM-10PM			3.17	0.91
Weekday 10PM-2AM			2.85	1.13
Weekday 2AM-6AM			6.28	1.18
Weekend 6AM-10AM				0.87
Weekend 10AM-2PM	0.68			0.88
Weekend 2PM-6PM		0.77		0.87
Weekend 6PM-10PM		0.80	2.71	0.87
Weekend 10PM-2AM			1.92	1.25
Weekend 2AM-6AM			2.72	1.24

 Table 38 - Multinomial model results for universities and further education institutions, presented as risk rate ratios

NOTES: Reference category: unemployed people, 1.85 kilometres of a university or further education institution, 2PM to 6PM on weekdays; ***p < 0.001; **p < 0.01; *p < 0.05; -2 Log-likelihood = 37,471.5; AIC = 37,663.5.

Public houses and bars

The reference category for the pubs and bars model was school pupils, within 300 metres of a pub or bar, between 2PM and 6PM on weekdays. Table 39 displays the results of this model and, taking workers as an example, shows that workers in the environs of pubs and bars between 2AM and 6AM on weekdays have a relative risk over thirty times that of school pupils on weekday afternoons. Between 2PM and 6PM at weekends, workers have a much lower risk of victimisation in the environs of pubs and bars than the reference category.

According to the RRR-ratios in Table 39, as expected, most groups have a raised relative risk of victimisation in the environs of pubs and bars, in the late evening and night-time hours, particularly at weekends. This is especially true for students and workers and is consistent with other studies (Tilley et al., 2004; Smith, 2003). Non-workers show no such discernible trend which, considering this sub-group is mostly comprised of retired people and homemakers who are unlikely to often be in the vicinity of these facilities, is unsurprising. Additionally, students, non-workers, unemployed people and workers exhibit a higher relative risk on weekday mornings near to these facilities, but since pubs and bars are closed at those times it would appear that this is a spurious finding. Instead, it is possible that facilities that are in close proximity of pubs and bars – such as shops, banks, offices and other commercial buildings – are driving this association. Robberies committed early in the day might be explained by drug addicts needing a 'fix' upon waking (Deakin et al., 2007).

For workers all periods on weekdays, barring the middle of the day, are significant and noteworthy. This could again relate to the co-location of pubs and bars in urban centres which host a number of functional facilities used by workers in working hours. The relative risk of victimisation for workers becomes especially acute between 2AM and 6AM on weekend days. Finally, it is important to note that the RRR-ratios strongly demonstrate an increase in relative risk to students and workers in the late evening and night at the weekends for those within 300 metres of a bar compared to their peers elsewhere. Thus students may well frequent non-student bars at weekends in contrast to their weekday socialisation patterns. Taken together, the results from Table 39 support H6, but demonstrate that unemployed people are also at a greater risk of robbery victimisation within the environs of this facility type.

Potential explanations for these relationships can be found from the rich evidence base on the relationship between bars and crime. At a conceptual level, pubs and bars can mutually act as crime *generators* and *attractors*, in that they attract a large number of people to highly accessible places in the urban landscape that both opportunistic and intentional offenders can capitalise on

	Non workers	Students	Unemployed	Workers
(Intercept)	0.54***	0.34***	2.67***	2.17***
Inside 300m threshold to a ba	r			
Weekday 6AM-10AM	3.31**	1.19	2.77**	3.49***
Weekday 10AM-2PM	2.53***	1.53	3.17***	2.00**
Weekday 6PM-10PM	0.80	2.85***	1.09	1.51*
Weekday 10PM-2AM	1.57	11.47***	3.01***	5.11***
Weekday 2AM-6AM	2.77	89.63***	10.34**	30.71***
Weekend 6AM-10AM	3.07	0.99	1.50	3.68*
Weekend 10AM-2PM	2.31*	0.75	0.73	1.41
Weekend 2PM-6PM	0.76	0.50	0.48***	0.61*
Weekend 6PM-10PM	0.57*	1.62*	0.51***	0.92
Weekend 10PM-2AM	1.24	5.64***	1.81**	4.03***
Weekend 2AM-6AM	4.63	82.14***	14.26***	74.06***
Outside 300m threshold to a b	ar			
Weekday 6AM-10AM	2.13**	1.11	2.31***	2.14***
Weekday 10AM-2PM	3.27***	1.16	2.86***	1.81***
Weekday 2PM-6PM	1.18	0.61*	0.78	0.77
Weekday 6PM-10PM	0.88	1.52	0.84	1.18
Weekday 10PM-2AM	1.84*	4.72***	2.43***	4.02***
Weekday 2AM-6AM	2.46	35.90***	9.74***	18.12***
Weekend 6AM-10AM	4.47**	2.55	1.34	4.61***
Weekend 10AM-2PM	4.61***	0.62	0.83	1.44
Weekend 2PM-6PM	0.73	0.72	0.33***	0.50***
Weekend 6PM-10PM	0.42***	0.73	0.48***	0.87
Weekend 10PM-2AM	0.88	2.51***	1.08	2.66***
Weekend 2AM-6AM	1.47	13.40***	3.63***	11.87***
RRR-ratios (inside/outside)				
Weekday 6AM-10AM	1.56		1.20	1.63
Weekday 10AM-2PM	0.77		1.11	1.10
Weekday 6PM-10PM		1.87		1.28
Weekday 10PM-2AM		2.43	1.24	1.27
Weekday 2AM-6AM		2.50	1.06	1.69
Weekend 6AM-10AM				0.80
Weekend 10AM-2PM	0.50			
Weekend 2PM-6PM				
Weekend 6PM-10PM		2.21		
Weekend 10PM-2AM		2.25	1.68	1.52
Weekend 2AM-6AM		6.13	3.93	6.24

 Table 39 - Multinomial model results for public houses and bars, presented as risk rate ratios

NOTES: Reference category: school pupils, within 300 metres of a pub or bar, 2PM to 6PM on weekdays; ***p < 0.001; **p < 0.01; *p < 0.05; -2 Log-likelihood = 37,607; AIC = 37,799

(Brantingham & Brantingham, 1995). The dominant activity that people go to bars for – drinking alcohol – can increase people's vulnerability and is associated with cash transactions, which fulfil the requirement for a suitable victim (Tilley et al., 2004). Lastly, it is the manner in which people depart bars, often at the closing time, that manufactures the assemblage of victims and offenders in the same place at the same time. Many bars may lack *place managers* (Eck, 1995) and other people likely to act in a guardian capacity to prevent offences happening.

Train stations

The reference category for the train stations model was unemployed people, within 800 metres of a station, between 10AM and 2PM on weekdays. The results in Table 40 show that workers are at a heightened relative risk of victimisation in the environs of train stations at all times compared to unemployed people at similar locations (but between 10AM and 2PM). Conversely, non-workers are seldom at an increased relative risk compared to the reference group, with the weekend 10AM to 6PM periods as the exception to this general trend.

The RRR-ratio results in Table 40 indicate that all sub-groups of victims experience a relative increase in victimisation risk between 10AM and 2PM on weekend days in the environs of train stations. However it is worth stating that the counts of victims in the 10AM-2PM weekend interval were very low – see Table 34 – which suggests this may be a spurious finding. Further, when the reference space-time category is changed to 10PM to 2AM on weekdays the coefficients for students and workers become non-significant for the 10AM-2PM weekend interval.

As indicated through the RRR-ratios the relative risk of victimisation increases for students in the environs of train stations between 6PM and 6AM on weekdays, and for all time periods on weekend days. This may relate to the fact that UK students commonly rely on public transport. For workers we see a different pattern: this sub-group appears to have a heightened relative risk in time periods in which commuting activities are likely (6AM to 10AM and 6PM to 10PM on weekdays). The latter of these two periods might also account for recreational activities once the work day concludes. These patterns are possibly a consequence of peak, or non-peak usage of the station during these hours²⁰ (see for example, Clarke et al., 1996), since this will affect the number of victims and potential guardians in the area.

²⁰ I was not able to obtain any data that permitted a test of this assertion.

	Non-workers	Pupils	Students	Workers
(Intercept)	0.19***	0.16***	0.06***	0.53***
Inside 800m threshold to a station				
Weekday 6AM-10AM	1.03	0.73	0.89	1.78***
Weekday 2PM-6PM	1.30	2.96***	1.79*	1.50***
Weekday 6PM-10PM	1.17	2.68***	5.75***	2.36***
Weekday 10PM-2AM	0.66*	0.79	6.84***	2.72***
Weekday 2AM-6AM	0.13**	0.17*	15.20***	3.69***
Weekend 6AM-10AM	2.56	1.60	6.50**	4.86***
Weekend 10AM-2PM	6.50***	4.26***	4.16**	3.89***
Weekend 2PM-6PM	1.84**	5.31***	3.61***	2.20***
Weekend 6PM-10PM	0.84	4.40***	5.24***	2.46***
Weekend 10PM-2AM	0.56*	1.69**	5.79***	3.68***
Weekend 2AM-6AM	0.34*	0.49	12.34***	7.49***
Outside 800m threshold to a station				
Weekday 6AM-10AM	1.05	1.15	0.94	1.42*
Weekday 10AM-2PM	1.12	0.66*	0.73	0.95
Weekday 2PM-6PM	1.45*	2.68***	1.60	1.56***
Weekday 6PM-10PM	0.79	2.49***	2.86***	1.95***
Weekday 10PM-2AM	0.70	1.03	3.85***	2.39***
Weekday 2AM-6AM	0.47	0.35	5.68***	3.36***
Weekend 6AM-10AM	3.28***	1.79	1.25	4.75***
Weekend 10AM-2PM	3.99***	2.37**	0.29	2.16***
Weekend 2PM-6PM	2.22***	7.24***	2.95**	2.09***
Weekend 6PM-10PM	1.21	5.47***	2.93***	3.17***
Weekend 10PM-2AM	1.04	1.94***	4.61***	3.51***
Weekend 2AM-6AM	0.44*	0.39	5.33***	4.98***
RRR-ratios (inside/outside)				
Weekday 6AM-10AM				1.25
Weekday 2PM-6PM		1.10	1.12	0.96
Weekday 6PM-10PM		1.08	2.01	1.21
Weekday 10PM-2AM			1.78	1.14
Weekday 2AM-6AM			2.68	1.10
Weekend 6AM-10AM			5.20	1.02
Weekend 10AM-2PM	1.63	1.80	14.30	1.80
Weekend 2PM-6PM	0.83	0.73	1.23	1.05
Weekend 6PM-10PM		0.80	1.79	0.77
Weekend 10PM-2AM		0.87	1.26	1.05
Weekend 2AM-6AM			2.32	1.50

Table 40 - Multinomial model results for train stations, presented as risk rate ratios

NOTES: Reference category: unemployed people, within 800 metres of a station, 10AM to 2PM on weekdays ***p < 0.001; **p < 0.01; *p < 0.05; -2 Log-likelihood = 37,605.6; AIC = 37,797.6

The early hours of weekend days (2AM to 6AM) also convey an increased relative risk for workers, in terms of the RRR-ratio, but as trains are not in operation during this period²¹ it would seem that they are acting as a proxy for other facility types. Train stations are often co-located with taxi firms, and may also have fast food restaurants (and potentially other facilities) nearby that might be open at these times and attracting customers. Collectively these results provide support for H7, although in addition they demonstrate that train stations influence the relative victimisation risk of a wider range of people than just workers - students being a notable second group.

6.4 Discussion

In the current study I demonstrate that spatio-temporal patterns in street robbery are related to facility types that are socially relevant to particular victim occupations. Applying multinomial logistic regression, facilities with a clear link to domain-specific activities such as education, employment or leisure are found to act as crime generators or attractors for specific types of victim sub-groups, often at specific times. In doing so, this is one of the first empirical studies – of which I am aware - to situate the type of victim at the heart of a time-sensitive, place-based analytic inquiry.

Several findings emerge from this research. First, that pubs and bars are associated with increased relative risks across a broad spectrum of victim sub-groups; plausibly because they feature in many people's activity spaces (Brantingham & Brantingham, 1984). Moreover, the various sub-groups are observed to have similar temporal profiles for heightened relative risk of victimisation at these facilities in the late evening and early morning hours compared to elsewhere (Table 39).

A reasonable explanation for this is that at these hours of the day pubs and bars draw non-locals to their environs for recreational activities, due to their ecological positioning in urban centres. (Recall that the majority of robbery in this study area concentrates in the city of Glasgow.) In these urban centres it may be the case that victims are targeted in their 'unawareness spaces' which lie, by definition, outside or on the fringes of the activity spaces defined by habitual routine activities (Hodgkinson & Tilley, 2007). This point chimes with Wiles and Costello's (2000) assertion that victims are more likely to be non-locals in settings that attract a miscellany of locals and non-locals. This is also consistent with offender's accounts on robbery targeting processes; robbers prefer people who are unaware of their surroundings or unfamiliar with the environment they find themselves in (Deakin et al., 2007). Bars also increase victimisation risk through their patrons becoming intoxicated. An alternative, or complementary, explanation would be that guardianship is

²¹ Train timetables were inspected for a range of lines within the study area. Generally trains commenced around 6AM and ceased by midnight.

ineffective during these times at these places; possibly due to the natural conditions (e.g. lack of light) inhibiting monitoring behaviour by guardians or due to the social climate engendering feelings of unsafety and hence a reluctance to intervene in any crimes witnessed. Reynald's (2010) work on decision-making by guardians posits that the risks to personal safety are one of the key factors in a guardian's decision to intervene if they witness a crime event.

The second finding to emanate from this research is that, in contrast to the above, facilities which are closely coupled to particular occupations (e.g. school pupils, university students) exhibit much more specific victim profiles. The environs of schools are particularly associated with school pupils being victimised in the ensuing hours after school closes (Table 37). Similarly, the environs of universities and further education confer an elevated relative risk for victimisation for students in hours demarcated for socialising (6PM to 6AM on both weekdays and weekend days – see Table 38). This was explained by the typical social behaviour of students in the UK context in conjunction with the fact that the student residences are often on campus or nearby. Since students were identified in the UK research evidence as a quintessential victim type in the eyes of offenders, it could be posited that this sub-group are deliberately targeted by offenders who see them as a low risk victim type.

Thus far the findings described relate solely to discretionary activities. The environs of train stations were also associated with an elevated risk of victimisation for workers, in particular during hours traditionally thought of as commuting time (6AM to 10AM is especially notable for this group and 6PM to 10PM is also of significance). Since workers comprise a sizable portion of all victims this is important trend. However this category is heterogeneous, comprising many occupations. Undoubtedly these could be disaggregated in future research to clarify the spatio-temporal risk of specific occupations (such as taxi drivers, teachers, bar staff). It may well be that the trends found for workers were obscured by this aggregate category and that more nuanced patterns would be revealed in a focus on more specific occupational domains. Nevertheless, as the first known study on the spatio-temporal relationships between victims and their relative risk of victimisation, these categories seemed a sensible starting point for building the evidence base. It also appears that weekend periods between 10AM and 2PM show general increases in relative risks in the environs of train stations across occupational groups, perhaps suggesting that these places are just particularly risky places to be at these times.

Whilst this study was unable to estimate *absolute* risk, the findings from *relative* risk estimates can still be useful for informing crime prevention activities. As articulated in this Chapter, the problem of street robbery is multifaceted and covers many different scenarios in terms of target selection (Monk et al., 2010; Smith, 2003; Tilley et al., 2004). Each sub-set of scenarios will differ, and require a commensurate response on behalf of the police and crime reduction agencies. Localised spacetime responses for different victim groups can be used to disaggregate the composite robbery problem into its constituent parts, which speaks to the shift-based nature of police work. On the basis of the findings from the current study, I could advise that the local police should proactivity target the policing of workers in the environs of train stations on weekday mornings and early evenings; school pupils near schools on weekday afternoons; and students near universities and bars in the evenings and overnight period. Directing police attention sensitivity to the relative risk of victimisation optimises the potential crime reductive effects and makes prudent use of limited resources.

Limitations

Naturally this study is constrained by the use of police-recorded data, which has well-rehearsed limitations (Maguire, 2007). Due to the disincentives for criminally active people to report crime to the police (Jacobs & Wright, 2008), offenders are presumed to be especially underrepresented in official data. I was able to explore this through a data field denoting whether the victim had a criminal conviction with the Scottish Criminal Records Office. Congruent with other research on the victim-offender overlap (Bottoms & Costello, 2010) a substantial proportion of robbery was found to be reported by people with a criminal conviction (just under a third, n=4,217). This assuages concerns on the representativeness of the data used, but also raises some important questions – not able to be explored here - regarding the causal processes linking victims and offenders.

The critical shortcoming of this study is that it could not account for the ambient (i.e. street) population. Thus, it cannot be discerned whether a particular group is especially targeted in an absolute sense in a given area (at a given time) without data on non-victims as a counterfactual. School pupils may be victimised proximal to schools as this is where they spend a majority of their time, not because they are especially at risk in these situations (this becomes an *exposure to risk* issue – see Lemieux, 2011). Similarly, there may be other people present in the school environs who are *not* victimised, thus raising questions of what characteristics or situational contexts are causally related to offender targeting strategies. Thus the absence of information on absolute risk precludes theorising on whether offending is opportunistic or premeditated. Relatedly, it is not possible to establish whether facilities are acting as crime *generators* or crime *attractors* since this requires a denominator to calculate robbery rates (Clarke & Eck, 2003).

This study did not consider the influence of *risky facilities* (Eck et al., 2007). Based on the ubiquitous finding that crime concentrates at relatively few places (Weisburd, 2015), some facilities in this study would be expected to generate a large share of the robbery events in their environs, whereas others might be entirely crime free. This, however, would be a study of frequency of events, rather than relative risks of population sub-groups and would require a different research design. It was also not possible to account for the density and mixture of facilities in the modelling strategy, which has been shown to be important in the behaviour settings in which robbery occurs (Hart & Miethe, 2015). The standard disclaimer about the generalizability of these findings to other crime types is also relevant.

Further work

This study offers one of the first explorations of the spatio-temporal risks of victimisation of particular sub-groups of the population. However many theoretical questions remain. Foremost are the causal processes that render a target attractive to an offender. Data which holds the victim's address, as well as locational information on the crime event and their individual characteristics is difficult to obtain, but offers great potential for answering pressing questions regarding victimogeneity. For example, are people more likely to be victimised in their 'unawareness spaces' (Hodgkinson & Tilley, 2007) – those unfamiliar places, which may be space and time sensitive?

The criminology community is especially interested in the causal processes which underpin victimisation risk. These require a consideration of the interaction between the characteristics of the victims and offenders, as well as the situational context of their space-time confluence. Whilst victimisation surveys furnish information on the characteristics of the victim they typically do not probe for the space-time characteristics of the crime event at the facility level, nor pose questions on the victims' activities at the time of victimisation. Investigating the victimogeneity of routine activities would hence require rich in-depth interview data with victims and/or offenders and is a ripe avenue for further research.

Echoing a substantial body of research, this study found a considerable victim-offender overlap in the data (see Jennings et al., 2012 for a good summary). Whilst there is long-standing recognition of the synergetic relationship between victim and offender populations (Wilcox, 2010) the direction of the causal relationship is an unresolved scholarly debate, and is putatively bi-directional (Lauritsen, Sampson & Laub, 1991). Two themes emerge from the hypotheses advanced to explain the victim-offender intersection: *individual heterogeneity* and *state dependence* (Lauritsen & Laub, 2007). Succinctly put, heterogeneity hypotheses assume that the risk factors associated with both victimisation and offending behaviours are similar, and that these 'time stable traits' – be they low

self-control, risk-taking behaviour or shared social conditions – unify these groups. Few studies attempt to disambiguate the psychological traits of offenders and victims from the places in which they spend time. Findings from the PADS+ are beginning to show that propensity to offend strongly interacts with offender's lifestyle routines (Wikström et al., 2010). Our understanding of the causal processes linking victims and offenders would benefit from similar research with victims as the focus of enquiry.

In the past the focus on target suitability has been on *objects* or *properties* as being at particular risk; for example, Clarke's (1999) CRAVED acronym identifies the ideal elements of goods to steal. To advance the environmental criminology agenda further I submit that scholars need to examine the characteristics of (human) targets of crime that make them particularly vulnerable to crime within the spatio-temporal context of their everyday lives (e.g. see McNeeley, 2015 for an overview of risky lifestyle characteristics). That is not to imply that victims bear some responsibility for their victimisation but, in agreement with Lauritsen et al. (1991), I maintain that studying dimensions of risk enhances theories of victimisation and can explain why people find themselves in the wrong place at the wrong time.

Conclusion

In conclusion this study finds evidence that victims are targeted at facility types which are associated with key obligatory and discretionary activities, but this varies across victim occupation and setting. It is hard to say whether one type of activity is more dominant than the other, and greater insight can potentially be gained through further studies of the victimogeneity of routine activities. My findings lend weight to both the routine activity approach and the lifestyle perspective and justify the previous tendency of scholars to view them as analogous. What is certain is that the results conform to expectations that can be inferred from what we know about human activity patterns which underpins the rationale of the routine activity approach.

To paraphrase Wilcox (2010), robbery victimisation is a complex phenomenon, driven by an intricate mix of social and micro-situational influences. Disentangling these factors in the causal process requires a more precise conceptualisation of victim sub-groups and their attendant risky routine activities. It is my contention that centralising *who* is victimised into the focus of research inquiry is important for advancing theoretical etiologies of crime and informing crime prevention strategies. The ensuing Chapter is dedicated to elucidating the contribution this thesis has made to the literature in respect of these two reciprocal goals. In particular, the theoretical role of the ambient

population – not able to be estimated in this study – and its relation to effective guardianship is expanded upon.

7. DISCUSSION AND CONCLUSIONS

Chapter overview

The role of this final Chapter is to summarise the main findings of the thesis and to reflect on the consequent implications for criminological theory and crime prevention. The Chapter begins by recapping the findings produced in Chapters 3 to 6, before considering their composite meaning. The limitations of the research are then considered and how these may have affected the results obtained and the subsequent conclusions. Next, the theoretical ramifications of the findings are elucidated. This then leads into a discussion on how the police and other crime reduction agencies could translate the findings produced in this research into practical crime prevention activities. Finally, suggestions are made for future research that would advance micro-level testing of the tenets of the routine activity approach.

7.1 Summary of findings

Revisiting the aims of the research

This thesis is primarily concerned with understanding spatio-temporal patterns in robbery through the lens of the routine activity approach (Cohen & Felson, 1979). A core assumption made throughout is that the places in which crime happens are not constantly conducive to crime; there are certain time windows where criminogenic (i.e. crime producing) features coalesce with motivated offenders to produce optimal conditions for crime to occur. At other times fewer criminogenic features are present in settings. The micro approach taken in this research aims to align with the rhythms of human activity that are causally relevant to these dynamics.

That opportunities for crime are ever-changing relates to the *environmental backcloth* (Brantingham & Brantingham, 1993). This can be thought of as the context in which crime happens and, as articulated in Chapter 2, is influenced by the social and physical environment, which is in constant flux. Thus, in the eyes of the offender, "target suitability is tied to both the characteristics of the target and to the characteristics of the target's surroundings" (Brantingham & Brantingham, 1993a: 263). One of the central aims of this thesis was to unpack some of the features of robbery locations which can be considered to be integral to a time-varying criminogenic environmental backcloth.

In Chapter 2 I argued that the types of people present in a place at a specific time, along with the nature of the activities that they are engaged in, give rise to opportunities for street robbery. The summative effect of people's activities creates regular patterns of behaviour across small units of

space, which is referred to in the literature as the *routine activities of places* (Reynald & Elffers, 2009; Sherman et al., 1989). This notion is analogous to the concept of *behaviour settings* adopted by ecological psychologists (Barker, 1968) which are micro-temporal places with recurrent events. Hence, settings and micro-temporal places are used interchangeably throughout the thesis. The activities that bring people together in these places in specific time windows is posited in this thesis as setting the *social climate*, which has a bearing on the potential for informal social control (Wikström & Sampson, 2003).

In the context of these theoretical propositions, the following overarching research question was posed: 'what makes a place criminogenic for street robbery at some times and not others?' This was at the heart of four analytic Chapters that studied spatio-temporal patterns in police-recorded street robbery data. The results emanating from these Chapters are briefly summarised below, with the key themes drawn out in the synthesis that follows.

Spatio-temporal patterns in robbery

In Chapter 3 it was established that the street robbery data were clustered at a range of spatial scales. In particular, and consistent with previous research (Flatley et al., 2010), robbery was shown to be acutely concentrated in the metropolitan district in which the city of Glasgow was located. Due to this concentration, repeat locations of robbery events were found at both the street segment and precise location unit of analysis. When the space-time interaction was analysed it was shown that repeat victimisation (at the same location) persisted across a long time period; that is, locations with repeat events were found to be overrepresented in the data, up to six months from an antecedent event. In combination, these results suggest that a small number of locations offer favourable conditions for robbery at regular intervals, whereas most locations do not.

A long term downward trend was observed when the ten years of data were viewed descriptively as a time-series. This conforms to the widely-acknowledged international crime drop since the 1990s (Tseloni et al., 2010; Farrell et al., 2011). Additional temporal rhythms were observed in the data. First, robbery was seen to peak volumetrically on weekend days (including Fridays). Second, distinct time profiles for individual days were seen. Robbery was less common in the morning (daytime) hours on weekend days - compared to weekdays - but more common in the early morning (night-time) hours. Such trends suggest that robbery chiefly occurs in the discretionary time that people are afforded outside of a conventional work or educational pattern. Overall, Chapter 3 revealed that aggregation bias, commonly observed in geographic criminology, was similarly a threat to research on crime and place when micro-temporal patterns were ignored.

Darkness as a facilitating condition of robbery

Chapter 4 set out to test H1: the presence of darkness will increase the likelihood of street robbery occurring when seasonal variations in temperature are accounted for. The ARIMA modelling in this Chapter confirmed that seasonality was present in the street robbery data at both a month and week level of aggregation. When metrics of darkness and temperature were incorporated at these units of analysis into the ARIMAX models (in the form of the monthly/weekly mean minutes of darkness and the monthly/weekly mean temperature) they were found to be unrelated to counts of robbery. This finding suggested that using month and week intervals were too coarse to detect correlations between the independent and dependent variables. Hence, justification was found for the need for micro units of analysis.

The second set of analyses was concerned with explaining this seasonality using a unit of analysis that could account for different lighting conditions (and temperature) across the year. Consequently, each day in the data period was split into four intervals of six-hours. The 4PM to 10PM interval was particularly noteworthy as this is the period of the greatest variation of darkness over the year and it represents time when people are typically engaged in discretionary activities. Negative binomial regression models were used to model the influence of conditions of darkness, twilight and temperature, with controls for the trends revealed through the time series analysis.

The results given in Chapter 4 showed that the natural environmental condition of darkness was significantly associated with an increase in robberies. Temperature, a variable used extensively in previous research (Cohn, 1990), exhibited a weaker relationship with increases in robbery. On the basis of this it was argued that darkness is a crucial inhibitor of guardianship, as defined within the tenets of the routine activity approach. In addition, hours of darkness are associated with the routine activity patterns of certain sub-groups of the population (e.g. young people), who are typically overrepresented in both victim and offender populations for robbery (Smith, 2003; Tilley et al., 2004).

Weather and routine activities

Chapter 5 challenged the implicit assumption in much of the research on weather and crime – that its impact is universal across different temporal dimensions. In this an argument was advanced that it is people's subjective interpretation of weather that is the mechanism that influences their subsequent outdoor activity. I argued that perceptions of weather are relative to: the overall climate for a region; the expected weather for the season; recent trends; and also to expectations of future weather. Two sets of complementary analyses were performed to cross-validate the effect of

weather across time intervals in the day: negative binomial regression and seemingly unrelated regression. All models employed the same unit of analysis as used in Chapter 4. The following hypotheses were tested:

H2: Reductions in street robbery will be associated with adverse unseasonal weather and increases in robbery will be associated with favourable unseasonal weather.

H3: Weather will have a stronger influence on robbery when travel is (in general) more likely to be optional.

The results indicated that there was support for H2 - that when weather is unseasonal that people are more or less likely to venture outdoors depending on whether it makes conditions more or less favourable than expected. In particular, clement conditions in winter (that is, increased temperatures and decreased wind speeds) were associated with increases in robbery. Affirmative evidence was also found in support of H3: that variation in weather has a stronger effect on time periods that are demarcated for discretionary activities. The results showed that robbery at night-time and weekends were especially affected by adverse weather conditions such as low temperatures, rain and higher wind speeds - when it can be presumed that travel and spending time in public space is optional. It was concluded that the micro-temporal approach taken in this study engendered greater explanatory power for the variation in robbery over time than had been seen in prior research looking at the relationship between crime and weather.

Victimisation, routine activity patterns and the built environment

The last empirical analysis presented in Chapter 6 focused on land use and use of land over time. In this, I examined the timing of victimisation for different occupational sub-groups in relation to facilities associated with key obligatory or recreational activities. These comprised pubs and bars; schools; train stations; and universities and further education facilities. Time periods judged to be of the greatest social relevance to these facilities formed the basis for the units of analysis; six four-hour intervals across weekdays and weekends (twelve in total). The following facility-specific hypotheses, derived from the robbery victimisation literature, were tested:

H4: The environs of schools will be associated with the disproportionate relative risk of school pupils being victimised on weekdays, in the hours after schools close. (In these hours pupils will be making their way home from these facilities and socialising nearby).

H5: The environs of universities and further education institutions will be associated with the disproportionate relative risk of students being victimised in the late evening and very

early morning hours on weekends. (Students will socialise near to these facilities at these times due to their residential proximity).

H6: The environs of pubs and bars will be associated with the disproportionate relative risk of workers and students being victimised in the evening hours on weekdays and weekends. (Workers and students have the recreational time and resources to use drinking establishments in these hours).

H7: The environs of train stations will be associated with the disproportionate relative risk of workers being victimised in the daytime and early evening hours on weekdays. (Workers will be using these facilities for commuting purposes at these times).

Applying multinomial logistic regression the findings showed that facilities with a clear link to domain-specific activities such as education or leisure act as crime generators or attractors for different types of victim sub-groups. Two major conclusions can be made from these analyses: 1) that the environs of facilities pertaining to recreational activities affect a broad spectrum of victim groups, and 2) that, contrarily, the environs of facilities with a strong relationship to specific occupations, such as schools and universities, are seen to have distinct victim profiles. Collectively these results speak to both the routine activity approach (Cohen & Felson, 1979) and the lifestyle perspective (Hindelang et al., 1978), as they are both underpinned by human mobility patterns.

Synthesis of findings

This research sought to unpack the situational dynamics of the locations in which street robbery occurs, so that temporal patterns in robbery could be explained. The findings provide a number of recognisable contributions to the field of crime science and crime pattern research:

- 1) Seasonal patterns in robbery in the study area are (partly) driven by the condition of darkness.
- 2) Weather features exert their influence on the robbery event differentially over different seasons, days of the week and hours of the day.
- Spatio-temporal patterns in street robbery are related to facility types that are socially relevant to particular victim occupations.

These findings are unified by their focus on human mobility patterns. To return to the routine activity approach, a crime opportunity is the interaction of a motivated offender and a suitable target in the absence of a capable guardian (Cohen & Felson, 1979). In the scenario of a street

robbery, and based on the definition of guardians advanced by Hollis-Peel et al. (2013), all three of these agents are human, and thus mobile, and their confluence in space and time determines the opportunity structure. (CCTV is an object designed to replace humans for monitoring purposes and can be static or mobile). Therefore, the presence and composition of people in space at a given moment in time is the principal intervening variable between places and street robbery, since this determines both target, offender and guardian availability.

A recurrent finding throughout the empirical work in this thesis is that variations in levels of robbery seem to be strongly coupled to discretionary activities. This can only be properly explored when the unit of analysis is sensitive to these micro-rhythms in human mobility patterns. In this research I attempted to ameliorate concerns of temporal aggregation bias (Dorling & Openshaw, 1992) by employing various sub-day time intervals in the analysis. In doing so, periods when people are free to pursue discretionary activities were better represented which appears to offer greater prospects for predicting variations in volumes of robbery.

This research elucidated several influences on human mobility patterns, in particular relating to discretionary activities. At a macro level, weather and climate play a perceptible role in defining what human activities can and cannot occur. As offenders are assumed to adopt the same geographical behaviour as the wider population (Brantingham & Brantingham, 1984), we can expect offenders, victims and guardians to be similarly influenced by weather. It seems self-evident to state that all will be inclined to spend more discretionary time in public settings when the weather is pleasant, in comparison to when it is adverse. It follows that the frequency of the convergence of offenders and victims will increase when weather is conducive to people lingering in street settings.

Darkness also impacts on mobility patterns. Humans have a distinctly diurnal existence, with the biological need to sleep imposing temporal constraints on behaviour (Ratcliffe, 2006). The opening hours of many businesses are synchronised with these circadian rhythms, that is to say they operate in the daytime. Accordingly, discretionary activities are typically undertaken outside of these times, in the evening hours and at weekends. Facilities that are open in the evening hours service these discretionary pursuits and are fewer in number. Thus, human mobility is constrained spatially in hours of darkness by fewer public places being open. This serves to distillate people into more compact geographical spaces in time, which would logically be expected to increase the convergence rates of the triad of actors in RAA.

Whilst much of the population can spend time in public space in bad weather conditions or after the sun has set, many choose not to do so in their discretionary time. Research has suggested that fear

of crime levels increase for some people in conditions of darkness (Painter, 1996), and thus people who are risk-adverse may not venture out at night-time. The inverted argument is that only the risk-takers go out after dark. Whilst a gross oversimplification, what this does infer is that people who choose to be in public space in conditions of darkness may inherently hold behavioural tendencies that self-select themselves into criminogenic settings (Wikström et al., 2010). Offenders may be especially drawn to such settings which have permissive social climates.

A crime such as robbery is wholly dependent on target availability (as well as target suitability). Rossmo (2000) reasons that *suitable* targets - deemed so by offenders - are not uniformly distributed across the physical landscape. Instead, their availability can vary significantly across space and time; thereby generating a *victim backcloth*. Understanding the victim backcloth that robbery depends upon is a necessary precursor to understanding the mechanisms that drive target selection, and the causal pathways through which offending is stimulated. Hence the clustering of suitable victims into particular micro-temporal places, which may be particularly pronounced when recreational activities are pursued in dark and clement conditions, can partially explain the opportunity structure for street robbery.

However if guardians effectively protect victims (see more below), the mere presence of people in outdoor places is not sufficient for explaining robbery occurrence. For that we need to consider social factors such as *who* is present and what activities they are engaged in, and how these contribute to the criminogeneity of places. The social mix of people in a micro-temporal place will likely alter an offender's decision making. A motivated offender might perceive others in a setting as suitable *or* unsuitable targets, capable *or* incapable guardians. On this basis I posit that all unsuitable targets fall into one of the categories of guardians from the offender's perspective.

The situational and social environment is likely to influence an offender's perception of who is a capable versus an incapable guardian. Impaired visibility, whether this is through adverse weather conditions or the absence of light, means that an offender can be more confident that their actions will go unnoticed. The social dimension of the setting (i.e. who is there, for what activities, and in the context of what social rules) may well alter the offender's perception of what Tilley (2009) calls the *credibility* of a guardian. Hence, even if an offender can be seen by others, if those others do not present a threat in terms of physicality, the guardian is incapable of protecting the victim in a direct way. Instead it might be the case that they are more likely to act as *passive* guardians and call the police or alert others (Leclerc & Reynald, 2015), although this might not be obvious to the offender.

Considered in this way, social and situational elements of the environmental backcloth contribute to the risk-effort-reward calculus that offenders are presumed to employ under the rubric of the rational choice perspective (Cornish & Clarke, 1986). These elements can affect the social processes governing the effectiveness of informal social control – exerted through guardianship – which has important implications for crime prevention. In short, the constellation of the people present in a micro-temporal place, with their individual and composite characteristics, can produce the conditions that are favourable (or not) for robbery occurrence.

Limitations of the research

This research was solely dependent on secondary data sources which, as mentioned elsewhere in this thesis, have some notable shortcomings for micro-level spatio-temporal research. The foremost pertain to police-recorded crime data, which are frequently criticised for not including the *dark figure* of crime (Maguire, 2007). In Chapter 2, I suggested that police-recorded crime data is reliant on the memory of the victim, which may be imperfect. Moreover, street robbery takes place in indefinite locations; those types of public places that are referred to as 'non-addressables' as they are unrelated to a postal address. These are not easily geocoded by police gazetteer systems. Hence, both spatial and temporal inaccuracies may creep into the robbery recording process which may impinge on analysis that uses these data. In this research I sought to minimise the impact of these inaccuracies.

The other secondary data sources – weather and astronomical data – were used to approximate the natural environmental conditions of the robbery events in this research. Evidently, these lacked the precision that would ideally be required. The study on darkness in Chapter 4 only measured natural light; it was not able to account for man-made street lighting or moonlight. This may be an important influence on the likelihood of robbery occurrence, but it was out of the scope of the research to collect street-level estimates of artificial light and no data were available on night-time illumination from the moon. These inaccuracies may have encroached on the precision of the analytic findings, but were nevertheless unavoidable.

One of the aspects of the robbery event that was not explored was whether attempted robberies, comprising around 15 per cent of the data, differed from successful ones. In her analysis of theft from the person and street robbery Thompson (2014) found that, in contrast to victim characteristics, situational incident characteristics were important predictors of whether an offence was 'completed' or not. Important insights about the function of guardianship, and as a corollary,

informal social control, may be gleaned from the analysis of these different data samples in future work.

The routine activity theoretic framework used in this thesis has some notable flaws; chief among them are that the causal processes underpinning crime causation are underdeveloped (Wikström et al., 2010). Since the analytic procedures in this research were concerned with correlational relationships between the environment and street robbery no definitive causal statements can be made in relation to *why* particular offenders targeted particular victims in micro-temporal places. There are undoubtedly many features of the environment, including the characteristics of the offender and victim, missing from these analyses. That said, the findings *can* be used to generate advancements in theory as to *why* some human mobility patterns produce confluences of victims and offenders in settings where effective guardianship is not present, and the impact this has on spatio-temporal patterns of robbery. This is the focus of the next section.

The most critical shortcoming of this research is that it was not able to directly measure target, offender or guardian density. This is true of all research done in the tradition of the routine activity approach, and undermines the testing of the theoretical propositions of this theory and its intellectual cousin, crime pattern theory. In the later section on future research I expand on the types of data and techniques that might be employed to overcome this.

It goes without saying that the results from one study are never the definitive evidential word on a topic. It remains to be seen whether the results produced in this research are generalizable to other regions, climates, cultures, or crime types. Whilst the findings are in line with predictions made from the routine activity approach, replication studies will be needed to establish the external validity of the claims made herein.

Summary

Taken together, the findings generated in this research indicate that routine activity patterns hold considerable explanatory weight for spatio-temporal patterns in street robbery. In particular, time demarcated for discretionary, or recreational, activities appears to be strongly coupled with variability in temporal patterns in robbery. The natural environment; that is, weather and lighting conditions is suggested to have a direct bearing on who spends time in public space at these times (i.e. evenings and weekends) which is argued to be the mechanism which underpins spatio-temporal patterns in robbery.

Consistent with predictions from crime pattern theory, robbery victims were found to be victimised in space-time propinquity to facilities that have a strong bearing on obligatory (e.g. school attendance) and discretionary activities (e.g. socialising at bars). From this it was inferred that specific victim sub-groups, such as school pupils and university students, form a distinct victim backcloth on which offenders depend to commit their robberies (whether opportunistically or not). Facilities associated with a range of population sub-groups were found to have a wider spectrum of victim types victimised in their environs.

In sum, I argue that to understand the spatio-temporal patterns of robbery it is necessary to consider the drivers behind the spatio-temporal mobility of victims, offenders and guardians. The natural and built environments contribute to the contextual conditions that make robbery a more attractive prospect to offenders. Importantly, the relationship between robbery and the on-street population is not linear - in some circumstances increased use of public space might encourage offences (e.g. better weather) and in others (e.g. darkness) reduced use might facilitate offences. This demonstrates the importance of taking a disaggregate approach to analysis. Hence, the answer to the question 'what makes a place criminogenic for street robbery at some times and not others' is an interaction between the blend of people – victims, offenders and guardians - using a space at a particular time, combined with the attendant social climate and physical environment.

7.2 Implications for theory

This analysis has yielded a number of findings which fill a gap within the criminological literature. In this section I expand on the ramifications of these findings for existing theory on crime causation. The underpinning argument is that people's routine activity patterns produce the ambient (i.e. street) population, which in turn produces confluences of actors in the crime event. The arguments made are particularly salient to street robbery, but can potentially be extended to other types of interpersonal crime such as violence between strangers.

At a broad level of abstraction, changing societal routines might impact on the frequency and spatiotemporal distribution of street robbery. For example, the demise of the UK pub and nightclub industries has been widely-documented in the media in the last decade²². This is attributed to increased levels of alcohol consumption in the home (Jennings, 2011), the diversification of the leisure industry (Greater London Authority, 2007) and, speculatively, the shift to social interaction on

²² See <u>http://www.telegraph.co.uk/finance/newsbysector/retailandconsumer/11283995/The-real-reasons-for-the-tragic-demise-of-the-British-pub-industry.html</u> for one account.

social media and other forms of entertainment provided by technology²³. Since this research has shown – in keeping with much of the literature – that pubs and nightclubs are associated with robbery occurrence, it follows that a reduction in patronage equates to a reduction in the volume of suitable targets and motivated offenders circulating in these areas. Whilst it was not possible to measure this in the study area, the decline of the pub and nightclub industry is a putative explanation for the steady drop in robberies seen across the UK in the last decade, and may have wider implications for the *crime drop* literature (Tseloni et al., 2010; Farrell et al., 2011).

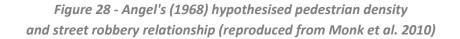
A central theme of this thesis has been the critical role of guardianship in the robbery event. As outlined in Chapter 2, Reynald (2009b) categorises the dimensions of effective guardianship into: 1) the availability of guardians; 2) their capability for monitoring; and 3) their willingness to intervene. In what follows I consider theoretically plausible spatial and temporal influences on these three dimensions. The next section is primarily concerned with the availability of guardians.

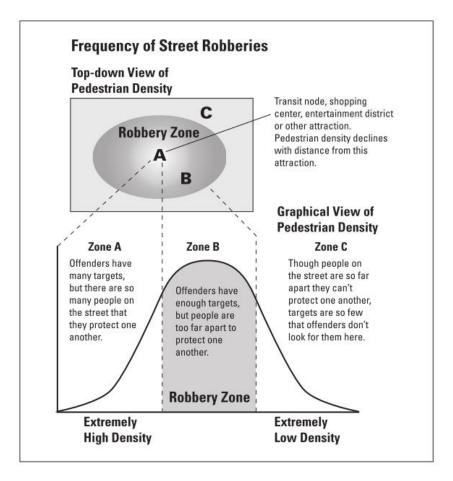
Pedestrian density

As indicated throughout this research, the natural and physical environments have a bearing on the human mobility patterns that underpin pedestrian density. While the relationship between street robbery and urban centres appears to be ubiquitous in the research literature (Flatley et al., 2010), it is not necessarily the case that increases in pedestrian density equate to increases in robbery occurrence. Hence, the frequency of street robbery in urban environments such as the city centre might not be a function of victimisation risk *per se* (Wikström, 1995). Instead, the relationship between the pedestrian, or ambient, population on the street is theorised as being more complex than just a linear correlation.

Set in the annals of environmental criminology is Angel's (1968) hypothesis pertaining to pedestrian traffic intensity and street robbery (Brantingham & Brantingham, 1993b; 1995; Clarke et al., 1996). Angel argued that robberies were unlikely to occur when the streets were too crowded or too empty. He posited that different types of land use would affect the probability that a witness would be in spatial range of an offence being committed. Hence, places with a very high volume of pedestrian traffic would have plenty of potential victims, but also (in the terminology of environmental criminologists) many guardians. Conversely, low traffic places would not contain enough suitable victims to attract offenders. Instead, moderately populated places create a *critical intensity zone* where street crimes are hypothesised to take place. Monk et al. (2010) created a useful schematic to visualise these suppositions (see Figure 28).

²³ <u>http://www.theguardian.com/commentisfree/2015/aug/11/clubs-closing-nightlife-uk</u>





Due to the prohibitive costs of collecting fine-grain pedestrian population data, and inhibited by the rarity of street robbery occurrence (even in high crime areas), Angel's hypothesis has yet to be directly tested. Partial tests using proxy variables for pedestrian traffic have produced mixed results. For example, Block and Block (2000) in their study of robbery and rapid transit stations operationalise the intensity of place use with distances measured from robberies to stations. Their findings lend support to Angel's hypothesis.

Clarke et al. (1996) similarly studied the public transportation system in the form of robberies on subway station platforms. This analysis used hourly passenger data (measured by the counts of people entering and exiting a sample of stations) for two consecutive days and police recorded robberies that occurred on the platforms of the sampled stations. The findings revealed that station robbery rates were inversely correlated with passenger densities. Hence, subway robbery appeared to be more strongly related to low passenger density. This trend was intensified for the late-night/early-hours period.

Clarke et al. (1996) suggest that subway platforms are fundamentally different from street settings. In essence, in hours of infrequent trains, platforms represent a temporary capsule environment where passengers are static. In contrast, in sparsely populated streets people are more likely to be in motion. Thus, their findings are not generalizable to the wider streetscape. In addition, Clarke et al. (1996) suggest that, as proposed by Angel, predatory robbers might depend on the moderately populated areas to seek out suitable targets, whereas opportunistic street robberies might be precipitated by settings with a low density of people.

A study on violent crime in Chicago by Browning and Jackson (2013) attempted to model pedestrian density more directly. These scholars employed video data, collected via systematic social observation (Raudenbush & Sampson, 1999), which captured the presence of people on street segments between 7AM and 7PM. Consistent with Angel's hypothesis, they found that a curvilinear relationship existed between what they termed *active street prevalence* (defined as at least one adult on the street segment at the time of observation) and violence. This finding held for both police-recorded homicide data and victimisation data on violence. They concluded that neighbourhoods with a preponderance of active streets benefitted from "the regulatory effects of spatially dispersed monitoring" (2013: 1012).

Whilst Browning and Jackson's (2013) study provides support for the plausibility of Angel's hypothesis, the limitations of their data on active streets meant that they could not model the pedestrian density in the night-time period when violent crime was most notably concentrated. Moreover, the authors posited that the same finding might not be generalizable for premeditated robbery, which is strongly and positively related to increased commercial and residential density (Browning et al., 2010). In sum, robustly testing Angel's pedestrian density hypothesis requires specific situational data that relate to the timing of street robbery occurrence which, for understandable reasons, has yet to be collected on a scale that would permit analysis with street robbery volumes.

All of the studies discussed in this section commonly note that the critical intensity zone is likely to vary according to routines over the course of the day and other temporal dimensions (Block & Block, 2000; Clarke et al., 1996; Monk et al., 2010). The research in this thesis supports this view. Thus, street robbery concentration is a product of the dosage of victims, offenders and guardians, which in turn is dictated by the spatio-temporal configuration of routine activities. This speaks to the first step of Reynald's (2009b) taxonomy of effective guardianship – the *availability* of guardians. The next section focuses on the other two steps: the *capability* of guardians and their *willingness to intervene*.

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Territoriality, land use and informal social control

In Chapter 2 I asserted that the situational conditions which foster effective guardianship are both environmental and social in nature. As demonstrated throughout this thesis, the environmental backcloth which provides the context for robbery occurrence is in constant flux, and thus it is plausible that the dynamics of effective guardianship similarly fluctuate across space and time. In particular, effective guardianship may be conditional on where people are at a given time, with whom, and under what social conditions (i.e. what routine activities are they performing in what social climates). Thus it is posited here that there are situational inducements that affect the effectiveness of guardianship, as originally conceived of by Felson (1987).

Taking the space dimension first, it is valuable to return to some of the founding principles of the crime-environment nexus literature. To recapitulate from Chapter 2, both Jacobs (1962) and Newman (1972) maintained that the flow of people on the streets was relevant to crime control, albeit they held divergent positons on the impact of the presence of strangers. Newman further proposed that territoriality exhibited by residents was crucial to realising the aims of defensible space.

Taylor (1988) reconceptualised Newman's concept of territoriality by integrating the underlying social processes into a new model of *human territorial functioning*. In his work he set out several tenets: that territorial functioning is highly place specific; it is a group-based process; and it is dependent on "some minimal bonds of acquaintanceship or interaction among the members of the group in question" (Taylor 1988: 5). Consonant to this, most other crime-design theories place a similar emphasis on the homogeneity of residents, and/or the social ties between them (Reynald & Elffers, 2009). Whereas much of this body of literature concentrates on property crime, Taylor et al. (1984) demonstrate that local social ties strengthen territorial functioning when predicting reductions in calls for service for interpersonal violence such as assault and robbery.

Both Jacobs (1962) and Taylor (1988) describe similar associations between land use and pedestrian traffic - that mixed-use neighbourhoods increase street activity. Unlike Jacobs though, Taylor views the pervading effect of 'outsiders' as increasing the sense of anonymity, which consequently causes a sense of insecurity among residents and a reluctance to use public space. Taylor purported that the interposing of commercial land use in residential spaces generates interstitial areas in the distribution of territoriality. The findings of Browning and colleagues (2010) provide evidence for Taylor's hypothesis that mixed land use is criminogenic for robbery. Interestingly, homicide and aggravated assault conformed to the predicted effects of Jacob's model, whereby the effect of

mixed land use was predicted to have a non-linear effect. Browning et al. (2010) construe this as robbery taking place over a shorter period of time and therefore being easier to commit unnoticed.

The role of strangers in the informal social control processes that are presumed to underpin crime prevention are thus a contentiously debated issue (Reynald & Elffers, 2009). A growing body of evidence suggests that more accessible, and therefore populated, streets are associated with increased crimes such as burglary (Davies & Johnson, 2015). It follows that more accessible areas provide greater prospects for 'outsiders' to pass through them. Coupled with this, higher pedestrian activity increases the difficulty for identifying suspicious behaviour (Roncek, 1981), thus inhibiting people's ability to monitor their surroundings effectively.

Towards a conceptual model of the mechanisms of temporal robbery patterns

Figure 29 is an attempt to draw these theorised causal processes together in a conceptual diagram, representing some generalised relationships. This shows that, on the left-hand side, the natural environment has little effect on obligatory activities, resulting in consistent mobility patterns which produce the predicable presence of victims in space-time settings. In turn this may create stable opportunities for offenders to exploit, thus increasing robbery. Consistent mobility patterns may conversely generate protective factors such as strong territorial functioning and hence reduce robbery.

The built environment concentrates people into land uses associated with obligatory activities on weekday daytimes, producing a high-moderate density of people *on the street* (at particular times such as commuting periods and lunch time) which may be causally related to victims in predictable space-time patterns. Such a density of people on the street may consequently engender more informal social control, as there is a greater availability of potential passers-by. The social environment in these places is characterised by a homogeneous population (people who share the same obligatory routine activities) which is arguably related to stronger social ties and subsequent stronger territorial functioning. Together these factors facilitate more informal social control which, along with opportunities in the form of victims in predictable space-time settings, may be causally related to stable temporal patterns of robbery.

In contrast, on the right-hand side of Figure 29, natural environment conditions (such as bad weather or darkness) can suppress discretionary activities which can result in varying mobility patterns, which produces less predictable patterns of victim availability in space-time settings. The varying mobility patterns may consequently lead to weak territorial functioning (as people are not familiar with the social rules of the setting). The built environment which hosts recreational land

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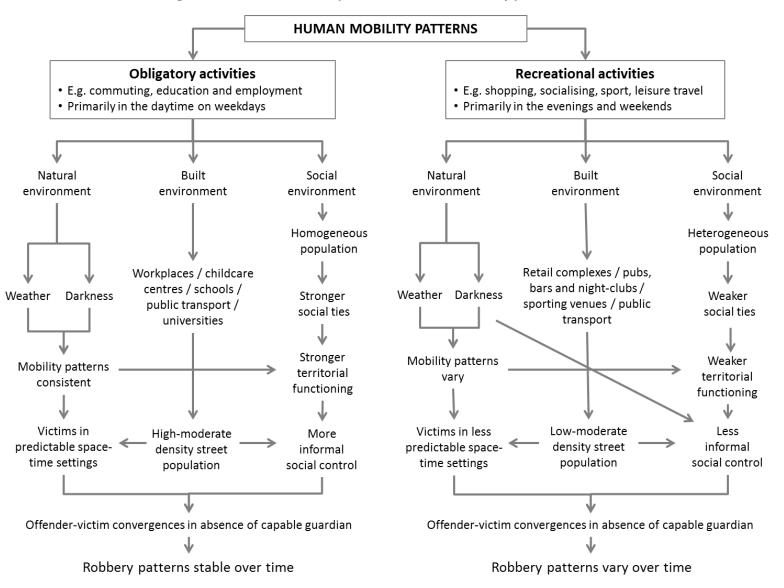


Figure 29 - Theorised causal processes related to robbery patterns in time

uses concentrates people, but this is likely to result in a low-moderate density of people *on the street* (at particular times), which can bring about victims in less-predictable space-time patterns and also less informal social control. These settings have a heterogeneous population, leading to weaker social ties and weaker territorial functioning, which, along with the varying mobility patterns contribute to less informal social control. Ultimately this is posited as causing irregular confluences of offenders and victims in the absence of capable guardians, and hence, produces robbery patterns that vary over time.

It is clear that Figure 29 is oversimplifying the causal processes at play in explaining how and why victims and offenders interact in space and time. It certainly cannot account for the heterogeneous range of scenarios documented in the robbery literature in Chapter 6 - in particular the difference between opportunistic and purposeful offending. The distinction between obligatory and discretionary activities is also not as delineated as this schematic suggests. Commuting is arguably an obligatory activity, but occurring in discretionary time. Shopping may be recreational or utilitarian in nature. Thus, as stated in Chapter 5, obligatory and discretionary activities lie on a continuum not expressed in Figure 29. Finally, these theorised causal processes are not predicting robbery *levels* (i.e. low or high crime), but their value instead lies in attempting to explain spatio-temporal patterns in robbery.

The situational dynamics of guardianship

In city centre areas, where much of the street robbery in my study took place, people of different social backgrounds congregate for short periods, thus producing a fluid heterogeneous environment. Such a concurrence of strangers produces low social integration and weak social ties. At least at some times, these places are also characterised by a permissive social climate where youths congregate in the absence of adults and people socialise and take intoxicating substances (Wikström, 1995). The anonymity afforded to people in these conditions is important, for it may undermine guardianship and informal social control (Roncek, 1981; Roncek & Maier, 1991).

While guardianship and informal social control are conceptually similar, Hollis et al. (2013) make the distinction that informal social control conveys an intentional process, whereas guardianship is unintentional. Taylor (1988) proposes that territorial functioning is comprised of both purposive and passive components, and hence it transcends both of these formulations of crime control. From the research presented in this thesis, I posit that territorial functioning is weak in the areas in which street robbery generally occurs; those city centres and pathways that intersperse the urban landscape. This is due to the lack of social ties among the people who converge in these spaces,

which undermines their familiarity with one another's routines and the expected norms for that setting (Groff, 2015). In brief, urban areas are impersonal places, which impede parochial and public forms of social control (Taylor, 1988).

Whether this, in turn, undermines the ability of bystanders to identify behaviour that precipitates street robbery, and their willingness to intervene should an event occur, is an unresolved question. Whilst many scholars presume that the willingness of guardians to intervene in a crime event is contingent on their feelings of territoriality and sense of goodwill or responsibility to the victim (Gillis & Hagan, 1982; Leclerc & Reynald, 2015; Taylor et al., 1984; Wikström, 1995), empirical evidence in support of this supposition is thin on the ground. Indeed, in their study of violence Browning and Jackson (2013) found that the relationship between active streets and homicide appeared to function autonomously to social ties. They proffered that even if bystanders are unwilling to intervene in a violent offence occurring in their vicinity, their mere presence discourages violence. This chimes with Hollis-Peel and colleagues' (2011) assertion that the most important tasks for guardians are being available and monitoring the area.

The situational inducements for guardianship share similarities with the situational inducements for offending, in that both the physical and social environment must stimulate and/or facilitate action (Wortley, 2008). As stressed throughout this thesis it is theoretically plausible that effective guardianship is dynamic over time, so that in conditions of darkness, poor weather, or when particular sub-groups of the population converge, the availability and capability of guardians to monitor their environment is eroded. With highly urbanised areas such as city centres attracting a large turnover of visitors to the area, it cannot be assumed that guardianship – in the form of passers-by – will always be present to deter offending.

Traditionally crime control in these areas has been the responsibility of the police and the private security industry. However it seems that place managers (Eck & Weisburd, 1995) might be a more theoretically plausible control on reducing opportunities for robbery (and other crime types) in urban areas. Whilst akin to the original concept of guardians, place managers are individuals who are responsible for monitoring and controlling behaviour at specific places. This may be the primary role of their job (e.g. doorman, security guard), or a subsidiary role (e.g. newspaper kiosk worker, bus conductor). Thus, place managers control what Madensen and Eck (2012) call *proprietary places*, whereas guardians do not have any responsibility over places, but instead function to protect targets (see also Clarke & Eck, 2005).

On account of their professional role, the availability of place managers is somewhat more timestable and hence their ability to monitor their surroundings is greater than for police or passive guardians. Through habitually being in urban settings they are best poised to understand the *social legibility* of people, that is, which people belong in an area (Taylor, 1988). Similarly, they will understand the rhythms of activity better than the visitors to the area, and have a heightened capacity to identify suspicious or untoward behaviour.

Summary

As discerned in Chapter 2, social disorganisation theory assumes that informal social control is exerted by residents in their own neighbourhoods. Guardianship is a somewhat broader concept, relating to the presence of people *anywhere* whom might unintentionally inhibit criminal behaviour. The research presented in this thesis suggests that guardianship may be situationally influenced by the dynamic environmental backcloth, which relates to both physical and social contexts. Pedestrian density pertains to the *availability* of guardians, whereas the *capability* of guardians to monitor their surroundings can be influenced by visibility, instincts of territoriality and the ability to detect undesirable behaviour in a setting. Guardians' *willingness to intervene* may well be contingent on the social ties (or lack thereof) between those present in a setting (Gillis & Hagan, 1982). Considered collectively, these imply that guardianship may be a weak control in city centre areas which attract a medley of strangers, and that place managers might be a more effective means of inhibiting criminal behaviour.

7.3 Implications for practice

An ancillary objective of this research was to produce findings that might usefully inform crime prevention activities. To that end, in this section I outline the practical implications of the space-time patterns elicited from this research with respect to the existing literature on robbery prevention. These have an unashamedly problem-oriented focus; since proximal causes of offending are central to the crime science enterprise.

Inverting the opportunity hypothesis - that increased opportunities for crime, caused by spatiotemporal convergences of offenders and targets, increased crime rates – was the inspiration for the development of situational crime prevention - SCP (see Clarke, 1992; 1995). Hence, reduced opportunities should lead to reduced crime. Whilst not a theory *per se*, SCP provides a framework for identifying aspects of the environment which are amenable to manipulation; with the express purpose of blocking opportunities for crime. Under this rubric the *opportunity structure* is viewed as the immediate situational components of the context of crime (Cornish & Clarke, 2008). Many practical policies against crime have proliferated since the inception of SCP. The collection of case studies demonstrating its utility as a means of controlling crime grows apace (Clarke, 1997). Salient to this thesis, SCP efforts are typically directed to micro-places, since immediate opportunities for crime are structured within very small geographic areas, at specific times.

Presently, SCP has supplied 25 techniques that can be used to design crime prevention interventions; these are organised into five categories that align to mechanisms believed to causally inhibit crime. The first three comprise *increasing the effort* (of committing crime), *increasing the risks* (of apprehension) and *reducing the rewards*. Later additions include *reducing provocations* (Wortley, 1997; 1998) and *removing excuses* (Clarke & Homel, 1997). Proponents of SCP encourage these techniques to be directed to specifically-defined crime categories, since the opportunity structure for different expressions of criminal behaviour are manifestly dissimilar (Felson & Clarke, 1998). These mechanisms are used to organise the remainder of this section.

Increasing the effort

In the context of street robbery, *increasing the effort* requires a consideration of how offenders seek out and select their targets. In Chapter 6 I elucidated the research evidence on target selection by robbers; with the prominent point being made that opportunistic offenders often (albeit, not always) encounter their targets during the course of their own routine activities. Thus, the convergence settings for opportunistic offenders and victims are where their routine activities overlap. Predatory offenders, in contrast, may 'manufacture serendipity' (Jacobs, 2010) by circulating in target-rich areas. It therefore follows that if victims can be swiftly removed from these high-risk settings, offenders have to increase the effort they expend to locate a suitable victim – whether this is done intentionally or unintentionally.

Hence reducing target *availability* is one means of manipulating the frequency of victim-offender convergences. For example, when considering the problem of university students being victimised on their way home from nights out, Tilley and colleagues (2004) recommend increasing the late-night transportation options. Considering the frequency of late-night robbery in the study area, much of which occurs within the environs of pubs and bars, strengthening the transport options within the night-time economy would seem to be a prudent crime prevention strategy and should be a fundamental component of any city centre planning. Potentially, this could be extended to include school pupils commuting home from school, which may be especially important in the winter months when dark conditions are prevalent. Such public transport should be a safe environment in

itself, which may require situational measures such as CCTV and place managers in the form of conductors or stewards (Ceccato & Newton, 2015).

Increasing the risk

The mechanism of *increasing the risk* has the strongest connotations to the traditional activities of the police and other crime reduction agencies. High visibility police patrolling falls within this mechanism and is an enduring tactic that in recent years has become more proactive, more targeted and better studied by the research community (Sherman & Weisburd, 1995; Sorg et al., 2013; Wood et al., 2013). Research evidence to date on violence suggests that foot patrols are only effective in areas with pre-existing high levels of crime (Ratcliffe, Taniguchi, Groff & Wood, 2011). Since robbery is known to be one of the most spatially concentrated crime types (Chainey et al., 2008), primarily occurring in urban areas (see Chapter 3), it would seem that high visibility patrolling might be an effective tactic to employ for immediate crime control benefits (Jones & Tilly, 2004).

From the findings produced in this research it can be inferred that Glasgow city centre is the most suitable area in which to deploy high-visibility police patrolling. This is where it is hypothesised that multiple robbers search for victims. One of the advantages of targeting this area is that city centres usually, in addition to robbery, suffer a range of crime problems (see Newton, 2015) which means that police presence can be used to suppress a variety of criminal behaviour. It is though prudent to consider the temporal patterns in the data; as illustrated in Chapter 3. These showed that particular time periods – most notably the night-time hours – contained a large proportion of offending and thus offer the greatest prospects for robbery prevention. Accordingly, any patrolling strategy devised by the police needs to align to not just the *hot spots* but the *hot times* (Townsley & Pease, 2002). It may be the case that patrols are best suited to the seasonal spikes in robbery observed when the clocks change for daylight saving time in October, when conditions of darkness afford offenders favourable conditions for robbery. If operationally feasible, patrols might also be intensified when pleasant weather conditions encourage more people to use public space.

The tactic of high-visibility patrolling is though beset with a number of disadvantages. Chiefly, there is substantive evidence that patrolling is only effective whilst in operation, and does little to suppress crime outside of these hours (Ratcliffe et al., 2011). This pertains to the finding that deterrence is only associated with the visibility of the police (Kubrin, Messner, Deane, Mcgeever & Stucky, 2010). Moreover, persistent targeted patrolling might result in deterrence decay (Sorg et al., 2013); ostensibly because offenders adjust their estimation of risk over time (Sherman, 1990). Thus, to

optimise their effectiveness, patrols should aim to be short-term and rotated across numerous locations – a tactic referred to as 'pulse patrolling' in the UK (Tilley et al., 2004).

Displacement is a related concern. Evidence from a randomised control trial on foot patrol in Philadelphia suggested that spatial displacement of violent offences occurred whilst the patrol trial was underway (Ratcliffe et al., 2011). This however was not absolute, and net reductions in violence were experienced in the hotspot areas patrolled. A follow up study by the same researchers revealed that the spatial patterns of violent crimes migrated back to the patrol areas (from the displacement areas) after the trial had concluded (Sorg et al., 2013). This underscores the temporary and short-lived crime reductive effects of targeted patrol.

Of course, of vital importance is what police do whilst patrolling. They can gather intelligence on the prolific offenders operating in the area (Sorg & Taylor, 2011), apply stop and search tactics (Ashby and Tompson, 2015) or build relationships with the community (Wood et al., 2013). Salient to the study area, stop and search tactics could be aligned to the space-time patterns elicited in Chapter 3 to confiscate weapons that might be used in robbery (thus increasing the effort required).

Weisburd et al. (2015) recently reported on a police patrolling approach that looked to build collective efficacy in patrol areas amongst residents and business owners, by encouraging social ties between them and galvanising them into collective action. This has the potential to foster place management which, as discussed below, may be an important means of crime control at facilities which are associated with crime concentration. In all dealings with the public, offending and non-offending, care should be taken to embrace principles of procedural justice so that police-community relations are not undermined (Braga & Weisburd, 2010).

In sum, whilst targeted police patrols may be limited in the longevity of their effect, there is nevertheless some evidence that they can reduce robbery whilst they are in operation (Jones & Tilly, 2004). Since the research literature suggests that the effect of apprehension can be a strong deterrent to first-time robbery offenders (Feeney & Weir, 1975), it would seem that there is merit to this tactic as a crime prevention tool. To do so optimally, however, requires a thorough understanding of recent spatio-temporal patterns of robbery, as well as the victim profiles, and the careful production of tailored patrol strategies to the problem dynamics at a local level. Importantly, as revealed through this research, high-visibility patrols would be best directed to facilities associated with the routine activity patterns of suitable robbery victims.

As shown in Chapter 3, street robberies are typically over in minutes, and the timing of repeat events that happen in the same or nearby locations may be irregular. Therefore traditional police patrolling tactics are likely to be limited in their impact outside of chronic hotspots, as the chance of being present when a robbery occurs is infinitesimal. Instead, I now turn to the other controls from the problem analysis triangle (Figure 1 in Chapter 2); guardians and place managers.

To be effective guardians, like police officers, need to be present during the fleeting moments when robbery occurs. Their effectiveness, in terms of intervening in a crime, is thought to be contingent on their social ties to suitable victims (Gillis & Hagan, 1982; Reynald & Elffers, 2009). Manufacturing guardianship requires the conversion of non-guardians (or incapable guardians) to effective guardians. An example of this can be found in Tilley et al. (2004) who report that school pupils were encouraged to walk in groups on the way home from school, with older boys taking responsibility over younger ones. Thus people who are already acquainted offer a good means of enhancing guardianship in a setting. Similar initiatives to instil a sense of responsibility over one's acquaintances could be introduced to other victim types identified in Chapter 6 at the places and times when they are most likely to be victimised, such as university students in the evening and night-time hours near to their campuses or non-student bars.

In addition to the police, workers in criminogenic settings - such as the city centre area – are in the best position to act as *place managers* (Eck, 1994). For the reasons outlined in section 7.2, place managers are more likely to be present in the micro-temporal places when robbery concentrates. Mobilising and sensitising place managers is though likely to fall to the police, and is perhaps best initiated by multi-agency partnerships such as city centre management schemes. Other or supplementary partnerships might fruitfully be created between public transport operatives; security guards; schools; university security officers; shop owners; bar staff and door staff; and any other people with responsibility over the locations where robbery hotspots occur. Stockdale and Gresham (1998) report on the CityWatch Association operating in the Glasgow area, which indicates that such partnerships have been mobilised in the study area in the past.

Reducing the rewards

Altering target *attractiveness* offers prospects for reducing robbery through the mechanism of reducing the rewards. Offender accounts report that opportunities are often identified through observing a victim with conspicuous items of value (e.g. cash, mobile phones, consumer goods [Brookman et al., 2007]). Thus if potential victims can be discouraged from visibly displaying high value items in space-time sensitive criminogenic settings, this might stymie offenders identifying good opportunities for robbery. Crime prevention publicity campaigns are one means of fostering a

change in victim self-protective behaviour (Thompson, 2014) and can have an indirect positive effect by alerting observant offenders to the increased police attention (Barthe, 2004).

To be effective, publicity campaigns need to convey a clearly defined message and be targeted towards a very specific audience in a very specific location (Johnson & Bowers, 2003; Barthe, 2004). From the findings in Chapter 6 we can refine this statement further to add that (potential) victim audiences in micro-temporal spaces might benefit best from such messages; since their victimisation risk plausibly varies through the course of their daily routine activities. Hence, students can be forewarned of the risks of stumbling home after a night out; school pupils can be educated about keeping their valuables out of sight on their journeys home from school; visitors to the city centre and patrons of the night-time economy can be encouraged to stay in the company of others.

Tailored crime prevention advice hence needs to be dispensed to different audiences with slightly different messages, depending on the drivers underpinning the robbery problems associated with the respective groups. Doing so requires a good understanding of victim profiles in different micro-temporal places, as revealed by the analysis presented in Chapter 6. Whether (or not) the publicity messages should inform people of specific risky times and places requires careful consideration to balance the twin aims of not increasing fear of crime and being instructive so that potential victims are receptive to the message.

Removing provocations and removing excuses

Removing provocations and *reducing excuses* are two mechanisms that speak to the precipitators of criminal behaviour. These originate from Wortley's (2001) critique of the rational choice perspective, and relate to reducing the emotional triggers that can cause criminal behaviour – those "factors within the crime setting itself that may prompt, provoke, pressure, or permit an individual to offend" (Wortley, 2008: 49). For example, minimising truanting removes emotional inducements, such as boredom, to commit robbery (amongst other crimes). This would also block the opportunity for offending in school-hours. Thus, multi-agency partnership interventions that involve schools, police and social services can be levelled at reducing truancy rates in the study area and encourage young people to spend their time constructively in educational settings (Stockdale & Gresham, 1998).

That said, schools can concentrate offenders and victims in space and time (Jacob & Lefgren, 2003). The analysis in Chapter 6 revealed that school pupils comprise over ten per cent of the victim population (see Table 34), and are likely to be victimised in the environs of schools after the school day. Therefore, one strategy to reduce emotional inducements to offending involves multi-agency

partnerships working with schools to implement effective anti-bullying policies (Stockdale & Gresham, 1998). This has the potential to fire multiple mechanisms which relate to removing provocations and reducing excuses: 1) it can reduce the number of disputes, which can be a precursor to some robbery events (Brookman et al., 2007); 2) it can neutralise peer pressure to be involved in bullying or offending behaviour; 3) it can set rules; and 4) it can alert consciences.

Summary

Taken collectively, a myriad of possible interventions exist that might prevent robbery in the study area. As emphasised throughout this section, these need to be tailored to the spatio-temporal dynamics of robbery concentration, such as facilities related to victims' routine activities and the attributes of victims that make them attractive to offenders. The mechanism of increasing the risk offers the greatest range of tactics that might be employed to deter offending behaviour. However it should be acknowledged that some interventions span multiple mechanisms (e.g. anti-bullying policies). From the discussion on high-visibility patrolling it should be evident that police presence is just a drop in the ocean when it comes to providing 'eyes on the street' (Jacobs, 1962). Therefore other controls, such as the manufacturing of guardianship and the mobilisation of place managers should play a central role in robbery prevention at the times and places where robbery is found to concentrate.

The role of crime prevention spans many agencies, and consequently, the messages that emerge from this thesis are relevant to urban planners; local government; public transport providers; policy-makers; teachers; communities; universities; and other public agencies. A cost-effective approach is therefore to foster multi-agency working within a problem-solving framework. Also known as problem-oriented policing, this involves breaking crime problems into their constituent parts and devising tailored responses that address the facilitating criminogenic conditions (Eck, 2006). The findings from this research can usefully inform such an endeavour.

7.4 Avenues for future research

Each of the constituent parts of this research has generated new questions deserving of scholarly attention. Complementing what has already been discussed in the individual empirical Chapters, this final section suggests some avenues for future research. These centre on sources of data and analytic techniques that can be used to generate further insight into the micro-level time-varying dynamics of robbery settings.

To advance the present findings, more precise measures of the situational characteristics of robbery settings are needed at the micro-level. Collecting these would involve going beyond the secondary data sets which are conventionally available. Instead, primary data collection such as street surveys, pedestrian modelling counts and ethnographic studies on the users of micro-spaces would assist in ascertaining the criminogenic features of micro-temporal places. In particular, observational studies on the social psychology of hotspot areas at hot times would provide insights into the mechanisms facilitating or inhibiting informal social control processes, since measuring guardianship directly can only be achieved through observation (Hollis-Peel et al., 2011). Undertaking such research would be time-intensive and hence this is best done at well-defined micro-settings.

The ambient (i.e. street) population is notoriously challenging to estimate, and this becomes particularly pronounced when trying to account for the important temporal variation in pedestrian traffic. This impinges on estimating victim, offender and guardian density which, as argued throughout this thesis, is central to understanding spatio-temporal patterns in robbery. Malleson and Andresen (2015) have recently shown that crowd-sourced social media data can be used as a proxy for ambient population at improved levels of spatial and temporal resolution; however this does of course bias the data towards certain technology-savvy groups. Future studies on the dynamics of the ambient population might prosper from modelling strategies that seek to integrate pedestrian throughput potential, calculated with betweenness metrics (see Davies & Johnson, 2015), with the size and capacity of workplaces and public facilities. Such facilities could be broadly delineated into those that primarily operate in the daytime – that is, workplaces and shops – and those that are open for business in the evenings, such as bars and entertainment venues. Scholars in other time-sensitive studies have begun to collect data on business opening hours (Haberman & Ratcliffe, 2015; Ruiter & Steenbeek, 2015). In taking such an approach, time-sensitive ambient populations could be approximated.

The lack of fine-grained ambient population data is a serious impediment to environmental criminology research. A contemporary approach which circumvents this problem is agent-based modelling (Groff, 2007). This uses a simulation environment to examine the macro-level patterns of the interactions of agents who are assigned individual characteristics and general behavioural rules (Johnson & Groff, 2014). It is thus a promising and cost-effective means of testing the tenets of the routine activity approach and allied theoretical frameworks.

The findings on the drivers of human mobility patterns generated in this research could be used to add some nuanced individual-level variation into the models that have been produced to date (see Groff, 2007). For example, agents can be assigned victim characteristics such as age, gender and

occupation, and these could be used to dictate the proportion of time spent at home, at work, and at facilities associated with recreational pursuits. At a broader level, natural environmental conditions such as darkness and weather can be mathematically formalised into probabilities of the time agents spend in public settings. Finally, agents traversing through city centre areas and the convergence settings of youths (i.e. facilities which attract youths in the absence of parental controls) at specific times could be made to be more attractive as targets, or more motivated to act criminally, to reflect the theorised effect of a permissive social climate and the impact of anonymity (see section 7.2). The macro-level crime patterns emerging from such analysis could be compared to the spatio-temporal rhythms in street robbery data to ascertain their theoretical plausibility.

Much of the crime and place literature to date has been solely correlational in nature (albeit with increasingly sophisticated modelling techniques). Yet, to establish the causal mechanisms underlying crime concentration requires not only correlation between variables, but a *counterfactual* (Woodward, 2004). Monte-Carlo simulation offers one means of generating a counterfactual for the presence and absence of criminogenic features in a setting. Data generated through this process could then be used as a pseudo control group in statistical models to test whether those features are significantly related to crime events. For example whether the presence of darkness is significantly correlated with robbery, in comparison to a random set of times when robbery did not occur.

An experimental method such as this has the potential to advance the study of the relationship between crime and place by producing a higher degree of confidence in the observed effects than can be achieved through traditional correlation analyses. This final suggestion relates to an analytic strategy that was devised for this thesis, but could not be executed due to delays with obtaining census data approximating the daytime (ambient) population in various spatial units. When these data are published I intend to advance the findings of the present research via this analytic strategy.

7.5 Conclusion

The aim of this thesis was to expand knowledge as to *why* street robbery clusters contemporaneously in space and time. The research question **'what makes a place criminogenic for street robbery at some times and not others?'** was used to frame seven hypotheses relating to some of the features of the environment that can be considered integral to a criminogenic backcloth (Brantingham & Brantingham, 1993a). These pertained to the time-varying influence of darkness; weather conditions; and the use of land by different groups. Through a variety of statistical methods, and data analyses at various micro-units of analysis, it was shown that all of these environmental features are associated with temporal patterns in robbery.

Importantly, the micro-level approach taken in this thesis engendered nuanced findings that elicit insight into the characteristics of settings where street robbery concentrates. In turn, this facilitated theorising on the mechanisms governing the micro-level encounters of victims and offenders, and the processes by which effective guardianship is situationally influenced by the dynamic backcloth. Collectively this advances our understanding of crime causation and provides, it is hoped, a platform for further research on micro-temporal patterns in crime data.

Hence, the answer to the question 'what makes a place criminogenic for street robbery at some times and not others' is an interaction between the blend of people – victims, offenders and guardians - using a space at a particular time, combined with the attendant social climate and physical environment. The findings revealed through the current study can be used to refine efforts to predict where and when street robbery is likely, thus enabling prevention activities to be aligned accordingly. Ultimately we must never lose sight of the fact that each crime record relates to a victim and their hardship. Our motivation should never waver from striving to reduce those numbers. Understanding the causal processes between place, time and crime is an important pathway to achieving this.

APPENDIX A

This methodological appendix describes the analytic process that was undertaken to determine the criminogenic reach of each facility type on robbery, for both Euclidean and street network buffer distances. The results of the location quotients (LQs) generated with the Euclidean buffers are also presented for information. These were not used in the regression analyses in Chapter 6, but provide an interesting comparison to the LQs derived from the street network buffers.

Euclidean buffers

The 'multiple ring buffer' tool in ArcGIS was used to create Euclidean distance buffers around train stations, schools and universities at distances in increments of 50 metres up to 1,000 metres, and for 0 - 5 metres to capture the immediate environment. A spatial join was subsequently performed to calculate the number of robberies that fell within each buffer distance, for each facility type, and the LQ was computed from the resulting robbery density.

Potentially due to the fact that public houses and bars are often located in very close proximity to one another, ArcGIS could not run the standard 'multiple ring buffer' dissolve option on these point data. For this facility type, multiple *overlapping* buffers were created, and the robbery counts were produced for each using the process described above. Subsequently, the area and robbery counts for the immediately smaller buffer were subtracted from the totals before the robbery density was calculated. The final LQs were computed using this adjusted robbery density as the numerator. All LQs produced from the Euclidean buffers are shown in Table 41.

For all the facility types in Table 41 the LQs, and hence the robbery concentration, are greatest in the shortest distance Euclidean buffer areas, and thereafter decrease monotonically. Consistent with other research (Groff, 2013b; Ratcliffe, 2012), bars have acute robbery concentration in the immediate vicinity (0 - 5 metres) – over 400 times more robbery than elsewhere in the settlement area, and this decays sharply over the ensuing buffer distances. At distances greater than 100 metres the LQ falls below the threshold of two (see section 6.2).

The land use data for schools and universities were available in polygonal form, meaning that *on site* LQs could be generated for these facility types. For example the LQ for schools indicates that the robbery is 277 per cent higher on school sites than the regional trend. Interestingly, the robbery concentration at schools is highly localised to 'on the site' or in the immediate vicinity (0 - 5 metres). Subsequently the rate of robbery per area is on par with the wider trend.

Buffer distance	Pubs and bars	Schools	Stations	Universities
On site	-	3.77	-	2.98
0 - 5 metres	406.73	<u>2.35</u>	0	0
5 - 50 metres	12.33	0.94	6.37	6.60
50 - 100 metres	<u>5.56</u>	1.16	5.54	5.40
100 - 150 metres	1.85	1.11	4.80	4.93
150 - 200 metres	1.69	1.13	4.19	4.78
200 - 250 metres	1.26	0.96	2.95	4.79
250 - 300 metres	0.84	0.85	2.47	4.77
300 - 350 metres	0.79	0.77	<u>2.31</u>	3.23
350 - 400 metres	0.58	0.64	1.77	3.59
400 - 450 metres	0.49	0.58	1.59	3.68
450 - 500 metres	0.47	0.47	1.16	3.43
500 - 550 metres	0.32	0.37	1.00	3.22
550 - 600 metres	0.31	0.33	0.92	2.78
600 - 650 metres	0.29	0.28	0.78	2.57
650 - 700 metres	0.24	0.32	0.68	2.41
700 - 750 metres	0.21	0.18	0.57	2.59
750 - 800 metres	0.20	0.20	0.52	2.45
800 - 850 metres	0.17	0.21	0.44	<u>2.23</u>
850 - 900 metres	0.18	0.17	0.46	1.41
900 - 950 metres	0.12	0.15	0.37	1.50
950 – 1,000 metres	0.13	0.17	0.38	1.42

Table 41 – Euclidean buffer derived location quotients for all four facility types (underlined values denote the distance threshold)

Train stations exhibit robbery concentration (with an LQ over two) up to 350 metres from the facility, whereas for universities and further education institutions this distance extends up to 850 metres. Comparing the LQs in Table 41 with Table 36 we see that on the whole street network buffers produce higher LQ values as they contain a smaller area, and thus produce a higher robbery density. At very small distances (e.g. 5 - 50 metres) Euclidean buffers can have a higher LQ than street network buffers.

Network buffer creation

Groff (2011; 2013a; 2013b) used *service areas* generated in ArcGIS to create polygonal network buffers in Seattle. In a grid-like street network this creates diamond shapes around the facility of interest. However, on the irregular UK street network the service areas generated from this function did not appear to be appropriate. Manipulating the 'trim polygon' parameter for the service area tool improved the topological relationship between the service areas and the facilities, but was still considered to be unfit for purpose (see Figure 30a).

A different analysis was thus performed whereby service areas were computed using the 'lines' parameter. This generated network buffer line segments along the street network from the point of the network closest to the centroid of the facility in the distance increments specified in section 6.2. These lines are displayed in Figure 30b.

Some universities had the street network running through the campus. Supplementary analysis was done using re-processed ITN data that excluded street segments interspersing the university campuses. Put differently, these network buffers were created along the streets that fell *outside* the polygons representing the university campuses. However, for unknown reasons, using this re-processed ITN data in ArcGIS resulted in a handful of universities not having network buffers created. The original street network data was thus retained to compute these buffers. For all the facility types ArcGIS appeared to select the street segment that fell closest to the centroid of the facility to begin calculating the network distances, hence potentially resulting in inaccuracies in the distance calculations.

Based on the distribution in Table 5 (in Chapter 3) individual buffers of 25 metres were created externally to the network buffer segments. This distance was chosen as it encapsulated approximately three-quarter of all robberies. An example of the resulting network derived buffers can be seen in Figure 30c. A spatial join was then performed to count the number of robberies falling within each buffer distance, and LQs were subsequently computed.

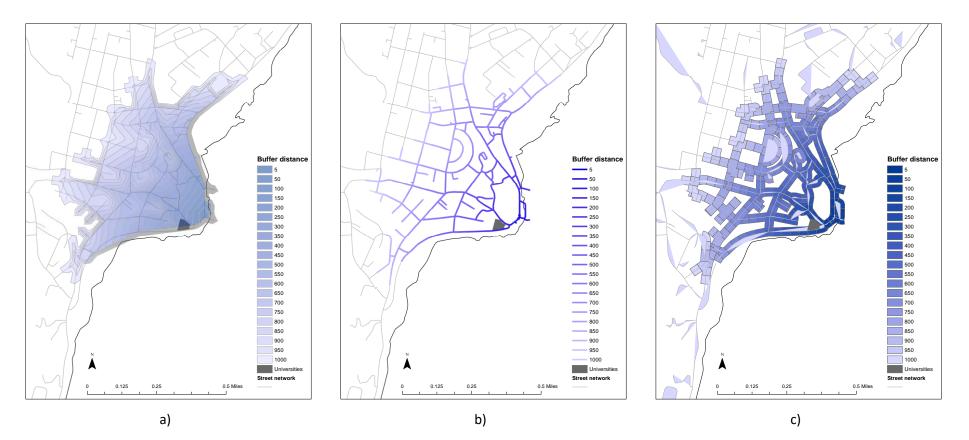


Figure 30 – Illustration of service areas generated in ArcGIS using a) polygons, b) lines and c) buffered lines

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